An Integrated Assessment of Air Pollutant Abatement Opportunities in a Computable General Equilibrium Framework

by

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Abstract

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Air pollution and anthropogenic greenhouse gas emission reduction policies are desirable to reduce smog, tropospheric concentrations of ozone precursors, acid rain, and other adverse effects on human health, the environment, and the economy. While reduction of both air pollution and greenhouse gas emissions is often attained through economic instruments such as taxes, caps, and other regulation, emission controls in both developed and developing countries often achieves reduction through policies that target air pollution and greenhouse gases separately. However, because the emissions of both air pollution and greenhouse gases are often intrinsically linked to the same sources, any attempt to design policies to optimally achieve desired reduction goals must consider the complex socioeconomic interactions that produce both kinds of emissions as they collectively react to regulatory constraints.

Integrated assessment models have often been used as tools to inform policy design by representing the interactions between technology, economics, policy, and the environment within a self-contained framework. Many contemporary integrated assessment models consider emissions of greenhouse gases while others also consider air pollution emissions. While greenhouse gas reduction opportunities are often represented endogenously in the models through the availability of backstop technologies such as carbon capture and storage or by shifts away from carbon intensive to less carbon intensive production, representation of air pollutant reduction has largely been represented within integrated assessment models exogenously based on empirically observed trends. By treating air pollution reduction opportunities exogenously, such models are unable to represent many key considerations important to policy design including the true economic impact of air pollutant reduction policy, the impact such policies may have on the market penetration of backstop energy production technologies, and the ancillary co-benefits of air pollution policy on greenhouse gas emission reduction.

To overcome current limitations imposed by exogenous representation of air pollution abatement, I develop a new method for representing air pollutant abatement opportunities endogenously within an integrated assessment model designed using a computable general equilibrium (CGE) framework. CGE models are often used to simulate macroeconomic activity based on microeconomic theory and are well suited for emission policy analysis because of their ability to represent the interactions between multiple economic regions and sectors, to connect emission sources to economic activity, and to accommodate a large degree of technological detail not captured by other macroeconomic models. Using this new method, I demonstrate how the parameters needed to represent the abatement opportunities are derived from engineering data on specific abatement technologies available within each economic sector and for distinct fuel types as air pollution is largely generated through the combustion of hydrocarbon fuels. With both the methodology and parameterization established, I represent sulfur dioxide and nitrous oxide abatement opportunities in the MIT Emissions Prediction and Policy Analysis (EPPA) model and compare model results with previous representations of air quality pollutant reduction methodologies based on exogenous trends. An example of how the model predicts co-benefits for CO_2 reduction and policy costs in China is then presented. Overall, the new model demonstrates the ability to fully capture important effects relevant to policy design not captured in integrated assessment models where air pollution abatement is exogenously represented.

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In Nichomachean Ethics, Aristotle states that "intellectual excellence owes its birth and growth mainly to instruction..." Throughout my education at MIT I have been impressed that there is very little we can truly call our own, especially when it comes to academic achievement and success. If there is any "intellectual excellence" I may have achieved in my attempt to improve existing methodologies and tools for studying the interaction of air pollutant abatement costs on the economy and environment I owe it largely to the instruction and guidance of my advisors, colleagues, and sponsor.

Specifically, I would like to thank my advisor John Reilly for giving me the opportunity to work in the Joint Program, for granting me the perfect balance of flexibility to explore this topic according to my own interests while providing sound guidance as I moved into new and uncharted territory, and for his jovial and amiable nature which is enough to brighten anyone's spirits through cold Cambridge winters. I would also like to thank Sergey Paltsev and Mustafa Babiker for their unmatched expertise and for unlocking to me the mysteries of the EPPA model. Many thanks go to M. Mayer, R. Hyman, M. Sarofim, A. de Masin, and M. Webster for blazing the trail on pollution abatement opportunity representation. A special thanks to Noelle Selin for providing thoughtful guidance and direction regarding the best ways to consider air pollutants within a general equilibrium framework. I hope this work benefits her future studies pertaining to air pollutant health effects. Thanks to my colleagues Valarie Karplus, Christopher Gillespie, Jennifer Morris and Jonathan Baker for their patience and resilience in answering a never ending string of GAMS related questions and for helping me remain sane through countless compilation and convergence issues with the EPPA model. A very special thanks to BP for graciously sponsoring this work, especially to Andrew Cockerill and Rosie Albinson for making me feel welcome as a member of the BP Project.

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1 Introduction

Over the last 200 years the movement toward industrialized economies in many countries has had an unprecedented effect on economic development and change in societal structure. Of particular significance, the movement toward industrialization has had a profound impact on short and long term trends in population growth, the increase in demand for transport of goods and the availability and ease of international transportation, the expansion of manufacturing as a key component of economic development, the increase in life expectancy, the organization of labor and the ethics regarding treatment of workers, urbanization and the migration of populations toward large metropolitan areas, and improvements in standards of living and overall societal welfare. While much has been said and argued regarding both the beneficial and adverse aspects of industrialized economic activity, what remains certain is that current trends indicate an increase in future industrial growth in developed and developing economies that see industrialization as key to improving economic productivity and prosperity.

One of the major challenges introduced by the continued expansion of industrialization, and in particular the shift towards more manufacturing based and energy intensive economies in developing countries, has been the identification, management, and control of the many adverse effects of industrialization on human health and the environment (Grosman and Krueger 1995). Byproducts of processes used in mining, manufacturing, transportation, chemical use and production, and energy generation and consumption, have led to unprecedented levels of air and water contamination. More recently, anthropogenic emissions of greenhouse gases and the potential for catastrophic risks associated with climate change introduce additional risks to human health, the environment, and economic prosperity that are intrinsically complex in nature with much remaining to be understood (Solomon, et al. 2007). Often referred to as externalities, these adverse effects of industrial activity result in additional costs to society that are not incurred, priced, or valued by the agents that produce them and diminish from many of the societal and economic benefits that increased industrialization is intended to achieve.

In order to reduce the negative impact of industrial externalities on the environment and human health, policy controls have been put in place in many developed and developing countries to reduce levels of pollution associated with industrial economic activities. However, to fully reap all the benefits of industrialized economic growth, while at the same time minimizing the adverse effects of industrial externalities, policy instruments must be designed carefully. One the one hand, policy controls should be stringent enough to reduce external costs of pollution by mitigating adverse effects as much as possible, however, if policy controls are too stringent, the cost of the policy in terms of reduced economic activity and production may greatly exceed the benefits of reduced external costs and can be just as damaging as the externalities themselves. Ideally, policy to mitigate externalities caused by industrial activity should strike an optimal balance between both extremes, however, this is often challenging to achieve in practice. In order to attain optimal policy solutions that meet the required policy objectives while at the same time minimizing the associated impact on economic activity and growth, the availability of tools capable of providing rigorous policy analysis to compare benefits and tradeoffs of different policy options has become increasingly important (Sanstad and Greening 1998).

As the identification and understanding of specific adverse pollution-related externalities of industrialization has improved, so has the realization that the interactions between the corresponding industrial activities, and the various human health and environmental policy controls designed to mitigate adverse effects, are increasingly complex. While some interactions are well defined and fall well within the confines of a single discipline or methodology (epidemiology, atmospheric chemistry, ecology, economics, oceanography, etc.), other interactions are much more far reaching and extend beyond a single framework of analysis or area of expertise. It is the policy considerations affected by these more interdisciplinary kinds of interactions that are often of most importance but are also the most difficult to analyze and understand. To better address this category of policy considerations, integrated assessment methodologies spanning multiple disciplines have been developed and are increasingly used to inform policy decision making and evaluate the effectiveness and tradeoffs of various policy designs.

While most of the work in the integrated assessment modeling community over the last few decades has focused on climate change and understanding and quantifying the interrelated effects associated with greenhouse gas reduction policy controls, greenhouse gas emissions, energy technology mix, energy costs, economic impact on welfare and GDP, and the corresponding impact on various earth systems and the environment; significantly less work focused on how the more traditional non-greenhouse gas air pollutants affect these interactions and are effected by climate policy (Rotmans and van Asselt 2003).

Considering the interactions of policies aimed at the so-called traditional air pollutants is important for multiple reasons. First, since non-greenhouse gas air pollution is largely emitted from the same processes and same sources that emit carbon and other greenhouse gases, greenhouse gas and air pollution policy is intrinsically linked and the stringency of a policy control on one species of pollutant can have a significant impact on the others. Any policy analysis that evaluates greenhouse gas and air pollution policy in isolation will not be capable of capturing how the policies interact and how the economy responds to the controls associated with each policy. Second, much of the policy consideration regarding permissible levels of air pollution is determined by weighing the benefits of less pollution on human mortality and morbidity against the technology costs due to investment in air pollution abatement for existing pollution intensive activities, or the loss in productivity incurred by shifting to less pollution intensive activities. As these considerations span multiple disciplines, the questions of most interest in informing air pollution policy are inherently integrated. Finally, as will be shown shortly in an overview of the traditional air pollutants, since the costs of externalities associated with traditional air pollutants are currently much better understood and involve significantly less uncertainty than the damage costs of global warming externalities, the benefits of air pollution policy are more readily quantifiable. In the event policy that reduces greenhouse gases provides significant ancillary benefits for air pollution reduction, the argument for more stringent air quality regulation can provide a strong argument for the benefits of climate policy while the benefits and costs of damages from climate change remain less quantifiable and remain subject to greater uncertainty. This may especially be the case in developing countries such as China that increasingly are placing a higher premium on air quality as standards of living improve.

Because many of the more important considerations regarding air pollution policy can only be addressed in a multidisciplinary manner, in this thesis I address the development of sound methodologies for properly analyzing the interrelated effects of air pollution on the environment and economy, and the interaction among policies that target both greenhouse gas and traditional air pollution species. Of critical importance in capturing these interrelated effects are a sound understanding and representation of the opportunities and costs of air pollution emission reduction technologies that are available for various kinds of industrial activities. As previously stated, while much integrated assessment work recently has been done to assess costs and interactions associated with greenhouse gas emissions and climate change, less work has been done to represent the so called traditional air pollutants in the same kind of interrelated framework providing a rich opportunity for improvement in this area. While some methodologies have been proposed, as will be shown, many contain drawbacks that limit their ability to fully represent the underlying economics and nonlinear feedback effects that can dominate the economic response to shocks induced by air pollution controls.

To provide researchers and policymakers with better tools when considering the interrelated impacts of air pollution on energy, the economy, human health, and the environment, I present a new methodology that seeks to overcome many of the limitations of previous methodologies. The motivation of the new method is to provide a "bottom-up in a top-down" framework that directly accounts for "bottom-up" individual technical detail of specific abatement technologies that are crucial to proper representation of air pollution control opportunities, but does so in a way that can be utilized in a larger "top-down" integrated assessment modeling framework that shines light on many macro-level effects such as total pollution emissions, change in the energy technology mix, and GDP.

In the remainder of Section 1, I give an overview of the impact of traditional air pollutants on human health and the environment and in so doing establish the argument for why a strong policy response to air pollution is desirable. I then consider the role of integrated assessment as a tool to inform particular considerations of air pollution policy decision making. I then consider a specific kind of integrated assessment framework—computable general equilibrium—and evaluate the appropriateness of the framework for the kinds of policy questions of interest and identify the kinds of questions computable general equilibrium is most adept at analyzing. Limitations when using computable general equilibrium for policy analysis are then considered and some of the caveats of the methodology are identified. The kinds of air pollution policy questions that are most appropriate using the new methodology, and that would be difficult to address under any other kind of framework, are also considered. I then introduce a specific model that employs the computable general equilibrium framework—the MIT Emission Prediction and Policy Analysis model—which is later used as the primary tool for implementing the proposed new air pollution methodology.

In Section 2, I present an overview of previous approaches to represent the traditional air pollutants in an integrated assessment framework and identify some of the advantages and weaknesses of the methodologies. A variety of approaches for representing air pollutants in the MIT Emission Prediction and Policy Analysis model are then considered and specific shortcomings are identified that the new methodology is able to overcome. In Section 3, I provide a rigorous derivation of the new methodology as implemented in the computable general equilibrium framework and give an overview of key considerations for parameterizing the methodology for representation in any computable general equilibrium model. Parameters for representing SO_2 and NO_x specifically for the MIT Emission Prediction and Policy Analysis model are then derived, but the approach used can be applied generally to any computable general equilibrium integrated assessment model where the primary difference between EPPA and such models is the level of aggregation of the regions, sectors, and energy production mix. I also identify some of the shortcomings of the proposed methodology and suggest a series of improvements for future work. In Section 4, I present the results of an air pollution policy scenario run in EPPA using the new air pollution representation and compare specific interconnected effects predicted by the new methodology with some of the previous methodologies for representing air pollution in EPPA. An analysis using the new methodology to evaluate the potential for co-benefits of air pollution policy in reducing greenhouse gas emissions in China and the USA is then presented. This provides an example of the kinds of analysis and policy relevant questions that can be explored using the new methodology in an integrated assessment framework that cannot be done using methodologies that treat the economy, greenhouse gas emissions, energy generation mix, air pollution emissions, abatement opportunities and technologies, and policy mechanisms in isolation.

In Section 5, I conclude by recapitulating the value of this work in improving integrated assessment tools used to inform air pollution related policy analysis and summarize the primary improvements that have been made. A number of next steps for representing air pollution reduction opportunities in a computable general equilibrium framework are then discussed that have been identified and are necessary to build on the improvements made in this thesis going forward.

1.1 Impact of Air Pollution on Human Health and the Environment

The motivation for policy controls aimed at reducing traditional air pollutants, also commonly referred to as urban pollutants, has come from an extensive body of studies that collectively provide strong evidence of many adverse effects on human health and the environment due to air pollution. While the definition of an air pollutant can be very broad and can include anything from fluorinated greenhouse gases to dust, in this work we define air pollutants as the subset currently regulated in the United States by the Environmental Protection Agency (EPA) under the National Ambient Air Quality Standards. This subset of air pollutants includes tropospheric ozone (O_3), particulate matter (PM), carbon monoxide (CO), nitrogen oxides (NO_x), sulfur dioxide (SO_2), and lead (Pb) (U.S. EPA 2011). These pollutants are widely referred to as the criteria pollutants since the level of allowable atmospheric concentrations, and consequently the level of allowable emissions, is determined by permissible levels of exposure as identified by human-health based epidemiological studies and other scientific criteria. Extensive epidemiological studies have evaluated the effects of air pollutants on human mortality and morbidity while ecological studies have affirmed negative impacts of air pollution on the environment. We will now consider the primary sources of these pollutants from industrial economic activities and the impact of these pollutants on human health and the environment. In so doing we establish the argument for why reducing emissions of these pollutants is desirable from a policy standpoint.

Ozone (O_3)

Although ozone plays an important role in the stratosphere by absorbing high frequency ultraviolet light, in the lower troposphere it is highly undesirable. Produced largely by the reaction of other pollutants known as ozone precursors—primarily NO_x, CO, and volatile organic compounds (VOCs)—ozone has been shown to harm human health by causing significant disturbances to the respiratory system including coughing and throat irritation, reduced lung function, aggravation of asthma with heightened sensitivity to allergens, increased susceptibility to respiratory infections, inflammation and damage to the lining of the lungs, and exacerbation of other respiratory illnesses. While some of the adverse effects are acute, others can be chronic and lead to increased mortality rates in highly populated urban areas. Using data for the National Morbidity, Mortality, and Air Pollution Study for 95 large urban U.S. communities from 1987-2000, Bell et al. (2004) estimate the national average relative rate of mortality that can be associated with exposure to tropospheric ozone (Bell, et al. 2004). The study finds that a 10 part per billion (ppb) increase in tropospheric ozone results in a 0.52% increase in daily mortality and a 0.64% increase in cardiovascular and respiratory mortality. Other studies estimate that future global health and economic impacts of ozone could results in additional health costs of $580 billion (2000 USD) and mortalities from acute exposure exceeding 2 million by the year 2050 (Selin, et al. 2009).

In addition to adverse effects on human health, tropospheric ozone has also been found to reduce agricultural crop and commercial forest yields and increase the likelihood of various kinds of plant disease. Using a global 1° x 1° 2-way atmospheric chemical transport model, Van Dingenen et al. estimate the annual loss in crop yield in 2000 due to tropospheric ozone to be between 7% and 12% for wheat, 6% and 16% for soybeans, 3% and 4% for rice and 3% to 5% for maize (Van Dingenen, et al. 2009). The worldwide annual economic cost of lost agricultural yield in 2000 is estimated to be between $14-$26 billion (2000 USD).

Particulate Matter (PM)

Adverse health effects from particulate matter (PM) are similar to ozone. For the respiratory system, common health effects include coughing, difficulty breathing and irritation of the airways, decreased lung function, aggravation of asthma, and development of chronic bronchitis. For the cardiovascular system, PM exposure can lead to irregular heartbeat, heat attacks, and premature death in people with heart or lung disease. An overview of many the adverse health effects associated with inhalation of (PM) is provided by Pope and Dockery and is given in **Figure 1.1** (Pope III and Dockery 2006).

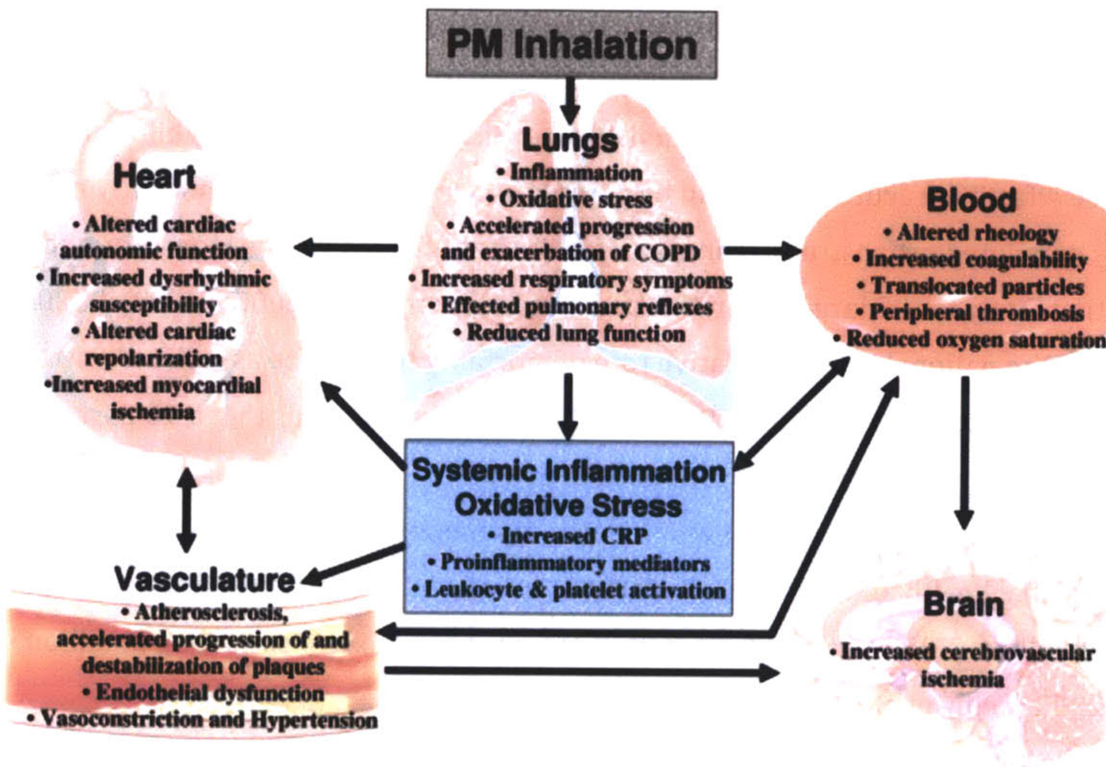


Figure 1.1. Adverse human health effects caused by exposure to particulate matter (PM). (As given in Pope and Dockery 2006.)

While PM generally refers to any particulate pollution, anthropogenic PM is largely comprised of sulfates originating from SO_2 emissions from sulfur in coal and oil combustion, nitrates originating from NO_x formation from the combustion of hydrocarbons, black carbon (BC) from incomplete hydrocarbon combustion, organic carbon (OC), trace metals from fossil fuel combustion and smelting, and other minerals and dust from soil disruption occurring from agriculture and forest-related activities. The relation between exposure to increased concentrations of PM and human mortality has been studied extensively over the years and has been shown to be strongly correlated. In their original landmark 1993 paper "An Association between Air Pollution and Mortality in Six U.S. Cities," Dockery et al. track PM pollution concentrations and the survival rate of a random selection of adults over a 16 year period in six U.S. cities with varying concentrations of PM. The study demonstrates that although mortality rates from PM are most strongly associated with cigarette smoking, after compensating for smoking and other confounding risk factors, the adjusted mortality-rate ratio (RR) for the most polluted cities considered in the study compared with the least polluted was 1.26 (the mortality-rate ratio is defined as the ratio of observed deaths to expected deaths in an epidemiological study). From this Dockery et al. conclude that air pollution is positively associated with death from lung cancer and cardiopulmonary disease (Dockery, et al. 1993).

Since the original Harvard Six Cities study, there has been an extensive body of literature that has expanded the investigation of PM health effects to other cities and has increased the sample sizes of the epidemiological studies in an attempt to more robustly quantify the relationship between mortality and increased PM exposure. In the most recent direct follow up to the Harvard Six Cities study, Laden et al. revisit the original six U.S. cities but extend the period of consideration from 1989 through 1998 to observe mortality effects in a period where PM concentrations are decreasing (Laden, et al. 2006). Over the initial period of increasing PM concentrations from 1974-1989, Laden et al. reaffirm an increase in mortality associated with each $10\mu g/m^3$ increase in $PM_{2.5}$ concentrations and calculate an RR of 1.27 for lung cancer and an RR of 1.28 for cardiovascular deaths. These numbers are consistent with the 1.26 total RR for a $10\mu g/m^3$ increase in $PM_{2.5}$ as shown in the original six cities study. However, in the second period from 1990-1998 where atmospheric sampling of $PM_{2.5}$ showed a decrease in concentrations—largely due to more stringent National Ambient Air Quality Standards— Laden et al. demonstrate that overall mortality actually improved showing a 0.73 RR for a $10\mu g/m^3$ reduction in $PM_{2.5}$. This demonstrates that while an increase in $PM_{2.5}$ concentration led to increased mortality, a reduction in $PM_{2.5}$ concentrations reduced mortality.

Greatly expanding the epidemiological study beyond the original six cities, Pope et al. consider the effect of decreased PM exposure on mortality in over 211 counties in 51 major U.S. metropolitan areas. The study concludes that a decrease of 10 ug/m^3 in the concentration of $PM_{2.5}$ resulted in an increased life expectancy of 0.61+/-0.20 year and that the reduction in $PM_{2.5}$ air pollution accounted for as much as 15% of the overall increase in life expectancy in some of the study areas (Pope III, Ezzati and Dockery, Fine-particulate Air Pollution and Life Expectancy in the United States 2009). Particular segments within the general populous may also be particularly prone to adverse health effects caused by PM and other pollution, especially asthmatics, the elderly, and children (O'Connor, et al. 2008).

Carbon Monoxide (CO)

Carbon monoxide is formed from the partial oxidation of carbon containing compounds when there is not enough oxygen available to form carbon dioxide. Formation of CO is therefore common in enclosures such as internal combustion engines or coal and gas furnaces where the availability of oxygen may be limited. As has already been mentioned, carbon monoxide is a primary precursor to tropospheric ozone formation and therefore contributes to all the adverse human health and environmental externalities associated with ozone as were given previously. In addition to being an ozone precursor, CO can also cause direct damage to human health by reducing the oxygen-carrying capacity of the blood. This in turn reduces the delivery of oxygen to vital bodily organs—such as the heart and brain—and to other tissues. At extremely high concentrations, respiration of CO can be fatal.

Nitrous Oxides (NO_x)

Various species of nitrogen oxides (such as NO, NO_2) are formed when nitrogen is present during combustion at high temperatures. Since nitrogen is plentiful in the atmosphere, NO_x emissions are common with any fossil fuel combustion regardless of the purity of the fuel. As has already been shown, NO_x is both an ozone precursor and leads to the formation of nitrate particulates and is therefore indirectly associate with all the adverse health and environmental effects already considered from exposure to ozone and PM. Independently, epidemiological studies suggest a positive association between increased NO_x concentrations, acute respiratory disease, and decreased pulmonary function (Kagawa 1984). NO_x is also the main precursor to the formation of nitric acid in the atmosphere which, when precipitates, leads to acidic rain, snow, and fog. Over an extended period of time, acid rain can cause significant damage to buildings and other structures, can damage trees and vegetation, and can cause acidification of bodies of water making them unsuitable for sustaining fish and other wildlife. NO_x emissions can also lead to large concentrations of nitrogen in bodies of water. Since nitrogen is a natural fertilizer, this can cause eutrophication where the nitrogen accelerates the growth of algae blooms. Such unnatural growth of algae has been shown to harm and kill fish and other marine life, throw off natural plant and animal diversity, and make recreational bodies of water unsuitable for human activities.

Sulfur Dioxide (SO_2)

Atmospheric concentrations of SO_2 stem largely from the combustion of fossil fuels that contain small traces of sulfur and other impurities. When fossil fuels burn, the sulfur reacts with oxygen in the atmosphere creating SO_2. Similar to NO_x, SO_2 is also a major precursor of fine particulate matter and leads to atmospheric particulate sulfates. Epidemiological studies suggest a positive association between increased concentrations of SO_2 and increased daily mortality, prevalence and persistence of cough and phlegm, morbidity and bronchial asthma, the symptomatic severity of asthma, and respiratory infection (Kagawa 1984). Atmospheric SO_2 also leads to the formation of sulfuric acid, and the associated damage caused by sulfuric acid rain.

Lead (Pb)

Historically, atmospheric concentrations of lead originated largely from the release of lead during the combustion of leaded gasoline. Due to more stringent regulatory controls by the EPA and the subsequent removal of Tetraethyl lead as an additive, leaded gasoline has almost entirely been phased out in the U.S. and concentrations of atmospheric lead in the U.S. have decreased by 94% between 1980 and 1999 (U.S. EPA 2011). Other sources of atmospheric concentrations of lead include metal processing—ferrous and nonferrous smelters—and battery manufacturing. The negative health effects associated with lead are well understood and include blood related disorders including damage to the kidneys and liver, heightened risk for neurological and brain disorders such as seizures and mental retardation, and other behavioral disorders. Young children and fetuses are especially susceptible to lead poisoning and damage to the nervous system.

1.2 Integrated Assessment as a Tool to Inform Policy Decision Making

As illustrated by the overview just presented of the many adverse health and environmental effects caused by traditional air pollutants, many important considerations that are of most interest when evaluating air pollution policy are multidisciplinary in nature and are not well confined to a single area of expertise or methodology. Of particular interest from a policy standpoint are: (1) how air pollution controls affect the energy generation mix as firms weigh the tradeoffs between paying for additional abatement from pollution intensive energy production, increasing input of less emission intensive energy production, moving to new non-emission intensive backstop generation technologies that do not clear the market in the absence of policy controls, or reducing energy as a primary input to production altogether; (2) how regional air pollution controls affect regional emissions; (3) the impact of air pollution controls on overall welfare and GDP; (4) the ancillary benefits of controls on certain species of pollutants on the reduction of emissions from other species (e.g the effect of SO_2 controls on carbon emissions); and (5) the effect of air pollution controls on adverse health impacts.

To help provide a structured framework within which expertise from various disciplines can be combined and inform policy decision making, integrated assessment models (IAMs) have become increasingly used over the last four decades. While most recent integrated assessment models have largely focused on global warming and climate change impacts, the definition of what an integrated assessment model entails remains fairly broad. One general definition given by William Nordhaus, considered by some to be one of the fathers of integrated assessment modeling of climate change impacts, is that, "Integrated Assessment Models can be defined as approaches that integrate knowledge from two or more domains into a single framework. These are sometimes theoretical but are increasingly computerized dynamic models of varying levels of complexity" (Nordhaus

2011). A second definition given by Parson and Fisher-Vanden is that, "Integrated assessment models seek to combine knowledge from multiple disciplines in formal integrated representations; inform policy-making, structure knowledge, and prioritize key uncertainties; and advance knowledge of broad system linkages and feedbacks, particularly between socioeconomic and biophysical processes" (Parson and Fisher-Vanden 1997).

This second definition is a bit more instructive in that it lays out some of the motivations and benefits of integrated assessment. First, in informing policy decision making, integrated assessment models can ultimately lead to recommendations regarding sound policy responses to complex problems; however, even if no straightforward recommendations are obtained, the process of going through an integrated assessment is still of great value as it helps guide policy makers in how to frame the policy evaluation process and identify the most important questions that should be considered regarding the complex problem at hand. Second, in structuring knowledge, integrated assessment models provide a coherent framework that can be used by both researchers and policy makers. Integrated assessment models help to organize an otherwise complex problem in the broader context of other policy relevant problems and can aid in exploring interconnected effects of a specific problem with other factors. This can be beneficial because it helps both policy makers and researchers from specific disciplines think more systematically about the interrelated elements of complex policy issues, and provides a format for identifying and quantifying key parameters. Third, in prioritizing key uncertainties, integrated assessment models help identify, clarify, and illuminate key kinds and sources of uncertainty and can help establish a better understanding of cause and effect chains within a large complex problem. Once the interdisciplinary components have been structured into a single system, key parameters can be evaluated to study the sensitivity and uncertainty in the overall model projections. Quantitatively looking at and evaluating complex problems using an integrated assessment model also helps to present the policy problem properly in terms of analyzing risk and highlights the importance of decision making under uncertainty as a key component of managing and reducing potential risks. In the case of climate change, this can lead to a proper formulation of the problem in terms of risk management and risk mitigation (Waugh 2011). Finally, in an effort to better understand causal connections, integrated assessment models provide insight into important linkages and feedbacks. This can aid both policy makers and researchers in setting priorities for future research and allocating resources to address the most pressing gaps in knowledge surrounding the complex problem.

The framework and methods used in integrated assessment have progressed significantly over the last four decades. Although most contemporary integrated assessment models focus on energy and climate change interactions, one of the first truly integrated assessments was the Climatic Impacts Assessment Program (CIAP) which was used to assess various impacts of stratospheric supersonic flight including jet engine design, atmospheric chemistry and radiation, and biological, economic, and social impacts (Grobecker, Coroniti and Cannon 1974). Around this same time, the first integrated assessment models of climate change began evolving from energy models that were used to explore ways of meeting energy demand by diversifying the U.S. energy technology mix and lessening dependence on oil and gas imports (Nordhaus 2011). One of the earliest energy models used for this purpose was the Energy Technology Assessment (ETA) model which was among the first to use non-linear computer algorithms to explore the economics of alternative fuels and electricity generation mix including synthetic fuels from coal, light water and fast breeder nuclear reactors, hydrogen from electrolysis, nuclear fusion, and central station solar power (Manne 1976). The introduction of mathematical programming models to study non-linear interconnected effects of both own and cross-price elasticities of demand on energy was particularly innovative and set the stage for the general computer-based approach of almost all integrated assessment models that have followed. Manne was also instrumental in developing some of the first energy and environmental models which were largely energy models with an emissions component. In these early models we see the first introduction of fuel-specific CO_2 emission coefficients which continue to play a central role in coupling greenhouse gas emissions to energy sources in contemporary integrated assessment models of climate change but are also widely used by the United Nations Framework Convention on Climate Change (UNFCCC) for greenhouse gas emissions reporting. A detailed overview of emission coefficients is given later in Section 2.1.

Building on these early developments, Nordhaus is credited with developing one of the first integrated assessment models to study the costs and benefits of climate policy response beyond mere emissions reporting that was done in the earlier energy/emissions models (Nordhaus 1977). In his earliest model, Nordhaus couples a very simple energy systems model based on macroeconomic theory that takes energy resources, income and population as inputs, and gives energy prices, energy consumption, and CO_2 emissions as outputs. The CO_2 emissions are then fed into a very simple atmosphere and climate model which determines the effect of CO_2 emissions on radiative forcing and global warming. Other early models used to project CO_2 emission pathways and the cost of meeting emissions constraints from particular energy scenarios include the Edmonds Reilly Model, which produced long-term CO_2 emission forecasts through disaggregation of fuel types, and by including regional detail, energy balance, and CO_2 energy flow accounting (Edmonds and Reilly 1983), and a linear input-output model built by the International Institute for Applied Systems Analysis (IIASA) (Hafele 1981).

While with earlier integrated assessment models, much of the focus was on maintaining transparency and simplicity so the models did not become "black boxes" that were convoluted and difficult to understand, starting in the late 1980's, we see integrated assessment models of climate change begin to grow in complexity as additional features were added in response to increased interest in the field, growing availability of funding for climate research, increased computing power, and most notably, the belief that managing climate change required a more detailed and in-depth understanding of the interactions among biophysical and socioeconomic domains. Among the most notable advances during this time are the inclusion of the non-CO_2 greenhouse gases (methane, nitrous oxide, and fluorinated gases) as first given in the Model of Warming Commitment (Mintzer 1987), and more advanced environmental impacts models that in addition to radiative forcing began modeling other biophysical warming effects, such as sea-level rise as first given in the Integrated Model for the Assessment of the Greenhouse Effect (IMAGE) (J. Rotmans 1990).

Since these developments, integrated assessment models of climate change have continued to grow in their level of complexity as computing power has become more readily available and methodologies for integrating earth and human systems has improved. With additional computing power, the earth systems component of integrated assessment models have become increasingly detailed with some of the more advanced models containing coupled atmosphere-ocean-land surface sub-models with non-linear atmospheric chemistry representation of the interactions among gas species, three dimensional ocean representation, and a detailed terrestrial global sub-model of biogeophysical, ecological, and natural biogeochemical flux components (Sokolov, et al. 2005). These advanced model features have enabled integrated assessment models to address detailed ecological impacts of climate change beyond the simple "damage functions" invoked in simpler models such as the Dynamic Integrated Climate Economy (DICE) model developed by Nordhaus (Nordhaus 1993). With grid-level representation of the globe often approaching 0.5°x0.5° , or even 0.1°x0.1° spatial resolution in the most state of the art models, these advanced earth systems models directly represent in high resolution, both temporally and spatially, the policy implications of sea level change, acidification and the carbon cycle in oceans, land use change, impacts on hydrology and water resources, impacts on agriculture, forestry, bio-energy, ecosystem productivity, three dimensional atmospheric chemical and dynamic processes, three dimensional dynamics and biological and chemical impacts in the oceans, latitudinal and longitudinal temperature variation and precipitation, and various human health effects. A flow chart of the interconnected feedbacks of one of the more advanced earth system integrated assessment models, the MIT Integrated Global System Model (IGSM), is given in **Figure 1.2**.

The primary difference among the various contemporary integrated assessment models of climate change largely involves the level of regional and sectoral aggregation of emission species, economic sectors, and energy production technologies, the level of detail and complexity of the earth system component of the model, the time horizon for model projections, and the methodology chosen to represent the socioeconomic sub-model used to predict emission pathways in response to policy constraints, and the availability and cost of advanced fuels and energy generation.

As observed by Boulanger (2005), the socioeconomic component of contemporary integrated assessment models largely takes on a variety of forms including: neo-Keynesian macroeconomic models, computable general equilibrium models, centralized optimization models, and system dynamic models.

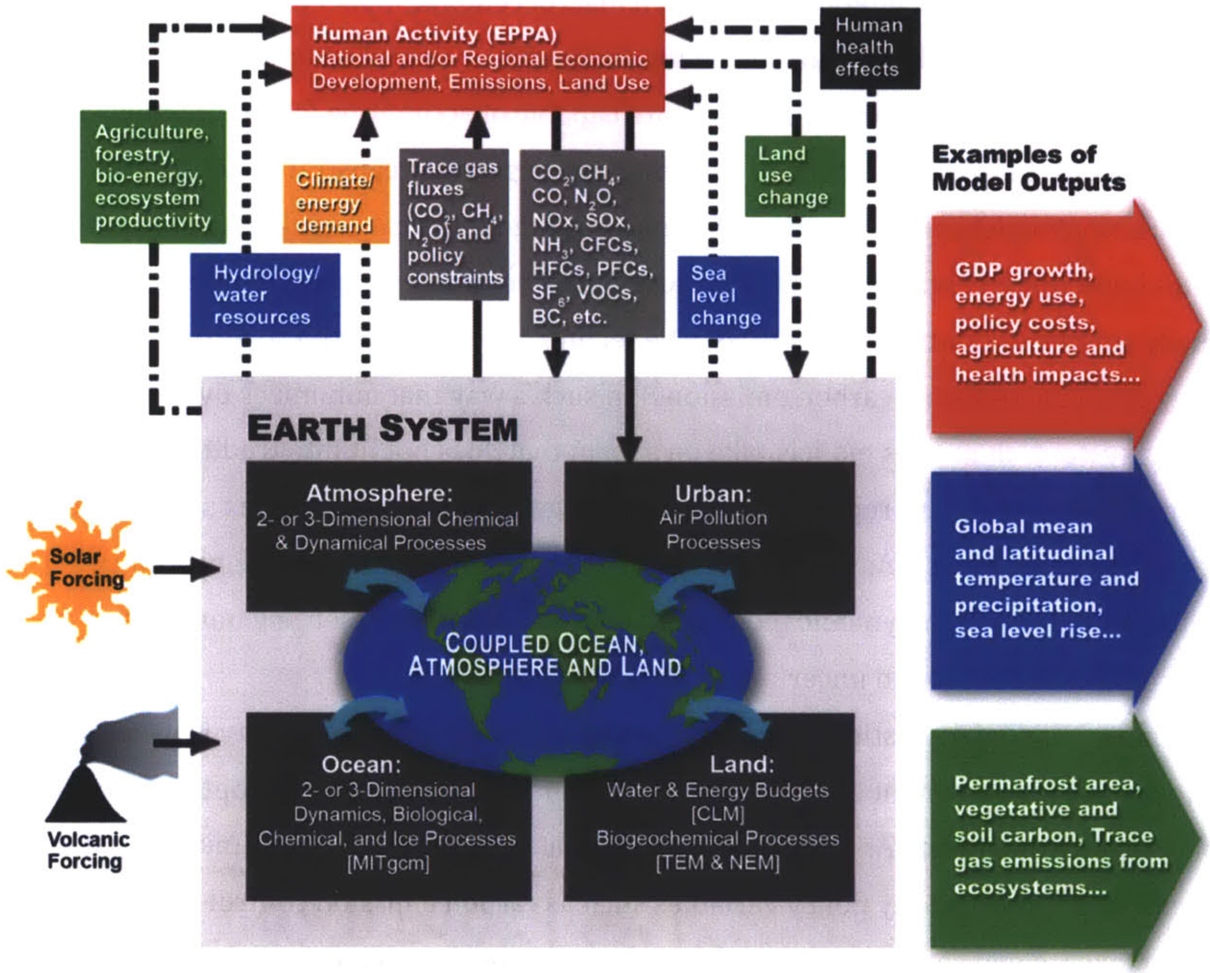


Figure 1.2. An advanced earth systems integrated assessment model, the MIT Integrated Global System Modeling (IGSM) framework.

Macroeconomic models involve a simulation system of simultaneous equations that are empirically calibrated by time-series or cross-sectoral data, and that deal with macro-level parameters such as GDP, price indices, output, and consumption. Because they do not model actions of individual agents the way microeconomic models do, the energy production representation of macroeconomic integrated assessment models is very simple and highly aggregated. In contrast, computable general equilibrium models are based on neo-classical economic theory that assumes an efficient market equilibrium where firms and consumers are profit and welfare maximizers respectively. Because of their ability to represent firm-level decision making regarding inputs to production, computable general equilibrium models have the potential to accommodate a larger degree of technological detail in production and energy sectors than macroeconomic models. Since prices and quantities of goods produced are solved for endogenously based on an original endowment of resources, general equilibrium models are capable of accounting for interconnect effects and shocks to the economy that can occur under a regulatory constraint. Centralized optimization models primarily focus on representing the decision-making on technology choice based on technology availability, cost, and other influencing parameters and are usually simple accounting frameworks. The technology mix is chosen so as to attain a given policy goal (e.g. reducing carbon emissions) in such a way that minimizes overall costs. Finally, systems dynamics models take on a form that does not fit into traditional economic theory but is designed to represents interactions generally in any complex system through the use of stocks, flows, and feedback loops. Because of the particular emphasis on feedback loops, system dynamic models are well suited for representing nonlinear interconnected effects and uncertainty.

Another important distinction in addition to what kind of methodology is used for the socioeconomic component of the model is whether the model is a policy optimization or policy evaluation model. As classified by Weyant et al. (1996), policy optimization models endeavor to "optimize key policy variables such as carbon emission control rates and carbon taxes, given certain policy goals (such as maximizing welfare or minimizing the cost of climate policy)." Policy optimization models tend to be less complex and are used primarily for cost-benefit or cost-effectiveness analysis to help identify optimal policy pathways over extended time periods usually on the order of hundreds of years. When used as cost benefit tools, such models are highly sensitive to the cost ascribed to, and the discount rate placed on, future economic and environmental damages making true cost-benefit analysis challenging (Weitzman 2007).

In contrast, policy evaluation models "try to evaluate the environmental, economic and social consequences of specific policy strategies" (Weyant, et al. 1996). In order to capture all the ways that a policy may affect the socioeconomic and biophysical systems, policy analysis models tend to be significantly more complex. The socioeconomic component can be as simple as a macroscopic Ramsey-type optimal growth model with highly aggregated detail of the energy and agricultural sectors, to a full-fledged computable general equilibrium model with comparatively much more disaggregated regional, sectoral, and technological detail. A summary of some of the most prominent contemporary integrated assessment models is given in **Table 1.1**.

Despite the significant progress made in integrated assessment modeling methodology over the last four decades, some of the ongoing challenges with integrated assessment include properly identifying what effects the model is and is not accurately representing, understanding what questions are most appropriate for assessment using an integrated modeling framework, and understanding the impact of sensitivity and uncertainty both within the model structure and architecture and among model parameters. Despite best efforts to represent all key influences, even the most thorough models do not correspond to reality and great care must be taken when interpreting results to acknowledge both what and how physical and socioeconomic process are being represented. As stated well by J. Rotmans, one of the early developers of the IMAGE model, "any attempt to fully represent a complex issue and its numerous interlinkages with other issues in a quantitative model is doomed to failure. Nevertheless, even a simplified but integrated model can provide a useful guide to complex issues and complement highly detailed models that cover only some parts of complex phenomena" (Rotmans and van Asselt 2003). In other words, while "top-down" integrated assessment models are highly valuable in informing certain key considerations of a complex policy question, highly detailed "bottom-up" models are equally important in understanding less interconnected problems with a smaller scope that are highly sensitive to key disaggregated detail. Rotmans goes on to list several strengths and weaknesses of integrated assessment models. Among the strengths Rotmans notes that integrated assessment models (1) allow for the exploration of interactions and feedbacks which studies limited to a single discipline or have a much narrower scope cannot offer, (2) provide flexible and rapid simulation tools that can be used to prototype modeling implementation of new concepts and scientific insights, (3) provide a self-consistent framework that helps in identifying critical uncertainties and gaps in knowledge of the complex problem, and (4) integrated assessment models provide a tool for researchers and policy analysts to communicate risk and the policy options posed by a complex problem.

Table 1.1. Prominent Integrated Assessment Models Used to Inform Policy Design

Model	Regions	Greenhouse Gases	Timeline; Time Step	Socioeconomic Model	Earth Systems Model[1]	Source
EPPA/ IGSM	16	CO_2, CH_4, N_2O, PFCs, HFCs, SF_6	2100; 5 year	Computable General Equilibrium	Advanced	Paltsev et al. (2005), Sokolov et al. (2005)
IMAGE[2]	26	CO_2, CH_4, N_2O, PFCs, HFCs, SF_6	2100; 10 year	Macroscopic Energy Demand	Advanced	Bouwman et al. (2006)
MESSAGE	11	CO_2, CH_4, N_2O, PFCs, HFCs, SF_6	(Variable); 10 year	Systems Engineering Optimization	Basic	Messner et al. (1995)
AIM	21	CO_2	2100; 10 year	Computable General Equilibrium	Advanced	Kainuma et al. (2008)
GCAM	14	CO_2, CH_4, N_2O, PFCs, HFCs, SF_6	2095; 15 year	Macroeconomic Market Equilibrium	Basic	GCAM (2006)
ReMIND	11	CO_2, CH_4, N_2O	2100; 5 year	Macroeconomic Ramsey-type Optimal Growth	Basic	Potsdam (2008)
GEM-E3	21	CO_2	2030, 1 year	Computable General Equilibrium	Basic	Leuven et al. (2008)
MERGE	9	CO_2, CH_4, N_2O	2150; 10 year	Computable General Equilibrium	Basic	MERGE (2004)
WITCH	12	CO_2, CH_4, N_2O, PFCs, HFCs, SF_6	2100; 5 year	Macroscopic Ramsey-type Optimal Growth	Basic	Bosetti et al. (2010)

[1] Earth system components involve significant variation in structure and from. Here we give a very general relative comparison between earth system components as either being more basic or more advanced.

[2] IMAGE consists of multiple sub-models (PHOENIX, TIMER, GTAP, HYDE, FAIR, etc.) with various time-steps. The time step recorded here is for HYDE.

With respect to the weaknesses of integrated assessment models, Rotmans observes that (1) many models often suffer from high levels of aggregation in both the socioeconomic and biophysical sub-models so that important micro-level phenomena is often unaccounted for, (2) because of the complexity and intensity of computer resources required to run the model, proper treatment and analysis of uncertainty is often inadequate and understudied, (3) while most natural and socioeconomic processes are inherently probabilistic, most models are deterministic in nature and lack the stochastic representation to properly analyze the effect of uncertainty in model parameters on long-term outcomes, and (4) because of the enormous number of parameters involved in benchmarking a large complex model, the amount of focus placed on proper calibration and validation of model parameters to empirically obtained variables and parameters is challenging when data is limited. Among these weaknesses the first and forth are intrinsically linked and require an important design tradeoff when constructing a model. Greater disaggregation and representation of important micro-level phenomena and detail requires increased parameterization and greater data requirements. However, because of limitations on the availability of the data required to represent micro-level phenomena, model design is often forced to aggregate over important details. As a result, models can often take on a more aggregated form that is indicative of the level of aggregation of the data that is available to benchmark the model.

1.3 Computable General Equilibrium Models

As illustrated by the major integrated assessment models used to inform climate policy decision making in Table 1.1, the computable general equilibrium (CGE) framework is commonly used for the socioeconomic component. In a paper addressing the appropriateness of CGE models for sustainability impact assessment, Bohringer and Loschel (2006) go as far as suggesting that CGE models are well structured to serve as a backbone tool for assessing simultaneous impacts of policy on economic performance, environmental quality, and social development in energy-environment-economic (so called E3) models. Bohringer and Loschel argue that one of the key strengths captured by the CGE framework is the ability to provide *ex ante* comparisons of different policy pathways by assessing possible outcomes both with a control in place as well as what would have happened if a policy instrument had not been implemented. As a result, "The main virtue of the CGE approach is its comprehensive micro-consistent representation of price-dependent market interactions" (Bohringer and Loschel 2006). In addition, as CGE models are able to incorporate several key indicators into a single micro-consistent framework, CGE models are able to provide a platform for systematic and rigorously quantitative tradeoff analysis between socioeconomic and environmental factors. Finally, due to the wide array and diversity of model outputs, CGE models can be readily implemented as a socioeconomic sub-model that interacts with other sub-models that are better suited for representing other effects of interest, thus expanding the integrated assessment framework to areas beyond CGE core strengths.

As a rebuttal to Bohringer and Loschel, Scrieciu (2007) argues against the use of CGE models as a backbone tool for the integrated assessment models of sustainability and caution against the "inherent dangers" of computable general equilibrium models for sustainability impacts assessment (Scrieciu 2007). Of the critiques relevant to developments made in this thesis, Scriecui argues first that general equilibrium theory assumes economic activity is based on decisions of profit and welfare maximizing agents where trade occurs under market clearing conditions that result in a Pareto efficient economic outcome. In reality, economies are never in equilibrium but are subject to a never ending process of changing and dynamic forces. Because in reality economies are never in equilibrium, Scriecui concludes that the theory underpinning the CGE framework is incorrect. Second, Scriecui points out that CGE models solve for future time steps recursively as opposed to using time-series data, and are benchmarked entirely on parameters for the base year of the model where the market is assumed to be in equilibrium. However, methods for benchmarking the model are not falsifiable, making it difficult to validate the parameters in a traditional macroeconomic sense using time-series data. This is often referred to as the "econometric critique" of computable general equilibrium models. Third, vital to performing energy-economic-environmental analysis is the representation of the dynamics of endogenous technical change. CGE models, however, often assume exogenous technical change and for the few instances that technological change is implemented endogenously in a CGE model, it is done so in a very limited and restrictive fashion. Fourth, in dealing with at times highly aggregated data, CGE models risk over generalizing and homogenizing over different economic sectors and regions and therefore fail to account for key regional, sectoral, and technical change unique to specific regions. Due to the unique way that individual regional economies are structured, we would expect regions to react differently to external shocks which would suggest different implications for policy design from region to region. Fifth, Scriecui argues that CGE models are often quite primitive in capturing environmental effects such as complex localized environmental indicators such as air pollution. Sixth, is the common "black box" critique of all complex integrated assessment models, that modelers often fail to make their models transparent and do not explicitly indicate the methods and factors driving their results. Finally, the most crucial parameters to a CGE model other than the parameters used to benchmark the model in the base year are the elasticities of substitution between different inputs to production. Scriecui argues that in calibrating CGE models there is high uncertainty regarding the values of substitution elasticities and as CGE models are highly sensitive to these values, it is easy for modelers to highly influence model outcomes through slight tweaking of substitution elasticity values.

While some of the critiques of CGE modeling that Scriecui presents are reasonable, many are more of a critique of the way in which some CGE models can designed or perhaps have manipulated model parameters, but are not strictly a critique of the CGE framework itself. In response to the first critique that economies usually are not in equilibrium and therefore the equilibrium assumption of CGE models does not hold, the issue is more of a question regarding the magnitude or degree of disequilibrium. Most would agree with Scriecui that the economy is not always in a perfect equilibrium, however, if to the first order the economy was largely in equilibrium and the second and third order effects of disequilibrium were not influential to the overall outcome, then the fact that the economy is not always in perfect equilibrium really isn't an issue. Additionally, as stated by Bohringer and Loschel, the primary strength and CGE models is in studying *ex ante* comparisons of different policy pathways. If the policy questions of interest are focused on the comparative effects between different model scenarios as opposed to the absolute response of a single model result, any effects of disequilibrium would be less important as they would be present in both scenarios being compared and first order disequilibrium effects would cancel out. In comparative analysis of policy effects what is of most interest is isolating the shock to the model due to the policy constraint and not necessarily the absolute prediction of future outcomes.

Concerning the second "econometric critique," that CGE models are not based on time-series data and are benchmarked in base year data that is not falsifiable and difficult to validate, this is largely a failure to recognize that the kinds of questions CGE models are used to address are once again *ex ante* comparisons of different policy pathways and not predictions of future behavior. In other words, the utility in a CGE model is not in giving a robust prediction of future economic activity and environmental impacts, but rather in providing a framework to systematically study how policy can affect future outcomes in different ways. As predictions of future outcomes from time-series data are based on extrapolation from historical empirical observations they do not lend themselves to studies where it is the counterfactual effects of different policy pathways that are of interest. In addition, just because it may be the case that some CGE models are benchmarked in datasets that are not well validated by empirical evidence does not mean that all CGE models necessarily cannot be benchmarked in data sets that are highly representative of the major economic indicators for a given region in a certain year. As CGE models have grown in complexity and efforts to move to more and more disaggregated representation has continued, much work has be made to improve the quality and accuracy of the datasets used to benchmark models. One particular example of an enormous undertaking in this regard is the GTAP database which provides worldwide base year data for 129 regions and 57 different economic sectors by combining major datasets from organizations like the World Bank, as well as hundreds of sources from various statistic bureaus and banks in individual countries (Aguiar, McDougall and Narayanan 2012).

The third critique that CGE models do a poor job representing endogenous technical change is reasonable; however this is a challenge not limited solely to CGE modeling but is a well-recognized challenge outside the CGE community as well (Weyant, et al. 1996). Despite the challenge, since understanding the role of technical change and the nature of technological response to policy instruments plays a major role in determining counterfactual future responses, much work has been done to improve CGE models in this regard (Gillingham, Newell and Pizer 2008). Since future air pollution reduction opportunities are heavily influenced by the endogenous response of abatement technologies, improving CGE models' ability to represent technical change of air pollution abatement technologies endogenously is a major goal for the present work. Therefore this thesis directly contributes to addressing this critique.

The fourth critique that CGE models over-generalize and homogenize economic regions and sectors is entirely a criticism of how some CGE models may have been designed but in no way does this critique undermine the core methodology. Provided that the appropriate databases are available and used, CGE models are more than capable of representing the unique conditions specific to different economic sectors and among individual countries and regions. As more detailed datasets with which to parameterize CGE models become available, such as the GTAP database, CGE models are increasingly able to represent the heterogeneity between economic regions and sectors and are well equipped to capture some of the key differences in policy responses especially among developed and developing economies.

The fifth critique that CGE models are very primitive when it comes to capturing environmental concerns such as complex localized environmental indicators like air pollution fails to recognize that CGE models are usually only one component of an overall integrated assessment model. It is because many integrated assessment modelers understand that CGE models are not as well equipped for representing biophysical and environmental interactions, the component of the integrated assessment model that represents the earth system usually takes on a much different form that is more conducive to capturing relevant biophysical processes. In addition, most CGE modelers understand that extremely localized questions that require significant detail, where the study of interrelated effects is not the primary focus, are questions that CGE models are not generally applied to and naturally belong to models with much more detail and narrower scope.

The sixth critique that CGE models are black boxes and non-transparent is more a critique of how individuals or groups of researchers treat and document their models and is not indicative of the CGE framework itself. CGE models and the methods used are inherently complex, not out of desire to hide processes, but rather out of necessity because the underlying interactions between socioeconomic and earth systems are complex themselves. Because of the complexity, researchers should be as open and transparent in their methods as they can, but at the same time critics or policy makers using results from CGE models must recognize that understanding the intricacies of a CGE model can require a good deal of training and expertise.

Finally, the seventh critique that there is a large degree of uncertainty in the substitution elasticities and that slight variations in the elasticity values can heavily influence the nature of the results is legitimate. While generally elasticities are sought that have some kind of empirical grounding, precise calibration of substitution elasticities remains a challenge. In this thesis we directly address this challenge when representing air pollution abatement opportunities by exploring different methods for benchmarking elasticities of substitution using empirical or engineering based data on available abatement technologies.

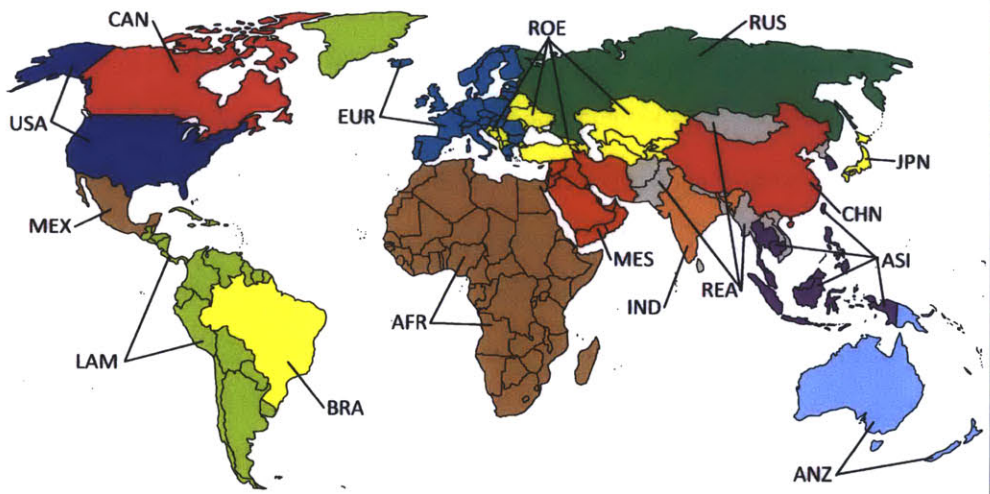
Despite the many critiques raised, Scrieciu does properly acknowledge that "CGE models do present powerful simulation devices for policy analysis based on a rigorous and consistent theoretical framework, and address the workings of the economy as a whole, allowing for economy-wide inter-sectoral interactions, macro-economic feedback and spillover effects. They may be helpful particularly in the context for which they have been initially developed, e.g. medium term comparative impacts of policy shocks on changes in relative prices, factor reallocation, and the redistribution of sectoral output. The numbers they provide may also prove useful when aggregate estimates are needed, and only when these are used to give a sense of the significance and the relative order of the magnitude of potential policy induced impacts" (Scrieciu 2007).

As the primary goal of this thesis is to develop tools with which to study the *ex ante* comparisons of counterfactual policy pathways and how they impact various integrated policy questions concerning energy generation mix, regional air pollutant emissions, regional welfare and GDP, ancillary emission benefits on other gas species, health impacts, and impacts on earth systems and the environment, we conclude the CGE framework is the most appropriate for representing the interconnected effect of interest and that the many of the critiques of the methodology although reasonable are not insurmountable but rather identify rich opportunities for improvements in model methodology and parameterization.

1.4 The MIT Emissions Prediction and Policy Analysis Model

To establish a framework within which to study the air pollution policy questions of interest, we implement the proposed methodology for representing air pollution reduction opportunities using the fifth version of the MIT Emission Prediction and Policy Analysis (EPPA) Model. EPPA 5 is a dynamically recursive multiregional general equilibrium model of the world economy that is used largely to study the effects of energy and environmental policy on the economy and on anthropogenic emissions of greenhouse gases and traditional air pollutants, but also consists of modified versions for looking at health effects, household transportation, and advanced energy generation technologies (Paltsev et al., 2005). As a multiregional model, EPPA simulates the world economy by dividing the world into 16 regional economies that represent individual countries or groups of countries. Each regional economy is then permitted to trade with the other economies where most goods are treated using the Armington convention where imported goods are not perfect substitutes for domestic goods. As a general equilibrium model, EPPA simulates each regional economy through the circular flow of goods and services between households and producers. Households receive payments from the production sectors for the labor and capital services they provide and in return, households use the income they receive to pay production sectors for the goods and services consumed. In its base form, EPPA 5 contains 14 sectors with additional technological detail and disaggregation in the energy and agricultural sectors as these are most important to greenhouse gas and air pollution emission effects. A map of the EPPA 5 regions along with a table of the economic sectors and their abbreviation is given in **Figure 1.3**. For each region, sectoral output is used for intermediate use, final use, investment, and exports.

Like all computable general equilibrium models, EPPA solves as a Pareto efficiency optimization model where producers and consumers seek to optimize profits and welfare respectively. Therefore, one of the fundamental features that is captured in EPPA, and what makes it such a powerful tool for studying counterfactual *ex ante* comparisons of different policy pathways, is its ability to represent the ability of consumers and producers to make decisions and change consumption habits or input factors to production in response to a shock on the economy caused by a policy constraint.



EPPA 5 Sectors	
LIVE	Livestock
CROP	Crops
FORS	Forestry
FOOD	Food
EINT	Energy Intensive Industry
HTRN	Household Transportation
TRAN	Other Transportation
OTHR	Other
SERV	Services
ELEC	Electricity
OIL	Oil
ROIL	Refined Oil
COAL	Coal
GAS	Gas

Figure 1.3. The MIT Emissions Prediction and Policy Analysis verion 5 regions and sectors.

Also consistent with the CGE modeling framework, EPPA is benchmarked to a base year where the economy is assumed, at least to the first order, to be in equilibrium. The critical data used to benchmark EPPA are contained in Social Accounting Matrices (SAMs) and represent a snapshot of the world economy for the EPPA 5 base year of 2004. The SAMs are obtained from the Global Trade Analysis Project (GTAP) database version 7 (Badri and Walmsley 2008). In addition to the SAMs for benchmarking economic data, EPPA also benchmarks an inventory of both greenhouse gases and traditional air pollutants for the base year. For EPPA 5, the greenhouse gases carbon dioxide (CO_2), methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), and sulfur hexafluoride (SF6) are benchmarked using data from the Emissions Dataset for Global Atmospheric Research (EDGAR) version 4.1 (van Aardenne, et al. 2009). Similarly, the dataset used to benchmark the traditional air pollutants carbon monoxide (CO), sulfur dioxide (SO_2), nitrous oxides (NO_x), ammonia (NH3), black carbon (BC), organic carbon (OC), and non-methane volatile organic compounds (NMVOCs) were obtained using the EDGAR-HTAP dataset (HTAP 2009). As many data sets for creating emission inventories are available, a complete discussion regarding the decision criteria that went into choosing the EPPA 5 emission inventories is given in Waugh et. al (2011).

As a dynamically recursive model, EPPA solves recursively from the base year in five year intervals producing projections of gross domestic product, final demand, energy consumption, and emissions of GHGs and traditional air pollutants. The timeline for policy analysis can vary depending on the specific questions that are being studied; however, typical climate policy analysis tends to go through 2100. Since what is of most interest are the *ex ante* counterfactual effects of different policy pathways, simulations run with a shock to the economy due to a policy constraint are always compared to a baseline business as usual scenario where no shock is present. In addition to running as a standalone model, EPPA can also run jointly with the MIT Integrated Global System Model (IGSM) to study how changes in anthropogenic emissions impact various earth systems and the environment (Sokolov et al., 2005). By coupling the CGE model with a separate highly advanced earth systems model, EPPA is able to take advantages of the benefits of computable general equilibrium for representing the socioeconomic interactions but also represent significant detail in biophysical processes and the earth system that other integrated assessment models with less developed earth systems components are unable to account for.

While EPPA has largely been used to study the effects of climate policy, work has also been done to represent the traditional air pollutants; however, in its current form, the representation largely consists of exogenous forcing of the emission intensity of air pollution emitting sectors and therefore does not capture the endogenous response to a policy shock that should occur. Also, the way traditional air pollutants are currently integrated into the production sectors as being used in fixed proportion with fuel use and other pollutants is not conducive to capturing the interconnected effects that constraints on one pollution species may have on other species (e.g. the way constraints on SO_2 will effects emissions of NO_x and CO_2, etc.). Before presenting the proposed solution to how these deficiencies can be overcome, we first consider previous methodologies that have been used to represent air pollution reduction opportunities in a CGE framework.

2 Previous Methods for Modeling Air Pollution Abatement

Several methods have been developed and implemented to represent air pollution abatement opportunities in a CGE framework allowing integrated assessment models the capability to represent future emission levels based on the economic response of air pollution reduction policy. As already mentioned, many of these methods represent abatement opportunities as a change in the level of emissions per unit of economic activity in each sector through exogenously determined trends. Other methods represent abatement opportunities endogenously by including emissions as an input to production. The advantage of the endogenous approach is that it allows models to capture interconnected economic effects such as total abatement cost, change in energy technology production mix, change in energy cost, and the overall policy impact on welfare and GDP.

In this section, many of the previous methods used to represent urban pollutant abatement opportunities in a CGE framework are given, along with an overview of the advantages and disadvantages of each method. Upon evaluating these existing methods, several important limitations are observed that show how integrated assessment models built on these methods may not fully represent the true economic impact of policies aimed at reducing air pollutant emissions. Due to these limitations in existing methods, new methodologies will be required to expand integrated assessment models as a tool for evaluating the interconnected environmental and economic impact of various air pollutant related policies. Once the previous methods have been considered, the proposed method for improved representation of abatement costs within a CGE framework is then given in Section 3.

Many methods currently exist to evaluate air pollution related policy by modeling the effects or air pollutant abatement technologies on emissions reduction, fuel consumption, economic output, and welfare. The methods available can generally be divided into two categories of representation: 1) representation of abatement as a change in the level of emissions per unit of activity within a specific sector of the economy, and 2) representation of abatement where emissions are treated as an input instead of as an output to production processes. Representation of abatement as a change in the level of emissions per unit of economic activity is often represented within integrated assessment models exogenously where the emission intensity of a sector is derived from empirically observed time-trends quantified from historic emissions reduction. On the other hand, representation of abatement costs by treating emissions as an input to production, fits extremely well into CGE frameworks comprised of nested constant elasticity of substitution (CES) production functions and allows abatement to be treated endogenously. Representing emissions as an input to production has the advantage of capturing many of the interconnected influences a policy constraint may have on the energy technology mix and policy costs; these effects are not captured by models that represent abatement opportunities exogenously. One disadvantage, however, of treating emissions as inputs to production is that the parameters needed for endogenous representation can be more difficult to come by, especially if the goal is to have a more disaggregated and heterogeneous representation that identifies abatement opportunities unique to specific regions and sectors within the model. Methods based on exogenous representation of air pollution emission will now be considered.

2.1 Emissions Coefficients Approach to Modeling Pollution and Abatement

One of the more common methods for representing anthropogenic emissions is by multiplying the total economic activity of a given sector by an emissions coefficient that gives the quantity of emissions per unit of economic activity and represents the emissions intensity of the sector. As mentioned previously in our discussion of the early energy and environmental models—such as the ETA model developed by Manne—emission coefficients date back to the early days of energy emissions modeling and today are used as the fundamental framework of the Intergovernmental Panel on Climate Change (IPCC) three-tier methodology for greenhouse gas emissions reporting (IPCC 2011). The IPCC three-tier framework provides guidelines for establishing emission coefficients based on varying degrees of aggregation in the data available for parameterization. In the framework each subsequent tier provides improved and increasingly less aggregated emission coefficients by accounting for sectoral variation from region to region as well as region and sector specific technological detail. Tier one is characterized by high aggregation and relatively less restrictive data requirements, whereas tier three is highly disaggregated but requires particularly detailed data for coefficient parameterization. Although these more detailed emission coefficients provide more accurate representation of pollution sources and specific abatement opportunities, the data required must have significant detail and is often hard to obtain, especially for many of the developing countries with less well established statistics bureaus. The choice of tier is therefore largely a function of the availability of data with which to benchmark the emission coefficient parameters.

The tier one representation of the IPCC methodology is the simplest of the three and is the least intensive in terms of data required, but also contains the highest level of aggregation. The method involves multiplying the total amount of activity in a given economic sector by an emission factor that is assumed to be globally constant for activity in the sector being considered. For example, if one wanted to calculate the total amount of SO_2 emissions in the United States from electricity production, one would multiply the total output of the electricity sector in the US by a globally determined emissions factor that gives the quantity of SO_2 emitted per unit of electricity produced. Using the tier one method, the emissions from pollutant i in region **j** for sector **k** are expressed using a global sectoral emission factor as given by **Equation 2.1**:

$$Emissions_{i,j,k}(kg) = Emission\ \ Factor_{i,k}\left({}^{kg}\!/_{unit}\right) \times Activity_{j,k}(unit) \tag{2.1}$$

The activity unit varies by activity type. For fossil energy production the unit is typically the energy content of the fuel (e.g. the energy content of coal in gigajoules, GJ).

Tier two methodology differs from tier one only in that emission factors are no longer assumed to be constant globally but account for heterogeneity among regions. This is done to account for the fact that inputs to economic activity and the emission intensity of the activity can vary among regions due to technological variation of energy production, the composition of the regional economy, and the stringency of regional emission controls that influence abatement. For example, the emission intensity of any pollutant—SO_2, NO_x, Hg, BC, from the electric sector in Norway would be much less than in China due primarily to technological variation; Norwegian electricity is generated almost entirely from hydroelectric power plants which generate no air pollution while ~80% of Chinese electricity generation comes from coal-fired plants. For the tier two methodology, the emissions of pollutant **i** in region **j** for sector **k** are expressed using a sector and region specific emissions factor as given in **Equation 2.2**:

$$Emissions_{i,j,k}(kg) = Emission\ \ Factor_{i,j,k}\left(\frac{kg}{unit}\right) \times Activity_{j,k}(unit) \tag{2.2}$$

Tier three methodology involves the lowest level of aggregation and is based on either taking direct measurements of emissions from the source—e.g. an SO_2 monitor on a coal-fired power plant, or detailed emissions modeling that takes into account specific technologies or conditions under which an activity is conducted within a region and sector. For example, Tier 3 methodology would account for the difference in the sulfur content of different grades of coal being burned in a given region and sector. The overall coal used in the sector would be disaggregated by type and a grade specific emissions coefficient would be used for each grade of coal. In addition, SO_2 emissions from coal may also vary within a region and sector due to other technological variation such as the cost of abatement technologies like scrubbers and electrostatic precipitators, and the stringency of emission controls in the region. In this case, the emissions factor becomes a technology specific factor accounting for all the individual technologies within a given region and sector. For tier three methodology, the emissions of gas i in region **j** for sector **k** using technology **t** is expressed in **Equation 2.3** as:

$$Emissions_{i,j,k}(kg) = \sum_{t}\left(Emission\ \ Factor_{i,k,t}\left(\frac{kg}{unit}\right) \times Activity_{j,k,t}(unit)\right) \tag{2.3}$$

As has been seen, the substantive difference between the different tiers is largely the level of disaggregation. The underlying assumption is that a more precise description of the activity will result in a more precise estimate of the emissions factor and hence less potential error introduced by virtue of the fact that more grossly determined average emission factors inadequately represent the variation of sub-types of activities in different regions. Often the determining factor for which tier is used lies in the level of disaggregation of the available data. While the third tier provides the least aggregated representation, tiers one or two may be invoked out of necessity when less aggregated data for benchmarking emission factors is unavailable. Once a tier level and the corresponding emission coefficients are determined from a given data set, those coefficients can be used to benchmark the emission intensity of a given production sector in the base year of a CGE model (e.g. benchmark the amount of SO_2 that is emitted from coal used in the electricity production sector). However, the emission intensity of an activity, and therefore the emission coefficients, are not static and change over time. We will now consider two methods used to address the change in emission intensity and emission coefficients exogenously.

2.1.1 Income-related Representation Emission Coefficient Trends

Once base year emission coefficients are determined based on the level of aggregation of available data, one must consider how the emission coefficients will change over time and vary from their initial values. Factors that influence the change in emission coefficients include change in the sectoral composition of the economy (e.g. over time economies tend to shift away from or towards certain emission intensive activities), technological improvements that reduce the emissions intensity, changes in consumer preferences, government policy and regulation aimed at emission reduction, and the autonomous energy efficiency improvement (AEEI) that has been empirically observed as a voluntary improvement in energy efficiency that is not driven by market mechanisms.

Selden and Song argue that in general, the behavior of emission trends exhibit an inverted-U or "Kuznets" curve where emissions increase while an economy is industrializing and agricultural modernization occurs, but over time decrease due to "positive elasticities for environmental quality; changes in composition of production and consumption; increasing levels of education and environmental awareness; and more open political systems" (Seldon and Song 1994). These trends are observed for traditional air pollutants such as SO_2, NO_x, lead, and chloroflourocarbons. Selden and Song go on to derive an empirically based negative relationship between GDP per capita and the emission intensity of economic activity. Their work suggests that emission coefficients are income-related and decrease over time as GDP per capita increases. A similar result is also observed by Grosman and Kruger (Grosman and Krueger 1995). Although the environmental Kuznets curve hypothesis has shown reasonable agreement with trends in traditional air pollutants, critics claim that it may not necessarily be an appropriate theory for other pollutants such as carbon where it is uncertain at what income level abatement will take precedence over economic growth.

Using the environmental Kuznets curve hypothesis, Mayer et al. presents a method for representing urban pollutant emissions in a computable general equilibrium framework by benchmarking the model to baseline emission coefficients that then changes over time as the model predicts future changes in per capita GDP (Mayer, et al. 2000). By fitting emissions, population, GDP, and economic output data to exponential and power functions, negative relationships between emission coefficients and GDP per capita are derived for electric power generation, energy intensive industry, household consumption, and agriculture. A sample of one of the relationships is given in **Figure 2.1** which shows the emission factor (defined here as the emission coefficient of a given year normalized to the benchmarked emissions coefficient of the base year) for coal used in electricity production.

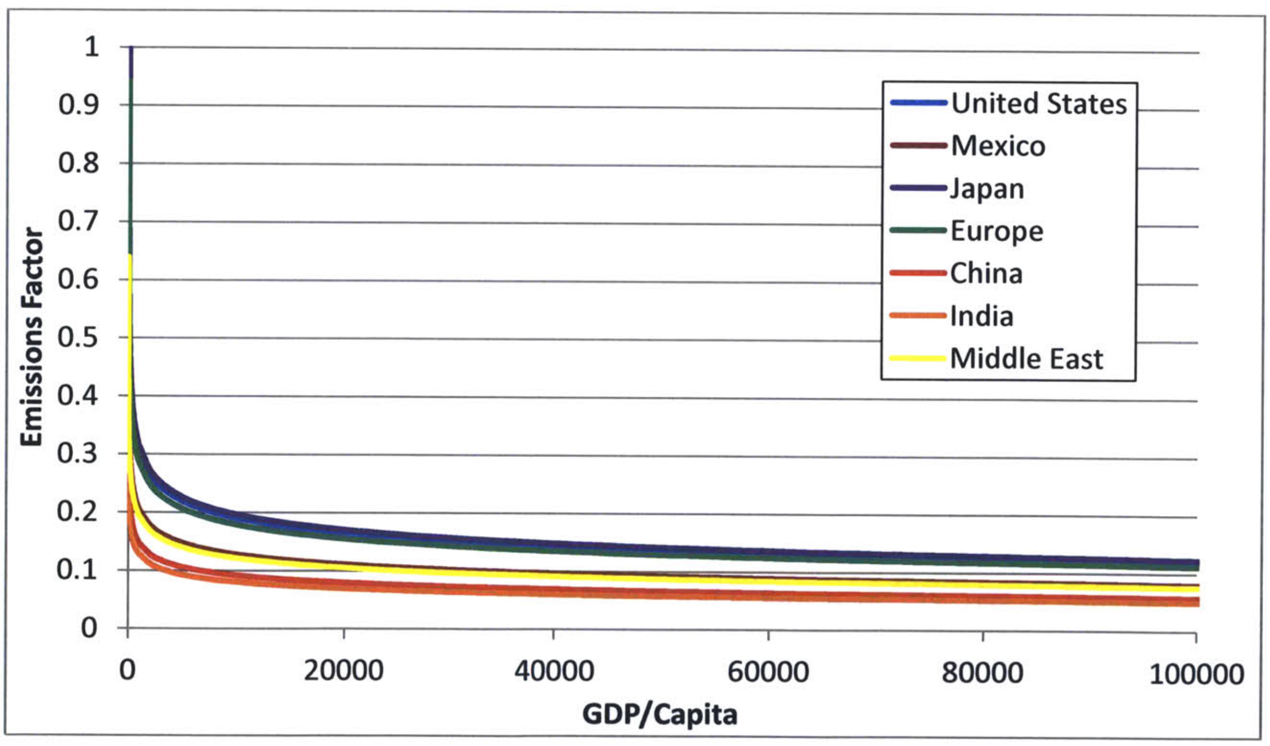


Figure 2.1. Income-related trend in emission factors for coal used in electricity production for major regions. The emission factor in this case is defined as the emission coefficient of a sector normalized to the base year coefficient (as given by Mayer et al., 2000).

The emission factor remains higher for developed economies, such as Japan, Europe and the United States compared to developing economies like China and India.

In a CGE framework, implementing this approach to represent time evolving emission coefficients based on the Kuznets curve is straight forward. As the CGE model solves recursively for each subsequent time step beyond the base year, the previous period's population and GDP parameters are used to compute the new period's emissions factor using empirically derived emission factor-GDP exponential and power functions. The resulting formula for the case of coal emissions is given by **Equation 2.4** as:

$$E_{r,s,t} = F_{0_{r,s}} \cdot \alpha \cdot \left(\frac{GDP_{R,t}}{Population_{R,t}} \right)^{-\beta} \tag{2.4}$$

where $E_{r,s,t}$ is the emissions factor at time **t**, $F_{0_{r,s}}$ is the initial benchmarked emission coefficient per region and sector for the base year, and α and β are parameters obtained by regressing the power function to empirically obtained emissions, GDP, and population data in the base year. Of these parameters, $F_{0_{r,s}}$, α, β, and $Population_{R,t}$ are imposed exogenously. Only $GDP_{R,t}$ is provided endogenously within the model. Although this method provides some level of endogenizing the emission coefficients within the model—based on the Kuznets hypothesis—that leads to an empirically observed reduction in emission intensity as GDP increases, the representation does not account for the cost of emissions reduction and abatement opportunities pursued, and therefore limits the integrated assessment in its ability to illuminate policy considerations affected by the cost of emission policy controls.

2.1.2 Time-related Representation of Emission Coefficient Trends

An argument against using the environmental Kuznets curve hypothesis for representing trends in emission coefficients is that the reductions in emissions are more appropriately represented as being time-related rather than income-related. Stern and Common argue that many studies that derive environmental Kuznets curves for emissions mainly considered only high-income countries and do not account for middle to low-income countries in their analysis. If accounted for, Stern and Common show a stronger relationship between emissions reduction and time than for per capita GDP as suggested by Selden and Song (Stern and Common 2001). Stern and Common go on to argue, based on empirical observations, that trends in sulfur emissions have reversed and are declining and that most countries over time are gradually converging towards a best practice technology frontier that takes advantage of all available abatement technologies (D. I. Stern 2005). Stern then provides estimates of future emissions, based on past emission reduction trends, for how long it will take certain countries to reach a best practice frontier.

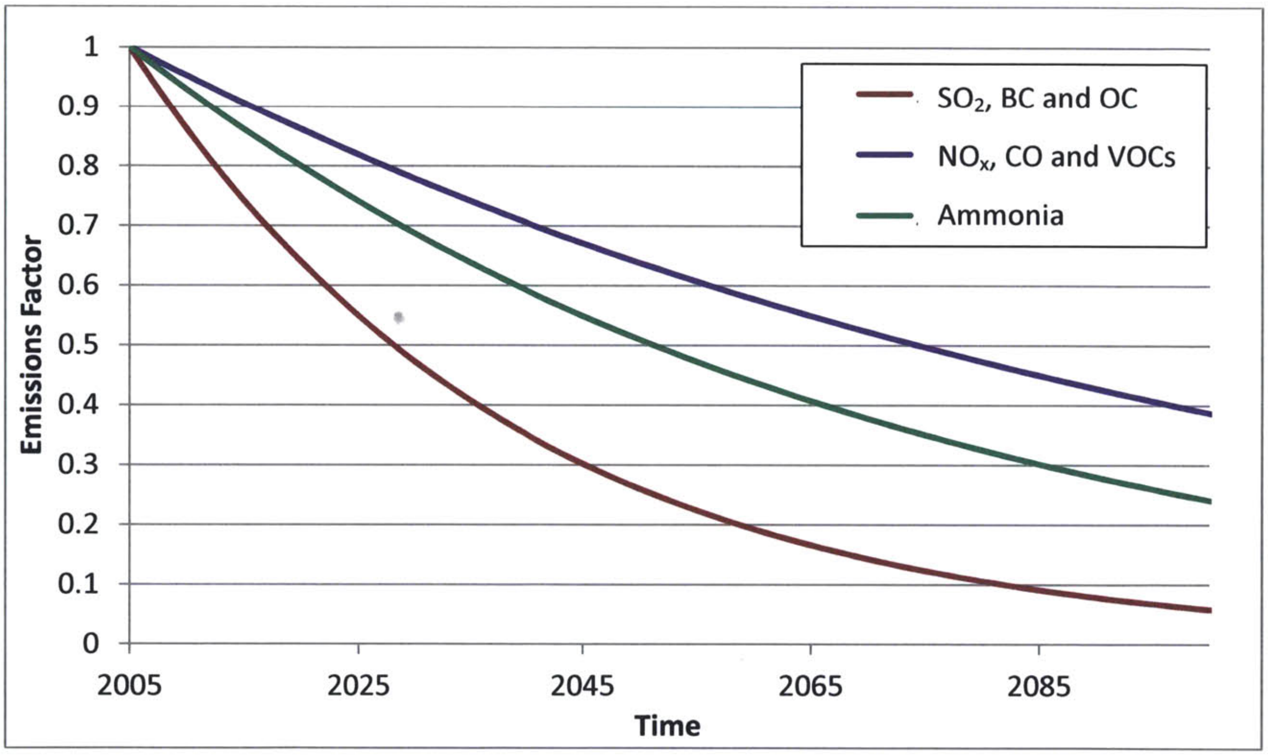


Figure 2.2. Time-related trends in urban pollutant emission factors for coal as an input to electricity production (as given by Webster et al., **2008).**

In a CGE framework, the time-related emissions coefficient as proposed by Stern can also readily be implemented by allowing the emissions factor to vary over time based on historical empirically observed time trends. By extrapolating for future emission coefficients based on historical trends, M. Webster presents a method for representing urban emissions within a CGE framework by imposing exogenously time varying changes to emission coefficients (Webster, et al. 2008). This representation retains a similar form to the per capita GDP trends given by M. Mayer in Equation 2.4, however, the fitted function becomes a time dependent decaying exponential. This representation is given in **Equation 2.5.**

$$E_{r,s,t} = F_{0_{r,s}} \cdot e^{-\beta \cdot t} \tag{2.5}$$

An example of the relationship showing a reduction in emission intensity over time derived by Webster for SO_2, NO_x, CO, BC, OC, VOCs and ammonia is given in **Figure 2.2**. All three plots show a decrease in emission factors over time with the greatest reduction coming for SO_2, BC, and OC. Although the benchmarked emission coefficient is region specific, the emission factors are not.

2.2 Modeling Pollutants Endogenously as Inputs to Production

One of the primary limitations of using exogenously determined trends—both income-related and time-related trends—in emission coefficients to represent abatement in a CGE framework is the inability to capture many of the economic interactions that occur when an emissions constraint is imposed, such as the firm level decision between paying for additional abatement technologies, paying the regulatory cost for emitting, or shifting away from emission intensive inputs to production. While the exogenous methods that utilize emission coefficients may accurately capture the change in emission intensity within a sector over time, and therefore do a reasonable job capturing long term projections of future emissions due to changes in economic activity, exogenously changing emission coefficients do not directly capture the costs incurred for abatement and therefore are unable to represent the true economic impact of air pollution policy. The inability to capture abatement costs limits the scope of questions that can be addressed using CGE models that use exogenous trend-based methodologies and consequently cannot provide a complete picture of the overall economic impact when comparing multiple policy pathways. This limitation is an important one as policy costs are often one of the key considerations when considering air pollution policy options.

As an alternative to representing change in emission intensity through exogenous trends, several methods for representing abatement endogenously within the CGE framework have been proposed to capture the abatement costs for non-CO_2 greenhouse gases. One such approach is to create a "clean-up" sector within each regional economy that takes capital, labor, and other inputs and produces emissions reduction as output. Under a policy constraint, emission producing sectors can purchase abatement from the clean-up sector to meet regulatory constraints. This approach captures both the empirically observed improvement in emission intensity over time as well as cost effects. However, the drawback is that since abatement opportunities are technology specific, a separate clean-up sector is needed to represent the cost and pollution removal efficiency associated with each individual abatement technology. With many abatement technologies available across different regions and sectors, implementing clean-up sectors for all abatement technologies would be non-trivial and would require significant modification to existing model frameworks. In addition, each technology specific clean-up sector would have to be specified for the sector(s) in which it can be utilized since abatement technologies are largely sector specific, e.g. multiple clean-up sectors from SO_2 for coal used in electricity production would need to be included to represent abatement through different technologies such as scrubbers and electrostatic precipitators, while hydrodesulphurization would only be available for sulfur removal in refined oil and natural gas.

A second method for implementing abatement costs endogenously within a CGE framework is to create alternative production sectors that produce the same goods as the originals, but are less emission intensive and take into account the additional costs of abatement. Constraints imposed on emissions will push production away from the more emission intensive sectors with lower production cost to the less emission intensive sector with higher production cost. This method is already widely applied in the MIT EPPA model to represent alternative electricity generation technologies. For example, one electricity production sector could represent current levels of abatement and emissions while alternative electricity production sectors would be available with each additional sector incrementally including more and more abatement opportunities while increasing costs and decreasing emissions. When there is only one or two alternative production sectors this method works quite well. However, when there are numerous abatement technologies to be represented, this approach has the similar limitation as the clean-up sector approach in that many alternative production sectors would be required to represent the gamut of available air pollution abatement technologies. Preferably whatever method that is used to represent abatement opportunities endogenously should require minimal change to the existing model structure to reduce the effort of implementation.

2.2.1 Modeling Non-CO_2 Greenhouse Gas Emissions as Inputs to Production

A third approach for endogenizing pollution abatement opportunities, that does not require the introduction of multiple technology specific clean up sectors nor alternative production sectors with varying degrees of emission intensity, but rather builds on the existing sector infrastructure, was developed for non-CO_2 greenhouse gas emissions (methane, nitrous oxide, hydrofluourcarbons, perfluourcarbons, and sulfur hexafloride) by Hyman et al., 2002. In this approach, instead of being treated as outputs, emissions are treated as inputs to production with an associated quantity and price. Any sector using an emission intensive input to production must also "purchase" the emissions corresponding to that input as an additional input. Although representing emissions as an input may seem counterintuitive since emissions are generally viewed as environmental externalities that are byproducts of primary outputs of production, the representation is effectively equivalent, (i.e. restricting emissions as an output of production has the exact same response within the model in terms of quantity of pollutant and cost as what would occur by restricting emissions as an input to production). This representation also fits well with the manner in which policy instruments are implemented within the CGE framework. Under a policy constraint, regional and sectoral emissions are restricted by either a cap or a tax or some other control scheme such as an energy portfolio standard. If the policy instrument were a cap, then within the CGE framework there would be an initial endowment of pollution permits available for producers that use emission intensive sources for production and the emissions within each sector would be limited by the quantity of permits the sector purchases. Similarly, a tax can also be implemented within the CGE framework by increasing the price of emissions relative to the market value at equilibrium.

Treated as an input to production, Hyman et al. place the pollutant as an input in the upper-most nest of each nested constant elasticity of substitution (CES) production block. Under this representation, a rise in the price of emitting a pollutant will cause a shift away from using the pollutant as an input to production and towards all other conventional inputs. This implies that abatement technologies require a proportional increase in all inputs that relate to the production of the good.

These conventional inputs include value added (capital and labor), as well as resource-intensive inputs (land, intermediate inputs from other sectors, and energy inputs such as electricity, coal, oil, refined oil and gas). With a greater demand for conventional inputs under a policy constraint, overall production costs increase.

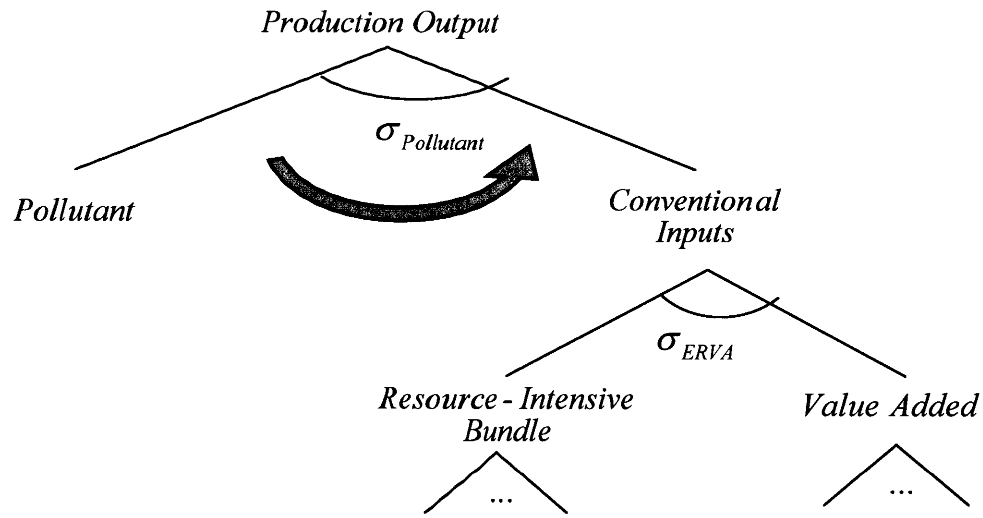


Figure 2.3. Endogenous representation of pollutant as input to production for non-CO_2 greenhouse gas emissions (as given by Hyman et al.**). Under a constraint, production shifts away from the pollutant and towards other conventional inputs.**

This increase in cost is interpreted as representing the additional cost the sector incurs for paying for pollution abatement under the constraint with the abatement being represented indirectly under the conventional input bundle. An illustration of the nested production block with the pollutant as an input to production at the top of the nest, along with the conventional inputs to production, is given in **Figure 2.3**.

This representation is readily implemented in the CGE framework as a nested CES production function. The pollutant is placed in the upper-most CES nest and initial input shares for both the pollutant and conventional inputs are given along with the elasticity of substitution between the pollutant and conventional inputs. The CES production function for the topmost nest in Figure 2.3 is given in Equation 2.5 as,

$$X_O = \left[\phi \cdot X_P^{\frac{\sigma-1}{\sigma}} + (1-\phi) \cdot X_C^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{2.5}$$

where X_O is the production output of the sector, X_P is the pollutant expenditure input, X_C is the conventional input nest, ϕ is the value share of the pollutant, and $\sigma_{Pollutant}$ (or just σ for simplicity) is the elasticity of substitution between the pollutant and other conventional inputs. In the CES production function, X_O, X_P and X_C are determined endogenously by the model while ϕ and σ are exogenously specified parameters. In this case, future abatement opportunities are primarily captured in the elasticity of substitution parameter σ. If many abatement opportunities exist, σ will be very elastic, allowing the sector to easily shift away from emitting and towards abatement. On the other hand, if few abatement opportunities exist, σ will be very inelastic, and the sector will be less capable of shifting toward abatement.

For the case of non-CO_2 greenhouse gases, Hyman et al. assume that few abatement opportunities have been utilized and that in the base year there are few policy constraints on GHG emissions. Under these assumptions the initial price of the pollutant is zero resulting in a zero value share for emitting. In practice, the value share must be nonzero for the numerical model to solve so the value is set to an arbitrarily small quantity. The elasticity of substitution is obtained based on the relation that the supply of abatement opportunities, as given by an empirically obtained marginal abatement cost (MAC) curve, is the inverse of the demand for abatement. Once the price elasticity of demand for emitting, ε_{D_E}, is determined from the MAC, Hyman et al. show that for non-CO_2 greenhouse gases, σ is given as:

$$\sigma = -\varepsilon_{D_E} \tag{2.6}$$

Because of heterogeneity in economic composition among regions, we would expect abatement opportunities for non-CO_2 greenhouse gases to vary from region to region. For example, abatement opportunities for CH_4 and N_2O in Brazil, with an economy that has a large share of agricultural production, would be quite different than abatement opportunities in Japan with little agricultural production. Likewise, abatement opportunities within a region will also differ among sectors; the abatement methods used to limit methane emissions from coal, oil, and natural gas production are different than those used to reduce methane from enteric fermentation in livestock. This is an important consideration and speaks to the critique given earlier by Scriecui that CGE models often homogenize and generalize over regional and sectoral detail. To accurately capture abatement opportunities through Hyman's method using elasticities of substitution, unique elasticities must be determined for emissions used as inputs in individual regions and sectors. Using MAC data on abatement opportunities provided by the U.S. Environmental Protection Agency and the International Energy Association, Hyman et al. derive unique elasticity of substitution parameters for several individual sectors and regions.

2.2.2 Modeling Air Pollutant Emissions as an Input to Production

In his PhD thesis, M. Sarofim expands on the methodology of Hyman et al. to represent air pollutant abatement opportunities for SO_2, NO_x and BC using a similar structure with air pollution represented as an input to production in the upper-most nest of the production function (Sarofim 2007). Sarofim then uses MAC abatement opportunity data from the Regional Air Pollution Information and Simulation (RAINS) model to benchmark the elasticities of substitution between pollution and other conventional inputs. Although, as was mentioned previously, we expect heterogeneity among abatement opportunities in specific regions and sectors, the RAINS model at that time only contained abatement opportunity data for Europe and China (International Institute for Applied System Analysis (IIASA) 2003). Under this limitation, Sarofim assumes that unlike non-CO_2 greenhouse gases, urban pollution abatement opportunities are more homogenous across regions and that the primary influence on the availability of future abatement options is the stringency of existing air pollution emission constraints. For example, in regions with existing policy that is relatively stringent, many abatement technologies will have already been implemented to meet policy requirements so that few additional abatement options may be available. In regions with less stringent or no policy, no abatement technologies will have been implemented so that all abatement options are still available. Since the stringency of existing air pollution controls are a strong function of whether a regional economy is developed or developing, Sarofim uses the elasticities of substitution obtained for Europe to be representative of abatement opportunities of developed countries, while elasticities of substitution from China are used to represent abatement opportunities in developing countries.

Despite homogenizing over developed and developing regions using substitution elasticities for Europe and China respectively, Sarofim acknowledges that due to different existing air pollution reduction policies and abatement opportunities, parameters are much more likely to be heterogeneous across regions. He says, "Ideally, each pollutant in each sector in each region would be given a separate elasticity. However, the estimation problem is large: 6 major pollutants (CO, VOCs, BC, OC, SO_2, and NO_x) multiplied by sixteen sectors plus eleven electric generation technologies with relevant emissions possibility including different fuels for each sector would mean over a hundred different elasticities to estimate, and then attempting to make estimates for each of the sixteen regions would make the problem completely unmanageable." Another consideration is that unlike the non-CO_2 greenhouse gases, air pollutants are largely associated with fossil fuel consumption and may not necessarily respond to a policy control in the same way as non-CO_2 greenhouse gases. In the CGE framework, fossil fuels are included as inputs under the resource-intensive bundle in the production block nest. As shown in **Figure 2.4**, as air pollution emissions are constrained under the Hyman representation, production will shift away from the pollutants toward greater demand for conventional inputs. However, the conventional inputs nest includes the resource-intensive bundle and subsequently fossil fuels. This leads to a model response where fuel consumption increases as emissions are constrained. This behavior can occur in the case where abatement technologies decrease the efficiency of production. For example, scrubbers used in a coal-fired power plant decrease the overall plant efficiency and more coal is needed for the same amount of electricity production without the scrubbers. However, when policy controls become increasingly stringent, we would eventually expect firms to shift away from certain fuels as a production inputs when abatement and policy costs become exorbitant and towards less emission intensive inputs.

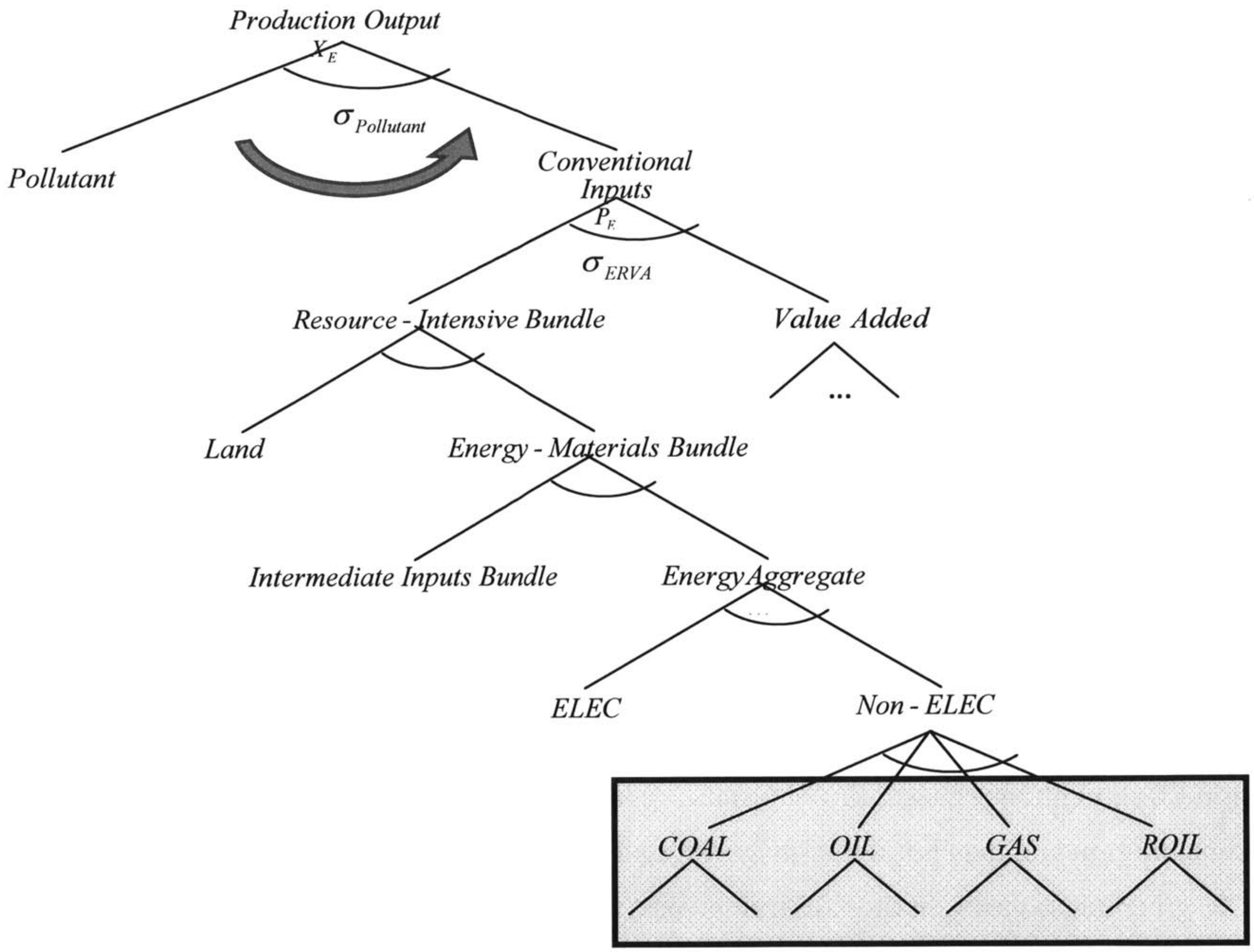
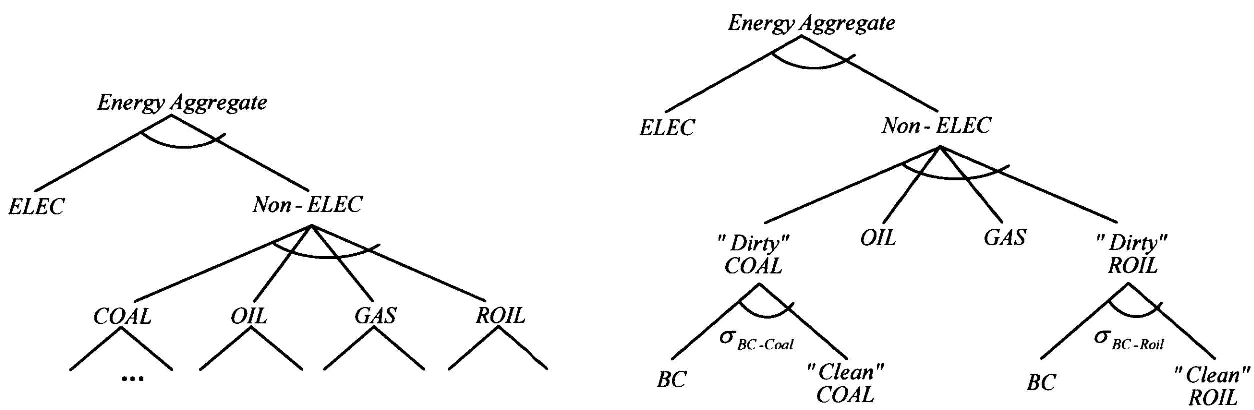


Figure 2.4. Using non-CO_2 greenhouse gas representation of abatement opportunities leads to unrealistic result: tighter emissions controls leading to increased fuel consumption.

In contrast to air pollution emissions, the reason this representation works for Hyman et. al is that non-CO_2 GHGs are largely not associated with fuel consumption and therefore placing non-CO_2 greenhouse gas emissions in the top nest does not result in the same model response. For example, methane and nitrous oxide emissions are largely associated with agriculture, industrial production, and fugitive emissions from natural gas, coal, and oil production. Additionally, the fluorinated gases (HFCs, PFCs and SF_6) are the products of various industrial processes and do not derive from fuel consumption.

A variation of the method by Hyman et al. that continues to treat emissions as inputs to production, but accounts for air pollution largely being associated with fossil fuel consumption, is presented by de Masin for black carbon (BC) emissions (de Masin 2003). The formulation used is largely the same as that of Sarofim except that BC emissions from non-fuel related sources and fossil fuel combustion are treated separately in the production block. Non-fuel related emissions continue to be treated as an input in the upper-most nest of the CES block; however, emissions associated with fuel use are given as inputs to production in the same nest as the fuel. The original aggregate energy bundle under this representation is given in **Figure 2.5(a)** while the modified bundle with BC from fuel combustion as an input to production is given in **Figure 2.5(b)**.



(a) (b)

Figure 2.5. (a) The Energy Aggregate bundle without BC emissions as an input to production. (b) The Energy Aggregate bundle with BC emission as an input to production for both coal and refined oil.

In the modified bundle, fuel-related BC emissions are separated between emissions stemming from coal combustion and emissions from refined oil (abbreviated in the figure using the EPPA notation ROIL). As the price of BC increases, production in both the coal and refined oil nests will shift production away from emitting BC and towards "cleaner" coal that has been produced with additional BC abatement technologies. de Masin goes on to obtain the fuel related elasticities of substitution for coal and refined oil using fuel specific

MACs from the Regional Air Pollution Information and Simulation (RAINS) model. However, as was the case with Sarofim, since the RAINS model only provides abatement data for Europe and China, de Masin makes the same assumption as Sarofim that European and Chinese elasticities of substitution are representative of all developed and developing countries respectively.

Although de Masin's representation of abatement opportunities in a CGE framework properly distinguishes between fuel and non-fuel related air pollutant emissions, and therefore provides an improvement over Sarofim's representation, the structure of the nest de Masin invokes makes it difficult to represent multiple air pollutants in addition to BC that are also associated with coal and refined oil and that would also be constrained under air pollution policy. Thus one of the integrated analysis goals identified earlier of understanding the interconnected effects that policy controls on one pollution species have on other species are not attainable using de Masin's framework. For example, the way in which de Masin separates "dirty coal" from "clean coal" and then allows substitution between BC and clean coal can only capture substitution between a single pollutant and "clean coal" and is not expandable to cover additional pollutants from coals. In order to represent multiple pollutants within a single framework and therefore represent comprehensive air pollution policy, approaches similar to de Masin's method but with multiple pollutant representation would need to be made to consider policy impacts on emissions of SO_2, NO_x, CO, Hg, lead, and other particulate matter that are also associated with fossil fuel consumption.

2.3 Need for Improved Representation of Abatement Opportunities

We have now reviewed many of the approaches for representing air pollution abatement within a CGE framework and have discussed some of the advantages and limitations of existing methods. While modeling the change in emission intensity through either GDP per capita or time related trends in emission coefficients can account for some abatement effects including changes in consumer preference, shifts in economic activity away from emission intensive production, and the autonomous energy efficiency improvement; representing abatement opportunities in this manner is incapable of fully capturing abatement costs and subsequently a proposed air pollution control policy's overall impact on welfare and GDP. Therefore, while exogenously determined emission coefficient trends may be adequate for predicting future emissions, their application for integrated assessment models aimed at policy analysis is limited as regulatory costs and economic outcomes are key considerations when considering multiple policy pathways.

While many methods have also been developed to represent air pollution abatement endogenously as an input to production, improvements on these existing methodologies, and/or the implementation of such methodologies, are needed for a complete representation of multiple air pollutants associated with fuel and non-fuel related sources. Of these representations, the method proposed by Sarofim, which builds on the method used previously by Hyman for non-CO_2 greenhouse gases, has abatement requiring a proportional increase in all inputs for the same level of production output without a policy control. As abatement technologies are not necessarily produced using an increase in all inputs, we would like a method that provides greater flexibility in the mix of inputs associated with abatement. In addition, as air pollutants are much more strongly associated with fuel consumption, we would also like a method that provides greater flexibility in treating fuel and non-fuel related emissions separately as the model response may be different than for non-CO_2 greenhouse gases that are not directly associated with fossil fuel use. The method proposed by de Masin builds on the earlier developments by Hyman and Sarofim by providing a framework in which fuel and non-fuel related emissions can be treated separately, however, de Masin limited his investigation to a single pollutant and we would like to have a method that is capable of representing multiple pollutants simultaneously. In the end, the goal is to build on these earlier developments to create a new methodology, with sufficiently disaggregated technical data for heterogeneous representation of abatement opportunities, to represent multiple pollutants simultaneously and endogenously within the same framework. A proposed methodology that largely accomplishes these goals and its implementation will now be considered.

3 Air Pollutant Abatement Opportunities in a CGE Framework

In this section a new method for representing air pollution abatement is proposed that addresses many of the limitations of the previous methods considered. Full implementation of the methodology within the EPPA model version 5 is also presented. The method proposed is similar to the approach of Hyman et al., Sarofim, and de Masin, but advances these approaches by simultaneously 1) treating abatement opportunities for fuel and non-fuel related emissions separately, 2) providing a framework capable of representing abatement opportunities for multiple air pollutants, 3) providing regional and sector specific representation of available abatement technologies, and 4) accounting for the fact that existing policy constraints on air pollutants in many countries have already achieved significant level of emissions reduction while little or no air pollution control policy exists in other regions, particularly in developing countries. This fourth criterion is significant because unlike climate policy which has yet to establish meaningful reduction in GHGs in most countries, significant air pollution reduction controls are already in place. Because of this, knowledge of the level of abatement already occurring under existing controls is required in addition to knowledge of available abatement technologies. The importance of this distinction is discussed in detail later when we consider the derivation of model parameters from MACs. The abatement opportunities identified, therefore, must be abatement opportunities available above and beyond the level of abatement already obtained through existing controls.

3.1 Representation of Abatement Opportunities

For nonfuel-related air pollution, we adapt the structure of Hyman et al. by treating urban emissions as an input to production in the upper-most nest of the CES production block as shown previously in Figure 2.3. Just as in the non-CO_2 GHG case, as policy constraints become increasingly stringent, production will shift away from emitting and towards the other conventional inputs. For fuel-related pollution, we adopt a simplified version of the "clean-up" sector approach where only capital is used as an input. This is reasonable as abatement is largely achieved through capital investment in abatement technologies although other inputs to abatement production could be used as well. The major difference, however, between the proposed approach and the more traditional clean-up sector approach is that instead of creating a clean-up sector for the gamut of every available abatement technology, we create a single clean-up sector that provides capital for abatement that is then provided to fuel consuming sectors. The technological detail of abatement opportunities is then contained within the fuel consuming production sectors using elasticities of substitution that allow production to shift away from emitting.

We also make use of the fact that air pollution on average is typically produced in fixed proportion with the quantity of fuel consumed. While this is not strictly the case as different fuel types can have different concentrations of pollution causing impurities (e.g. various concentrations of sulfur and mercury content in different grades of coal lead to different levels of emission intensity), we can account for the different pollution concentration in different fuel grades as part of the technology mix of abatement opportunities in the MAC. We implement the relationship for fuel-related pollution into the CES nest structure using a Leontief production function which takes as inputs fuel and pollution, but has zero elasticity of substitution so that the inputs are always used in fixed proportion according to the value share. By using a Leontief block for the first nest, we establish the total amount of fuel-related pollution as constant. In the absence of emission controls there will be no cost for emitting and no abatement opportunities will be pursued; all of the pollution will be emitted. On the other hand, when policy constraints are imposed, abatement opportunities are implemented so that part of the pollution is abated with the rest being emitted. What determines the quantity of pollutant abated vs. quantity emitted is the availability and cost of abatement technologies as well as the stringency of imposed emissions constraints. As policy becomes more stringent and the quantity of allowable emissions is reduced, production will either be forced to reduce fuel as an input to production since total pollution is used in fixed proportion with fuel consumption, shift to other less pollution intensive fuels, or pay for additional abatement technologies to meet emissions reduction targets. The tradeoff between reducing fuel as a production input and shifting away from emitting towards greater abatement can easily be represented in the

CES nest structure by allowing production to substitute between pollution emitted and pollution abated.

Figure 3.1 shows the modified fuel-emissions bundle for a single fuel type (e.g. coal, oil, gas, or refined oil) where X_F is the fuel input expenditure, X_P is the expenditure on total pollutant associated with fuel combustion, X_A is the expenditure on pollutant abated, X_E is the expenditure on pollution emitted, and σ_{fuel} is the elasticity of substitution between emitting and abating fuel-related pollution. Each expenditure is given as the quantity of the good times the price (e.g. $X_E=P_E*x_E$ where P_E is the price of emission and x_E is the quantity of emissions, $X_A=MC_A*x_A$ where MC_A is the marginal cost of abatement and x_A is the quantity of abatement).

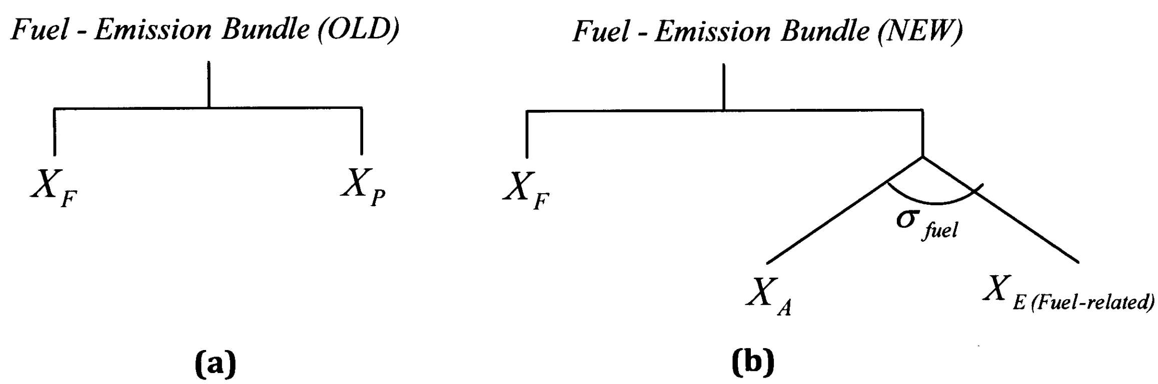


Figure 3.1. (a) Previous fuel-emissions bundle representation in EPPA, (b) new fuel-emissions bundle in EPPA with pollution abatement opportunities. X_F is the fuel input expenditure, X_P is the expenditure on total pollutant associated with fuel combustion, X_A is the expenditure on pollutant abated, X_E is the expenditure on pollution emitted, and σ_{fuel} is the elasticity of substitution between emitting and abating fuel-related pollution

In this formulation, the availability of abatement technologies is directly represented by the σ_{fuel} term. As more abatement technologies become available for reducing emissions, σ_{fuel} becomes more inelastic and it becomes easier for production to substitute abating pollution for emitting. If less abatement technologies are available, σ_{fuel} becomes more inelastic and it becomes more difficult for the firm to make the substitution.

The primary advantage of this method over the method proposed by Sarofim is that by representing fuel-related emissions in the fuel bundle, instead of in the top most nest of the production block, we avoid the unrealistic result that more stringent urban pollution emission controls will lead to an increase in fuel consumption. In addition, the method offers a significant advantage over the method proposed by de Masin. Since all pollution is generated in fixed proportion with fuel consumption, the existing fuel-emissions block (Figure 3.1a) that is contained within the resource-intensive bundle in the nested CES production block (Figure 2.4) can easily be expanded to represent multiple pollutants within a single Leontief nest with minimal change in the existing model structure. A fuel-emissions bundle illustrating how multiple pollution abatement opportunities can be represented using this approach is given in **Figure 3.2** and can be expanded to represent any number of pollutants. While only SO_2, NO_x, and BC are given, the block can easily be expanded to include additional pollutants of policy interest such as CO, mercury, or ammonia that are also emitted relatively in fixed proportion with fuel consumed. Using this representation, SO_{2A}, SO_{2E}, NO_{xA}, NO_{2E}, BC_A, BC_E are the input abated and emitted pollutants and σ_{SO_2-Coal}, σ_{NO_X-Coal}, and $\sigma_{BC-Coal}$ are the pollutant specific elasticities of substitution between emitting and abating for SO_2, NO_x, and BC respectively.

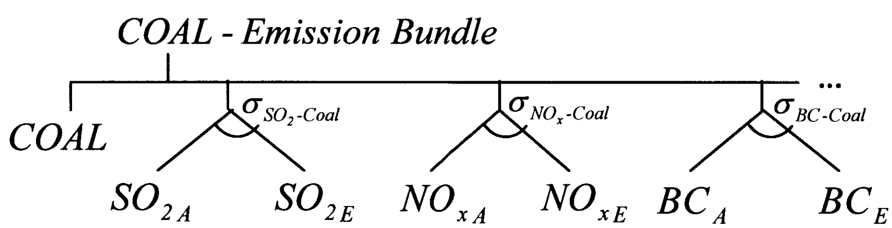


Figure 3.2. Fuel-emissions bundle for coal with SO_2, NO_x and BC.

Combining the new fuel-related emissions representation with the nonfuel-related representation gives the overall modified production nest shown in **Figure 3.3**. As can be seen, nonfuel-related emissions are given in the very top nest of the production block similar to the nest in Figure 2.3, with corresponding elasticities of substitution between emission species (in this case SO_2, NO_x, and BC) and the other conventional inputs.

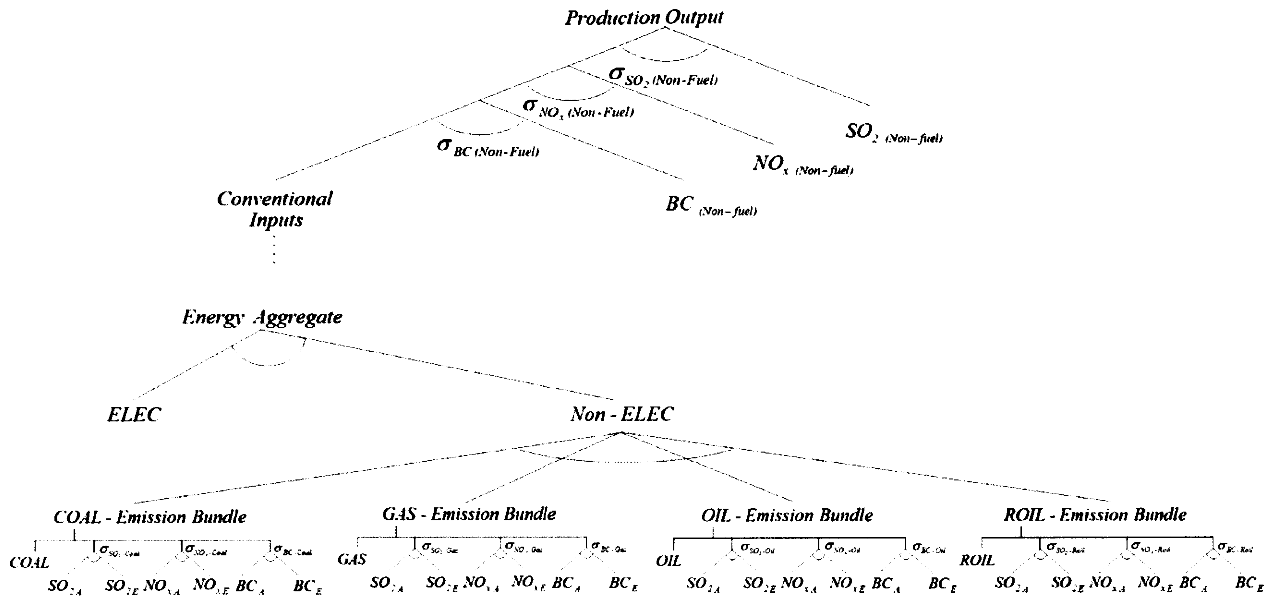


Figure 3.3. Overall production block with fuel and non-fuel related emissions and abatement opportunities.

Emissions of SO_2, NO_x, and BC related to consumption of coal, gas, oil and refined oil (ROIL) are given in the non-electricity energy aggregate bundle which is shown in the figure as "Non-ELEC." Within the energy aggregate bundle, abatement opportunities for pollutants stemming from each fuel type are represented as a substitution between pollutant emitted and pollutant abated with the total pollution (abated and emitted) occurring in fixed proportion with the quantity of fuel consumed.

With this new representation, we satisfy the first two objectives of the new methodology which were to 1) separate fuel and non-fuel related emissions and 2) provide a framework capable of representing abatement opportunities for multiple air pollutants. The next two criteria, 3) providing regional and sector specific representation of available abatement technologies, and 4) accounting for the varying degree in which existing policies already constrain air pollutants, are dependent on the level of disaggregation and detail of the data used to determine CES parameters. We will later introduce a data set which allows for the needed level of disaggregation and has sufficient detail to determine existing levels of abatement under existing policy constrains, but for now will assume the data is available. With this framework in place we now turn to the task of deriving the parameters that must be specified exogenously to represent abatement opportunities using a CES function. As mentioned previously, these parameters include the value share of one of the inputs to production and the elasticity of substitution between inputs.

As has already been discussed, one of the challenges of designing integrated assessment models is that you are often seeking to inform macro-level questions concerning policy effects but whose outcome is highly dependent on micro-level detail. The challenge then is to create a framework that is sufficiently disaggregated to represent the crucial micro-level detail without making the model too detailed so that the level of disaggregation in the required data is unattainable or that the model is too complex for numerical methods to solve. In the current case of representing available abatement opportunities within a CGE framework, we would like to represent the micro-level detail of the gamut of abatement technologies available in every region and sector, but in doing so, are seeking to answer questions regarding the macro-level effects of air pollution policy constraints. Given that we've already constrained the integrated assessment model to a CGE framework which is built on nested CES production functions, the proposed methodology must represent the aggregate of abatement technologies within all regions and sectors by means of a value share, ϕ, and elasticity of substitution, σ, in accordance to the form of Equation 2.5.

A novel approach for bridging the gap between representing individual abatement technologies unique to a region and sector, and the CES form which requires a value share and elasticity of substitution, can be derived from the price elasticity of demand for emitting, ε_{D_E}, using basic microeconomic theory. In the derivation, the price elasticity of demand for emitting is shown to be equivalent to the price elasticity of supply for abating, ε_{S_A}, which in turn is shown to be readily obtainable from region and sector specific marginal abatement cost curves of available abatement technologies. We now turn to the task of deriving the relationship between σ and ε_{D_E} from microeconomic theory.

3.1.1 Elasticity of Substitution from Price Elasticity of Demand

As will now be shown, the relationship between the elasticity of substitution, σ, and price elasticity of demand for pollution emitted, ε_{D_E}, can be derived from basic microeconomic theory where firms seeks to maximize profit subject to a budget constraint. The relationship between σ and ε_{D_E} will then be used to determine a firm's ability to substitute between abating and emitting urban pollutants in the presence of a policy constraint. As will be shown later on in section 3.1.3, price elasticities of demand for abatement can be obtained from a log-linear regression on marginal abatement cost (MAC) curves which can be derived from detail rich engineering data consisting of sector and region specific abatement technologies. While the relationship between σ and ε_{D_E} in this derivation is given specifically for the case of fuel-related pollution where emissions and abatement are inputs to production, the relationship also holds for the nonfuel-related CES nest at the top of the production block where the two inputs are emissions and all other conventional inputs.

We start the derivation of the fuel-related case with the CES production function for pollution as depicted previously as being nested in a Leontief with fuel as shown earlier in Figure 3.1(b). The mathematical form of the nest is given by **Equation 3.1**:

$$X_P = \gamma\left(\phi X_E^{\frac{\sigma-1}{\sigma}} + (1-\phi)X_A^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{3.1}$$

where γ is the efficiency parameter that sets the returns to scale of production, ϕ is the distribution parameter that establishes the initial share distribution between pollution abated and pollution emitted as inputs to production, X_P is the total pollution expenditure associated with consumption of fuel X_F, X_E is the emitted pollution expenditure as an input to production, X_A is the abated pollution expenditure as an input to production, and σ is the elasticity of substitution between X_E and X_A. Although γ in the end will have no impact on the final relationship between ε_{D_E} and σ, this is not immediately apparent so we include the term in the derivation for completeness. At the level of the firm, total production is limited by a budget constraint given by the cost function in **Equation 3.2**:

$$C_P = X_E P_E + X_A P_A \tag{3.2}$$

where C_P is the total cost of pollution associated with fuel consumption, P_E is the price of emitting the pollution as determined by existing policy controls, and P_A is the price of abating pollution as determined by the marginal costs of abatement. From this we seek to derive a production function for X_P in terms of P_E , P_A, and C_P from which we will eventually establish the relationship between ε_{D_E} and σ. The first step in this process will be to derive the demand functions for X_E and X_A in terms of P_E, P_A, and C_P.

The firm's response to a policy constraint can be thought of in two different ways: the firm can seek to minimize total cost subject to a pollution constraint (i.e minimize 3.2 subject to the constraint imposed by 3.1), or the firm can seek to purchase as much pollution as possible subject to a cost constraint (i.e. maximize 3.1 subject to the constraint imposed by 3.2). Mathematically this end up being the same problem and for this derivation we solve the second of the dual problem. Under profit maximization then, the firm will seek the appropriate quantities of X_E and X_A so as to maximize its total pollution output subject to the constraint imposed by the cost function. We therefore seek to optimize (3.1) as the objective function subject to the constraint imposed by (3.2). The optimization problem is given by **Equation 3.3**.

$$\max X_P = \gamma\left(\phi X_E^{\frac{\sigma-1}{\sigma}} + (1-\phi)X_A^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \quad \text{s.t. } C_P = X_E P_E + X_A P_A \tag{3.3}$$

To solve for the demand functions for X_E and X_A, we use the method of Lagrange with Lagrangian multiplier λ and define the Lagrangian as given in **Equation 3.4**.

$$L = \gamma\left(\phi X_E^{\frac{\sigma-1}{\sigma}} + (1-\phi)X_A^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} + \lambda\left(C_P - X_E P_E + X_A P_A\right) \tag{3.4}$$

Taking the first order conditions for X_E and X_A results in the marginal products of both inputs which, when set equal to zero, gives **Equations 3.5a** and **3.5b** which are represented here in terms of the Lagrangian multiplier. The third first order condition given by **Equation 3.5c** results in the same budget constraint shown previously in (3.2).

$$\frac{\partial L}{\partial X_E}=0\rightarrow\lambda=\frac{\phi\gamma}{P_E}X_E^{-\frac{1}{\sigma}}\left(\phi X_E^{\frac{\sigma-1}{\sigma}}+(1-\phi)X_A^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{\sigma-1}} \quad (3.5a)$$

$$\frac{\partial L}{\partial X_A}=0\rightarrow\lambda=\frac{(1-\phi)\gamma}{P_A}X_A^{-\frac{1}{\sigma}}\left(\phi X_E^{\frac{\sigma-1}{\sigma}}+(1-\phi)X_A^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{\sigma-1}} \quad (3.5b)$$

$$\frac{\partial L}{\partial \lambda}=0\rightarrow C_P=X_E P_E+X_A P_A \quad (3.5c)$$

From here we set (3.5a) equal to (3.5b) and solve for the demand functions of both the abatement and emission inputs in terms of the other input. This results in **Equations 3.6a** and **3.6b**.

$$X_E=\left(\frac{1-\phi}{\phi}\frac{P_E}{P_A}\right)^{-\sigma}X_A \quad (3.6a)$$

$$X_A=\left(\frac{1-\phi}{\phi}\frac{P_E}{P_A}\right)^{\sigma}X_E \quad (3.6b)$$

Although this provides demand functions for X_E and X_A, a firm's production capability is limited by the total cost of production as given by the third first order condition, so we would like to express both demand for X_E and X_A in terms of C_P. This is done by substituting (3.6a) and (3.6b) back into (3.2) and solving for X_E and X_A. Doing so produces the demand functions given by **Equations 3.7a** and **3.7b.**

$$X_E=C_P\left(P_E+\left(\frac{1-\phi}{\phi}\frac{P_E}{P_A}\right)^{\sigma}P_A\right)^{-1} \quad (3.7a)$$

$$X_A=C_P\left(P_A+\left(\frac{1-\phi}{\phi}\frac{P_E}{P_A}\right)^{\sigma}P_E\right)^{-1} \quad (3.7b)$$

With demand functions for X_E and X_A, in terms of P_E , P_A, and C_P, we derive the production function of pollution, X_P, in terms of P_E , P_A, and C_P by substituting (3.7a) and (3.7b) back into the original production function (3.1).

$$X_P = \gamma\left(\phi\left(C_P\left(P_E + \left(\frac{1-\phi}{\phi}\frac{P_E}{P_A}\right)^{\sigma} P_A\right)^{-1}\right)^{\frac{\sigma-1}{\sigma}} + (1-\phi)\left(C_P\left(P_A + \left(\frac{1-\phi}{\phi}\frac{P_E}{P_A}\right)^{\sigma} P_E\right)^{-1}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \qquad (3.8)$$

After a somewhat tedious algebraic exercise, the production function of pollution—as a function of total pollution cost, price of abatement, and price of emitting—reduces to a much simpler form given by **Equation 3.9** which we also express for future use in terms of the budget constraint by the form given by **Equation 3.10**.

$$X_P = C_P\gamma\left(\phi^{\sigma} P_E^{1-\sigma} + (1-\phi)^{\sigma} P_A^{1-\sigma}\right)^{\frac{1}{\sigma-1}} \qquad (3.9)$$

$$C_P = \frac{X_P}{\gamma}\left(\phi^{\sigma} P_E^{\;1-\sigma} + (1-\phi)^{\sigma} P_A^{\;1-\sigma}\right)^{\frac{1}{1-\sigma}} \qquad (3.10)$$

With an expression for production in terms of the budget constraint, C_P, and the price of abatement and emitting, P_E and P_A, we now derive the conditional factor demand function for the inputs solely in terms of the budget constrain and input price. We do this using Shepard's Lemma which is given as:

$$X_i \equiv \frac{\partial C_P}{\partial P_i} \qquad \text{(Shepard's Lemma)}$$

After taking the partial derivative of C_P , as expressed in (3.10), with respect to P_E and P_A, we obtain the conditional factor demands for emitting and abating given in **Equations 3.11a** and **3.11b**:

$$X_E = \frac{X_P}{\gamma}\left(\frac{\gamma}{X_P}\phi\frac{C_P}{P_E}\right)^{\sigma} \tag{3.11a}$$

$$X_A = \frac{X_P}{\gamma}\left(\frac{\gamma}{X_P}(1-\phi)\frac{C_P}{P_A}\right)^{\sigma} \tag{3.11b}$$

We pause now to recall the definition of the price elasticity of demand which gives the percent change in quantity demanded in response to a one percent change in price:

$$\varepsilon_{D_E} \equiv \frac{\partial X_E}{\partial P_E}\frac{P_E}{X_E} \qquad \text{(Def. Price Elasticity of Demand)}$$

Using this definition we derive the price elasticity of demand for emitting by substituting (3.10) back in to (3.11a) and then take the partial derivative of (3.11a) with respect to P_E:

$$\frac{\partial X_E}{\partial P_E} = \frac{\partial}{\partial P_E}\left[\frac{X_P}{\gamma}\left(\frac{\gamma}{X_P}\phi\frac{C_P}{P_E}\right)\sigma\right];\ where,\ C_P = \frac{X_P}{\gamma}\left(\phi^{\sigma}P_E^{\,1-\sigma} + (1-\phi)^{\sigma}P_A^{\,1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{3.12}$$

Although a bit tedious to work out algebraically, this eventually reduces to the partial derivative expression given by **Equation 3.13**:

$$\frac{\partial X_E}{\partial P_E} = -\frac{\sigma}{P_E}X_E + \frac{\sigma}{C_P}X_E^{\,2} \tag{3.13}$$

At this point we see that $\partial X_E / \partial P_E$ is independent of γ. From here we simply multiply (3.13) by P_E / X_E to get the price elasticity of demand of emitting:

$$\varepsilon_{D_E} = \frac{\partial X_E}{\partial P_E}\frac{P_E}{X_E} = \left(-\frac{\sigma}{P_E}X_E + \frac{\sigma}{C_P}X_E^{\,2}\right)\frac{P_E}{X_E} \tag{3.14}$$

Rearranging the terms leads to the desired relationship between the elasticity of substitution and price elasticity of demand for X_E which is given by Equation 3.15.

$$\sigma = \frac{-\varepsilon_{D_E}}{1 - \frac{X_E P_E}{C_P}} \tag{3.15}$$

Upon closer inspection, the relationship can be simplified further. Since $C_P = X_E P_E + X_A P_A$, the right hand term in the denominator is simply the value share of pollution emitted as an input to production (θ_E). This allows σ to be expressed solely in terms of ε_{D_E} and θ_E as given in **Equation 3.16.**

$$\sigma = \frac{-\varepsilon_{D_E}}{1-\theta_E}, \qquad \text{where } \theta_E = \frac{X_E P_E}{C_P} = \frac{X_E P_E}{X_E P_E + X_A P_A} \tag{3.16}$$

In their models, Hyman, Sarofim, and de Masin assume that that θ_E << 1 so that $\sigma \approx -\varepsilon_{D_E}$. This was shown previously in Equation 2.6. Hyman is able to assert this on the basis that since there are currently few regulatory constraints of greenhouse gas emissions, the control costs of non-CO_2 greenhouse gases are a small share of the total production costs of all the other conventional inputs. The value share of emissions in this case is effectively zero. Sarofim and de Masin assume that even though significant policy constraints are in effect for air pollution emissions, control costs are still comparatively low when compared to the costs of all other conventional inputs. For the nonfuel-related air pollution emissions, this is most likely the case and we accept the assumption that control costs are a small fraction of overall production costs. For nonfuel-related emissions (3.16) reduces to:

$$\boxed{\sigma = -\varepsilon_{D_E} \textit{(nonfuel} - \textit{related emissions)}} \tag{3.17}$$

However, for fuel-related air pollution, we know that stringent policy controls are already in effect in many regions—particularly in developed countries—so that substantial emissions reduction and capital invested in pollution abatement has already occurred. Since, at the fuel-related level, the substitution is between abated and emitted pollution, the simplification that θ_E << 1 does not hold and the $\sigma \approx -\varepsilon_{D_E}$ assumption becomes invalid.

Under market equilibrium, firms would only adopt abatement technologies up until the point where the cost for additional abatement opportunities is equal to the cost of regulatory compliance. Therefore, under market equilibrium subject to a regulatory constraint, the price of emitting, P_E, will equal the price of abating, P_A. Taking into account emission controls and abatement costs under equilibrium reduces the value share of emissions, θ_E, to simply the percentage of overall pollution emitted as given in **Equation 3.18**:

$$\theta_E = \frac{X_E P_E}{X_E P_E + X_A P_A}, \quad since \quad PE = PA \quad \rightarrow \quad \theta_E = \frac{X_E}{X_E + X_A} = \%Emitted \tag{3.18}$$

Combining Equations 3.18 and 3.16 gives the final relationship between σ and ε_{D_E} for the fuel-related emissions case:

$$\boxed{\sigma = \frac{-\varepsilon_{D_E}}{1-\%Emitted} = \frac{-\varepsilon_{D_E}}{\%Abated} \quad (fuel\text{-}related\ emissions)} \tag{3.19}$$

Despite the length of the derivation, the resulting functional forms given by Equations 3.17 and 3.19 are remarkably simple and capture the fundamental endogenous feedbacks of what we would intuitively expect to observe. Initially, in the absence of any policy, the ability to substitute between emitting and abating will be fixed according to the opportunities allowed by abatement technologies. In the presence of existing emission policy controls, a certain level of abatement will already have been realized and opportunities for further abatement will be limited to those technologies that have yet to be implemented. As the percentage of total abated pollution (*%Abated*) increases, substitution away from emitting becomes more difficult since many of the previously available abatement opportunities will have already been realized. Over time, this causes the elasticity of substitution to become increasingly more inelastic. When this occurs, firms will be forced to resolve to other ways to comply with air pollution reduction policies such as substituting to less emission intensive fuel types and production, or reducing fuel consumption altogether.

3.1.2 Emitting Price Elasticity of Demand from Abating Price Elasticity of Supply

With a relationship between σ and ε_{D_E}, we now look to establish a relationship between ε_{D_E} and the abating price elasticity of supply, ε_{S_A}. Once this relationship is established ε_{S_A} can be obtained from MAC derived from the engineering and cost details of specific abatement technologies.

We recall from (3.11a) in the previous derivation the conditional factor CES demand function for emitting:

$$X_E = \frac{X_P}{\gamma}\left(\frac{\gamma}{X_P}\phi\frac{C_P}{P_E}\right)^{\sigma} \tag{3.20}$$

Solving (3.20) for the price of emitting in terms of quantity of pollution emitted results in **Equation 3.21**:

$$P_E = \phi \cdot C_P\left(\frac{\gamma}{X_P}\right)^{\sigma-1/\sigma} X_E^{-1/\sigma} \tag{3.21}$$

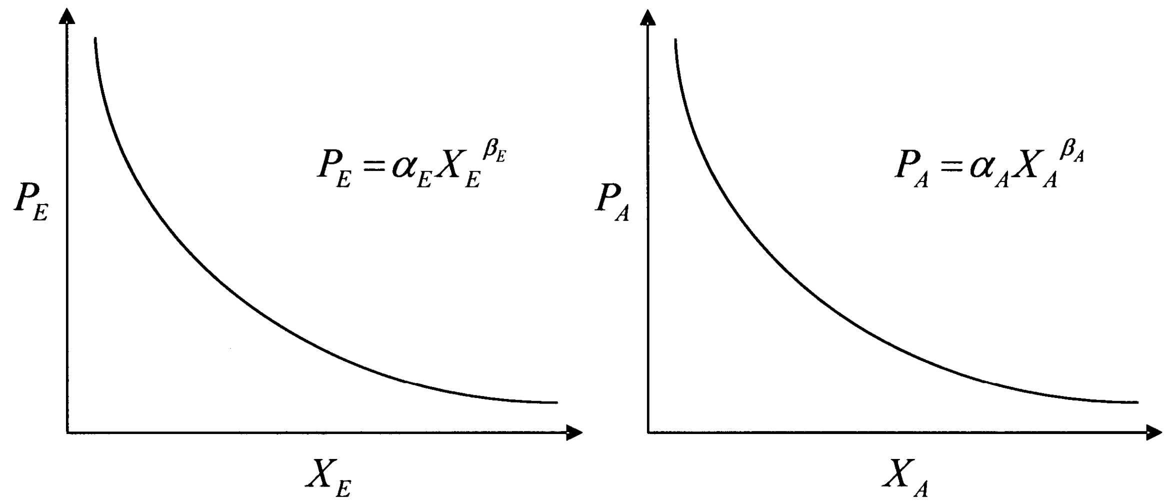
Since ϕ, C_P, X_P, γ, and σ are constant, we can reduce the overall demand function to an expression with only two parameters:

$$P_E = \alpha_E X_E^{\beta_E},\ where\ \alpha_E = \phi \cdot C_P\left(\frac{\gamma}{X_P}\right)^{\sigma-1/\sigma},and\ \ \beta_E = -1/\sigma \tag{3.22a}$$

Similarly we obtain a two term parameterized expression for the conditional factor demand function for abating in terms of α_A and β_A:

$$P_A = \alpha_A X_A^{\beta_A},\ where\ \alpha_A = (1-\phi)\cdot C_P\left(\frac{\gamma}{X_P}\right)^{\sigma-1/\sigma},and\ \ \beta_A = -1/\sigma \tag{3.22b}$$

With $\alpha_A > 0$, $\alpha_E > 0$, $\beta_E = \beta_A < 0$, the demand curves for Equations 3.22a and 3.22b take on the familiar microeconomic demand curve shape where demand for emitting and abating increases as prices decline. The resulting curves for demand of emissions and abatement are given in **Figures 3.4a and 3.4b** respectively:



(a) **(b)**

Figure 3.4. (a) Emitted pollution parameterized demand function and curve, (b) abated pollution parameterized demand function and curve.

We now look at the case of fuel-related pollution. In the proposed method, we recall that the total pollution is produced in fixed proportion with the total fuel consumed as represented by a Leontief production block where the elasticity of substitution is perfectly inelastic. A block diagram of this representation was given earlier in Figure 3.1b. Since substitution between the fuel and pollution is perfectly inelastic, the quantity of pollution required is constant for a given quantity of fuel demanded regardless of the price.
On the pollution abated and emitted demand curves, this is shown as a vertical line as given in **Figures 3.5a** and **3.5b**. When total pollution is completely inelastic, the pollution required for a fixed quantity of fuel consumed is just the sum of the quantity of pollution emitted and pollution abated:

$$X_P = X_E + X_A \tag{3.23}$$

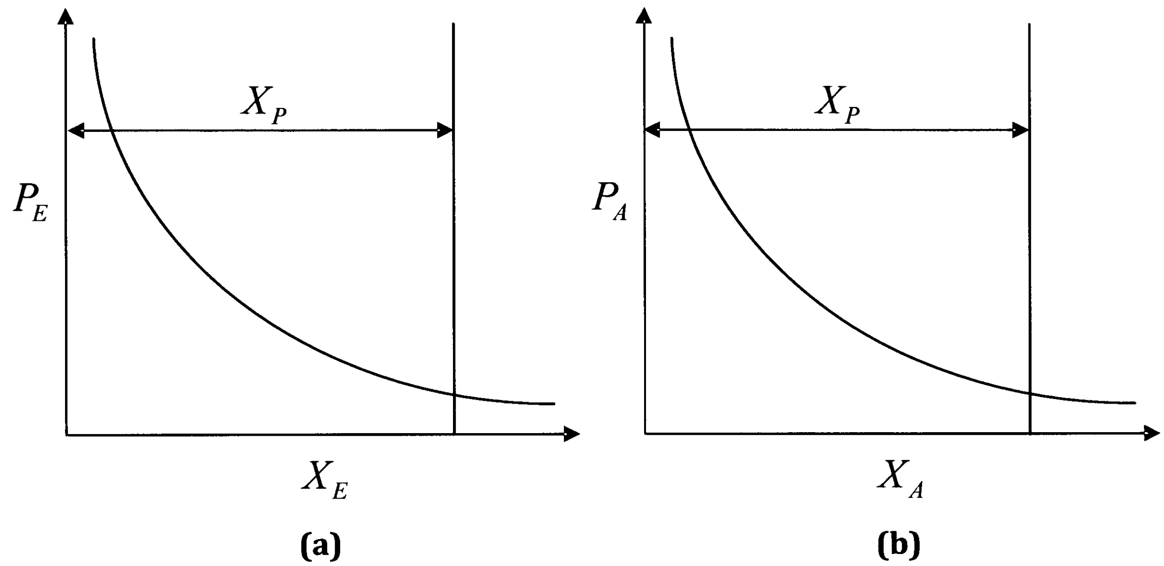


Figure 3.5. (a) Emitted pollution demand curve with inelastic pollution demand, X_P, (b) abated pollution demand curve with inelastic pollution demand, X_P .

Because this is always the case for completely inelastic demand of X_P, we can superimpose the pollution abated and pollution emitted demand curves by rotating the pollution emitted curve about the vertical axis and then fitting the axis to the vertical total pollution, X_P, line as shown in **Figure 3.6**. For the base year, the firm is indifferent between emitting and abating pollution and the price of pollution emitted, P_{E_O}, equals the price of pollution abated, P_{A_O}, leading to an economically efficient outcome. The quantity of pollution emitted and pollution abated in equilibrium are given by X_{E_O} and X_{A_O} respectively.

In the presence of an emission control that is more stringent than that of the base year, the same amount of total pollution for fuel consumed is constant—i.e. the demand for total pollution is inelastic— resulting in an increased demand for abatement and a decreased demand for emitting. This has the effect of shifting the demand for emitting to the left in Figure 3.6 and up the D_E curve resulting in an increase in price. However, since X_P is perfectly inelastic, any decrease in emitting must be met by an equal increase in abatement so that the demand curve for emitting is in effect equivalent to the supply curve for abating. Put another way, if we know what the supply curve is for abatement, we simultaneously know what the demand is for emitting since, due to total pollution being constant, all pollution not abated must be emitted and vice versa.

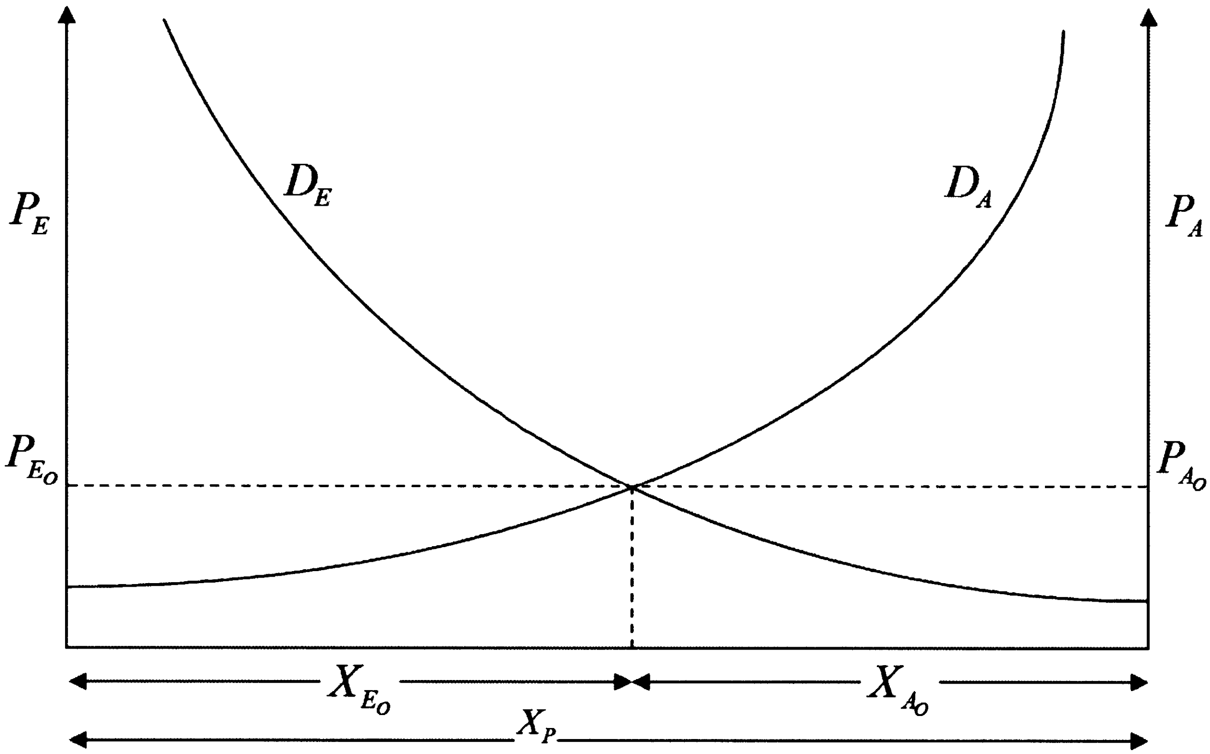


Figure 3.6. (a) Emitted pollution demand curve with inelastic pollution demand, flipped vertically and superimposed on the abated pollution demand curve.

For the non-fuel related emissions, this does not entirely hold since the top most nest in the production block is not Leontief; however, since we expect the cost of other conventional inputs to greatly exceed the costs of non-fuel related emissions, the relationship still serves as a good approximation.

3.1.3 Abating Elasticity of Supply from Marginal Abatement Cost Curves

With a relationship between ε_{D_E} and ε_{S_A} .we now turn to deriving ε_{S_A} from technologically rich abatement engineering data. It is in this step that we make the connection by parameterizing the "top-down" price elasticity of supply parameters using rich "bottom-up" technological detail. As has been shown previously, the abating elasticity of supply is readily obtained from marginal abatement cost (MACs) curves which provide an overview of the technical opportunities available for emission reduction. For air pollution reduction technologies, the MAC is obtained from technology specific engineering data that provides an estimate of the additional abatement opportunities the technology affords along with the marginal cost of the technology. Placing the abatement opportunities afforded by each technology in order of increasing marginal cost gives the overall MAC. In essence, the MAC gives the supply curve for abatement, ε_{S_A} . An example of a MAC for abatement of SO_2 from refined oil (ROIL) used in the USA for 2005 is given in **Figure 3.7**.

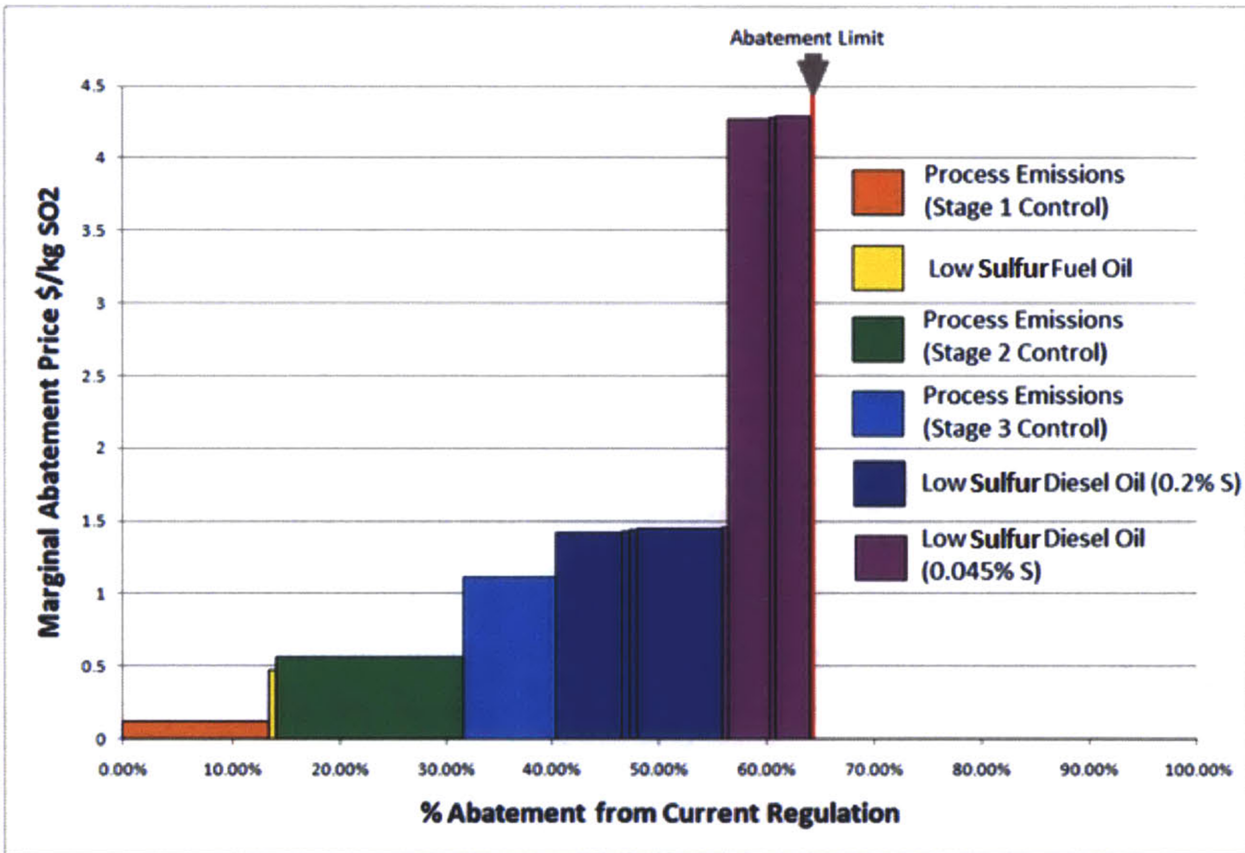


Figure 3.7. Marginal abatement cost curve (MAC) for SO_2 emissions from refined oil products (gasoline and diesel) used in the USA in 2005.

In the curve, the technology specific abatement opportunities include a wide range of fuel desulfurization technologies and process emission controls for stationary combustion. According to the MAC, 2005 abatement technologies are capable of reducing emissions by up to an additional 65% on top of what has already been achieved under existing policy controls. Once the 65% mark is reached all abatement opportunities are exhausted so that any additional emissions reduction will have to come from a reduction in refined oil use and potentially a shift towards other less sulfur intensive energy sources (e.g. compressed natural gas or electric vehicles in the transportation sector).

With the technology specific abatement opportunities given by the MAC, the price elasticity of supply for abatement is obtained by performing a log-linear regression using the conditional factor CES demand function for emitting given previously in Equation 3.22a. However, since the demand curve for emitting is the same as the supply curve for abatement, the demand price of emitting and supply price for abating are the same, $P_E = P_A$, and since demand for pollution is inelastic with fuel consumption, the quantity of emissions equals the total pollution minus pollution abated, $X_E = X_P - X_A$. Substituting this into Equation 3.22a, we obtain the functional form of the MAC as given by **Equation 3.24**.

$$P_A = \alpha \cdot (X_P - X_A)^{\beta} \tag{3.24}$$

We see that the log-linear regression is an appropriate form to regress against the functional form of the MAC as it can be expressed in a log-linear form as given by Equation 3.25.

$$P_A = \alpha \cdot (X_P - X_A)^{\beta} \quad \rightarrow \quad \log(P_A) = \log(\alpha) + \beta \cdot \log(X_P - X_A) \tag{3.25}$$

In logarithmic form, the price elasticity of demand is defined as:

$$\varepsilon_{D_E} \equiv \frac{\partial \log(X_E)}{\partial \log(P_A)} \qquad \text{(Definition of Price Elasticity)}$$

Since $\log(\alpha)$ is constant, taking the total partial derivative of (3.25) leads to the desired expression for ε_{D_E}:

$$\varepsilon_{D_E} = \frac{\partial \log(X_E)}{\partial \log(P_A)} = {}^{1}\!/\!_{\beta} \tag{3.26}$$

From this we see that the price elasticity of demand for emitting is simply $1/\beta$ from the Poisson regression on the MAC. The elasticity of substitution is obtained from this as shown previously using Equation 3.19.

Although the method for obtaining the price elasticity of supply for abatement is straightforward, there are a number of important considerations to be made when using parameters derived from a MAC in order to properly interpret the data when benchmarking a CGE model. First, the availability of future abatement opportunities will be subject to how much abatement has already been realized under existing policy controls. This is particularly important when considering abatement of air pollution since, unlike with carbon and other greenhouse gas policy, relatively stringent controls to limit air pollution emissions are already in place in many countries. Recognizing the effect of existing policy controls on present abatement leads to two conceptually different MACs, the theoretical no-control curve that includes the marginal cost of past abatement already realized, and the control curve that only considers abatement opportunities above and beyond what has already been achieved through existing policy. Both curves are given in **Figure 3.8.**

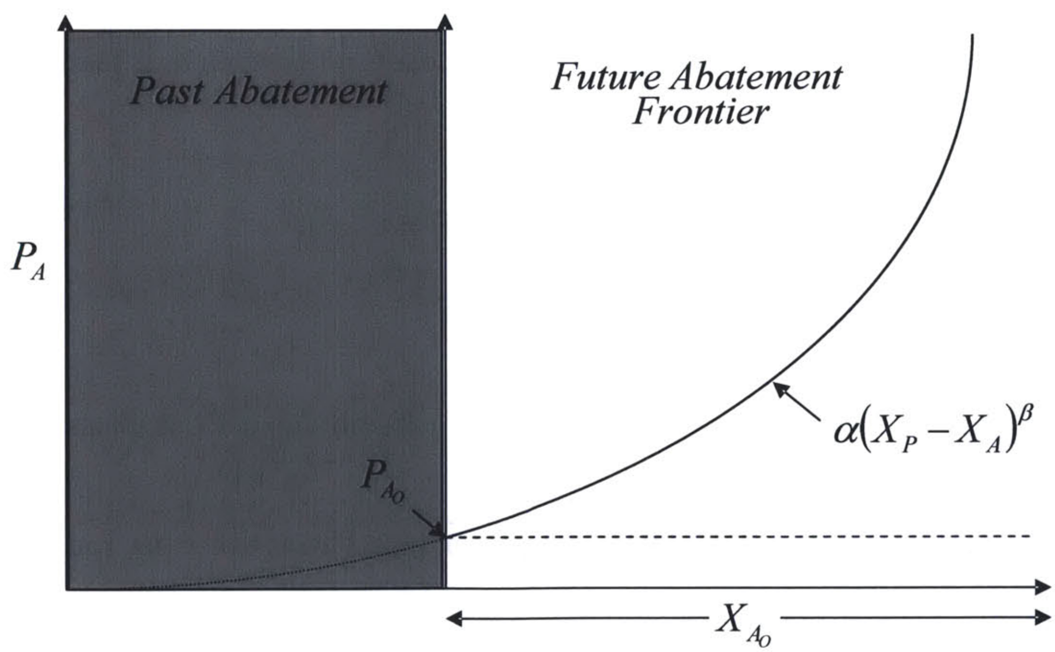


Figure 3.8. Functional form of the marginal abatement cost curve (MAC) including past abatement already realized under existing policy, and the future abatement frontier of available abatement opportunities.

In the figure, the theoretical no-control curve includes past abatement as well as the future abatement frontier, whereas the curve that only accounts for abatement in addition to existing controls begins with an initial price for abatement, P_{A_0}, and then only identifies opportunities given by the future abatement frontier. The theoretical no-control curve is much more difficult to obtain in practice as it is often difficult to distinguish past marginal cost of abatement already realized—shown in the figure by the shaded region—as well as the overall quantity of pollution abated that can be attributed to existing regulation.

Another consideration is the variation of abatement opportunities among regions. This can occur due heterogeneity in the stringency of emission controls between regions and the availability and cost of abatement opportunities. We expect the opportunities for abatement to be relatively the same among regions as abatement technologies such as scrubbers and flue gas desulphurization are in general universally available regardless of region. However, there may be some variation among regions when abatement opportunities are identified such as switching away from fuel types with high pollution content (e.g. switching from high sulfur to low sulfur grade coal). The variation in the level of abatement among regions is therefore due primarily to the level of stringency of existing policy in a given region.

With the availability of abatement technologies given uniformly among regions, and with the stringency of emission controls acting as the main contributor to regional variation of future abatement opportunities, we can think of abatement opportunities for all regions lying somewhere on a global MAC where individual regions are positioned depending on the stringency of existing controls. An illustration of a global MAC with various hypothetical regions is given in **Figure 3.9**.

In the figure four regions—R1, R2, R3, and R4—are indicative of regions where various levels of abatement have already been achieved according to existing air quality regulation. In this case, region R1 would have the weakest emission controls, region R4 would have the strongest, with R2 and R3 lying in between. With less stringent emission controls, R1 will have achieved less percentage of abatement than R4 and the initial marginal cost for additional abatement for R1, $P_{A_0(R1)}$, will be less than that of R4, $P_{A_0(R4)}$.

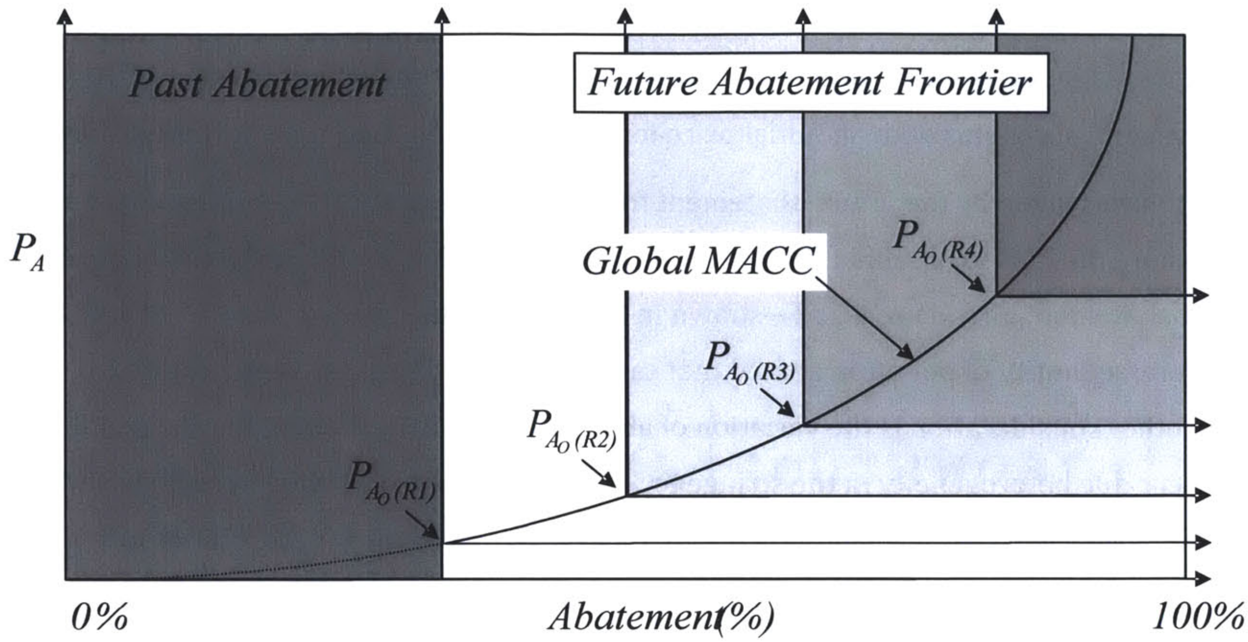


Figure 3.9. Global MAC giving four future abatement frontiers for four different regions—R1, R2, R3, and R4— based on the stringency of existing emission controls.

In the case that more stringent policy is implemented, R1 faces the largest future abatement frontier and the most opportunity for additional abatement. On the other hand, R4—starting at a point much higher up the global MAC—will have a much smaller future abatement frontier and limited options for future abatement with the remaining abatement options becoming increasingly costly. In general, as regions adopt stricter air pollution regulation and increase their overall percentage of pollution abated, they gradually move up the curve and opportunities for future abatement are incrementally exhausted while becoming increasingly costly.

In terms of how these considerations affect selection of MACs for benchmarking abatement opportunities within a CGE model, we note that since the stringency of policy controls will vary among regions, we will need region and sector specific MACs to provide a more accurate representation of the future abatement frontiers unique to each region. Previously this was accomplished in part in the representations of Sarofim and de Masin, with Europe and China being representative of developed and developing countries respectively. However, even among developed and developing countries we see large variation in air pollution standards both in terms of the quantity of pollution allowed and the species of pollutants that are targeted. Properly benchmarking CES production functions within a CGE framework will therefore require region specific data to allow for heterogeneous parameterization.

3.2 Parameterization of Abatement Opportunities

Thus far we have focused almost exclusively on representing abatement opportunities in a CGE framework through the elasticity of substitution between emitting and abating. However, to fully implement the method into a CGE model additional parameters are required to benchmark the value share of emissions in the base year. To do this we calibrate the value share using base year values for the quantity of pollution emitted, X_{E_0}, the quantity of pollution abated, X_{A_0}, the initial marginal price of pollution abated, P_{A_0}, and the initial marginal price of pollution emitted, P_{E_0}. As shown previously in Equation 3.18, at the margin under equilibrium, firms will be indifferent between emitting and abating so the value share for emitting is simply the percentage of total pollution emitted.

In implementing the new methodology into the EPPA model, we benchmark both σ and θ using data obtained from the Greenhouse Gas and Air Pollution Interactions and Synergies (GAINS) model developed by the International Institute for Applied Systems Analysis (IIASA) (Nguyen, Wagner and Schoepp 2011). GAINS is an integrated assessment model used to quantify the costs and environmental benefits of reducing emissions of greenhouse gases and urban air pollutants using a bottom-up approach based on highly detailed engineering data on emission sources and technology options. Greenhouse gases represented in the model include CO_2, CH_4, N_2O, and fluorinated gases. Air pollutants include SO_2, NO_x, PM, CO, NMVOCs, and NH3. The regions and sectors in GAINS are far more disaggregated than those in EPPA and with significant effort can be directly mapped to the corresponding regions and sectors in EPPA. The data from GAINS is benchmarked to 2005 which closely corresponds to EPPA's 2004 base year. Assuming little change in abatement opportunities, costs, and annual emissions occurred between 2004 and 2005, we use the 2005 GAINS data to benchmark the base year in EPPA.

Of interest in parameterizing abatement opportunities in a CGE framework, GAINS includes estimates of marginal abatement costs, present day cost of regulatory compliance, and emissions. Of the air pollutants, marginal abatement cost curves are only given for SO_2, NO_x and $PM_{2.5}$. However, since SO_2, NO_x and $PM_{2.5}$ are among the most important of the air pollutants targeted by air pollution regulation such as the National Ambient Air Quality Standards, this sample provides a good starting point for introducing the new methodology within a CGE framework and for looking at interrelated policy effects among traditional air pollution species. One caveat is that not all countries are currently represented in the GAINS model making it incomplete to fully represent all of the regions in a global CGE model, however, this does not affect regional studies. The countries that are represented by GAINS along with their corresponding EPPA regions are given in **Figure 3.10**.

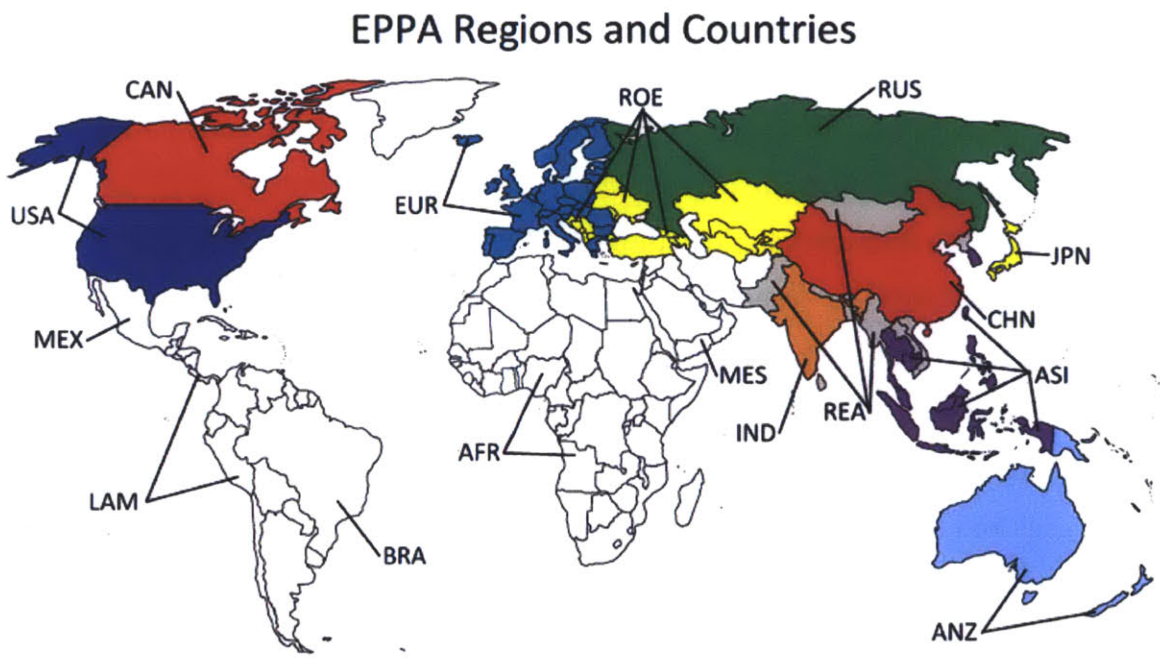


Figure 3.10. Regions represented in the GAINS model as mapped into the EPPA regions. The colored regions are those for which GAINS data is available for benchmarking SO_2, NO_x, and $PM_{2.5}$.

As can be seen, all of the largest developed economies such as the U.S., Europe, and Japan are represented as well as key developing economies such as China, India, and other rapidly developing economies in Asia. Missing from GAINS are all of Central and South America, Africa, and the Middle East countries.

The MAC provided by GAINS give control cost curves that represent future abatement opportunities beyond reduction already achieved by existing emission controls. Therefore MAC are for future abatement frontiers only and don't include the theoretical no-control curves that also give the marginal cost of past abatement already realized. Since the curves provided by GAINS do not contain any information on past abatement, the initial marginal cost for abatement and the total abatement achieved under existing emission controls must be obtained independently.

The initial marginal cost for abatement is obtained by introducing an additional term into the abatement supply function given earlier by Equation 3.25. The new term, P_O, provides an additional degree of freedom in the initial price as shown in **Equation 3.27**.

$$P_A = P_O + \alpha \cdot (X_P - X_A)^\beta \tag{3.27}$$

Or in the log-linear form:

$$\log(P_A - P_O) = \log(\alpha) + \beta \cdot \log(X_P - X_A) \tag{3.28}$$

The overall initial price, P_{A_O}, that includes both α and P_O is then just:

$$P_{A_O} = P_O + \alpha \cdot (X_P)^\beta \tag{3.29}$$

With an additional degree of freedom in the log-linear regression, we solve for P_O by optimizing the correlation coefficient of the Poisson regression of Equation 3.28 on abatement cost data given by the GAINS model. This has the effect of providing a reasonable estimate of the initial marginal price for abatement, P_{A_O}, which in turn provides a value for β that most closely matches the abatement opportunities as given from the engineering data in GAINS. As mentioned previously, since abatement opportunities vary among sectors and regions, the GAINS marginal cost data is first mapped into the corresponding EPPA regions and sectors based on the fuel type associated with the emissions (coal, gas, oil, and refined oil). All non-fuel related abatement opportunities are mapped into a separate MAC that is then used to parameterize the non-fuel related elasticity of substitution in the upper block of the production nest as illustrated previously in Figure 2.3. In taking into account regional and sectoral heterogeneity in elasticities of substitution mapping the abatement opportunities from the GAINS region and sectors end up generating unique 155 abatement opportunities for SO_2 abatement among the 9 EPPA regions, and 159 opportunities for NO_x. Because heterogeneous representation of SO_2 and NO_x abatement opportunities in the 9 regions for which GAINS data was available required the parameterization of 304 abatement opportunities, a Mathematica script was written to automate the process of (1) mapping the GAINS abatement opportunities into EPPA by region, sector and fuel type, (2) determining the value of P_O by optimizing the correlation coefficient of the Poisson regression to the GAINS data, (3) determine P_{A_0}, θ, ε_D, and σ, based on the value determined for P_O, and (4) formatting the benchmarked parameters so as to readily be implemented into the EPPA modeling language GAMS. While the entire results of all the parameterization of SO_2 and NO_x abatement opportunities are given in Appendix 1, an example of one of the regressions on the marginal abatement cost opportunities provided for SO_2 abatement from coal used in electricity production in China is given in **Figure 3.11**.

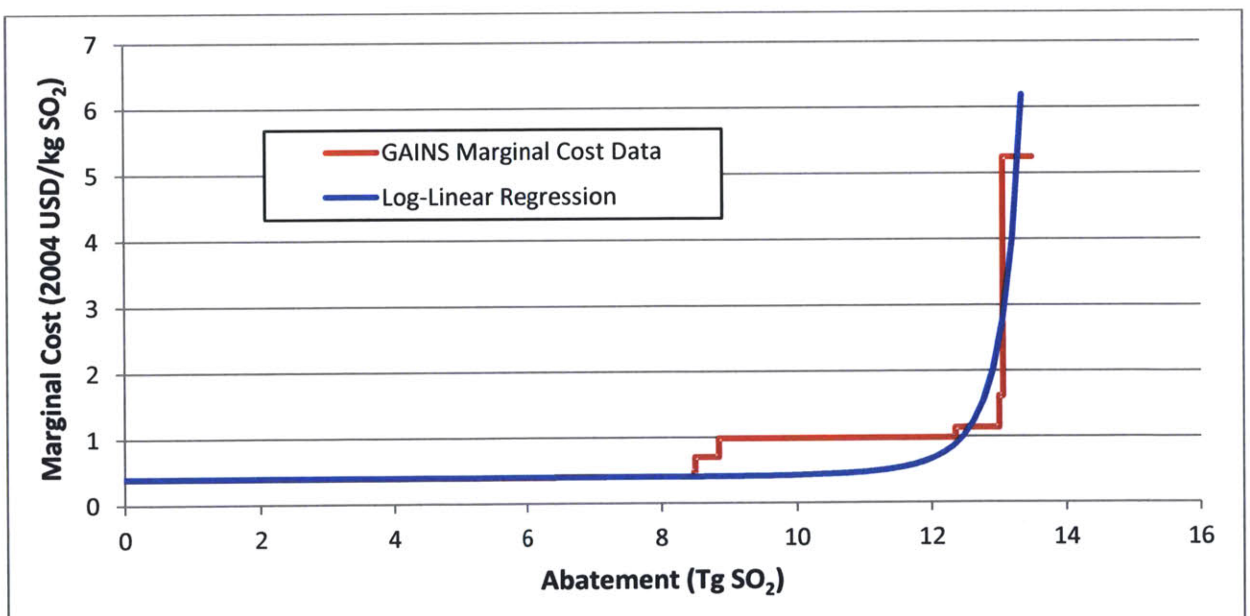


Figure 3.11. Log-linear regression of abatement supply function on data for abatement opportunities provided by GAINS for SO_2 from coal used in electricity production in China.

In the graph, the marginal cost per kg of SO_2 abated is given in 2004 USD which corresponds to the base year in EPPA. For this case, according to GAINS, in 2005 13.5 Tg of SO_2 was emitted from coal used in electricity production in China. Of the 15.61 Tg emitted, GAINS identified abatement opportunities from the available technologies for 13.5 Tg SO_2, or 86.5% of total pollution. From the log-linear regression we find the value of the free parameter, P_O, that optimizes the correlation coefficient to be \$0.395013 (2004 USD/kg SO_2). This corresponds to a correlation coefficient of 0.9975 giving an extremely good fit to the GAINS data.

While the marginal abatement cost data provided does not give information on past marginal abatement costs—as would be given by a "no-control" curve, GAINS does provide an estimate of the total current control costs of regulatory compliance by region and sector. From this, a reasonable estimate of the current level of abatement already achieved by abatement technologies implemented to comply with existing controls can be obtained by dividing the total existing control cost by the initial marginal cost of abatement obtained from the log-linear regression, P_{A_0}.

Parameter	Value
Initial Total Pollution	24.1395 (Tg SO_2)
Initial Emissions	15.6069 (Tg SO_2)
Initial Abatement	8.5326 (Tg SO_2)
Policy Cost	\$3.15 Billion (2004 USD)
Initial Price (P_{AO})	\$0.395246 (2004 USD/kg SO_2)
Value Share of Emissions (θ)	0.6465
Price Elasticity of Demand (ε_D)	-0.25
Initial Elasticity of Substitution (σ)	0.71
α	30.0324
β	-4.0070
Free Variable (P_o)	\$0.395013 (2004 USD/kg SO_2)
Correlation (r^2)	0.9975

Table 3.1. Table of GAINS data and regression parameters obtained for SO_2 abatement from coal used in electricity production in China.

For the case of the current level of abatement for SO_2 from coal used in electricity production in China, this method predicts that 8.53 Tg SO_2 is currently abated or ~35% of total SO_2 produced. A complete list of the parameters provided by GAINS and obtained from the abatement opportunities available for coal used in electricity production in China is given in **Table 3.1**. The parameters for other abatement opportunities are also given in Appendix 1.

With the framework to represent abatement opportunities implemented, air pollution controls can take the form of a variety of policy instruments. These can range from region specific air pollutions caps where regional economies are free to decide optimal reduction pathways that limit the policies economic impact, region and sector specific caps which require fixed reduction within specific sectors of the regional economy, Pigouvian taxes, and a whole range of region and/or sector specific caps with permit trading schemes in place. While all of these policy instruments can be deployed using the new methodology, we limit our consideration in implementing the policy in EPPA to region specific air pollution caps.

3.3 Limitations to Proposed Representation

We have now seen that the new proposed methodology offers multiple improvements over previous approaches to representing abatement opportunities in a CGE framework. Most notably are the ability to endogenize the costs associated with abatement, the representation of abatement opportunities for multiple pollutants within the same framework, and the ability to represent abatement opportunities unique to each region and sector by fuel-type or by non-fuel related abatement opportunities. Despite these improvements, several limitations should be considered.

The structure of CGE models assumes that the elasticity of substitution between inputs remains constant. While this may be true of many inputs to production in general, it is not necessarily true for abatement. As has been shown, price elasticities of supply for abatement are benchmarked on data of currently available abatement technologies—in the case of benchmarking the EPPA model, the abatement data used was for 2005. However, over time as demand for abatement increases in the presence of increasingly stringent emission controls, we would expect a certain amount of endogenous technological change to decrease the marginal cost of abatement due to: increased economies of scale, learning by doing, innovation to reduce cost of existing abatement technologies, and the introduction of new technologies currently not in existence. This limitation strikes at what was earlier identified as a core challenge of all CGE models which is how to properly represent induced technical change.

While methods for representing induced improvements in abatement technologies are still being explored, one significant advantage at least of the proposed methodology is that it decouples the effects of exhausting existing abatement opportunities from the effects due to new abatement opportunities becoming available through induced technical change. We recall from Equation 3.19 the relationship between the elasticity of substitution, price elasticity of demand for emissions, and value share for emitting (i.e. the percentage of overall pollution emitted).

$$\sigma = \frac{-\varepsilon_{D_E}}{\%Abated} \tag{3.30}$$

When ε_{D_E} remains constant, we expect the percentage of pollution abated to increase over time as emission controls become more stringent and more pollution is abated. Although the original percent abated is benchmarked from estimations of abatement in the base year, the exhaustion of abatement opportunities can be obtained by recalibrating the elasticity of substitution during each time step by using the new percentage of pollution abated generated by the model from the previous time step. This dynamic calibration then forces the elasticity of substitution to gradually becomes more inelastic and eventually converge to the price elasticity of demand as all abatement opportunities are realized. On the other hand, the effect of additional abatement opportunities on the elasticity of substitution introduce by induced technological change could be achieved similarly by forcing the price elasticity of demand to become more inelastic overtime as a result of more stringent policy controls. Finding a way to do this dynamically within the recursive solving structure of EPPA would be an valuable next step for improving the methodology proposed.

Thus far we have looked at emissions reduction coming largely from the implementation of abatement technologies in the presence of increasingly stringent emission constraints. Other significant sources of emission reduction that are non-abatement related include the shift within a regional economy away from energy intensive production and the autonomous energy efficiency improvement (AEEI). Shifts away from emission intensive production can occur for a variety of reasons including loss in competitive advantage in energy intensive production such as manufacturing, and outsourcing of energy intensive production. In addition, the AEEI has been observed empirically to provide a non-market incentivized decrease in energy intensity that cannot be attributed to energy efficiency improvements motivated by policy or to change in the economic makeup of a region. These effects have little to do with emission abatement and are not captured explicitly under the proposed framework, but are accounted for elsewhere in the EPPA model.

Finally, under the proposed representation, abatement opportunities are specified as being available for a single pollutant species. Some technologies are available for SO_2, some for NO_x, and others for PM, etc. However, it is often the case that a given technology is capable of reducing multiple pollutants simultaneously. Under the GAINS model, when a technology is capable of reducing multiple pollutants, technical abatement opportunities and costs are repeated under each of the pollutants the technology is capable of reducing. Because of this, the costs associated with emission constraints may be partially overestimated in the case where you have a policy that is targeting multiple pollutants that can reduced through the same abatement technology. For example, SO_2 and PM can both be reduced through electrostatic precipitators and scrubbers. However since these technologies would be implemented separately for SO_2 and PM in the model, the cost of abatement would be double counted. While ideally a more precise policy cost estimate is desired, the methodology is still very useful. This caveat only informs the interpretation of model results that policy cost may represent an upper limit on what the true policy costs should be.

4 Model Results: Co-benefits of Pollutant Policy in China and USA

With the new methodology established for representing air pollution abatement opportunities endogenously in a CGE framework, and with the parameters derived for the representation of SO_2 and NO_x using the GAINS model, we consider the behavior of the new methodology for representing abatement opportunities and costs endogenously using the 5th version of the MIT Emission Prediction and Policy Analysis (EPPA) model. We start by comparing the new endogenous representation with the exogenous time-trend and GDP/capita-trend representations used in previous versions of EPPA and highlight some of the advantages of the new representation where the previous representations did not fully capture some of the fundamental underlying economics. After contrasting the new and old methodologies we provide an example of the kind of integrated assessment policy analysis work related to air pollution reduction that can now be achieved using the new methodology. The integrated assessment we consider is a quantified evaluation of potential co-benefits of air pollution policy in China which demonstrates how current demand for greater air pollution controls may go a long way to helping China achieve carbon mitigation goals. Using the new representation, the integrated assessment performed by the model illuminates the extent to which air pollution targets can lead to a reduction in CO_2 emissions, the impact that such policy has on GDP, the shift in the energy technology mix, the introduction of backstop technologies that occurs in response to the shock from the emissions constraint, and the shadow price of emissions reduction.

4.1 Comparison with Exogenous Trend-based Abatement Methods

Previously we identified multiple reasons why existing methods for representing air pollution reduction in a CGE framework were insufficient to capture important interconnected effects and policy costs associated with more stringent emission controls. Exogenous trend based representation—both empirically determined GDP/capita relations and time-trends based on historical emissions reduction—fail to fully represent the cost of additional abatement measures and the feedback response in abatement realized under varying degrees of stringency in emission reduction controls. Previous work to endogenize air pollution abatement opportunities were limited in that they were unable to distinguish between fuel-related and nonfuel-related pollution, were unable to account for heterogeneity in abatement opportunities unique to specific sectors in individual regions, and were not capable of representing multiple pollutants simultaneously within the same framework. While up until this point, we have only talked about the limitations of previous abatement representation in a general sense, we will now consider a specific policy scenario that illustrates quantitatively how the different methods for representing abatement lead to significantly different projections in emission reduction, energy consumption, change in GDP, energy technology mix, and the shadow cost of emissions.

In comparing methods, we will consider the effects of an SO_2 emission reduction policy on China and the USA. We choose China and the USA since, as discussed previously, we expect the effects of emission reduction policy to vary significantly between developed and developing countries as they lie on separate ends of the hypothetical "global MAC" given in Figure 3.8. Illustrating the results for China and the USA allows for direct comparison of these differences. For the policy we set an ambitiously stringent target that requires a 10% emission reduction every five years starting in 2010. We deliberately choose an overly ambitious target because doing so highly constrains the model and increases the magnitude of the effects we would like to contrast making them more immediately observable. While the policy only targets reduction in SO_2, we evaluate the effects the SO_2 control policy has on NO_x emissions to gauge whether each methodology is accurately capturing the interconnected effects a policy constraint on one air pollutant species may have on another species that originates from the same source. Since the abatement technologies for SO_2 and NO_x are independent of each other (e.g. sulfur is removed from coal emission using flu gas desulphurization while NO_x is reduced using staged combustion techniques or catalytic converters).. Additionally, because the abatement technologies are independent, a constraint on SO_2 should only reduce NO_x emissions to the extent that it leads to less fuel consumption.

In order to provide an *ex ante* comparison, we contrast a policy case that constrains the model with an unconstrained reference case which is indicative of what would occur if levels of abatement continue according to the abatement costs established for the base year of EPPA. In the analysis we consider the model results for the reference and policy scenarios for three methodologies being considered: the exogenous time-trend emission coefficient representation, the exogenous GDP/capita trend emission coefficient representation, and the new endogenous abatement opportunity representation. We start by comparing the projections in annual emissions under a policy scenario that requires a 10% reduction in SO_2 every 5 years starting in 2010 and evaluate the policy through 2030; the model results for emission of SO_2 and NO_x under this policy are given in **Figure 4.1**.

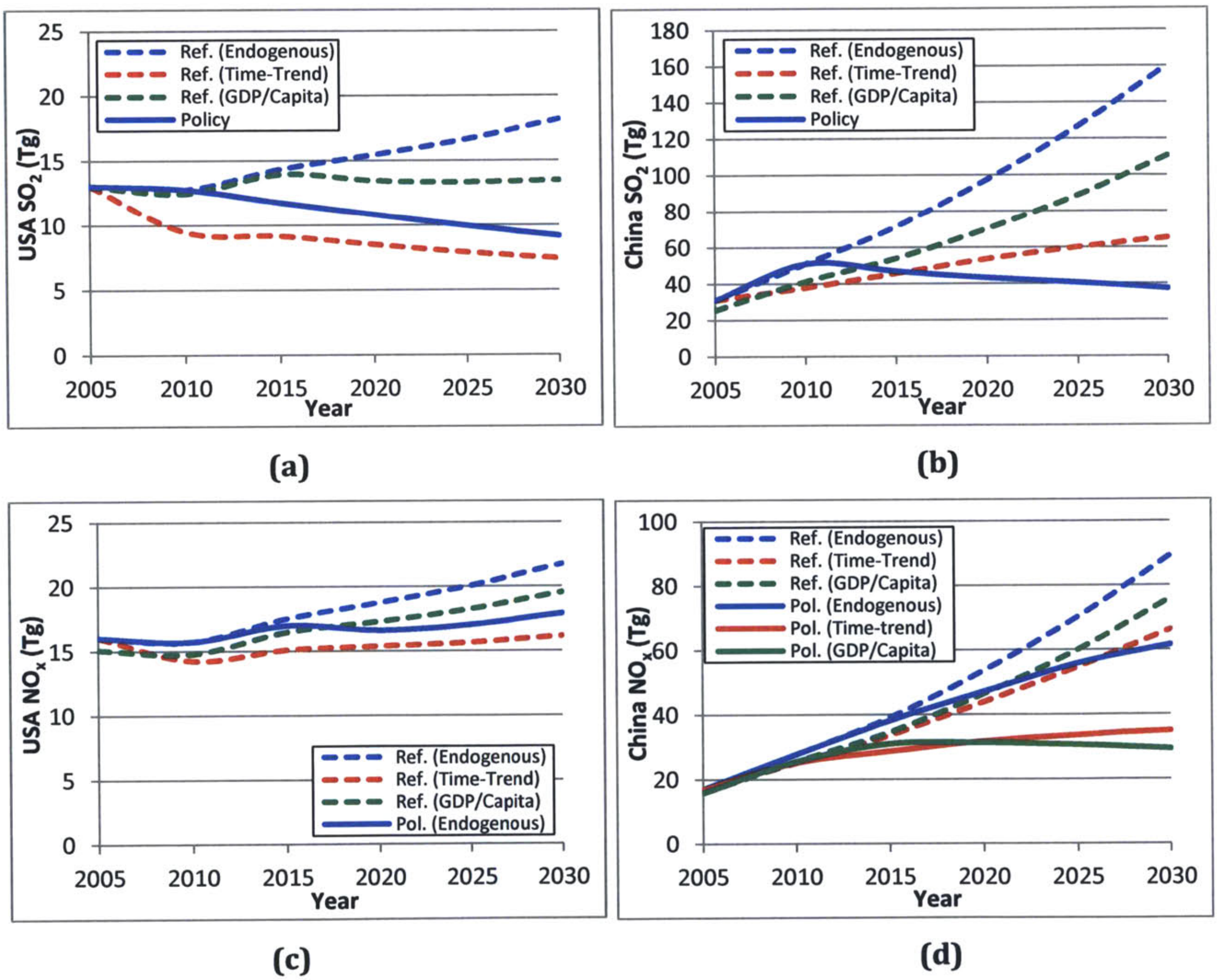


Figure 4.1. Comparison of reference (dotted line) and policy (solid line) scenarios for SO_2 and NO_x emissions in the USA and China using endogenous abatement (in blue), exogenous time-trend (in red), and exogenous GDP/capita (in green) abatement representation in the EPPA model.

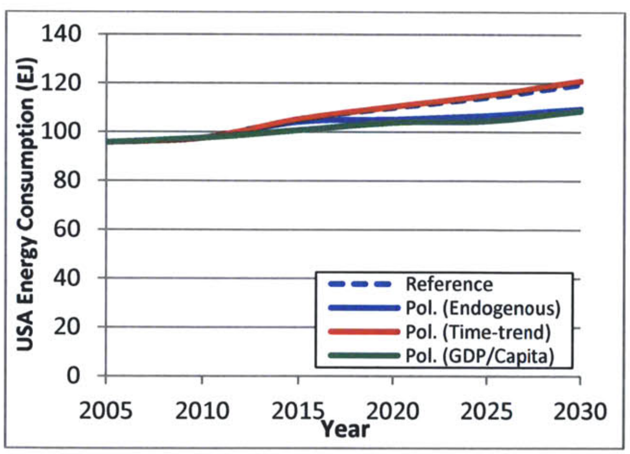
In the figure the blue lines represent the new endogenous abatement representation model results, the red lines give the results using the exogenous time-trend representation, and the green lines give the results of the exogenous GDP/capita representation. The dotted lines represent the reference case model results while the solid lines represent the model results under the policy constraint. In **Figure 4.1 (a)** we see the reference case—i.e. the case where we are locked into current policy—SO_2 emissions in the USA for the three methods. We first note that the emission levels for both the exogenous time-trend and GDP/capita reference cases are lower than the reference case of the endogenous abatement representation. This shows that the model is capturing the exogenous forcing that occurs in the reference case even when no policy constraint is imposed. It is also worth noting that the time-trend reference emission levels are lower than the emissions reduction target set by the policy constraint over the entire 2005 to 2030 time period under consideration. This reflects one of the primary issues with exogenous abatement representation in that significant reduction and abatement occurs automatically without any shock or constraint being imposed by policy controls, i.e. abatement is exogenously forced. In essence this is assuming that future emission reduction will follow past trends and the policy needed to achieve reduction goals will automatically be implemented without any corresponding cost. In this case Figure 4.1 (a) shows that there would be no cost for the time-trend representation of the policy in the USA because the emissions projections set by the time-trend reference cases do not constrain the model, in fact they under constrain it. In contrast, the endogenous representation reference case in Figure 4.1 (a)—the dotted blue line—shows a gradual increase with emissions reaching 18.17 Tg by 2030 compared to the policy case where emissions are constrained to 9.14 Tg by 2030.

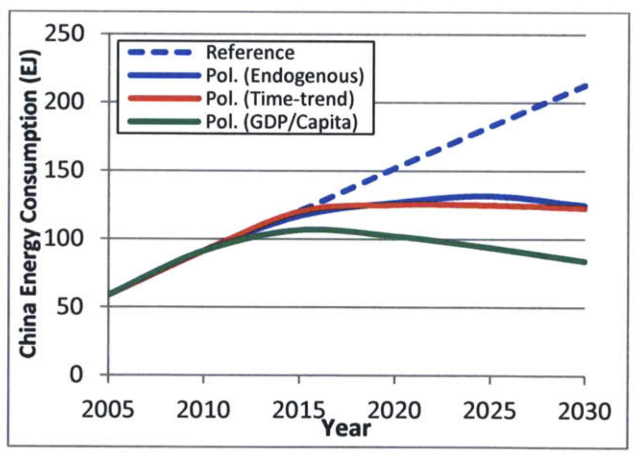
In **Figure 4.1 (b)** we see the SO_2 emissions trends for the same abatement representations for China. Overall the growth in emissions under each methodology is much greater than the corresponding emissions in the USA, which is to be expected from a developing economy that is rapidly industrializing and highly dependent on energy intensive production to fuel economic growth. Left uncontrolled, the reference case emission levels for all methods exceed the policy target by 2015, however, the GDP/capita and time-trend methods show that significant reduction towards the policy target already occurs automatically compared to the endogenous abatement representation reference emissions. Figure 4.1 (b) also demonstrates an additional limitation to both exogenous representations. Since the abatement opportunities were forced exogenously, there is no feedback on the abatement response and no additional abatement can occur beyond the fixed abatement accounted for in the trends under the reference case. This means that in cases where the policy constraint is more stringent than the reference level emissions—which is the case for both the GDP/capita and time-trend reference levels for China after 2015—the only way for the remaining emissions reduction to occur in order to comply with the policy target is by reducing fuel consumption.

Figures 4.1 (c) and **4.1 (d)** demonstrate the effect of the SO_2 policy on NO_x emissions for the USA and China respectively. As mentioned before looking at the effects on NO_x is important since emission targets are often set for multiple pollutants coming from a single source—e.g. burning coal releases SO_2, NO_x, mercury, and BC—and the abatement options for one pollutant can be different and independent from abatement options for other pollutants coming from the same source. In Figure 4.1 (c) we see the emissions in the time-trend method remaining the same as the reference for the policy case, which is to be expected since the SO_2 policy did not constrain the model as the SO_2 emission targets were already met under the reference cases. For the endogenous representation, we start to see a slight reduction in NO_x emissions in 2015 which gradually increases out to 2030. Since the abatement opportunities for NO_x and SO_2 are independent, the effect of SO_2 controls on the reduction in NO_x can be attributed to the SO_2 control introducing a reduction in fuel consumption.

In Figure 4.1 (d), NO_x emissions in China are reduced compared to the reference case under each methodology, however, the reduction for the GDP/capita and time-trend methods are significantly more than with the endogenous representation. As just mentioned, in China the policy targets are more aggressive then the level of abatement achievable by the exogenous trend representations and therefore any additional reduction beyond what is given by the trends must come by reducing fuel consumption. However, for the endogenous abatement representation, additional abatement opportunities for SO_2 are available under the more stringent target that are not available in the time-trend and GDP/capita exogenous representations. Because of this, in the endogenous representation less emission reduction has to come through reduced fuel consumption since more emission reduction is coming from abatement—i.e. with the endogenous representation the production sectors are taking advantage of available abatement technologies and are able to meet policy goals without as large of a reduction in fuel consumption. In addition, because the abatement technologies of SO_2 are independent from the abatement technologies for NO_x, policy aimed at reducing SO_2—such as the policy we are considering—should have little effect on reducing NO_x emissions. *Only the endogenous representation properly captures this effect.* Early on in the policy, from 2010 to 2020, there is significant reduction in SO_2 emissions but very little in NO_x, which shows that most of the SO_2 emission reduction is occurring due to the implementation of abatement technologies. From 2020 to 2030, however, we continue to see a large reduction in SO_2 in compliance with the policy, but we also start to see an increasingly significant amount of reduction in NO_x. As will shortly be shown, this is due to a reduction in fuel consumption as abatement opportunities are exhausted under the aggressively stringent policy case.

Figure 4.2 shows the total future energy consumption in exa-joules (EJ) projected under the different methodologies.



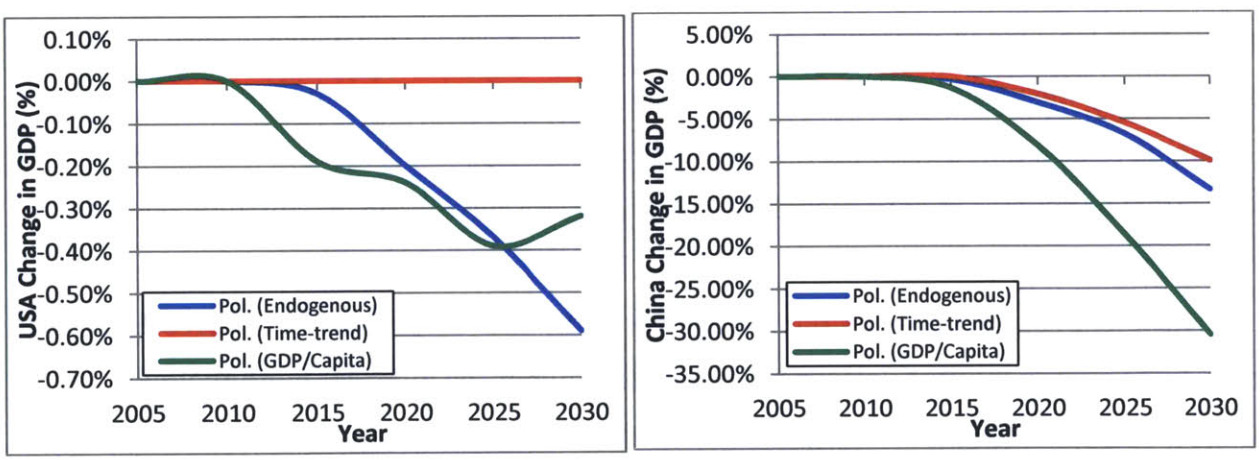


(a) (b)

Figure 4.2. Reference and policy energy consumption in exajoules (EJ) for the USA and China under endogenous abatement, exogenous time-trend, and exogenous GDP/capita abatement representation in the EPPA model.

In Figure 4.2 (a) we see that the energy consumption in the USA from the time-trend method remaining the same as the policy reference scenario which, once again, is to be expected as the SO_2 emissions were unconstrained compared to the non-exogenously forced endogenous abatement reference scenario. With the endogenous and GDP/capita representations we see a slight reduction in total energy consumption in the USA by about 10 EJ by 2030. In **Figure 4.2 (b)** we see the policy having a much more drastic effect on energy consumption in China as the policy is competing with a much more rapidly growing economy that is highly dependent on energy intensive production. From 2005 to 2030 we see the energy consumption for the reference scenario almost quadrupling, but because the policy scenario is so stringent, even with available abatement technologies the SO_2 emissions target cannot be met without a significant reduction in energy consumption. This reduction, although not shown in the plot, is entirely from reduction of sulfur intensive fuels, most notably coal, oil and refined oil.

The effect of the policy on economic output is shown in **Figure 4.3** which gives the difference in gross domestic product between the reference and policy scenario under the different methodologies.



(a) **(b)**

Figure 4.3. Change in GDP between reference and policy schenarios for endogenous abatement, exogenous time-trend, and GDP/capita abatement representation in the EPPA model.

In Figure 4.3 (a) we see no effect on USA GDP under the time-trend method since, as has already been observed, the emissions criteria were met by the reference scenario and the model was unconstrained. Under the endogenous abatement and GDP/capita representations we do see a slight impact with USA GDP falling by 0.6% and 0.3% respectively by 2030 compared to the uncontrolled case. In China the impact of the SO_2 policy is much stronger and reflects the country's current dependence on sulfur emitting fossil fuels (primarily coal) to fuel energy intensive economic growth. Figure 4.3 (b) shows significant reduction in China GDP occurring under all methodologies ranging from 10% reduction using the time-trend methodology to 30% under the GDP/capita method. The fact that the same policy in China is much more expensive than in the USA in terms of its effect on reducing GDP is somewhat counterintuitive. On the one hand we might expect the policy cost in China to be less expensive since more abatement opportunities are available as parameterized earlier by the elasticities of substitution for abatement being more elastic for China than the USA (e.g. the initial elasticity of substitution for abatement of coal used in electricity production is 0.71 for China compared to 0.16 in the USA). However, the advantage the Chinese have in terms of available abatement opportunities is overcome by significantly faster growth in energy consumption compared to the USA (as shown previously in Figures 4.2 (a) and (b), by a much greater dependence on energy intensive production for economic growth, by a greater dependence on coal which is very sulfur intensive, by the unavailability of cheap sulfur free backstops like natural gas, and by vintaging effects that do not allow capital intensive energy infrastructure to turn over instantly in response to extremely steep policy shocks such as the one introduced in the current analysis.

The impact of the policy on the energy mix in the USA is illustrated in **Figure 4.4** which shows the energy inputs to electricity production under the different methodologies in units of exa-joules of electricity generated from each source. In Figure 4.4 (a), we see the reference case scenario with almost all growth in electricity generation coming from an increase in coal. Figure 4.4 (b) gives the USA electricity generation energy mix for the endogenous abatement representation. Under the policy, overall electricity consumption is reduced by 2.17 EJ, but we see the non-SO_2 intensive natural gas electricity generation gain a wider presence in the market in 2015 and grow to 1.02 EJ of production—or 7% of total production—by 2030. We also see nuclear grow from 3.16 EJ to 3.37 EJ, hydroelectric power grow from 0.9 EJ to 1.15 EJ, and solar/wind grown from 1.49 EJ to 1.72 EJ by 2030 compared to the reference case. On the other hand electricity from coal generation declines, falling from 9.50 EJ of the electricity energy mix in 2005 to 5.94 EJ of total generation by 2030.

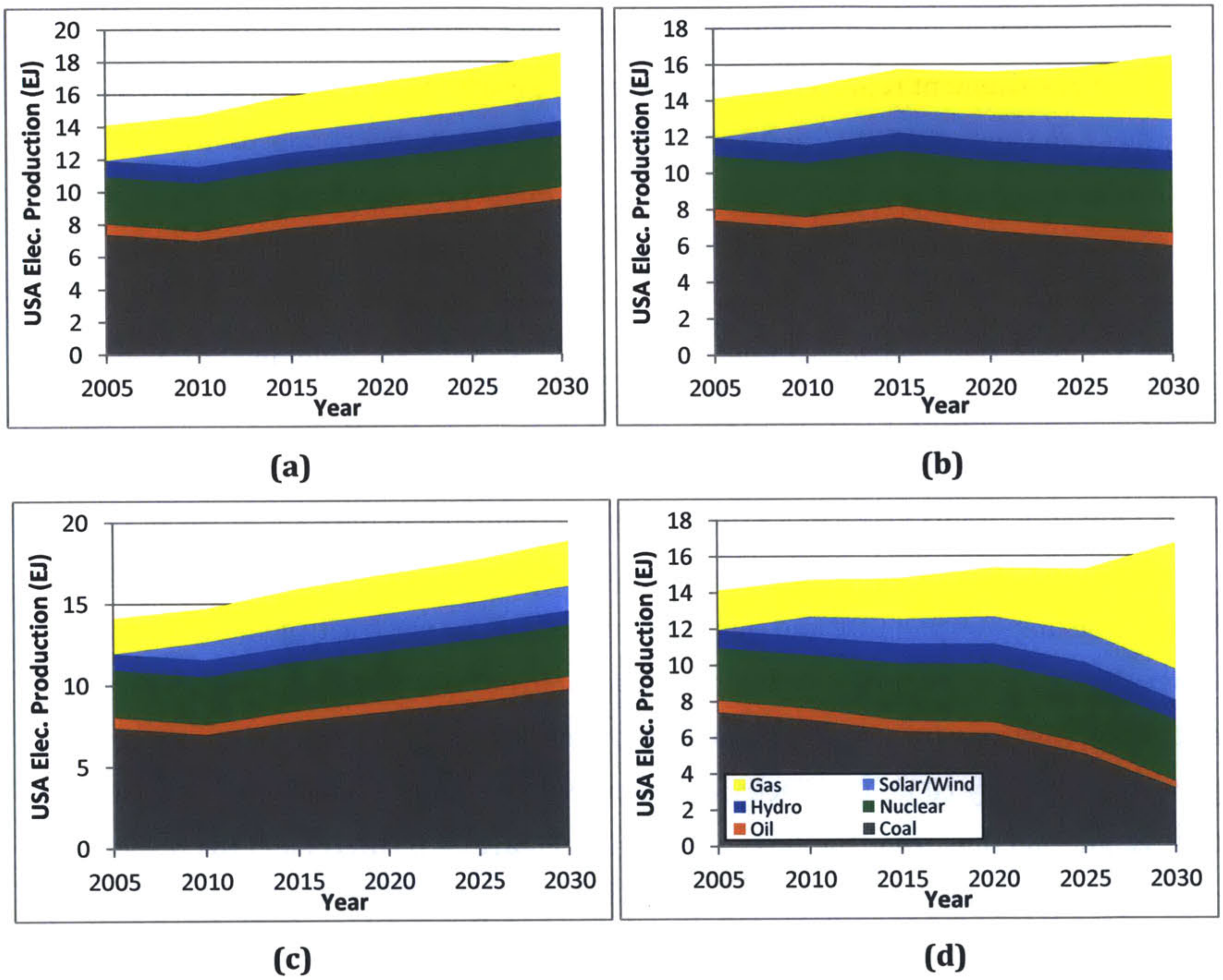


Figure 4.4. Electricity generation mix in the USA under SO_2 policy; (a) reference case, (b) endogenous representation, (c) time-trend representation, (d) GDP/capita representation.

In Figure 4.4 (c) we see the exogenous time-trend policy results which are no different from the reference scenario in Figure 4.4 (a) since, as mentioned before, the model was under constrained. In Figure 4.4 (d) we see the GDP/capita exogenous representation responding to the policy constraint similar to the endogenous representation in Figure 4.4

(b) with overall electricity production being reduced to 16.2 Tg by 2030. The electricity generation mix, however, is noticeably different and is marked by a significant growth in natural gas and reduction in coal compared to the endogenous representation. In the endogenous representation firms are able to meet reduction targets with coal by taking advantage of abatement opportunities to reduce sulfur emissions. Therefore for the endogenous abatement representation we see more coals use and less NGCC growth. On the other hand, with the GDP/capita representation, no abatement opportunities for coal are available so the only way to reach reduction targets is by reducing coal consumption and increasing generation from another source. Since natural is the next least costly alternative based on the EPPA 2004 benchmark, we see it making up for most of the lost coal generation. That said, in 2012 we are currently experiencing a glut in natural gas so the cost of natural gas is exceptionally low so that if we were going by today's standards we would see substitution towards natural gas across the board.

In China the results give a much different story compared to the USA. As we've already seen in Figures 4.2 and 4.3, the SO_2 emission control caused significant reduction in overall energy consumption and GDP and this is also evident in the electricity generation mix under all three methodologies. In the reference case shown in **Figure 4.5 (a)** we see the electricity generation mix largely dominated by coal with overall electricity production growing to 35 EJ by 2030. The electricity generation mix under the endogenous abatement, GDP/capita, and time trend methods are given by **Figures 4.5 (b), (c)** and **(d)** respectively, all of which show significant reduction in electricity generation. Of all technologies in the mix, coal is hit the hardest as would be expected since it is the most sulfur intensive. Under each methodology we see a large number of backstop electricity generation technologies clearing the market including coal (IGCAP), new nuclear generation, WINDBIO, and WINDGAS. In addition, we also see the share of non-SO_2 intensive generation increase as was the case in the USA. The most notable growth occurs for hydro power which goes from 1.93 EJ of generation in 2005 to 3.01 EJ by 2030.

With the energy mix graphs we also see a very strong indicator of the importance of the endogenous abatement representation. In the electricity generation mix for the GDP/capita, Figure 4.5 (c), and time-trend methods, Figure 4.5 (d), both plots show an immediate reduction in coal use as soon as the policy is implemented in 2015. However, in Figure 4.5 (b), coal based electricity generation increases up until 2025. This is due to the availability of abatement opportunities for coal generation provided by the endogenous representation. Instead of having to immediately reduce coal consumption, firms are able to continue to increase coal consumption for electricity generation for a decade longer as they are able to continue to meet the reduction targets when using more coal by paying for more abatement. It is only in 2025 when abatement opportunities seem to be exhausted or too costly that it becomes cheaper to reduce consumption and depend more on other energy generation backstops.

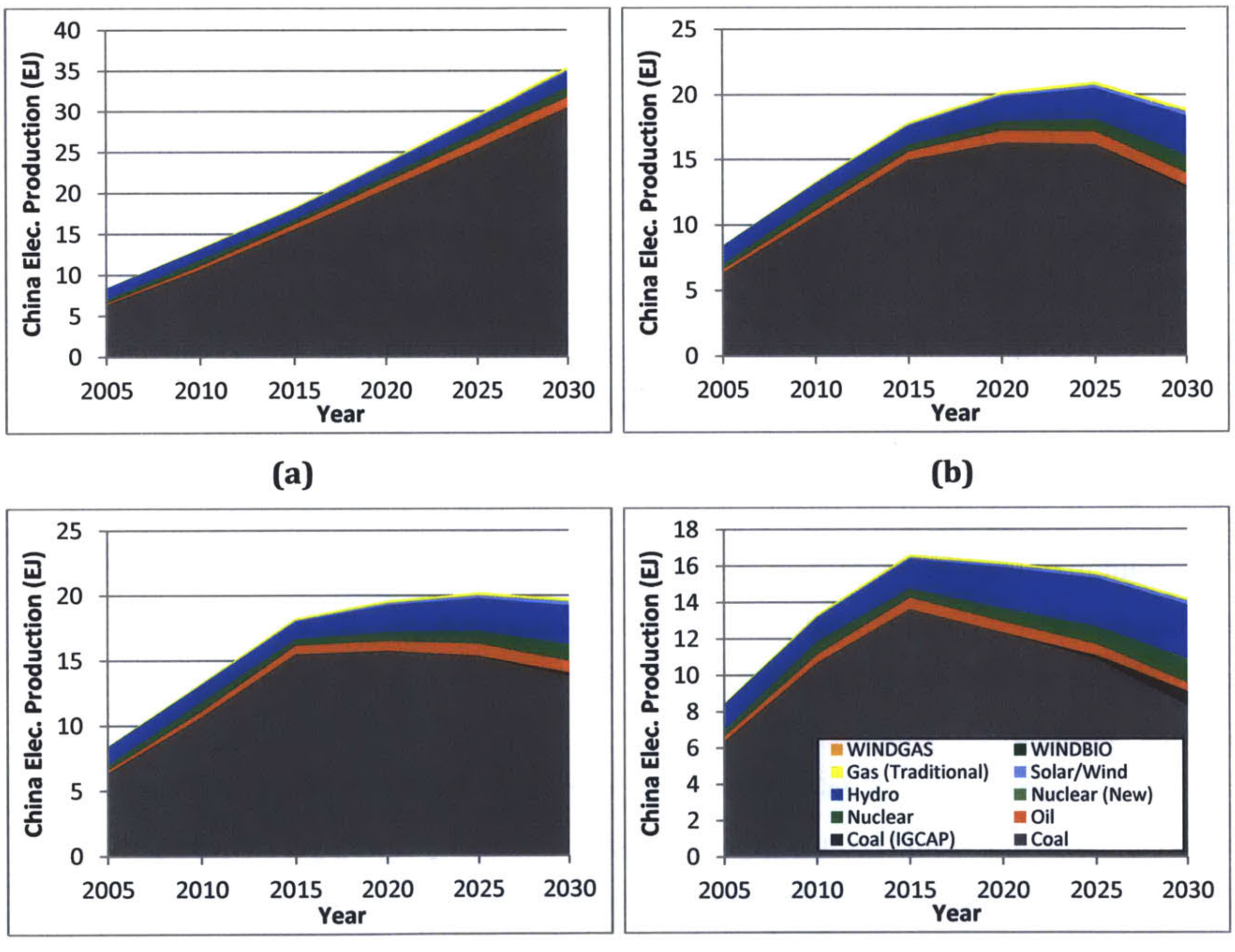


Figure 4.5. Electricity generation mix in China under SO_2 policy; (a) reference case, (b) endogenous representation of abatement costs, (c) exogenous time-trend representation of abatement, and (d) exogenous GDP/capita representation of abatement opportunities.

4.2 Co-benefits of Air Pollution and Climate Policy in China and the USA

Now that we have illustrated several advantages of the new methodology in capturing many important interconnected feedback effects, we now apply the methodology by providing an example of the kinds of policy analysis that can be done using the new capabilities that could not be considered previously. As was mentioned in the introduction, since the adverse effects of air pollution on human health and the environment are much better understood and quantifiable when compared to our current abilities to quantify the potential damages due to global warming and climate change, it has historically and in practice been much easier to make the argument for a strong policy response to traditional air pollution emissions. Since emissions of CO_2 largely stem from the same fossil fuel sources as other traditional air pollutants, implementation of more stringent air pollution reduction policies, that may be much easier to achieve politically, have the potential of carrying significant ancillary benefits for the reduction of CO_2. This is largely achieved by reduced consumption of fossil fuels in the presence of an air pollutant constraint, so that both the air pollutant and CO_2 emissions are reduced simultaneously. This is especially true in developing countries that are gradually placing a higher premium on clean air and are more likely to adopt more stringent air quality controls than climate policy in the short run. These so called "co-benefits" of air pollution policy on carbon emissions are particularly important in China where ~80% of electricity generation comes from coal, and where we are beginning to see some progress in addressing air quality. For a more rigorous treatment of the climate co-benefits of tighter SO_2 and NO_x regulations in China see (Waugh, et al. 2012).

As an example, we consider a progressive policy beginning in 2010 that aims at achieving a 5% additional reduction in SO_2 and NO_x emissions every year in comparison to the baseline emissions scenario (i.e. compared to the baseline scenario it therefore attains a 5% reduction from baseline emissions in 2011, a 9.5% reduction in 2012, a 14.2% reduction in 2013 etc.). The impact of this policy on SO_2 and NO_x emissions is given in **Figure 4.6 (a).** As can be seen, the policy achieves significant reduction in both SO_2 and NO_x emissions compared to the counterfactual baseline scenario. Emissions of SO_2 fall from 160Tg to 70Tg and emission of NO_x fall from 90Tg to 33Tg by 2030. In **Figure 4.6 (b)** we see the ancillary benefits the SO_2 and NO_x emission controls have on carbon emissions. In the reference case, 2030 emission of CO_2 are 18700 Tg but in the presence of the SO_2 and NO_x controls that number reduces to 13800 Tg. Although the ancillary benefits of the SO_2 and NO_x reduction are not strong enough to lead to a reduction of carbon emissions to achieve certain carbon concentration targets such as the 550 ppm target that many climate policy advocates would like, the 26% reduction in carbon emissions that could readily be achieved through a modest air pollution controls is promising.

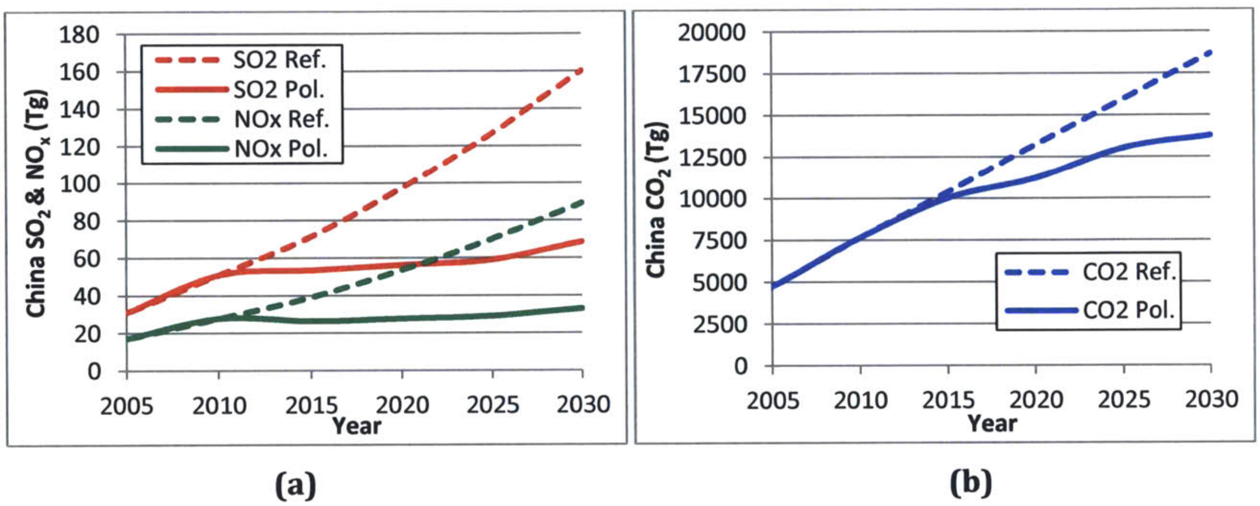
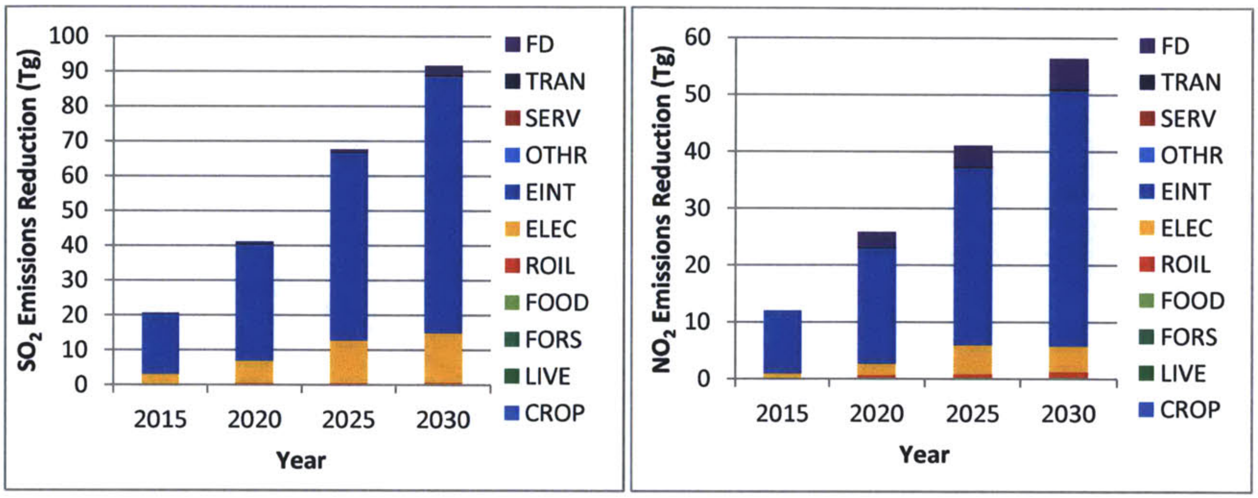


Figure 4.6. (a) China SO_2 and NO_x Emissions under joint SO_2 and NO_x control policy, (b) ancillary CO_2 emissions under joint SO_2 and NO_x reduction policy

In **Figures 4.7 (a)** and **(b)** we see a sectoral breakdown showing where the reduction in SO_2 and NO_x emissions come from which allows us to gain a better sense for how SO_2 and NO_x policy controls could potentially effect specific sectors in the Chinese economy. In both figures we see that the overwhelming amount of emission reduction comes from energy intensive industry (EINT) and electricity generation (ELEC), which is to be expected as these are the two sectors most dependent on coal and other fossil fuels. Initially we might have expected the emissions reduction of SO_2 and NO_x to come more from electricity generation than energy intensive industry, however, in the model EINT grows much faster than ELEC resulting in a faster increase in EINT emissions as well. For the reference case, SO_2 emissions from ELEC increase from 10Tg to 41Tg between 2004 and 2030 while during the same time, SO_2 emissions from EINT increase from 15Tg to 95Tg. Likewise, we see a similar trend for NO_x with emissions from ELEC increasing from 3.2Tg to 13Tg between 2004 and 2030 and emissions from EINT increasing from 8.4Tg to 55Tg over the same time period. From this we see that the larger volume of emissions coming from EINT allows for greater emission reduction than with ELEC, however, this can also be attributed to the difference in available abatement opportunities between EINT and ELEC.



(a) (b)

Figure 4.7. (a) SO_2 sector specific emission reduction due to policy, (b) NO_x sector specific emission reduction due to policy

In figure **Figure 4.8 (a)** we see the sectoral breakdown of CO_2 emissions reduction. In contrast to SO_2 and NO_x, for CO_2 we see more emissions reduction coming from ELEC than EINT. Initially this can be interpreted as being caused by greater availability of SO_2 and NO_x abatement opportunities for EINT than for ELEC, and upon closer inspection of the abatement opportunities and parameters derived from GAINS given in Appendix 1, this interpretation is confirmed. In the regression on the GAINS data, more abatement opportunities are identified for EINT than for ELEC and the substitution elasticities for EINT tend to be more elastic compared to ELEC (for example, the substitution elasticity for abatement of coal is 0.85 for EINT compared to 0.71 for ELEC). What this tells us is that emissions of EINT are reduced more through abatement opportunities than through reduced fuel consumption. In contrast, since less abatement opportunities are available for ELEC SO_2 and NO_x emissions, more fuel reduction must occur to achieve the level of emissions reduction needed to meet the policy constraint. Since reduction in CO_2 emissions is entirely due to reduced fuel consumption—i.e. no SO_2 or NO_x abatement technologies reduce emission of CO_2—greater CO_2 reduction is achieved from ELEC than for EINT.

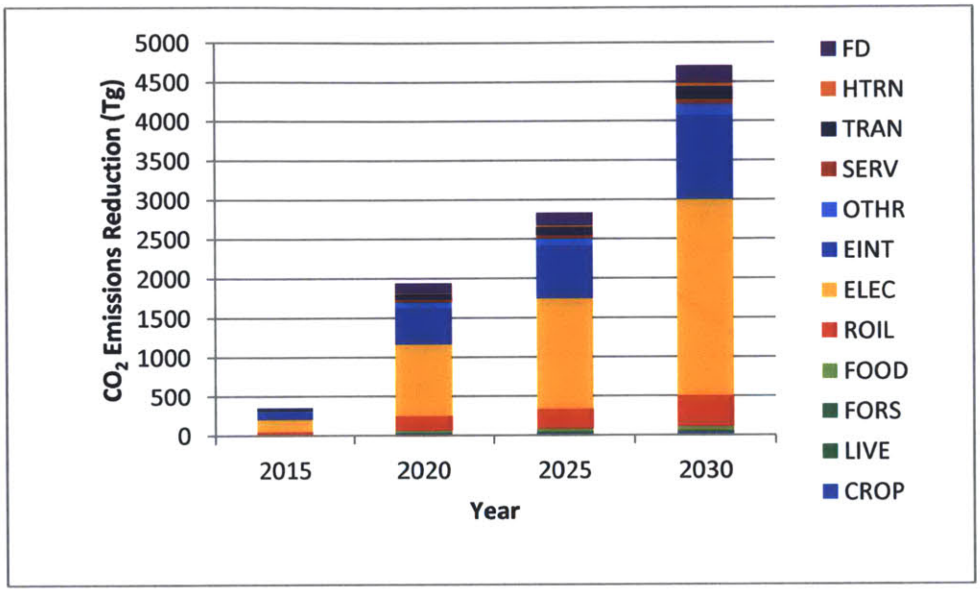
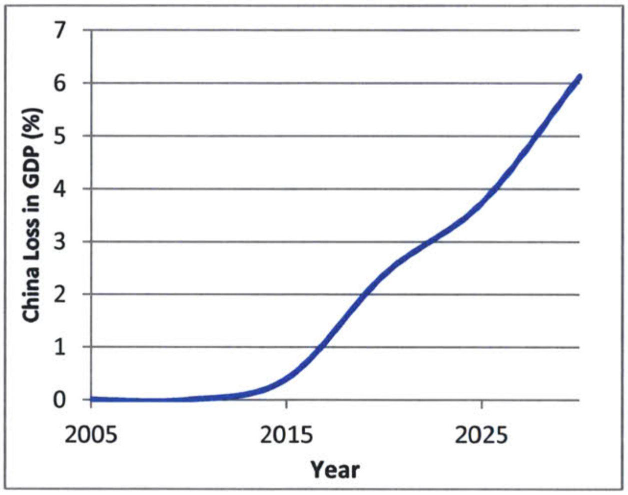
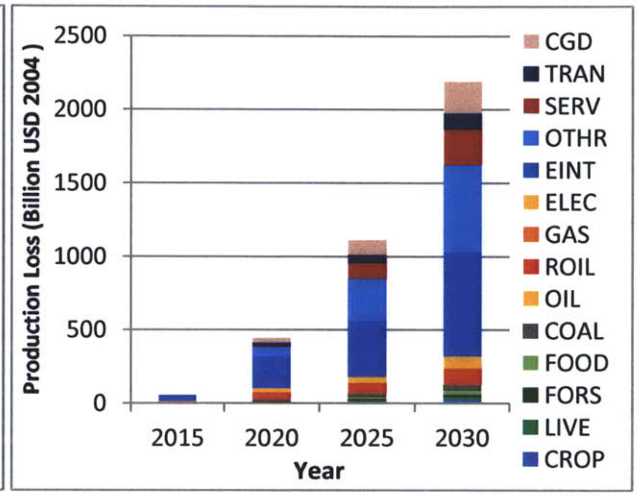


Figure 4.8. (a) CO_2 sector specific emission reduction due to SO_2 and NO_x controls.

In **Figure 4.9 (a)** we see the important cost impact effects of the policy on the overall economy with GDP loss beginning in 2015 and rising to 6.1% by 2030. In **Figure 4.9 (b)** overall production losses as well as a breakdown of production losses in individual sectors are given and illustrates the interconnected distributional effects that the air pollution policy has on economic productivity. Overall loss in production starts gradually with an estimated $53 billion (2004 USD) loss coming in 2015, but then grows significantly to $2.1 trillion (2004 USD) by 2030. Hit hardest by the policy is EINT and OTHR production, however, all sectors are adversely effected except for natural gas (GAS) which, although not distinguishable in the figure, experiences a small amount of growth. While we may expect to see significantly more growth in natural gas as a sulfur-free coal substitute in the presence of the SO_2 constraint, growth in natural gas is restricted due to limited Chinese natural gas resources. The insight gained on how air pollution emissions can effect sectoral production is an extremely important consideration for Chinese policy makers as the Chinese economy is heavily dependent in energy intensive industrial activities and manufacturing for economic growth. Even among non-energy intensive production such as OTHR, the impact that a SO_2 and NO_x constraint has on energy costs effects all sectors in the economy so that air quality reduction targets will have to be set carefully to meet human health and environmental criteria with minimal impact on economic growth.





(a) **(b)**

Figure 4.9. (a) Overall percent loss in GDP due to SO_2 and NO_x reduction policy, (b) sector specific production loss due to SO_2 and NO_x reduction policy.

In **Figure 4.10 (a)** and **(b)** the resulting electricity generation technology mix for the reference case and policy scenarios are given respectively. In comparison to the SO_2 policy considered in the previous section that required a 10% decrease from 2010 emissions every 5 years, the model under the current less stringent policy controls is much less constrained. While overall electricity output dips some—from 35.4 EJ to 28.3 EJ by 2030—the reduction in electricity generation isn't nearly as drastic as what was required to meet the stringent policy targets shown in Figure 4.5 (b). As would be expected, most of the reduction in electricity generation is due to the reduced expansion of coal power plants. That fact that coal generation continues to grow between 2015 and 2030 even though SO_2 and NO_x emissions remain relatively flat over this time—as shown earlier in Figure 4.6 (a)—is particularly insightful as it shows that even in the presence of tighter controls on SO_2 and NO_x, by taking advantage of abatement opportunities coal continues to be competitive. Although we see some growth in hydroelectric power, nuclear, and wind and solar, these contributions still remain small when compared to the continued growth of coal generation. Even more telling is the absence of any other backstop energy generation technologies clearing the market. Under the stringent constraint in Figure 4.5 (b), we see a whole host of backstop generation come online which we do not see in Figure 4.10 (b). This suggests that the role of alternative electricity generation technologies may be limited in China, even in the presence of significant air quality regulation, as abatement opportunities for coal generation are still widely available.

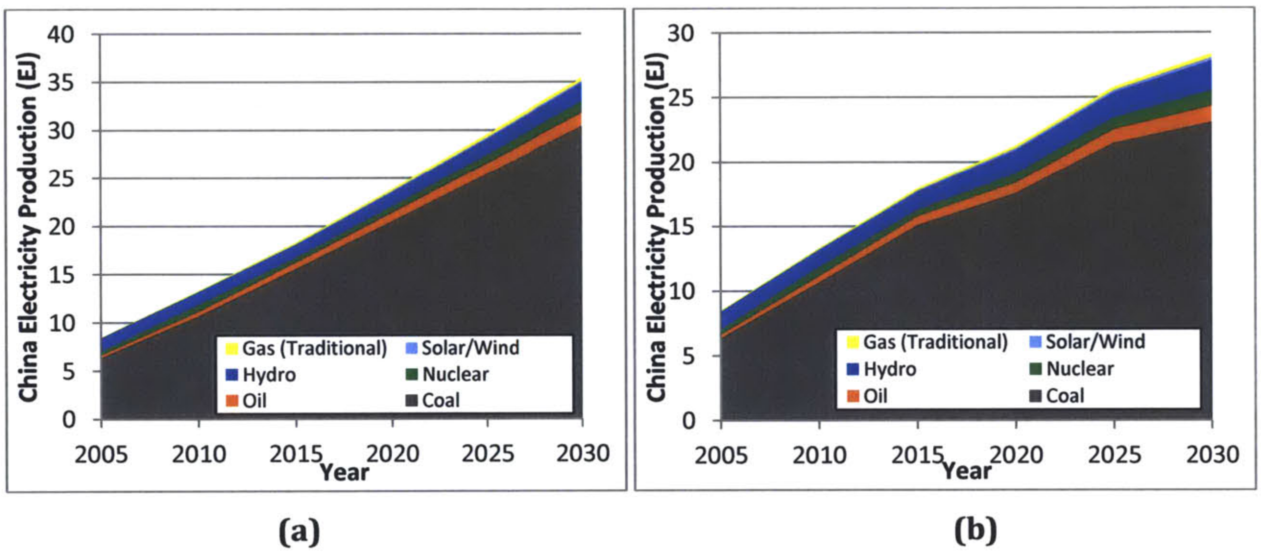


Figure 4.10. (a) Baseline electricity technology generation mix with output in exajoules (EJ), (b) electricity technology generation mix output under SO_2 and NO_x policy constraint.

5 Conclusion

In summary, we have seen that in addition to improvements in economic activity, societal welfare, improved standards of living, and increased life expectancy, the movement over the last 200 years towards industrialization has had an unprecedented impact on air and water pollution and the negative external costs associated with damages to human health and the environment. In order to best identify, manage, and control these industrial externalities, air pollution policy must be designed carefully to reduce adverse effects without heavily impacting economic growth. As many of the considerations of most interest in achieving optimal air quality policy design are multidisciplinary in nature, frameworks for structuring and analyzing the interconnected effects and feedbacks of different policy pathways play an important role in informing the policy-making process.

Over the last four decades, integrated assessment models have grown from simple energy models used to study ways of diversifying the US electricity generation mix to highly complex models covering the global non-linear effects of socioeconomic and biophysical earth systems in a coupled and integrated framework. Although much of the focus of these models has been on addressing climate change impacts and global warming, some work has been done to study interrelated effects of air pollution policy. Among such models, computable general equilibrium has been extensively used to model the socioeconomic interactions. While some critiques of the CGE modeling framework and criticisms of poor practices among CGE modelers may be reasonable, many of these critiques can be overcome by following best practices in model design and implementation while other critiques are well taken and present rich opportunities for improvement of current CGE methods. Overall the structure of CGE models best lends them as powerful tools for studying counterfactual *ex ante* comparisons of multiple policy pathways

In this thesis I have argued for the importance of sound methods for exploring the interconnected effects of air pollution policy within an integrated framework. Since traditional air pollutants are largely emitted from the same sources that emit carbon, air quality and climate policy are intrinsically linked and the stringency of a policy control on one pollution species can significantly affect emissions of other species. Any policy analysis of pollution species in isolation will not capture these effects. Also, many policy considerations regarding permissible levels of air pollution weigh the benefits of air quality, as determined from epidemiological and other environmental impact studies, with the economic costs of emission controls. As these considerations span multiple disciplines, the questions of most interest regarding policy benefits and costs are inherently integrated.

To provide researchers and policy makers with better tools when considering multiple policy pathways I designed and implemented a new methodology that overcomes many of the limitations of previous methodologies. Among the limitations of previous methodologies include: representing air pollution abatement opportunities exogenously, which fails to account for abatement costs and does not capture key economic feedbacks to policy shocks; and among endogenous representations, the new methodology overcomes failures to properly distinguish between fuel related and non-fuel related emissions and inabilities to provide a framework capable of representing multiple pollution species simultaneously.

Central to the new framework is representation of air pollution abatement opportunities that firms can pursue in the presence of stringent policy controls. These opportunities can be represented in constant elasticity of substitution (CES) production nests within existing CGE models by benchmarking elasticity of substitution and value share parameters on technology, sector, and region-specific abatement opportunities as specified by detail-rich engineering data in marginal abatement cost curves. Using this approach addresses one of the main critiques of CGE models—that they tend to overly aggregate and homogenize over important details—by providing "bottom-up" technical detail within a "top-down" integrated assessment framework. The theory underpinning the representation was derived in detail from microeconomic theory and important considerations regarding other parameters were considered. Finally, the new method was implemented into the 5th version of the MIT Emissions Prediction and Policy Analysis Model for SO_2 and NO_x using engineering data from the Greenhouse Gas and Air Pollution Interactions and Synergies model. In total 314 opportunities for SO_2 and NO_x were parameterized and implemented.

A comparison between the new methodology and previous exogenous methods for representing air pollution controls in EPPA was also given and demonstrated many key advantages. As an example of the kinds of policy analysis questions that can be explored using the new methodology, I presented a brief analysis of the co-benefits of a SO_2 and NO_x reduction policy on reducing CO_2 emissions in China. For the specific policy considered, we saw that air pollution controls can play a significant role in reducing carbon emissions, that carbon emission reductions due to air pollution controls may largely come from decreased coal consumption in electricity generation, that future cost impacts of air pollution controls on the Chinese economy can be significant, and that significant abatement opportunities for reducing SO_2 and NO_x emissions from coal powered electricity generation may leave few opportunities for adoption of other air pollution neutral energy technologies in the electricity generation mix.

Notwithstanding the improvements made in this thesis in representing abatement opportunities for air pollutants, many challenges remain. First, representation of induced technological change of abatement opportunities remains underdeveloped and next steps should explore ways of representing induced change endogenously in the model by dynamically adjusting the price elasticity of demand for emitting. Second, currently the only policy instruments that have been implemented in EPPA are region-specific emission caps. Further work should be done to represent other policy instruments including region and sector specific emission caps and Pigouvian taxes. Finally, as this thesis has focused almost entirely on methodology development and parameterization of abatement opportunities, careful consideration of uncertainty in the abatement parameters and the sensitivity of the EPPA model results to parameter variation must be considered as small changes in key parameters can significantly impact model results. These remaining challenges should provide rich opportunities for the next generation of integrated assessment modelers as we continue to develop stronger tools and methodologies to inform air pollution policy design.

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Appendix 1: Sulfur Dioxide and Nitrous Oxide CGE Parameters

This section contains the parameterization results for representing SO_2 and NO_x in the MIT Emissions Prediction and Policy Analysis (EPPA) model version 5. Data used in the parameterization was obtained from the Greenhouse Gas and Air Pollution Interactions and Synergies model which gives marginal abatement costs and emission reduction data at the technology specific level of disaggregation (Nguyen, Wagner and Schoepp 2011). For a complete discussion on the derivation of these parameters see section 3.2 "Parameterization of Abatement Opportunities." The symbols used in this appendix are consistent with the definition used throughout the thesis and are defined as follows: initial quantity of pollutant produced in gigagrams (X_P [Gg]), initial quantity of pollution emitted in gigagrams (X_E [Gg]), initial quantity of pollution abated in gigagrams (X_A [Gg]), initial marginal price of emitting (Po [(2004 USD)/kg]), initial value share of pollution emitted (θ), price elasticity of demand for emitting (ε_D), initial elasticity of substitution (σ), value of regression parameter α, value of regression parameter β, correlation coefficient (r^2). One should note that in many cases θ equals 1 suggesting that no abatement is achieved using the abatement opportunity in the base year and that the substitution elasticity is infinite. To account for this when calibrating the base year σ we set the initial θ in these cases to .95 and then let θ dynamically recalibrate in the model as abatement opportunities are realized.

Table A.1. SO_2 Abatement Opportunity Parameters

ANZ

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
FORS	PROCESS	14.82	14.08	0.74	0.58	1.00	-0.31	0.31	3.95	-3.25	1.00
EINT	COAL	27.02	25.67	1.35	2.05	1.00	-2.02	40.47	2.32	-0.49	0.91
EINT	OIL	61.28	39.13	22.15	0.59	0.64	-0.11	0.29	19.75	-9.44	1.00
EINT	ROIL	18.11	11.42	6.69	1.56	0.63	-1.41	3.82	2.17	-0.71	0.81
EINT	BOIL	3.29	3.13	0.16	6.96	1.00	-0.16	3.16	8.43	-6.32	0.94
EINT	PROCESS	883.18	839.02	44.16	0.21	1.00	-0.10	0.10	55.32	-10.47	0.55
TRAN	OIL	9.83	9.34	0.49	0.49	1.00	-0.13	2.54	4.25	-7.87	1.00
TRAN	ROIL	141.44	20.83	120.61	3.54	0.15	-1.31	1.53	3.59	-0.77	0.52
ELEC	COAL	1959.23	639.10	1320.13	0.54	0.33	-0.11	0.16	50.93	-9.48	0.81
ELEC	OIL	38.03	22.97	15.06	0.45	0.60	-0.13	0.32	11.62	-7.99	0.90

ELEC	ROIL	10.86	7.31	3.55	1.89	0.67	-1.59	4.85	1.89	-0.63	0.75
OIL	PROCESS	27.40	26.03	1.37	0.23	1.00	-0.05	0.05	37.55	-19.25	0.97
FD	COAL	5.53	5.25	0.28	0.46	1.00	-1.09	21.89	0.72	-0.91	0.99
FD	OIL	1.50	0.82	0.68	0.49	0.55	-0.13	0.28	-12.17	-7.90	1.00
FD	ROIL	12.49	6.12	6.37	1.53	0.49	-0.69	1.35	1.44	-1.45	1.00

ASI

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
FORS	PROCESS	26.89	25.55	1.34	0.39	0.99	-0.31	0.31	5.47	-3.24	1.00
EINT	COAL	342.86	325.72	17.14	0.96	1.00	-1.01	20.16	5.70	-0.99	0.99
EINT	OIL	840.99	252.95	588.04	0.54	0.30	-0.30	0.43	15.66	-3.35	0.84
EINT	ROIL	45.71	23.19	22.52	4.87	0.51	-7.16	14.54	2.02	-0.14	0.78
EINT	BOIL	59.82	56.83	2.99	3.35	1.00	-0.01	0.14	567.87	-140.96	0.98
EINT	PROCESS	227.00	168.93	58.07	0.44	0.74	-0.16	0.16	25.36	-6.10	0.88
TRAN	OIL	8.64	7.18	1.46	0.49	0.83	-0.13	0.75	3.15	-7.91	1.00
TRAN	ROIL	1388.83	62.36	1326.47	1.60	0.04	-1.20	1.26	3.90	-0.83	0.75
ELEC	OIL	589.02	185.04	403.98	0.51	0.31	-0.40	0.58	10.69	-2.51	0.92
ELEC	ROIL	37.36	16.63	20.73	5.42	0.45	-0.07	0.13	16.88	-13.82	1.00
ELEC	BOIL	18.42	17.50	0.92	2.54	1.00	-0.02	0.30	186.96	-66.34	0.89
OIL	PROCESS	117.11	111.25	5.86	0.16	0.99	-0.05	0.05	66.41	-19.49	0.99
FD	OIL	89.85	18.53	71.32	0.48	0.21	-0.13	0.16	16.12	-7.84	1.00
FD	ROIL	112.58	25.68	86.90	1.51	0.23	-0.34	0.44	9.89	-2.92	1.00
ELEC	COAL	5462.25	385.56	5076.69	0.35	0.07	-0.13	0.14	39.70	-7.81	0.72

CAN

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
FORS	PROCESS	262.52	127.18	135.34	0.41	0.48	-0.30	0.30	12.48	-3.28	1.00
EINT	COAL	12.31	11.69	0.62	0.57	1.00	-0.40	8.07	4.42	-2.48	0.93
EINT	OIL	384.55	224.35	160.20	0.11	0.58	-0.47	1.14	9.19	-2.11	0.97
EINT	ROIL	22.25	13.54	8.71	1.42	0.61	-1.32	3.38	2.32	-0.76	0.86
EINT	PROCESS	1866.18	722.23	1143.95	0.07	0.39	-0.11	0.11	48.53	-8.71	0.47
TRAN	OIL	51.49	48.92	2.57	0.49	1.00	-0.13	2.54	17.30	-7.88	1.00
TRAN	ROIL	298.01	42.28	255.73	1.67	0.14	-0.72	0.84	5.68	-1.38	0.76
ELEC	COAL	1040.75	461.30	579.45	0.38	0.44	-0.19	0.33	22.14	-5.41	0.77
ELEC	OIL	263.69	200.51	63.18	0.45	0.76	-0.17	0.70	20.44	-6.00	0.79
ELEC	ROIL	1.57	0.99	0.58	1.58	0.63	-1.30	3.52	0.45	-0.77	0.73
ELEC	BOIL	2.37	2.25	0.12	4.46	1.00	-0.02	0.46	36.64	-43.64	1.00
OIL	PROCESS	121.29	60.99	60.30	0.15	0.50	-0.05	0.05	60.04	-18.61	0.91
FD	COAL	0.78	0.74	0.04	0.43	1.00	-0.38	7.59	-2.13	-2.64	1.00
FD	OIL	69.30	37.80	31.50	0.49	0.55	-0.13	0.28	19.67	-7.90	1.00
FD	ROIL	103.26	50.59	52.67	1.53	0.49	-0.69	1.35	4.51	-1.45	1.00

CHN

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
FORS	PROCESS	140.78	133.74	7.04	0.39	0.95	-0.31	0.31	11.06	-3.27	1.00
EINT	COAL	20334.52	9635.12	10699.40	0.48	0.47	-0.45	0.85	19.68	-2.23	0.87
EINT	OIL	434.35	412.63	21.72	3.23	1.00	-0.13	2.53	35.93	-7.90	1.00

EINT	ROIL	119.43	113.46	5.97	1.51	1.00	-0.62	12.42	6.38	-1.61	1.00
EINT	PROCESS	6768.18	2895.01	3873.17	0.22	0.43	-0.15	0.15	49.25	-6.88	0.91
TRAN	ROIL	399.25	360.79	38.46	1.96	0.90	-1.18	12.20	5.68	-0.85	0.80
ELEC	COAL	24139.50	15606.86	8532.64	0.40	0.65	-0.25	0.71	30.03	-4.01	0.99
ELEC	OIL	33.57	31.89	1.68	1.88	1.00	-0.14	2.85	11.96	-7.02	0.88
FD	COAL	1625.07	1543.82	81.25	0.44	1.00	-0.13	2.56	50.91	-7.82	1.00
OIL	PROCESS	196.40	147.38	49.02	0.16	0.75	-0.06	0.06	67.23	-17.70	0.93
ELEC	ROIL	0.04	0.02	0.02	4.48	0.46	-0.13	0.24	-36.16	-7.88	1.00

EUR

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
EINT	COAL	699.47	286.83	412.64	0.44	0.41	-0.44	0.75	11.93	-2.25	0.96
EINT	OIL	1636.43	314.05	1322.38	0.56	0.19	-0.18	0.22	28.75	-5.58	1.00
EINT	ROIL	53.31	19.75	33.56	2.30	0.37	-1.26	2.00	3.20	-0.80	0.70
EINT	BOIL	26.82	13.94	12.88	8.21	0.52	-0.08	0.16	36.37	-13.00	0.81
EINT	PROCESS	2264.24	556.77	1707.47	0.41	0.25	-0.11	0.11	50.10	-8.79	0.92
TRAN	ROIL	3200.92	108.98	3091.94	3.53	0.03	-0.44	0.45	12.01	-2.29	0.39
ELEC	COAL	25881.22	4904.51	20976.71	0.29	0.19	-0.12	0.15	59.82	-8.46	0.60
ELEC	OIL	3976.55	780.67	3195.88	0.53	0.20	-0.49	0.61	13.06	-2.06	0.83
ELEC	BOIL	158.32	54.69	103.63	2.45	0.35	-0.09	0.14	44.97	-11.01	0.98
OIL	PROCESS	1330.00	205.40	1124.60	0.22	0.15	-0.03	0.03	141.26	-30.22	0.78
FD	COAL	397.78	360.17	37.61	0.32	0.91	-0.06	0.61	92.04	-17.45	1.00
FD	OIL	318.35	57.35	261.00	0.48	0.18	-0.13	0.16	25.54	-7.75	1.00
FD	ROIL	996.46	165.52	830.94	1.60	0.17	-0.42	0.50	11.19	-2.39	1.00
FORS	PROCESS	514.21	65.77	448.44	0.51	0.13	-0.14	0.14	23.87	-6.96	1.00
TRAN	OIL	111.09	103.60	7.49	0.48	0.93	-0.13	1.88	22.40	-7.87	1.00

IND

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
FORS	PROCESS	1.68	1.60	0.08	0.39	1.00	-0.30	0.30	-3.56	-3.28	1.00
EINT	COAL	2966.75	2818.41	148.34	0.70	1.00	-0.91	18.26	8.07	-1.10	0.96
EINT	OIL	4323.66	4107.48	216.18	0.39	1.00	-3.65	72.90	1.35	-0.27	0.82
EINT	ROIL	95.89	91.10	4.79	1.48	1.00	-0.42	8.42	7.99	-2.37	1.00
TRAN	OIL	18.14	17.23	0.91	0.49	1.00	-0.14	2.70	5.32	-7.40	1.00
ELEC	COAL	7004.67	6654.44	350.23	0.43	1.00	-0.66	13.29	10.86	-1.50	0.86
ELEC	OIL	764.62	726.39	38.23	0.02	1.00	-0.70	14.01	5.69	-1.43	0.76
ELEC	ROIL	28.68	27.25	1.43	1.88	1.00	-2.09	41.84	2.21	-0.48	0.70
OIL	PROCESS	399.22	379.26	19.96	0.11	1.00	-0.25	0.25	18.30	-4.00	0.83
FD	ROIL	82.38	45.62	36.76	4.44	0.55	-0.14	0.32	25.16	-7.06	1.00

JPN

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
FORS	PROCESS	104.60	27.17	77.43	1.26	0.26	-0.13	0.13	20.92	-7.61	1.00
EINT	COAL	191.89	76.90	114.99	1.81	0.40	-0.32	0.54	12.79	-3.11	0.99
EINT	OIL	446.14	86.45	359.69	0.91	0.19	-0.48	0.59	9.27	-2.10	0.67
EINT	ROIL	32.85	27.65	5.20	4.41	0.84	-0.13	0.80	16.17	-7.90	1.00
EINT	BOIL	15.07	9.26	5.81	0.96	0.61	-0.17	0.45	10.19	-5.81	0.74

EINT	PROCESS	430.78	105.35	325.43	1.37	0.24	-0.09	0.09	48.42	-10.95	0.88
TRAN	OIL	42.37	40.25	2.12	0.49	1.00	-0.16	3.22	19.74	-6.21	1.00
ELEC	COAL	2833.90	77.47	2756.43	2.11	0.03	-0.02	0.02	245.62	-60.45	0.94
ELEC	OIL	2413.40	60.11	2353.29	0.62	0.02	-0.05	0.06	65.30	-18.51	0.90
ELEC	ROIL	4.28	3.60	0.68	4.41	0.84	-0.13	0.80	-1.28	-7.90	1.00
ELEC	BOIL	104.58	99.35	5.23	0.49	1.00	-2.39	47.82	1.22	-0.42	1.00
OIL	PROCESS	167.14	57.18	109.96	1.21	0.34	-0.13	0.13	26.54	-7.60	1.00
FD	ROIL	71.07	59.81	11.26	4.41	0.84	-0.13	0.80	22.29	-7.90	1.00

REA

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
FORS	PROCESS	0.63	0.60	0.03	0.38	1.00	-0.31	0.31	-6.63	-3.22	1.00
EINT	COAL	1528.40	1451.98	76.42	0.00	1.00	-0.27	5.34	21.91	-3.75	0.97
EINT	OIL	320.84	274.88	45.96	0.50	0.86	-0.12	0.82	33.84	-8.49	0.85
EINT	ROIL	108.44	103.02	5.42	0.95	1.00	-1.64	32.70	2.78	-0.61	0.93
EINT	PROCESS	60.26	57.25	3.01	0.45	1.00	-0.28	0.28	9.39	-3.62	1.00
TRAN	ROIL	477.76	369.90	107.86	1.88	0.77	-1.93	8.54	3.70	-0.52	0.79
ELEC	COAL	2141.51	867.03	1274.48	0.15	0.40	-0.37	0.63	11.94	-2.67	0.88
ELEC	OIL	857.31	814.44	42.87	0.19	0.98	-0.72	14.32	5.82	-1.40	0.79
ELEC	ROIL	13.80	13.11	0.69	1.48	1.00	-2.22	44.35	1.55	-0.45	0.81
OIL	PROCESS	66.21	62.90	3.31	0.16	1.00	-0.06	0.06	48.20	-17.68	0.93
FD	COAL	47.40	45.03	2.37	0.42	1.00	-0.36	7.18	9.74	-2.79	0.99
FD	ROIL	70.09	66.59	3.50	1.54	0.96	-0.21	4.17	15.28	-4.80	0.99
TRAN	OIL	3.93	3.73	0.20	0.50	1.00	-0.13	2.53	-1.03	-7.90	1.00
FD	OIL	23.79	18.30	5.49	0.49	0.77	-0.13	0.55	10.13	-7.91	1.00

ROE

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
FORS	PROCESS	3.51	2.71	0.80	0.40	0.77	-0.30	0.30	-1.26	-3.34	1.00
EINT	COAL	401.80	381.71	20.09	0.31	1.00	-0.20	4.05	22.35	-4.93	0.93
EINT	OIL	161.89	117.91	43.98	0.59	0.73	-0.11	0.41	26.27	-8.99	0.73
EINT	ROIL	1.69	0.68	1.01	2.35	0.40	-1.99	3.32	0.66	-0.50	0.60
EINT	PROCESS	347.56	85.75	261.81	0.04	0.25	-0.15	0.15	23.09	-6.57	0.90
TRAN	ROIL	284.29	13.32	270.97	1.44	0.05	-0.43	0.45	6.34	-2.31	0.93
ELEC	COAL	1510.11	495.78	1014.33	0.20	0.33	-0.23	0.34	18.19	-4.33	0.60
ELEC	OIL	135.95	52.40	83.55	0.37	0.39	-0.19	0.31	11.81	-5.18	0.81
ELEC	ROIL	10.72	7.52	3.20	2.11	0.70	-1.99	6.66	1.76	-0.50	0.66
OIL	PROCESS	37.98	24.23	13.75	0.08	0.64	-0.29	0.29	6.98	-3.42	0.82
FD	COAL	30.54	29.01	1.53	0.43	1.00	-0.13	2.62	18.61	-7.62	1.00
FD	OIL	75.99	35.86	40.13	0.49	0.47	-0.13	0.24	18.42	-7.90	1.00
FD	ROIL	28.89	14.12	14.77	1.49	0.49	-0.67	1.31	2.55	-1.50	1.00
TRAN	OIL	4.66	4.43	0.23	0.49	1.00	-0.13	2.52	-1.64	-7.93	1.00
ELEC	BOIL	0.41	0.39	0.02	2.79	1.00	-0.42	8.39	-4.35	-2.38	1.00

RUS

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
FORS	PROCESS	57.00	27.61	29.39	0.41	0.48	-0.30	0.30	7.48	-3.29	1.00

EINT	COAL	57.78	46.12	11.66	0.39	0.80	-0.27	1.35	9.76	-3.68	0.91
EINT	OIL	160.45	106.03	54.42	0.56	0.66	-0.31	0.90	10.86	-3.28	0.99
EINT	ROIL	10.59	5.10	5.49	4.36	0.48	-0.13	0.24	1.19	-7.90	1.00
EINT	BOIL	25.49	24.22	1.27	0.66	1.00	-2.68	53.54	0.77	-0.37	0.93
EINT	PROCESS	347.78	134.08	213.70	0.24	0.39	-0.10	0.10	40.99	-9.84	0.92
TRAN	OIL	0.61	0.58	0.03	0.49	1.00	-0.13	2.53	-14.81	-7.90	1.00
TRAN	ROIL	242.85	44.96	197.89	2.31	0.19	-0.99	1.21	4.68	-1.01	0.60
ELEC	COAL	408.06	282.87	125.19	0.38	0.69	-0.28	0.92	12.17	-3.55	0.81
ELEC	OIL	421.00	321.10	99.90	0.42	0.76	-0.18	0.76	19.59	-5.52	0.90
ELEC	ROIL	6.54	3.15	3.39	4.36	0.48	-0.13	0.24	-2.62	-7.90	1.00
ELEC	BOIL	97.24	92.38	4.86	0.56	1.00	-1.17	23.32	1.72	-0.86	0.82
OIL	PROCESS	145.85	73.58	72.27	0.16	0.50	-0.06	0.06	61.56	-18.11	0.96
FD	COAL	46.25	43.94	2.31	0.32	1.00	-0.42	8.39	7.87	-2.38	1.00
FD	OIL	11.26	10.70	0.56	0.49	1.00	-0.13	2.53	8.27	-7.91	1.00
FD	ROIL	22.35	10.77	11.58	4.36	0.48	-0.13	0.24	7.07	-7.90	1.00

USA

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
FORS	PROCESS	519.08	281.65	237.43	0.41	0.54	-0.30	0.30	14.83	-3.28	1.00
EINT	COAL	612.41	569.82	42.59	0.54	0.93	-0.07	1.07	68.80	-13.43	0.79
EINT	OIL	611.42	576.64	34.78	0.56	0.94	-0.39	6.83	12.48	-2.58	0.95
EINT	ROIL	150.03	142.53	7.50	1.56	1.00	-1.71	34.18	3.35	-0.59	0.76
EINT	BOIL	43.07	40.92	2.15	6.61	1.00	-0.04	0.72	99.40	-27.69	0.99
EINT	PROCESS	1770.56	295.57	1474.99	0.08	0.17	-0.15	0.15	32.53	-6.56	0.88
TRAN	OIL	7.80	7.41	0.39	0.49	1.00	-0.13	2.54	2.44	-7.88	1.00
TRAN	ROIL	3783.76	289.74	3494.02	1.61	0.08	-0.86	0.93	7.06	-1.16	0.84
ELEC	COAL	32989.93	9662.70	23327.23	0.44	0.29	-0.11	0.16	65.62	-8.90	0.54
ELEC	OIL	2615.72	511.60	2104.12	0.45	0.20	-0.10	0.12	50.47	-10.02	0.81
ELEC	ROIL	30.25	28.74	1.51	1.75	1.00	-1.73	34.68	2.50	-0.58	0.69
ELEC	BOIL	57.79	54.90	2.89	4.38	1.00	-1.51	30.25	4.13	-0.66	1.00
OIL	PROCESS	1082.10	516.35	565.75	0.11	0.48	-0.27	0.27	19.75	-3.72	0.81
FD	COAL	123.44	54.87	68.57	0.43	0.44	-0.14	0.26	24.01	-7.02	1.00
FD	OIL	240.07	83.51	156.56	0.49	0.35	-0.13	0.19	27.53	-7.87	1.00
FD	ROIL	311.80	296.21	15.59	1.50	1.00	-0.59	11.89	7.05	-1.68	1.00

Table A.2. NO_x Abatement Opportunity Parameters

ANZ

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
EINT	COAL	18.74	17.80	0.94	0.17	1.00	-0.23	4.54	8.69	-4.40	0.99
EINT	OIL	8.99	8.54	0.45	0.08	1.00	-0.33	6.53	4.02	-3.06	0.97
EINT	ROIL	11.48	10.91	0.57	0.43	1.00	-0.02	0.44	77.34	-45.43	0.85
EINT	GAS	38.56	36.63	1.93	0.58	1.00	-0.20	3.95	13.81	-5.07	0.99
EINT	BOIL	20.11	19.10	1.01	0.49	1.00	-0.07	1.36	34.12	-14.68	0.64
EINT	PROCESS	40.88	38.84	2.04	0.18	1.00	-0.41	0.41	6.91	-2.46	0.98
ELEC	COAL	495.51	470.73	24.78	0.17	1.00	-0.15	2.97	33.76	-6.74	0.96
ELEC	OIL	4.79	4.55	0.24	0.08	1.00	-0.34	6.71	1.93	-2.98	0.95
ELEC	ROIL	5.48	5.21	0.27	0.35	1.00	-0.18	3.66	4.19	-5.46	1.00
ELEC	GAS	63.06	59.91	3.15	0.06	1.00	-0.25	4.96	13.61	-4.03	0.86
ELEC	BOIL	6.36	6.04	0.32	0.40	1.00	-0.13	2.57	7.76	-7.78	1.00
OIL	PROCESS	14.61	13.88	0.73	0.61	1.00	-0.56	0.56	4.16	-1.77	0.71
FD	OIL	0.17	0.16	0.01	0.81	1.00	-0.13	2.54	-21.48	-7.88	1.00
FD	ROIL	4.07	3.87	0.20	5.11	1.00	-0.34	6.87	5.57	-2.91	0.69
FD	GAS	11.20	10.64	0.56	2.02	1.00	-0.29	5.71	8.13	-3.50	1.00

ASI

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
EINT	COAL	188.52	179.09	9.43	0.13	1.00	-0.32	6.38	14.26	-3.14	0.99
EINT	OIL	80.51	76.48	4.03	0.25	1.00	-0.39	7.86	9.63	-2.54	0.94
EINT	ROIL	33.45	31.78	1.67	0.54	1.00	-0.52	10.38	6.05	-1.93	0.77
EINT	GAS	100.92	95.87	5.05	0.76	1.00	-0.21	4.20	18.61	-4.76	1.00
EINT	BOIL	114.52	108.79	5.73	0.49	1.00	-0.06	1.12	73.15	-17.92	0.68
EINT	PROCESS	187.68	178.30	9.38	0.37	0.97	-0.14	0.14	27.91	-7.21	0.97
ELEC	OIL	68.58	56.55	12.03	0.07	0.82	-0.24	1.39	13.82	-4.09	0.81
ELEC	ROIL	15.84	15.05	0.79	0.66	1.00	-1.37	27.44	1.56	-0.73	0.59
ELEC	GAS	224.57	213.34	11.23	0.25	0.99	-0.29	5.80	17.13	-3.45	0.85
ELEC	BOIL	70.07	17.88	52.19	0.00	0.26	-0.01	0.01	297.01	-106.19	0.76
OIL	PROCESS	44.05	41.85	2.20	1.05	1.00	-0.72	0.72	5.25	-1.39	0.69
FD	OIL	5.91	5.61	0.30	0.81	1.00	-0.13	2.54	6.52	-7.88	1.00
FD	ROIL	48.84	46.40	2.44	4.80	1.00	-0.33	6.67	13.08	-3.00	0.88
FD	GAS	7.20	6.84	0.36	2.42	1.00	-0.28	5.67	6.81	-3.53	1.00
ELEC	COAL	529.58	503.10	26.48	0.13	0.98	-0.26	5.15	19.90	-3.88	0.84

CAN

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
EINT	COAL	5.71	5.11	0.60	0.25	0.90	-0.13	1.22	7.70	-7.79	0.99
EINT	OIL	49.47	45.68	3.79	0.18	0.92	-0.39	5.05	8.14	-2.59	0.98
EINT	ROIL	14.68	13.95	0.73	0.38	1.00	-0.10	1.91	20.52	-10.46	0.85
EINT	GAS	99.86	94.87	4.99	0.53	1.00	-0.24	4.70	16.09	-4.25	1.00
EINT	BOIL	44.56	42.33	2.23	0.63	1.00	-0.13	2.54	22.20	-7.88	1.00
EINT	PROCESS	66.59	63.26	3.33	0.17	1.00	-0.35	0.35	8.96	-2.86	0.99
ELEC	COAL	865.31	174.55	690.76	0.11	0.20	-0.32	0.41	13.75	-3.09	0.90

ELEC	OIL	156.41	22.87	133.54	0.09	0.15	-0.24	0.29	10.40	-4.09	0.87
ELEC	ROIL	0.53	0.50	0.03	0.46	1.00	-1.57	31.35	-1.21	-0.64	0.84
ELEC	GAS	120.51	98.87	21.64	0.18	0.82	-0.32	1.77	12.75	-3.14	0.99
OIL	PROCESS	56.82	53.98	2.84	0.33	1.00	-0.57	0.57	5.84	-1.74	0.87
FD	OIL	9.18	8.72	0.46	0.81	1.00	-0.13	2.54	10.01	-7.88	1.00
FD	ROIL	26.86	25.52	1.34	5.13	1.00	-0.41	8.11	9.62	-2.47	0.75
FD	GAS	66.56	63.23	3.33	2.02	1.00	-0.29	5.70	14.38	-3.51	1.00

CHN

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
EINT	COAL	4614.36	4383.64	230.72	0.13	1.00	-0.26	5.21	30.11	-3.84	0.98
EINT	OIL	226.95	215.60	11.35	0.06	1.00	-0.29	5.81	15.75	-3.44	0.99
EINT	ROIL	217.62	206.74	10.88	0.15	1.00	-0.04	0.71	129.99	-28.23	0.72
EINT	GAS	66.12	62.81	3.31	0.09	1.00	-0.27	5.38	12.61	-3.71	1.00
EINT	BOIL	66.68	63.35	3.33	0.39	1.00	-0.13	2.54	24.90	-7.88	1.00
EINT	PROCESS	24713.99	2517.60	22196.39	0.15	0.10	-0.14	0.14	48.49	-7.33	0.97
ELEC	COAL	5584.01	4516.46	1067.55	0.12	0.81	-0.35	1.85	21.48	-2.82	0.59
ELEC	OIL	20.74	19.70	1.04	0.05	1.00	-0.29	5.82	7.30	-3.44	0.94
ELEC	GAS	22.17	21.06	1.11	0.55	1.00	-0.13	2.54	14.73	-7.88	1.00
FD	ROIL	7.32	6.95	0.37	8.84	1.00	-0.26	5.11	9.77	-3.92	0.97
FD	GAS	12.20	11.59	0.61	4.92	1.00	-0.29	5.71	9.36	-3.50	1.00
OIL	PROCESS	67.61	64.23	3.38	0.35	1.00	-0.07	0.07	44.26	-15.17	0.93
ELEC	ROIL	0.02	0.02	0.00	0.53	1.00	-0.13	2.54	-38.29	-7.88	1.00

EUR

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
EINT	COAL	287.77	107.97	179.80	0.19	0.38	-0.17	0.27	25.96	-5.98	0.98
EINT	OIL	232.90	108.35	124.55	0.23	0.47	-0.35	0.65	12.09	-2.89	0.97
EINT	ROIL	51.77	46.69	5.08	0.40	0.90	-0.58	5.89	5.74	-1.73	0.93
EINT	GAS	591.35	363.52	227.83	0.46	0.61	-0.23	0.61	22.90	-4.27	1.00
EINT	BOIL	48.39	45.97	2.42	0.48	0.97	-0.07	1.37	47.15	-14.63	0.72
EINT	PROCESS	2170.42	576.12	1594.30	0.28	0.27	-0.26	0.26	22.25	-3.91	0.98
ELEC	COAL	8900.77	1600.75	7300.02	0.21	0.18	-0.20	0.24	34.77	-5.07	0.93
ELEC	OIL	3818.94	246.12	3572.82	0.16	0.06	-0.21	0.23	24.28	-4.74	0.94
ELEC	ROIL	783.76	45.11	738.65	0.00	0.06	-0.10	0.10	31.32	-10.22	0.71
ELEC	GAS	3493.16	542.46	2950.70	0.17	0.16	-0.23	0.27	26.14	-4.43	0.98
ELEC	BOIL	416.41	153.17	263.24	0.43	0.37	-0.02	0.03	235.98	-50.15	0.93
OIL	PROCESS	362.51	88.67	273.84	1.15	0.24	-0.51	0.51	8.88	-1.95	0.83
FD	OIL	20.46	19.44	1.02	0.93	1.00	-0.13	2.54	16.45	-7.88	1.00
FD	ROIL	375.84	178.03	197.81	5.46	0.47	-0.21	0.40	26.19	-4.73	0.96
FD	GAS	1052.36	377.49	674.87	2.23	0.36	-0.26	0.40	23.42	-3.88	0.99
FORS	PROCESS	0.79	0.67	0.12	3.62	0.85	-0.84	0.84	-0.21	-1.19	1.00

IND

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
EINT	COAL	1243.02	1180.87	62.15	0.09	1.00	-0.31	6.16	20.60	-3.25	0.97
EINT	OIL	362.11	344.00	18.11	0.21	1.00	-0.37	7.36	14.33	-2.72	0.95

EINT	ROIL	36.77	34.93	1.84	0.57	1.00	-0.29	5.89	8.49	-3.40	1.00
EINT	GAS	11.12	10.56	0.56	0.12	1.00	-0.27	5.50	6.49	-3.64	1.00
EINT	PROCESS	495.86	471.07	24.79	0.37	1.00	-0.13	0.13	35.97	-7.45	0.95
ELEC	COAL	2408.96	2288.51	120.45	0.22	1.00	-0.23	4.63	28.27	-4.32	0.92
ELEC	OIL	46.05	43.75	2.30	0.16	1.00	-0.15	3.08	16.14	-6.50	0.92
ELEC	ROIL	6.68	6.35	0.33	0.53	1.00	-0.27	5.47	5.09	-3.66	1.00
ELEC	GAS	271.31	257.74	13.57	0.35	1.00	-0.08	1.64	50.86	-12.22	0.99
OIL	PROCESS	134.89	128.15	6.74	1.23	1.00	-1.06	1.06	4.81	-0.95	0.66
FD	ROIL	248.14	235.73	12.41	5.53	1.00	-0.16	3.11	34.82	-6.43	0.98
FD	GAS	5.52	5.24	0.28	2.42	1.00	-0.29	5.72	5.83	-3.50	1.00

JPN

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
EINT	COAL	265.54	41.74	223.80	0.26	0.16	-0.16	0.18	22.67	-6.43	0.98
EINT	OIL	151.71	36.77	114.94	0.54	0.24	-0.28	0.38	12.05	-3.52	0.92
EINT	ROIL	59.54	56.56	2.98	0.60	1.00	-0.63	12.62	5.89	-1.58	0.91
EINT	GAS	148.98	27.50	121.48	0.85	0.18	-0.13	0.15	23.43	-7.99	0.97
EINT	BOIL	13.81	13.12	0.69	0.79	1.00	-0.01	0.17	214.66	-116.15	0.89
EINT	PROCESS	508.27	79.89	428.38	0.50	0.16	-0.26	0.26	16.36	-3.89	0.73
ELEC	COAL	5906.59	143.04	5763.55	0.28	0.02	-0.06	0.06	79.12	-16.67	0.70
ELEC	OIL	2766.54	42.85	2723.69	0.30	0.02	-0.09	0.09	42.24	-11.56	0.94
ELEC	ROIL	3.39	3.22	0.17	0.51	1.00	-0.31	6.28	1.00	-3.18	0.94
ELEC	GAS	459.19	116.01	343.18	1.12	0.25	-0.24	0.32	19.96	-4.17	0.76
ELEC	BOIL	2264.48	13.39	2251.09	0.00	0.01	-0.04	0.04	53.79	-22.89	0.97
OIL	PROCESS	64.28	25.43	38.85	3.76	0.40	-0.13	0.13	19.98	-7.88	1.00
FD	OIL	6.01	5.71	0.30	0.81	1.00	-0.13	2.54	6.66	-7.88	1.00
FD	ROIL	109.59	104.11	5.48	5.50	1.00	-0.38	7.63	13.88	-2.62	0.76
FD	GAS	47.86	45.47	2.39	2.42	1.00	-0.29	5.71	13.41	-3.51	1.00

REA

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
EINT	COAL	192.58	182.95	9.63	0.11	1.00	-0.33	6.52	13.76	-3.07	0.98
EINT	OIL	36.01	34.21	1.80	0.13	0.98	-0.32	6.43	8.91	-3.11	0.93
EINT	ROIL	17.16	16.30	0.86	0.71	1.00	-0.08	1.63	25.78	-12.25	1.00
EINT	GAS	73.89	70.20	3.69	0.73	0.96	-0.25	5.07	14.60	-3.94	1.00
EINT	BOIL	39.23	37.27	1.96	0.49	1.00	-0.10	1.96	26.38	-10.20	0.73
EINT	PROCESS	95.29	90.53	4.76	0.25	1.00	-0.57	0.57	5.48	-1.75	1.00
ELEC	COAL	173.85	165.16	8.69	0.21	1.00	-0.13	2.67	29.90	-7.50	0.84
ELEC	OIL	63.69	60.51	3.18	0.16	1.00	-0.23	4.60	12.99	-4.35	0.88
ELEC	ROIL	1.80	1.71	0.09	0.66	1.00	-0.04	0.90	4.89	-22.29	1.00
ELEC	GAS	159.14	151.18	7.96	0.19	1.00	-0.35	7.04	12.58	-2.84	0.84
OIL	PROCESS	23.16	22.00	1.16	1.17	1.00	-0.93	0.93	3.49	-1.08	0.67
FD	ROIL	38.77	36.83	1.94	4.89	1.00	-0.34	6.72	12.32	-2.98	0.84
FD	GAS	53.18	50.52	2.66	2.42	1.00	-0.29	5.70	13.79	-3.51	1.00
FD	OIL	2.71	2.57	0.14	0.81	1.00	-0.13	2.54	0.42	-7.88	1.00

ROE

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
EINT	COAL	91.95	65.42	26.53	0.09	0.71	-0.27	0.94	12.91	-3.71	0.97
EINT	OIL	35.19	21.31	13.88	0.05	0.61	-0.29	0.74	7.51	-3.41	0.93
EINT	ROIL	3.22	3.06	0.16	0.66	1.00	-3.17	63.40	-0.06	-0.32	0.71
EINT	GAS	15.13	13.18	1.95	0.59	0.87	-0.20	1.53	9.02	-5.09	0.98
EINT	BOIL	1.09	1.04	0.05	0.39	1.00	-0.13	2.54	-7.47	-7.88	1.00
EINT	PROCESS	96.79	91.95	4.84	0.37	1.00	-0.18	0.18	17.89	-5.44	0.99
ELEC	COAL	73.34	69.67	3.67	0.21	1.00	-0.30	6.04	11.10	-3.31	0.98
ELEC	OIL	14.72	10.90	3.82	0.07	0.74	-0.30	1.17	5.24	-3.29	0.85
ELEC	ROIL	2.59	2.46	0.13	0.54	1.00	-0.22	4.47	3.42	-4.47	0.96
ELEC	GAS	43.94	41.74	2.20	0.25	0.98	-0.35	6.98	8.89	-2.86	0.89
OIL	PROCESS	10.42	9.90	0.52	1.25	1.00	-1.08	1.08	2.34	-0.92	0.66
FD	OIL	7.82	7.43	0.39	0.81	1.00	-0.13	2.54	8.76	-7.88	1.00
FD	ROIL	11.65	11.07	0.58	5.49	1.00	-0.39	7.79	7.88	-2.57	0.86
FD	GAS	14.65	13.92	0.73	2.05	1.00	-0.29	5.71	9.09	-3.50	1.00
ELEC	BOIL	0.37	0.35	0.02	0.33	1.00	-0.36	7.12	-4.05	-2.81	1.00

RUS

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
EINT	COAL	17.82	16.62	1.20	0.17	0.93	-0.14	2.11	14.77	-7.01	0.99
EINT	OIL	27.34	25.71	1.63	0.14	0.94	-0.36	6.00	7.10	-2.80	0.99
EINT	ROIL	8.83	8.39	0.44	0.55	1.00	-0.57	11.43	3.11	-1.75	0.86
EINT	GAS	75.25	71.49	3.76	0.82	0.96	-0.07	1.46	43.11	-13.66	0.98
EINT	BOIL	3.29	3.13	0.16	0.47	1.00	-0.19	3.80	1.93	-5.26	0.99
EINT	PROCESS	130.68	124.15	6.53	0.34	1.00	-0.19	0.19	21.50	-5.30	0.96
ELEC	COAL	129.56	123.08	6.48	0.13	1.00	-0.17	3.31	21.70	-6.04	0.91
ELEC	OIL	81.43	76.46	4.97	0.03	0.94	-0.30	4.85	11.15	-3.38	0.99
ELEC	ROIL	2.44	2.32	0.12	0.66	1.00	-0.02	0.31	13.97	-65.22	0.96
ELEC	GAS	757.08	719.23	37.85	0.04	0.97	-0.24	4.78	24.30	-4.19	0.73
ELEC	BOIL	13.48	12.81	0.67	0.50	1.00	-0.04	0.72	48.53	-27.92	1.00
OIL	PROCESS	44.96	42.71	2.25	1.13	1.00	-0.86	0.86	4.48	-1.16	0.68
FD	OIL	2.19	2.08	0.11	0.81	1.00	-0.13	2.54	-1.28	-7.88	1.00
FD	ROIL	12.62	11.99	0.63	4.72	1.00	-0.35	6.92	8.73	-2.89	0.90
FD	GAS	80.12	76.11	4.01	2.42	1.00	-0.29	5.71	15.21	-3.50	1.00

USA

Sector	Fuel	X_P	X_E	X_A	P_o	θ	ε_D	σ	α	β	r^2
EINT	COAL	173.53	162.78	10.75	0.16	0.94	-0.32	5.09	13.99	-3.17	0.96
EINT	OIL	155.55	147.77	7.78	0.17	0.96	-0.42	8.32	10.22	-2.41	0.97
EINT	ROIL	107.45	102.08	5.37	0.41	1.00	-0.09	1.88	41.98	-10.63	0.87
EINT	GAS	973.26	924.60	48.66	0.25	1.00	-0.25	4.95	23.92	-4.04	1.00
EINT	BOIL	182.94	173.79	9.15	0.49	1.00	-0.04	0.82	109.51	-24.34	0.85
EINT	PROCESS	430.07	408.57	21.50	0.20	1.00	-0.26	0.26	18.46	-3.78	0.98
ELEC	COAL	13000.55	3705.36	9295.19	0.21	0.29	-0.35	0.49	21.96	-2.86	0.86
ELEC	OIL	1776.32	176.93	1599.39	0.06	0.10	-0.22	0.24	21.03	-4.61	0.83
ELEC	ROIL	10.68	10.15	0.53	0.43	1.00	-0.09	1.80	18.51	-11.10	0.88

ELEC	GAS	2133.80	1108.92	1024.88	0.10	0.52	-0.25	0.53	25.32	-3.94	0.92
ELEC	BOIL	103.42	98.25	5.17	0.50	1.00	-0.02	0.43	182.86	-46.85	1.00
OIL	PROCESS	441.17	419.11	22.06	0.36	1.00	-0.68	0.68	7.88	-1.47	0.86
FD	OIL	31.45	29.88	1.57	0.65	1.00	-0.13	2.54	19.49	-7.88	1.00
FD	ROIL	159.18	151.22	7.96	4.04	1.00	-0.37	7.44	14.89	-2.69	0.66
FD	GAS	639.82	607.83	31.99	1.51	1.00	-0.29	5.71	22.03	-3.51	1.00

Appendix 2: GAMS Marginal Abatement Cost Curve Calculator Code

This appendix documents the code used to generate the marginal abatement cost curve and other parameters needed to represent that GAMS abatement opportunity data within the MIT Emission Prediction and Policy Analysis mode. The code is written in Mathematica 8.0 script.

```
(*## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ##

                GAINS MARGINAL ABATEMENT COST CURVE CALCULATOR

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        Policy of Global Change

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Description: This program calculates the parameters needed to represent urban pollution abatement
costs in the MIT Joint Program on the Science and Policy of Global Change EPPA model verison 5 with
household transport (HTRN) or EPPA5_HHTRN _PVT. The parameters include the price elasticity of
supply of abatement derived from the GAINS marginal abatement cost curves, the initial quantity of
pollutant abated, and initial price of pollutant. The price elasticity of supply of abatement is
calculated by first mapping the data from the GAINS regions, sectors, and fuels into corresonding
EPPA regions, sectors, and fuels. Afterwards the price elasticity is determined by performing an
ordinary least squares (OLS) regression on the specific technologies identified in the GAINS data
that are available for abatement within each region and sector and with each fuel type. To obtian
the best fit to the data, an additional variable for the initial price (Po) is included as a free
variable that is chosen to maximize the r^2 correlation coeffecient of the regression. All
parameters are then formatted into the GAMS format and exported as .dat files.

The code is divided into 3 sections for organization purposes:

 I. READ IN GAINS INPUT FILES AND INITIALIZE GLOBAL VARIABLES
 II. DEFINE LOOKUP, MAPPING AND FORMATTING FUNCTIONS
 III. DEFINE REGIONAL MAC REGRESSION FUNCTIONS
 IV. CALCULATE EPPA PARAMETERS

NOTE: The names of the GAINS input files must follow a specific format, 'GAS'_C _'GAINS Region'.txt
 for all cost files, 'GAS'_E _'GAINS Region'.txt for all emissions files, and
'GAS'_P _'GAINS Region'.txt for all policy cost files. Samples of properly formatted files include,
"NOx_C_Belgium.txt", "NOx_E_Macedonia", and "SO2_P_China_Hunan". The code will use the file name
 to identify the file contents so any files not properly named will produce an error.

#### ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ##

             I. READ IN GAINS INPUT FILES AND INITIALIZE GLOBAL VARIABLES
```

```
Description: Defines global variables for reading in the GAINS data input files, defines gases, GAINS
regions and sectors, EPPA regions and sectors, and a number of misc. global parameters used
throughout the code.
#### ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ###*)

(*Clear all Global Variables that may have been used previously.*)
Clear[gainsSourceDataDir,gainsResultsDir,eppaDestinationDir,mappingDataDir, macDataDir,
emissionsDataDir, gainsSectors, gainsFuel, gainsParameters, gases, eppaRegions,eppaSectors, eppaFuel,
anz, asi, can, chn, eur, ind, jpn, rea, roe, rus, usa, gainsRegions, printResults, numBins, precision,
nonZeroValueShare, currencyConversion];

(*Set the source directories for the GAINS data files and destination directories for the EPPA
parameters*)

gainsSourceDataDir="C:\\Users\\Caleb Waugh\\Documents\\My Dropbox\\GAINS Models\\GAINS
Data\\";
gainsResultsDir="C:\\Users\\Caleb Waugh\\Documents\\My Dropbox\\GAINS Models\\MAC Results\\";
eppaDestinationDir = "C:\\Users\\Caleb Waugh\\Documents\\Education\\MIT\\Joint Program\\GAMS
Models\\EPPA Models\\EPPA5_HHTRN_PVT\\data\\";

(*Set sub-directories within source directories for GAINS data files.*)

mappingDataDir = "Mapping\\";
macDataDir="MAC Data\\";
emissionsDataDir="Emissions Data\\";

(*Read in mapping files which establish rules for mapping GAINS sectors, and fuels into EPPA*)

gainsSectors=Import[gainsSourceDataDir<>mappingDataDir<>"GAINS_Sectors.csv","CSV"];
gainsFuel=Import[gainsSourceDataDir<>mappingDataDir<>"GAINS_Fuel.csv","CSV"];
gainsParameters=Import[gainsSourceDataDir<>mappingDataDir<>"GAINS_Parameters.csv","CSV"];

(*Gases for which to generate EPPA parameters.*)

gases={"SO2","NOx"};

(*EPPA regions, sectors, and fuel*)

eppaRegions={"ANZ","ASI","CAN","CHN","EUR","IND","JPN","REA","ROE","RUS","USA"};
eppaSectors={"LIVE","CROP","FORS","FOOD","EINT","TRAN","HTRN","OTHR","SERV","ELEC","OIL","SOIL
","BOIL","ROIL","COAL","GAS","SGAS","FD"};
eppaFuel={"COAL","OIL","ROIL","GAS","BOIL","PROCESS"};

(*Gains regions regions mapped into EPPA regions*)

anz={"Australia","NewZealand"};
```

```
asi={"Indonesia_Jakarta","Indonesia_Java","Indonesia_RestOf","Indonesia_Sumatra","SouthKorea_Nort
h","Malaysia_KualaLumpur","Malaysia_Peninsular","Malaysia_SarawakSabah","Philipinnes_BicolVisayas
Mindanao","Philipinnes_Luzon","Philipinnes_MetroMalina","Singapore","Thailand_Bangkok","Thailand_
CentralValley", "Thailand_NEPlateau","Thailand_NHeighlands","Thailand_SouthPeninsula"};
(*ASI still missing South Korea and Taiwan..needs to convert 2005 data.*)
can={"Canada"};
chn={"China_Anhui","China_Beijing","China_Chongqing","China_Fujian","China_Gansu","China_Guangd
ong","China_Guangxi","China_Guizhou","China_Hainan","China_Hebei","China_Heilongjiang","China_H
enan","China_HongKongMacau","China_Hubei","China_Hunan","China_InnerMongolia","China_Jiangsu
","China_Jiangxi",
"China_Jilin","China_Liaoning","China_Ningxia","China_Qinghai","China_Shaanxi","China_Shandong","C
hina_Shanghai","China_Shanxi","China_Sichuan","China_Tianjin","China_TibetXizang","China_Xinjiang",
"China_Yunnan","China_Zhejiang"};
eur={"Austria","Belgium","Bulgaria","Cyprus","CzechRepublic","Denmark","Estonia","Finland","France",
"Germany","Greece","Hungary","Iceland","Ireland","Italy","Latvia","Lithuania","Luxembourg","Malta","
Netherlands","Norway","Poland","Portugal","Romania","Slovakia","Slovenia","Spain","Sweden","Switze
rland","UnitedKingdom"};
ind={"India_AndhraPradesh","India_Assam","India_Bihar","India_Chhattisgarh","India_Delhi","India_Go
a","India_Gujarat","India_Haryana","India_HimachalPradesh","India_JammuKashmir","India_Jharkhand
","India_Kamataka","India_Kerala","India_MadhyaPradesh","India_MaharashtraDadraNagar","India_No
rthEast","India_Orissa","India_Punjab","India_Rajasthan","India_TamilNadu","India_Uttaranchal","India
_UttarPradesh","India_WestBengal"};
jpn={"Japan_Total"};
rea={"BangladeshDhaka","BangladeshRest","Bhutan","Brunei","Cambodia","Laos","Myanmar","Nepal","
Pakistan_FrontProvBalu","Pakistan_Karachi","Pakistan_Punjab","Pakistan_Sind","SriLanka","NorthVietm
an","SouthVietnam"}; (*REA missing North Korea...*)
roe={"Croatia","Turkey"};
rus={"Russia_Europe"};
usa={"USA"};
gainsRegions={anz,asi,can,chn,eur,ind,jpn,rea,roe,rus,usa};

(*Flag to display the results of the regression on the GAINS MAC cost data.*)

printResults= True;

(*Parameter used for the correlation coeffecient optimization algorithm in EdMaxLogLog and
EdMaxNormal*)

numBins=12;
precision=.000001;

(*Initializes all value shares to an initial non-zero value.*)

nonZeroValueShare=.95;

(*Sets which currency conversion value to use as specified in GAINS parameter file.*)
```

```
currencyConversion="USD(2004)/Euro(2000)";

(*## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ##

II. DEFINE LOOKUP MAPPING AND FORMATTING FUNCTIONS

Description: Defines a number of LOW LEVEL functions used for mapping the GAINS data into EPPA regions, sectors and fuels.

#### ## ## ## ## ## ## ## ## ## ## ### ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ##*)

(*Clear all function definitions that may have been used previously.*)

Clear[ContainsSub,Pair, SectorLookupCost, FuelLookupCost, FormatRawCost, SectorLookupEmissions,
FuelLookupEmissions, FormatRawEmissions, SumEmissions, SectorLookupPolicyCost,
FuelLookupPolicyCost, FormatRawPolicyCost, AggregateRawPolicyCost, AggregateRawCost,
AggregateRawEmissions,GamsFormatter];

(*ContainsSub[string,substring]: Searches 'string' and returns true is 'substring' is found within
string. If not then retruns false.*)

ContainsSub[string_,substring_]:=Module[{charString,charSub,stringLen,subLen,contains},
charString=Characters[string];
charSub=Characters[substring];
stringLen=Length[charString];
subLen=Length[charSub];
contains=False;
Do[
If[charSub==charString[[i;;i+subLen-1]],contains=True;
i=stringLen-subLen+1],
{i,1,stringLen-subLen+1,1}];
contains
];

(*Pair[x,y]: takes an array of x values and pairs them with an equal length array of y values.*)

Pair[x_,y_]:=Module[{pairs},
pairs={};
Do[
AppendTo[pairs,{x[[i]],y[[i]]}];
,{i,1,Length[x[[All]]],1}
];
pairs
];

(*SectorLookupCost[gainsDeg]: takes as input a GAINS 'Category/Class-Activity-Sector-Technology'
designation input and returns the corresponding EPPA sector from the GAINSSectors lookup table.*)
```

```
SectorLookupCost[gainsDeg_]:=Module[{n,secLen,sector,end},
n=1;
secLen=Length[gainsSectors[[All]]];
sector="NoMatch";
end=True;
While[end&&n<=secLen,
If[ContainsSub[gainsDeg,"-"<>gainsSectors[[n,1]]<>"-"],
sector=gainsSectors[[n,2]];
end=False];
n++];
sector
];

(*SectorLookupPolicyCost[gainsDeg]: takes as input a GAINS 'Category/Class-Activity-Sector-Technology'
designation input and returns the corresponding EPPA sector from the GAINSSectors lookup table.*)

SectorLookupPolicyCost[gainsDeg_]:=Module[{n,secLen,sector,end},
n=1;
secLen=Length[gainsSectors[[All]]];
sector="NoMatch";
end=True;
While[end&&n<=secLen,
If[ContainsSub["-"<>gainsDeg,"-"<>gainsSectors[[n,1]]<>"-"],
sector=gainsSectors[[n,2]];
end=False];
n++];
sector
];

(*SectorLookupEmissions[gainsDeg]: takes as input a GAINS 'Category/Class-Activity-Sector-Technology'
designation input and returns the corresponding EPPA sector from the GAINSSectors lookup table.*)

SectorLookupEmissions[gainsDeg_]:=Module[{n,secLen,sector,end},
n=1;
secLen=Length[gainsSectors[[All]]];
sector="NoMatch";
end=True;
While[end&&n<=secLen,
If[gainsDeg==gainsSectors[[n,1]],
sector=gainsSectors[[n,2]];
end=False];
n++];
sector
];

(*FuelLookupCost[gainsDeg]: takes as input a GAINS 'Category/Class-Activity-Sector-Technology'
```

designation input and returns the corresponding EPPA fuel from the GAINSFuel lookup table.*)

```
FuelLookupCost[gainsDeg_]:=Module[{n,fuelLen,fuel,end},
n=1;
fuelLen=Length[gainsFuel[[All]]];
fuel="NoMatch";
end=True;
While[end&&n<=fuelLen,
If[ContainsSub[gainsDeg,"-"<>gainsFuel[[n,1]]<>"-"],
fuel=gainsFuel[[n,2]];
end=False];
n++];
fuel
];
```

(*FuelLookupPolicyCost[gainsDeg]: takes as input a GAINS 'Category/Class-Activity-Sector-Technology' designation input and returns the corresponding EPPA fuel from the GAINSFuel lookup table.*)

```
FuelLookupPolicyCost[gainsDeg_]:=Module[{n,fuelLen,fuel,end},
n=1;
fuelLen=Length[gainsFuel[[All]]];
fuel="NoMatch";
end=True;
While[end&&n<=fuelLen,
If[ContainsSub[gainsDeg,"-"<>gainsFuel[[n,1]]<>"-"],
fuel=gainsFuel[[n,2]];
end=False];
n++];
fuel
];
```

(*FuelLookupEmissions[gainsDeg]: takes as input a GAINS 'Category/Class-Activity-Sector-Technology' designation input and returns the corresponding EPPA fuel from the GAINSFuel lookup table.*)

```
FuelLookupEmissions[gainsDeg_]:=Module[{n,fuelLen,fuel,end},
n=1;
fuelLen=Length[gainsFuel[[All]]];
fuel="NoMatch";
end=True;
While[end&&n<=fuelLen,
If[gainsDeg==gainsFuel[[n,1]],
fuel=gainsFuel[[n,2]];
end=False];
n++];
fuel
];
```

```
(*FormatRawCost[rawCostData]: Constructs a table that maps the EPPA sectors and fuel types to
the GAINS marginal cost and removed emissions data.*)

FormatRawCost[rawCostData_,gas_]:=Module[{outData,outRow,conv},
outData={{"EPPASector","EPPAFuel","GAINS: Category/Class-Activity-Sector-Technology","Marginal Cost
($US (2000)/ton "<>gas<>")","Removed Emissions (kt "<>gas<>")"}};
outRow=2;
Do[
If[gainsParameters[[row,1]]==currencyConversion,conv=gainsParameters[[row,2]]]
,{row,1,Length[gainsParameters[[All]]],1}
];
Do[
If[!(SectorLookupCost[rawCostData[[row,1]]]=="NoMatch"),
AppendTo[outData,{SectorLookupCost[rawCostData[[row,1]]],FuelLookupCost[rawCostData[[row,1]]],ra
wCostData[[row,1]],rawCostData[[row,3]]*conv/1000,rawCostData[[row,4]]}];
outRow++],{row,1,Length[rawCostData[[All]]],1}];
outData
];

(*FormatRawPolicyCost[rawPolicyCostData]: Constructs a table that maps the EPPA sectors and fuel
types to the GAINS marginal cost and removed emissions data.*)

FormatRawPolicyCost[rawPolicyCostData_]:=Module[{outData,outRow,conv},
outData={{"EPPASector","EPPAFuel","GAINS: Category/Class-Activity-Sector-Technology","Cost $USD
2004/year"}};
outRow=2;
Do[
If[gainsParameters[[row,1]]==currencyConversion,conv=gainsParameters[[row,2]]]
,{row,1,Length[gainsParameters[[All]]],1}
];
Do[
If[!(SectorLookupPolicyCost[rawPolicyCostData[[row,1]]]=="NoMatch"),
AppendTo[outData,{SectorLookupPolicyCost[rawPolicyCostData[[row,1]]],FuelLookupPolicyCost[rawPoli
cyCostData[[row,1]]],rawPolicyCostData[[row,1]],rawPolicyCostData[[row,4]]*conv*1000000}];
outRow++],{row,1,Length[rawPolicyCostData[[All]]],1}];
outData
];

(*FormatRawEmissions[rawEmissionsData]: Constructs a table that maps the EPPA sectors and fuel
types to the GAINS emissions data.*)

FormatRawEmissions[rawEmissionsData_]:=Module[{secAct,refRow,colLen,rowLen,outData,lookup,outR
ow},
secAct="Sector/Activity";
refRow=1;
While[rawEmissionsData[[refRow,1]]!=secAct&&refRow<= Length[rawEmissionsData[[All]]],refRow++];
colLen=Length[rawEmissionsData[[refRow,All]]]+1;
```

```
rowLen=2;
While[rawEmissionsData[[refRow+rowLen,1]]!="",rowLen++];
outData=Array["",{rowLen,colLen}];
Do[lookup=FuelLookupEmissions[rawEmissionsData[[refRow,col]]];
If[lookup!="NoMatch",
outData[[1,col+1]]=lookup;
,outData[[1,col+1]]=""];
outData[[2,col+1]]=rawEmissionsData[[refRow,col]],
{col,1,colLen-1,1}];
outData[[1;;2,1]]=outData[[rowLen,1]]="";
outRow=1;
Do[lookup=SectorLookupEmissions[rawEmissionsData[[row,1]]];
If[lookup!="NoMatch",outData[[outRow+2,1]]=lookup;
outRow++],
{row,1,refRow+rowLen,1}];
Do[outData[[row,col]]=rawEmissionsData[[refRow+row-1,col-1]];
,{row,3,rowLen,1},{col,2,colLen,1}];
outData
];

(*SumEmissions[emissionsData]: Sums the emissions over EPPA sectors and regions and returns an
nx3 list of all emissions coming from each sector/fuel combo.*)

SumEmissions[emissionsData_,gas_]:=Module[{rowLen,colLen,outData,outRow,sum},
rowLen=Length[emissionsData[[All]]];
colLen=Length[emissionsData[[1,All]]];
outData={{"EPPA Sector","EPPA Fuel","Emissions (kt "<>gas<>")"}};
outRow=1;
Do[
sum=0;
Do[
If[emissionsData[[1,col]]==eppaFuel[[fuel]]&&emissionsData[[row,1]]==eppaSectors[[sec]],
sum+=emissionsData[[row,col]]]
,{row,3,rowLen,1},{col,3,colLen,1}];
If[sum!=0,AppendTo[outData,{eppaSectors[[sec]],eppaFuel[[fuel]],sum}]]
,{sec,1,Length[eppaSectors[[All]]],1},{fuel,1,Length[eppaFuel[[All]]]}];
outData
];

(*AggregateRawCost[rawCostDataArray_]:Aggregates the cost data over multiple GAINS regions and
orders all cost data from least to greatest marginal cost.*)

AggregateRawCost[rawCostArray_,gas_]:=Module[{formCostArray,heading,formCost,lenFormCost,lenFo
rmCostArray,contains,header,sorted},
heading=FormatRawCost[rawCostArray[[1]],gas];
formCostArray={heading[[1]]};
Do[
```

```
formCost=FormatRawCost[rawCostArray[[i]],gas];
lenFormCost=Length[formCost[[All]]];
Do[
contains=False;
lenFormCostArray=Length[formCostArray[[All]]];

(*Aggregate by combining like GAINS technologies then taking a weighted average of marginal
abatement costs.*)

Do[
If[formCost[[j,3]]==formCostArray[[k,3]]&&formCost[[j,5]]!=0&&Length[formCostArray[[All]]]>1,
formCostArray[[k,4]]=(formCostArray[[k,5]]*formCostArray[[k,4]]+formCost[[j,5]]*formCost[[j,4]])/(form
CostArray[[k,5]]+formCost[[j,5]]);
formCostArray[[k,5]]=formCost[[j,5]]+formCostArray[[k,5]];
contains=True]
,{k,1,lenFormCostArray,1}
];

If[!contains&&formCost[[j,5]]!=0,AppendTo[formCostArray,formCost[[j]]]];
,{j,2,lenFormCost,1}
];
,{i,1,Length[rawCostArray[[All]]],1}
];
header={formCostArray[[1]]};
sorted =Sort[formCostArray[[2;;Length[formCostArray[[All]]]]],#1[[4]]<#2[[4]]&];
Do[
AppendTo[header,sorted[[i]]],{i,1,Length[sorted[[All]]],1}];
header
];

(*AggregateRawPolicyCost[rawCostDataArray]:Aggregates the policy cost data over multiple GAINS
regions.*)

AggregateRawPolicyCost[rawPolicyCostArray_]:=Module[{formPolicyCostArray,heading,formPolicyCost,l
enFormPolicyCost,lenFormPolicyCostArray,contains,header,sorted},
heading=FormatRawPolicyCost[rawPolicyCostArray[[1]]];
formPolicyCostArray={heading[[1]]};
Do[
formPolicyCost=FormatRawPolicyCost[rawPolicyCostArray[[i]]];
lenFormPolicyCost=Length[formPolicyCost[[All]]];
Do[
contains=False;
lenFormPolicyCostArray=Length[formPolicyCostArray[[All]]];
Do[
If[formPolicyCost[[j,3]]==formPolicyCostArray[[k,3]]&&Length[formPolicyCostArray[[All]]]>1,
formPolicyCostArray[[k,4]]=formPolicyCostArray[[k,4]]+formPolicyCost[[j,4]];
contains=True]
```

```
,{k,1,lenFormPolicyCostArray,1}
];
If[!contains,AppendTo[formPolicyCostArray,formPolicyCost[[j]]]];
,{j,2,lenFormPolicyCost,1}
];
,{i,1,Length[rawPolicyCostArray[[All]]],1}
];
formPolicyCostArray
];

(*AggregateRawEmissions[rawEmissionsArray_]: Aggregates raw emissions data array and returns
the total emissions over all regions by sector and fuel type.*)

AggregateRawEmissions[rawEmissionsArray_,gas_]:=Module[{sumEmissionsArray,outData,outLen,sumE
missions,contains,outRow},
sumEmissionsArray=Array["",Length[rawEmissionsArray[[All]]]];
Do[
sumEmissionsArray[[i]]=SumEmissions[FormatRawEmissions[rawEmissionsArray[[i]]],gas],
{i,1,Length[rawEmissionsArray[[All]]],1}
];
outData={sumEmissionsArray[[1,1]]};
Do[
outLen=Length[outData[[All]]];
sumEmissions=sumEmissionsArray[[i]];
Do[
contains=False;
outRow=1;
While[outRow<=outLen&&!contains,
If[sumEmissions[[j,1]]==outData[[outRow,1]]&&sumEmissions[[j,2]]==outData[[outRow,2]],outData[[out
Row,3]]=outData[[outRow,3]]+sumEmissions[[j,3]];
contains=True];
outRow++];
If[!contains,AppendTo[outData, sumEmissions[[j]]]]
,{j,2,Length[sumEmissionsArray[[i,All]]],1}
];
,{i,1,Length[rawEmissionsArray[[All]]],1}
];
outData
];

(*GamsFormatter[number]: takes any number as an input and puts it in a format that can be read by
GAMS.*)

GamsFormatter[passNum_]:=Module[{meNum, numb, number,mantissa, formNum},

If[passNum<0,number=-1*passNum,number=passNum];
meNum= MantissaExponent[number];
```

```
numb=PaddedForm[meNum[[1]]*10,{14,13}];
mantissa = meNum[[2]]-1;

formNum=Which[number>=10^10,Row[{numb,"E+",mantissa}],10^10>number>=10,Row[{numb,"E+0",
mantissa}],10>number>=1,Row[{numb,"E+0",mantissa}],1>number>10^-10,Row[{numb,"E-
0",Abs[mantissa]}],10^-10>=number>0,Row[{numb,"E-",mantissa}],number==0,Row[{1.0,"E-",7}]];
If[passNum<0,formNum=-1*formNum];

formNum
];

(*## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ##

III. DEFINE REGIONAL MAC REGRESSION FUNCTIONS

Description: Defines the HIGH LEVEL functions used for calculating EPPA parameters
## ## ## ## ## ## ## ## # ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## #*)

Clear[EdMaxLogLog, EdMaxNormal, CalcEPPAParms, RegionalParms];

(*EdMaxLogLog[totalEmis,percentReduct,marginalCost]: Returns the initial price Po free variable for the
log linear form of the abatement supply function. Po is chosen to maximize the correlation coeffecient
of the log linear regression on the GAINS abatement data.*)

EdMaxLogLog[totalEmis_,percentReduct_,marginalCost_]:=Module[{lowerBound,upperBound,price,r2Ar
ray,bins,maxBin},

(*CorRegLogLog[totalE,percentR,marginalC,Po]: function within EdMaxLogLog that returns the
correlation  coeffecient of the log-linear regression*)

CorRegLogLog[totalE_,percentR_,marginalC_,Po_]:=Module[{xyPairs,logX,logY,logYfit,fit,a,b},
logX=Log[(1-percentR)*totalE];
logY:=Log[marginalC-Po];
xyPairs=Pair[logX,logY];
fit=Fit[xyPairs,{1,x},x];
a=fit/.x->0;
b=(fit/.x->1)-a;
logYfit=Table[fit,{x,logX}];
Correlation[logY,logYfit]
];

(*Algorithm to determine optimal value of Po.*)

lowerBound=0;
upperBound=Min[marginalCost];
While[upperBound-lowerBound>precision,
r2Array=Array[{},12];
```

```
bins=Table[lowerBound+(upperBound-lowerBound)/numBins*x,{x,0,numBins}];
maxBin=1;
Do[
r2Array[[i]]=CorRegLogLog[totalEmis,percentReduct,marginalCost,bins[[i]]];
If[i>1&&r2Array[[i]]>r2Array[[maxBin]],maxBin=i]
,{i,1,numBins,1}
];
price=bins[[maxBin]];
If[maxBin>1,lowerBound=bins[[maxBin-1]]];
If[maxBin<numBins,upperBound=bins[[maxBin+1]]];
];
price
];

(*EdMaxNormal[totalEmis,percentReduct,marginalCost]: Returns the initial price Po free variable for the
actual form of the abatement supply function. Po is chosen to maximize the correlation coeffecient
of the actual regression on the GAINS abatement data.*)
EdMaxNormal[totalEmis_,percentReduct_,marginalCost_]:=Module[{lowerBound,upperBound,price,r2A
rray,bins,maxBin},
CorRegNormal[totalE_,percentR_,marginalC_,Po_]:=Module[{xyPairs,logX,logY,yFit,fit,a,b},
logX=Log[(1-percentR)*totalE];
logY=Log[marginalC-Po];
xyPairs=Pair[logX,logY];
fit=Fit[xyPairs,{1,x},x];
a=fit/.x->0;
b=(fit/.x->1)-a;
yFit=Table[Po+Exp[a]*((1-x)*totalE)^b,{x,percentR}];
Correlation[yFit,marginalC]
];
(*Algorithm to determine optimal value of Po.*)
lowerBound=0;
upperBound=Min[marginalCost];
While[upperBound-lowerBound>precision,
r2Array=Array[{},12];
bins=Table[lowerBound+(upperBound-lowerBound)/numBins*x,{x,0,numBins}];
maxBin=1;
Do[
r2Array[[i]]=CorRegNormal[totalEmis,percentReduct,marginalCost,bins[[i]]];
If[i>1&&r2Array[[i]]>r2Array[[maxBin]],maxBin=i]
,{i,1,numBins,1}
];
price=bins[[maxBin]];
If[maxBin>1,lowerBound=bins[[maxBin-1]]];
If[maxBin<numBins,upperBound=bins[[maxBin+1]]];
];
price
];
```

```
(*CalcEPPAParms[aggCostData,emissionsData,policyCostData,region]: Calculates all abatement cost parameters for EPPA and returns them as well as the regression parameters for each sector/fuel pair in the specified region.*)

CalcEPPAParms[aggCostData_,emissionsData_,policyCostData_,region_]:=
Module[{outData,percentReduct,marginalCost,sumPolicyCost,totalEmissions,sumEmissions,abatePol,log
XlogYPairs,logXlogYoPairs,xyPairs,logX,logY,logYo,P,Po,fit,fito,a,ao,b,bo,r2Fit,r2oFit,r2Func,r2oFunc,vSha
re,sigma, sigmao,distParam,technologies},
outData={{"Sector","Fuel","Total Pollution (Tg)","Initial Emissions (Tg)","Initial Abatement (Tg)","Policy
Cost","Initial Price (2004 USD)/kg","Value Share of Emissions", "Price Elasticity of Demand", "Initial
Elasticity of Substitution", "alpha","beta", "Free Variable (Po)", "Correlation (r^2)"}};
Do[
percentReduct={};
marginalCost={};
sumPolicyCost=0;
totalEmissions = emissionsData[[i,3]];
sumEmissions=0;
vShare=0;
technologies ={};

(*Sums up all emissions from sources within each region, sector, and fuel type.*)

Do[
If[emissionsData[[i,1]]==aggCostData[[j,1]]&&emissionsData[[i,2]]==aggCostData[[j,2]],
sumEmissions=aggCostData[[j,5]]+sumEmissions;
AppendTo[percentReduct,sumEmissions/totalEmissions];
AppendTo[marginalCost,aggCostData[[j,4]]];
AppendTo[technologies,aggCostData[[j,3]]];
];
,{j,2,Length[aggCostData[[All]]],1}
];

(*Calculates total policy cost within each region, sector, and fuel type.*)

Do[
If[emissionsData[[i,1]]==policyCostData[[j,1]]&&emissionsData[[i,2]]==policyCostData[[j,2]],
sumPolicyCost=policyCostData[[j,4]]+sumPolicyCost;
];
,{j,2,Length[policyCostData[[All]]],1}
];

If[Length[percentReduct]>=1&&Max[percentReduct]<1,
If[Length[percentReduct]> 1,
If[StandardDeviation[marginalCost]<10^-9,
percentReduct={Max[percentReduct]};
marginalCost = {Max[marginalCost]};
```

```
];
];

If[Length[percentReduct]<= 2,
PrependTo[percentReduct,0];
AppendTo[percentReduct,Max[percentReduct]+(1-Max[percentReduct])*0.05];
PrependTo[marginalCost,Min[marginalCost]*0.8];
AppendTo[marginalCost,Max[marginalCost]*1.1];
];

P=EdMaxLogLog[totalEmissions,percentReduct,marginalCost];
logX=Log[(1-percentReduct)*totalEmissions];
logY:=Log[marginalCost-P];
logXlogYPairs=Pair[logX,logY];
fit=Fit[logXlogYPairs,{1,x},x];
a=fit/.x->0;
b=(fit/.x->1)-a;
r2Fit=Correlation[logY,Table[fit,{x,logX}]];
If[Length[r2Fit[[All]]]>1,r2Fit=1];
r2Func=Correlation[marginalCost,Table[P+Exp[a]*((1-x)*totalEmissions)^b,{x,percentReduct}]];
If[Length[r2Func[[All]]]>1,r2Func=1];

Po=EdMaxNormal[totalEmissions, percentReduct,marginalCost];
logYo:=Log[marginalCost-Po];
logXlogYoPairs=Pair[logX,logYo];
fito=Fit[logXlogYoPairs,{1,x},x];
ao=fito/.x->0;
bo=(fito/.x->1)-ao;
r2oFit=Correlation[logYo,Table[fito,{x,logX}]];
If[Length[r2oFit[[All]]]>1,r2oFit=1];
r2oFunc=Correlation[marginalCost,Table[Po+Exp[ao]*((1-x)*totalEmissions)^bo,{x,percentReduct}]];
If[Length[r2oFunc[[All]]]>1,r2oFunc=1];

vShare=((Po+Exp[ao]*(totalEmissions)^bo)*sumEmissions*1000000)/(sumPolicyCost+(Po+Exp[ao]*(total
Emissions)^bo)*sumEmissions*1000000);
If[vShare>=nonZeroValueShare,
If[emissionsData[[i,2]]=="PROCESS",sigma=-(1/b),sigma=-(1/b)/(1-nonZeroValueShare)];
If[emissionsData[[i,2]]=="PROCESS",sigmao=-(1/bo),sigmao=-(1/bo)/(1-nonZeroValueShare)];
abatePol=emissionsData[[i,3]]*(1/nonZeroValueShare-1)/1000;,
If[emissionsData[[i,2]]=="PROCESS",sigma=-(1/b),sigma=-(1/b)/(1-vShare)];
If[emissionsData[[i,2]]=="PROCESS",sigmao=-(1/bo),sigmao=-(1/bo)/(1-vShare)];
abatePol=emissionsData[[i,3]]*(1/vShare-1)/1000
];

xyPairs=Pair[percentReduct*totalEmissions,marginalCost];

If[printResults,
```

```
(*Print header with plot information.*)

Print["____________________________________________________________________________________"];
Print["-Po Chosen to Maximize Log-Linear Abatement Supply Function (Blue Plot)"];
Print["Region: ",region," Sector: ",emissionsData[[i,1]]," Fuel: ",emissionsData[[i,2]]," a: ",a," b: ",b," P: ",P+Exp[a]*(totalEmissions)^b," r2fit: ",r2Fit," r2Func: ",r2Func];
Print["Policy Cost: ",sumPolicyCost," Po: ",P+Exp[a]*(totalEmissions)^b," SumEmissions: ",sumEmissions*1000000," \[Theta]: ",
((Po+Exp[ao]*(totalEmissions)^bo)*sumEmissions*1000000)/(sumPolicyCost+(Po+Exp[ao]*(totalEmissions)^bo)*sumEmissions*1000000)," \[Epsilon]d: ",1/b," \[Sigma]: ",sigma];
Print["-Po Chosen to Maximize Normal Abatement Supply Function (Green Plot)"];
Print["Region: ",region," Sector: ",emissionsData[[i,1]]," Fuel: ",emissionsData[[i,2]]," ao: ",ao," bo: ",bo," Po:",Po+Exp[ao]*(totalEmissions)^bo," r2ofit: ",r2oFit," r2oFunc: ",r2oFunc];
Print["Policy Cost: ",sumPolicyCost," Po: ",Po+Exp[ao]*(totalEmissions)^bo," SumEmissions: ",sumEmissions*1000000," \[Theta]: ",
((Po+Exp[ao]*(totalEmissions)^bo)*sumEmissions*1000000)/(sumPolicyCost+(Po+Exp[ao]*(totalEmissions)^bo)*sumEmissions*1000000)," \[Epsilon]d: ",1/bo," \[Sigma]: ", sigmao];
Print[Show[ListPlot[xyPairs,PlotStyle->Red,PlotRange->{{0,totalEmissions},{0,1.5*Max[xyPairs[[All,2]]]}}],Plot[(P+Exp[a]*(totalEmissions-x)^(b)),{x,0,totalEmissions},PlotStyle->Blue,PlotRange->{{0,totalEmissions},{0,1.5*Max[xyPairs[[All,2]]]}},AxesLabel->{"Tg Removed","Price (2004 USD)/(kg)"}],Plot[(Po+Exp[ao]*(totalEmissions-x)^(bo)),{x,0,totalEmissions},PlotStyle->Green,PlotRange->{{0,totalEmissions},{0,1.5*Max[xyPairs[[All,2]]]}}],AxesLabel->{"Tg Removed","Price (2004 USD)/kg"}]
];
];

AppendTo[outData,{emissionsData[[i,1]],emissionsData[[i,2]],emissionsData[[i,3]]/1000+abatePol,emissionsData[[i,3]]/1000,abatePol,sumPolicyCost,(Po+Exp[ao]*(totalEmissions)^bo),vShare,1/bo,sigmao,ao,bo,Po,r2oFunc}];
];
,{i,2,Length[emissionsData[[All]]],1}];
outData
]

(*RegionalParms[region,subRegions,gas]: Calculates all regional parameters by reading in GAINS data files, mapping it to EPPA regions, and sectors, and then calling CalcEPPAParms to calculate the parameters.*)

RegionalParms[region_,subRegions_,gas_]:=Module[{rawCost,rawEmissions,rawPolicyCost,formCost,formEmissions,formPolicyCost,ed},

rawCost=Array["",Length[subRegions]];
rawEmissions=Array["",Length[subRegions]];
rawPolicyCost=Array["",Length[subRegions]];
```

```
Do[rawCost[[i]]=Import[gainsSourceDataDir<>macDataDir<>gas<>"_C_"<>subRegions[[i]]<>".txt","CSV",
CharacterEncoding->"Unicode"],{i,Length[subRegions]}];
Do[rawEmissions[[i]]=Import[gainsSourceDataDir<>macDataDir<>gas<>"_E_"<>subRegions[[i]]<>".txt","
CSV",CharacterEncoding->"Unicode"],{i,Length[subRegions]}];
Do[rawPolicyCost[[i]]=Import[gainsSourceDataDir<>macDataDir<>gas<>"_P_"<>subRegions[[i]]<>".txt","
CSV",CharacterEncoding->"Unicode"],{i,Length[subRegions]}];

formCost=AggregateRawCost[rawCost,gas];
formEmissions=AggregateRawEmissions[rawEmissions,gas];
formPolicyCost=AggregateRawPolicyCost[rawPolicyCost];

ed=CalcEPPAParms[formCost,formEmissions,formPolicyCost,region]
];


(*## ## ##  ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ##

                    Calculations

Descriptions: With functions and global parameters defined in Sections I, II, and III, this section
calls those functions to calculate EPPA abatement parameters and then exports them to the EPPA
data folder specified by 'eppaDestinationDir'.
#### ## ### ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ## ##*)

Clear[elasParms,abatePol,emisPol,abatePrice,macParms,formElasParms,formAbatePol, formEmisPol];

elasParms = {};
abatePol= {};
emisPol = {};
abatePrice = {};
macParms =  Array["",{Length[gases[[All]]],Length[eppaRegions[[All]]]}];

Do[
Do[

(*Calculate GAINS marginal abatement cost curves and other EPPA parameters.*)

Print["********************************************************************************"];
Print["EPPA Regional Parameters for: ",eppaRegions[[r]]," ",gases[[g]]];
Print["********************************************************************************"];
macParms[[g,r]]=RegionalParms[eppaRegions[[r]],gainsRegions[[r]],gases[[g]]];

(*Format the data GAMS.*)

Do[

formElasParms=GamsFormatter[macParms[[g,r,s,9]]];
```

```
AppendTo[elasParms,gases[[g]]<>"."<>eppaRegions[[r]]<>"."<>macParms[[g,r,s,1]]<>"."<>macParms[[g,
r,s,2]]<>"  "<>ToString[formElasParms]<>"\r"];

formAbatePol = GamsFormatter[macParms[[g,r,s,5]]];
AppendTo[abatePol,gases[[g]]<>"."<>eppaRegions[[r]]<>"."<>macParms[[g,r,s,1]]<>"."<>macParms[[g,r,
s,2]]<>"  "<>ToString[formAbatePol]<>"\r"];

formEmisPol = GamsFormatter[macParms[[g,r,s,4]]];
AppendTo[emisPol,gases[[g]]<>"."<>eppaRegions[[r]]<>"."<>macParms[[g,r,s,1]]<>"."<>macParms[[g,r,s,
2]]<>"  "<>ToString[formEmisPol]<>"\r"];

formAbatePrice = GamsFormatter[macParms[[g,r,s,7]]];
AppendTo[abatePrice,gases[[g]]<>"."<>eppaRegions[[r]]<>"."<>macParms[[g,r,s,1]]<>"."<>macParms[[g,
r,s,2]]<>"  "<>ToString[formAbatePrice]<>"\r"];

,{s,2,Length[macParms[[g,r,All]]]}];
,{r,1,Length[gainsRegions[[All]]]}];

(*Export results of the parameter calculatiosn to an excel sheet for easier review.*)

Export[gainsResultsDir<>gases[[g]]<>" Parameters.xls", {"ANZ"->macParms[[g,1]],"ASI"-
>macParms[[g,2]],"CAN"->macParms[[g,3]],"CHN"->macParms[[g,4]],"EUR"->macParms[[g,5]],"IND"-
>macParms[[g,6]],"JPN"->macParms[[g,7]],"REA"->macParms[[g,8]],"ROE"->macParms[[g,9]],"RUS"-
>macParms[[g,10]],"USA"->macParms[[g,11]]},"XLS"];
,{g,1,Length[gases[[All]]]}];

(*Flatten parameter data into 1D array so it can be sent to a .dat file type.*)

elasParms = Flatten[Join[{"parameter gainsElas /"}, elasParms, {"/;"}]];
Print[elasParms];
abatePol= Flatten[Join[{"parameter gainsAbate /"}, abatePol, {"/;"}]];
Print[abatePol];
emisPol= Flatten[Join[{"parameter gainsEmis /"}, emisPol, {"/;"}]];
Print[emisPol];
abatePrice = Flatten[Join[{"parameter gainsAbatePrice /"}, abatePrice, {"/;"}]];
Print[abatePrice];

(*Export the EPPA parameters to the EPPA data directory.*)

Export[eppaDestinationDir <>"gains_elas.dat", elasParms,"CSV"];
Export[eppaDestinationDir <>"gains_abatePol.dat", abatePol,"CSV"];
Export[eppaDestinationDir <>"gains_emisPol.dat", emisPol,"CSV"];
Export[eppaDestinationDir <>"gains_priceEmis.dat", abatePrice,"CSV"];

Print["**************************************************************************"];
Print["EPPA Parameter Calculations Complete"];
Print["**************************************************************************"];
```