Hybrid Simulation Modeling to Estimate U.S. Energy Elasticities

by

Adam C. Baylin-Stern

B.A. & Sc. (Economics and Cell/Molecular Biology), McGill University, 2008

THESIS SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF
MASTER OF RESOURCE MANAGEMENT

Project No. 535

in the
School of Resource and Environmental Management
Faculty of Environment

SIMON FRASER UNIVERSITY

Summer 2012

Approval

Name: **Adam C. Baylin-Stern**

Degree: **Master of Resource Management**

Project No.: **535**

Title of Thesis: ***Hybrid Simulation Modeling to Estimate U.S. Energy Elasticities***

Examining Committee:

Chair: Jacob Fox
Master of Resource Management candidate

Mark Jaccard
Senior Supervisor
Professor, School of Resource and Environmental Management, Simon Fraser University

Jotham Peters
Supervisor
Adjunct Professor, School of Resource and Environmental Management, Simon Fraser University; Senior Managing Partner at Navius Research Inc.

Date Defended/Approved: May 18, 2012

Abstract

This paper demonstrates how an U.S. application of CIMS, a technologically explicit and behaviourally realistic energy-economy simulation model which includes macro-economic feedbacks, can be used to derive estimates of elasticity of substitution (ESUB) and autonomous energy efficiency index (AEEI) parameters.

The ability of economies to reduce greenhouse gas emissions depends on the potential for households and industry to decrease overall energy usage, and move from higher to lower emissions fuels. Energy economists commonly refer to ESUB estimates to understand the degree of responsiveness of various sectors of an economy, and use estimates to inform computable general equilibrium models used to study climate policies.

Using CIMS, I have generated a set of future, ‘pseudo-data’ based on a series of simulations in which I vary energy and capital input prices over a wide range. I then used this data set to estimate the parameters for transcendental logarithmic production functions using regression techniques. From the production function parameter estimates, I calculated an array of elasticity of substitution values between input pairs.

Additionally, this paper demonstrates how CIMS can be used to calculate price-independent changes in energy-efficiency in the form of the AEEI, by comparing energy consumption between technologically frozen and ‘business as usual’ simulations.

The paper concludes with some ideas for model and methodological improvement, and how these might figure into future work in the estimation of ESUBs from CIMS.

Keywords: Elasticity of substitution; hybrid energy-economy model; translog; autonomous energy efficiency index; rebound effect; fuel switching.

Acknowledgements

Thanks to everyone who helped with this project:

I would like to thank my senior supervisor, Mark Jaccard for his unwavering support and faith in me. He has shown me tremendous respect, encouraging me to think differently, and serving as an excellent supervisor throughout the past few years.

Thank you to my supervisor Jotham Peters for his continued advice, research support, and extensive hockey banter (go Habs). As well, I am very grateful to Chris Bataille and Nic Rivers for their critical guidance pertaining to my research.

I thank the Energy and Materials Research Group, the Canadian Energy End-use Data and Analysis Centre, Simon Fraser University, the Canadian District Energy Association, and Sustainable Prosperity for financial assistance and research funding.

I thank the EMRG family that I have come to know and love for their camaraderie and assistance –John Nyboer, Noory Meghji, Caroline Lee, Kristin Lutes, Sally Rudd, Jacob Fox, Anusha Baji, Stephen Healey, Michael Wolinetz, Michelle Bennett, Katya Petropavlova and Karen Mascarenhas. I thank Suzanne Goldberg, Steven Groves, Rose Murphy and Jodie Capling in particular for assistance relating to my research along the way.

As well, I would like to thank the many friends, teachers, administrators and colleagues within the REM program. I value this group of people enormously, and feel lucky to be in such good company.

Finally, I would like to thank my family for their love, support and encouragement – they are my role models– my brother Sach Baylin-Stern for being a source of inspiration to me and lending an ear whenever I ask; my father Ron Stern for simplifying what appears complex, and then making it funny (and giving me an appreciation of all things feline); and my mother Judy Baylin-Stern, for encouraging me to follow my desires and filling me with strength and kindness. Thank you.

Table of Contents

List of Tables

List of Figures

List of Acronyms

AEEI	Autonomous energy efficiency index
AES	Allen elasticity of substitution
BAU	Business as usual
BEA	U.S. Bureau of Economic Analysis
CES	Constant elasticity of substitution
CGE	Computable general equilibrium
CO_2	Carbon dioxide
CO_2e	Carbon dioxide equivalent
DCC	Declining capital cost
DIC	Declining intangible cost
E	Energy or Electricity depending on context
ELEC	Electricity
ESUB	Elasticity of substitution
GHG	Greenhouse gas
K	Capital
MES	Morishima elasticity of substitution
NG	Natural gas
O	Refined petroleum products
PED	Price elasticity of demand
RPP	Refined petroleum products
SUR	Seemingly unrelated regression
TRANSLOG	Transcendental Logarithmic
VA	Value added

1. Introduction, Research Objectives and Literature Review

1.1. Challenges to Energy-Economy Modeling: The Importance of Substitution

> "The key to analyzing the economic impacts of energy and environmental policy is the substitutability among productive inputs, especially energy inputs, in response to price changes induced by policy." (Goettle, et al. 2011)

The responsiveness of the economy to changes in energy prices is a key concern of policy makers for assessing the ability of price-related policies to reduce greenhouse gas emissions or reduce reliability on certain forms of energy. For many decades, economists using aggregate energy-economy models have estimated price elasticities using aggregate time series and cross-section data. However, the general approach has been subject to certain criticisms and concerns. These include issues relating to the sources of historical data, the functional forms assumed, the specification of the elasticity measures, and the ability of historical data to sufficiently capture future technological advances.

In this project, I have used an alternative approach to estimate long-run U.S. price elasticities based on a set of simulated 'pseudo-data' generated using a technologically explicit, behaviourally realistic energy-economy simulation model which includes realistic macro-economic feedbacks – CIMS (Jaccard, Nyboer, et al. 2003, Rivers and Jaccard 2005).

Energy-economy models are useful tools for analyzing and designing energy and climate policy. At a time when the threats of climate change are clear, and the need to act is increasingly recognized as vital to human welfare, the importance of better understanding, and better forecasting the likely economic effects of climate policies is elevated.

Supplying the amount of greenhouse gas (GHG) emissions-free energy necessary to stabilize atmospheric greenhouse gas concentrations at ambitious and commonly agreed upon targets will be a challenging task. Assuming realistic improvements in energy efficiency, we will require an enormous amount of carbon-free energy in the near future (Hoffert, et al. 1998). Scalable methods to meet this need are not yet adequately available. The world is facing the enormous challenge of supplying this energy while avoiding environmental damage. As we move-forward, energy systems must evolve to avoid the dangers of climate change. Energy-economy modeling can help decision making as governments and citizens contribute to changing energy systems around the world.

In this study, I focus on energy elasticity of substitution values – measures that indicate how substitution between energy types, and away from energy might contribute to the evolution of our energy system. This paper contributes to the existing elasticity of substitution body of research by advancing the unique approach of using simulated pseudo-data (as opposed to historical data) to derive price elasticity estimates. While my focus is on methodological details, the elasticity measures that I derive have widespread implications over how our energy system might evolve, and how it might respond to alternate future policy scenarios.

1.2. Outline of the Report

I have chosen to include the literature review elements of my project in Chapter 2, “Background”. Chapter 3, “Methods and Data”, includes the details of my methodology for price-shocking CIMS in order to generate a set of ‘pseudo-data’, descriptions of how I specify the capital-energy and inter-fuel translog production models that I use for parameter estimation, and a description of how I calculate elasticities from estimated translog cost function parameters. Chapter 3 also includes a description of my technique for calculating AEEI parameters from CIMS outputs, and describes some of the challenges with the methodology. In Chapter 4, I present my ESUB and AEEI results, with parameter estimates for energy-capital and inter-fuel ESUBs and AEEI values presented at national and sectoral levels of aggregation. Chapter 5 provides interpretation of the ESUB and AEEI estimates, as well as discussion about how my values compare to some external values. In Chapter 6 ("Conclusions and Future Research"), I review some of the key conclusions from the research, discuss remaining issues, and explore ideas for methodological and modeling improvements in future research. There are several appendices that follow, which include an overview of the key CIMS algorithm, a single-table overview of the ESUB results, data on input cost shares, and a presentation of my elasticity results in the form of price elasticities of demand.

The next chapter provides an overview of common frameworks for energy and climate policy analysis. I will describe opposing "top-down" and "bottom-up" approaches, and then show how the CIMS model reconciles advantages and drawbacks from those opposing frameworks.

2. Background

2.1. Top-down versus Bottom-up Modeling

An energy-economy model refers to any conceptual depiction of a regional or global economy, with a focus on its energy system. More generally, a scientific model is a “numerical simulation of a highly parameterized complex system” (Oreskes 2003, 14). In other words, a model is an abstraction of reality that provides a useful framework for people to better understand different aspects of the true situation. Energy-economy modeling in particular employs a mathematical abstraction of a regional economy that is useful to test the effects of policies which effect energy use, to assess the various trade-offs that exist among policy options, and to rank alternative actions. Modellers are attempting to predict, using the best available information, how the future will unfold. Predictions can never be perfect, but hopefully they can be sufficiently realistic to offer a meaningful evaluation, and help in the design of policy.

Energy-economy modeling is one of the most important techniques for understanding how best to move forward towards a sustainable energy system. This is because the modeling results are often what policymakers rely upon for evaluating the economic and social implications of plans designed to prevent climate change impacts, to assess mitigation and adaptation options, and hopefully to inform the development of alternative region-specific climate and energy management. Sound energy-economy models are essential for researchers to effectively communicate climate change issues and solutions to the government, industry, and the general public.

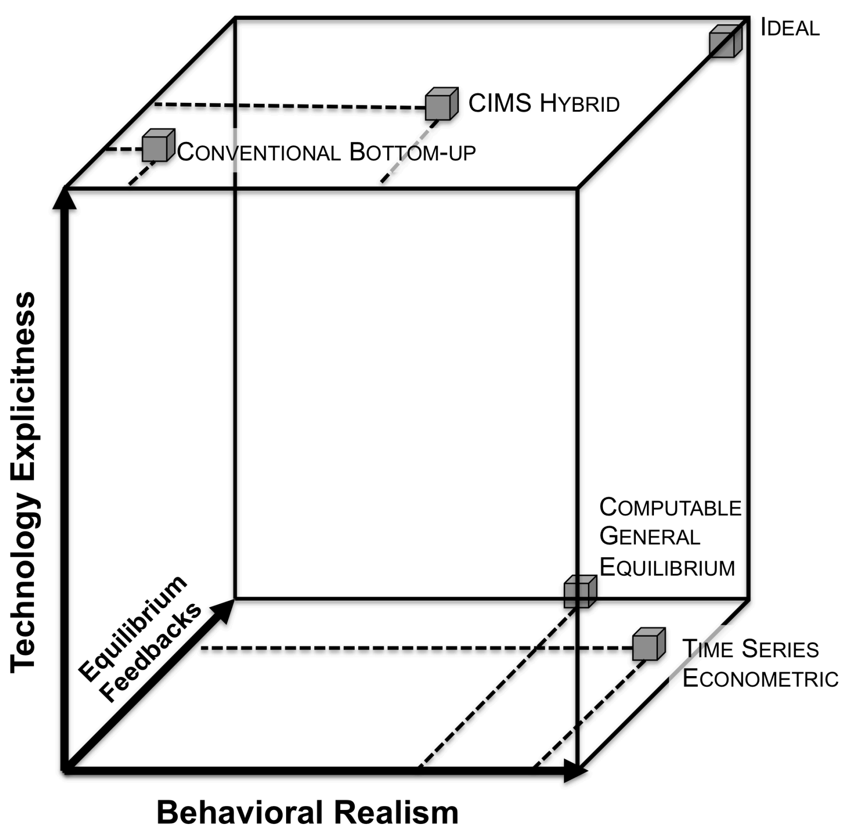
Three of the most important and desirable characteristics of energy-economy models which are used to analyze energy and climate policies – and which often help to distinguish different classes of models – are:

1. **Technological explicitness** – The level of detail in which a model represents energy usage and production technologies. For example, a

model can represent technology very abstractly, or with a high level of engineering detail (i.e. fuel consumption attributes, ratios, lifespan, cost information, etc.) for a given technology.

2. **Behavioural realism** – The extent to which the simulated development of production and consumption mimics decision-making in the real world. This characteristic refers to the fact that humans do not always make optimal/rational decisions.
3. **Macroeconomic feedbacks** – The attribute of a model which accounts for transactions in all key markets, and the interactions between them. In the case of an energy-economy model, this refers to the incorporation of realistic aggregate financial flows in response to stimuli.

Figure 1 Characteristics for Comparing Energy-economy Models (Source: Jaccard, Nyboer et al. (2003), adapted with permission)



The ideal model would incorporate all three of the attributes listed above (in Figure 1, it would be located in the top right corner). However in practice, a trade-off exists between models which are technologically explicit and those that fully adhere to economic theory. Models that have a reasonably detailed treatment of technology tend to not (fully) incorporate general equilibrium responses, and their portrayal of firm and consumer behaviour tends to be derived from aggregated historical data that may not be sufficiently realistic (Rivers and Sawyer 2008). In the context of modeling the impacts of environmental policy such as carbon pricing, researchers commonly employ two opposing modeling frameworks. These opposing frameworks allude to one of the most common distinctions amongst energy-economy models - the distinction between 'top-down' and 'bottom-up' models.

Top-down models – benefits and drawbacks

Top-down modeling involves estimating energy use, fuel switching, and emissions abatement potential from historical time series data (Loschel 2002, Jaccard 2009). Parameters that indicate responsiveness to changes in energy prices, as well as the rate at which energy efficiency improves independent of energy cost, are normally estimated based on historical market data. Computable General Equilibrium (CGE) models are a common variety of top-down models, and often used in the analysis of climate and energy policy.

Employed mainly by economists, top-down models tend to be highly aggregated as compared to other economic models, and as such they tend to exhibit low technology detail. These models are based upon descriptions of the economy consistent with economic theory (Loschel 2002). Due to all of the general equilibrium interactions that exist in an economy, increasing the complexity of a model by adding a high number of sectors, or by using many households, often results in the model being impossible or impractical to solve.

A common criticism of top-down models is that they are most often based on historical time-series data – many would argue that parameterizing and calibrating a model to historical data prevents it from capturing the advances in technology that may occur in the future. Moreover, given that the models depend so heavily on these estimated parameters, any misspecification of model parameters can impact results. Model parameters are often 'guesstimated', and thus highly open to alternative subjective views.

Given limited technological detail, top-down models often miss important dynamics associated with capital stock turnover (capital vintaging) and technology development. They often fail to account for the effects of cumulative production and market penetration on both the tangible (financial) and (perceived) cost of a given technology (Loschel 2002).

Bottom-up models – benefits and drawbacks

Bottom-up modeling involves the estimation of energy usage, fuel switching, and emissions abatement potential from technologically explicit analysis (Loschel 2002, Jaccard 2009). Bottom-up models explicitly account for technologies and engineering processes, which compete with each other on the basis of financial cost and performance attributes. This is the approach commonly undertaken by engineers, and sometimes favoured by environmental advocates since bottom-up models tend to show a lower social cost from the reduction of GHG emissions. Bottom-up energy-economy models are normally partial models of the energy sector which do not include interactions with the rest of the economy (Loschel 2002). Technologically explicit models are useful for computing the least-cost cost approach (from a limited financial cost perspective) for meeting a particular final energy demand or emissions target. However, this approach is poorly suited to studying phenomena that are likely to have economy-wide effects.

Drawbacks of the bottom-up approach include a lack of behavioural and macroeconomic realism. Perceptions of producers and consumers are difficult to estimate due to a lack of adequate market behaviour data at the technology level (Jaccard, Nyboer, et al. 2003). Moreover, these models are not behaviourally realistic, in part because they are not based on market-generated data. As a result, this class of models tend to lack micro-economic realism – they tend to not realistically portray the ways in which consumers and producers behave when faced with decisions related to energy use. The bottom-up modeling approach fails to account for risks and for the quality of energy technology services in modeling simulations.

To highlight the failure of bottom-up modeling techniques in capturing the bounded rationality that consumers and producers exhibit, two recent, highly influential reports by the management consulting firm McKinsey (McKinsey&Company 2007, McKinsey&Company 2009) made use of least-cost energy-efficiency curves and bottom-up modeling methodology. Their results indicate that the U.S. can make significant reductions at far lower costs than much of the research on the subject over the past 20 years, but the validity of these estimates has been challenged by those who note the shortcomings of the pure bottom-up approach (Murphy and Jaccard 2011).

Substitution in energy-economy models, and the contrasting role of substitution in bottom-up vs. top-down models

Substitution among productive inputs plays an important role in understanding the costs of climate change policy, since substitution possibilities underlie resilience and adaptability in an economy (Jorgenson, et al. 2000). Assumptions about substitution between forms of energy and other inputs have a large influence on the results of economic models used to study costs. Rigidity in a model tends to magnify economic costs, whereas flexibility tends to reduce them. There are exceptions, however. For example, substitution rigidity would obscure the increasing energy demands with the depletion of more readily accessible forms of a resource. Jorgenson et al. (2000) outline ways in which producers can substitute among the inputs to production (though they note that similar opportunities exist for consumers):

• less carbon-intensive fuels for more carbon-intensive fuels (for example, gas for coal);

• non-fossil energy sources for fossil fuels (nuclear, hydropower, geothermal, solar, and wind for coal, oil, and gas);

• non-energy inputs (materials, labor, and capital) for energy inputs (installing automation and process control equipment);

• energy conserving inputs for highly energy-using inputs (more energy-efficient vehicles, lighting, cooling, heating, production and computing equipment);

• less energy-intensive goods for more energy-intensive goods (greater use of high strength plastics and products made from recycled aluminum and steel);

• more competitive imported goods and services for the now more expensive domestic ones. (Jorgenson, et al. 2000).

Given the pervasiveness and importance of substitution in energy-economic models, it is helpful to note that within top-down and bottom-up models, substitution plays a contrasting role.

While substitution between different forms of energy, and non-energy inputs occurs in both top-down and bottom-up models, it occurs differently in each. In top-down models, substitution is guided by exogenously set model parameters (namely, elasticities of substitution – the focus of this study - which will be introduced later in this chapter). On the other hand, in bottom-up models, substitution most often is the by-product of technology evolution.

An alternative hybrid approach – description of the CIMS energy-economy model

As described above, while both bottom-up and top-down modeling approaches have strengths and appropriate uses, the drawbacks from each make them problematic for a broad analysis of environmental policy. "Hybrid" models attempt to incorporate attributes of both bottom-up and top-down methodologies. Ideally, a hybrid model incorporates all three model characteristics described above – it is technologically explicit, behaviourally realistic, and includes macroeconomic feedback effects (Hourcade, et al. 2006).

CIMS (Jaccard, Nyboer, et al. 2003, Rivers and Jaccard 2005, Jaccard 2009) is an integrated energy-economy simulation model and policy analysis tool developed by the Energy and Materials Research Group at Simon Fraser University, which is technologically explicit and behaviourally realistic. The model's primary use is to evaluate energy and climate policies and to determine the cost of reducing GHG emissions. CIMS has a detailed representation of technologies that produce goods and services throughout the economy and attempts to simulate capital stock turnover and choice between these technologies in a realistic way. This is accomplished by incorporating stated preferences (via discrete choice surveying techniques) as well as revealed preferences (via analysis of historical market data). It also includes a representation of equilibrium feedbacks, such that supply and demand for energy intensive goods and services adjust to reflect policy. This reflects the importance of considering how the macroeconomic evolution of the economy proceeds in terms of structural composition and total output. Also, it is an example of a hybrid model, as it incorporates macroeconomic feedback effects and detailed estimation of behavioural parameters within a technologically explicit model. See Appendix A for a description of the market share algorithm that is central to this model (along with the two algorithms for simulating endogenous technical change).

Behavioural parameters in CIMS, such as those representing market heterogeneity, intangible costs that consumers associate with certain technologies, and changes in consumer perceptions of technologies, are estimated from a combination of past technology choices (revealed preferences) and likely future technology choices (stated preferences). Stated preference research involves surveying various segments of a market to gauge, for example, willingness to pay for a plug-in hybrid electric vehicle compared to conventional vehicle options (Axsen, Mountain and Jaccard 2009). Researchers employ discrete choice models to provide an empirical basis for behavioural parameters in CIMS (Horne, Jaccard and Tiedemann 2005). Revealed preferences are incorporated in CIMS by studying existing market conditions and technology composition in a given market – thus using historical consumer and firm decisions about technology choices to inform the model.

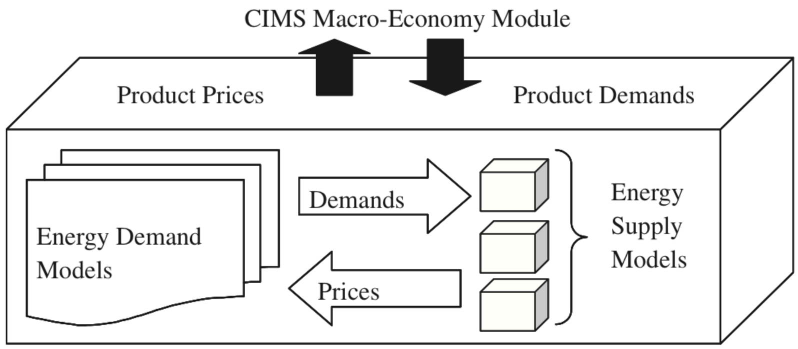
Though CIMS incorporates to a large extent the three model characteristics mentioned above, its representation of economic inputs and outputs is skewed toward energy supply and demand (Jaccard 2009). While this applies to technology attribute representation and representation of behaviourally realistic decision making by firms and consumers, the emphasis on energy is particularly notable in terms of CIMS' inclusion of macroeconomic feedback effects. CIMS includes detailed feedbacks between energy supply and demand among different sectors of the economy as well as trade effects, though unlike CGE models, it does not include equilibrium effects in terms of labour and investment markets.

CIMS functions by simulating the evolution of capital stocks over time via retiring, retrofitting, and purchasing of new technologies by consumers and firms in 5-year increments. CIMS calculates energy costs at every energy service demand node within each sector represented, and a model simulation iterates, using a convergence procedure, until differences fall below a specified threshold. The competition of available (represented) technologies at each service node is based upon life-cycle cost of competing technologies, which have embedded technology-specific controls (Jaccard 2009). Life-cycle costs are the basis for how the model determines the market share of competing technologies, and is influenced by consumer preferences, financial attributes, and technological attributes. Several behavioural parameters embedded in the technology competition algorithm enable the influence of aspects such as intangible (non-price) differences in technologies, time-preferences of consumers, and market heterogeneity.

There are two functions within CIMS for simulating endogenous change in the attributes of individual technologies in response to stimuli: the declining capital cost (DCC) and the declining intangible cost (DIC) functions. The DCC function allows for decreases in a technology's financial cost as an effect of cumulative production, which reflects economies-of-scale and learning effects. The DIC function allows for decreases in a technology's intangible cost (a portion of a technology's cost that represents risk and other intangible aspects that may decrease adoption) in a given period as a function of market share in the previous period, reflecting the decreases in perceived risk and greater awareness of a technology as it gains market share (the 'champion or neighbour effect').

CIMS is composed of sub-models that account for nearly all of the energy consumption and production in the economy (CIMS excludes energy consumption in construction, forestry and agriculture sectors unrelated to off-road transportation, and also excludes non-energy usage of fuels). Figure 2 gives a diagrammatic overview of the basic structure of CIMS.

Figure 2 ***Structure of the CIMS Model (Source: Murphy and Jaccard (2011), used with permission)***



The following table describes the goods and services represented within the sub-models that compose CIMS-U.S. Note that each sector includes space heating and cooling, pumping, compression, conveyance, hot water, steam, air displacement, and motor drive if applicable.

Table 1 Sector Sub-models in CIMS

CIMS Sector Model	Goods and Services Included
Residential	Cooking, refrigeration, hot water, plug-in electric load
Commercial/Institutional	Cooking, refrigeration, hot water, washers/dryers, plug-in electric load
Personal Transportation	Intercity and urban, split into single and high-occupancy vehicles, transit, walking, cycling, as well as off-road
Freight Transportation	Marine, air, road, and rail
Industry	
Chemical Products	Chlor-alkali, sodium chlorate, hydrogen peroxide, ammonia, methanol, and polymers
Industrial Minerals	Cement, lime, glass, and bricks
Iron and Steel	Slabs, blooms and billets
Non-Ferrous Metal Smelting	Lead, copper, nickel, titanium, magnesium, zinc and aluminum
Metals and Mineral Mining	Open-pit, underground, potash mining
Other Manufacturing	Food, tobacco, beverages, rubber, plastics, leather, textiles, clothing, wood products, furniture, printing, machinery, transportation equip., electrical and electronic equipment
Pulp and Paper	Pulp, newsprint, linerboard, uncoated/coated paper, and tissue
Energy Supply	
Coal Mining	Lignite, sub-bituminous, bituminous and anthracite coal
Electricity Generation	Electricity
Natural Gas Extraction	Natural gas and liquefied natural gas, transportation of product
Petroleum Crude Extraction	Light and heavy crude oil, synthetic crude oil
Petroleum Refining	Gasoline, diesel, kerosene, naphtha, aviation fuel, petroleum coke
Biofuels	Ethanol and biodiesel (represented as separate sub-models within CIMS, but combined within this study)
Agriculture	Soil practices, manure management, vehicles/tractors
Waste	Flaring or electricity generation from methane release

2.2. Elasticity of Substitution (ESUB) and Autonomous Energy Efficiency Index (AEEI) Values in Energy and Climate Policy Modeling

Definition of ESUB

Within economics, “elasticity” refers to how changes in one variable impact another. More specifically, elasticity refers to a measure of the relationship between price and demand for two variables (Ramskov and Munksgaard 2001). Thus, elasticities play a key role within production analysis and various economic models, since they determine the size and direction of demand adjustments that come about from price changes in a given market.

An elasticity of substitution (ESUB) in particular refers to the ratio of relative price changes to relative quantity changes for two inputs. Introduced by Hicks (1932), ESUBs have become fundamental, and highly debated economic parameters. They are useful in various capacities for production analysis, as inputs to economic models, as well as being informative stand-alone indicators of the relationships between pairs of economic inputs.

ESUBs indicate the responsiveness of a quantity to a change in price. “Own” price elasticities describe the responsiveness of a quantity of a variable to changes in its price. “Cross” price elasticities on the other hand describe the change in quantity of one variable as a result of changes to the price of another.

ESUBs can be short-run or long-run in nature. Short-run ESUBs indicate responsiveness to price changes over a time horizon that is in general less than a 5-year period. These changes include near-term adaptive responses such as turning off lights more frequently, and changing habits about driving (Wade 2003). On the other hand, long-run parameters involve changes in an economy or sector’s infrastructure in response to prices, which occur over time spans that allow for the turnover of capital stock, such as the replacement of used equipment and retrofits (Wade 2003). Lifespans of capital stocks can vary greatly – for example, in CIMS, they are on the order of 13 years for vehicles, and are over 50 years for very long-lived capital stock such as a hydroelectric dam. In the study at-hand, I use a 45-year simulation period in an attempt to look at long-term substitution responses. This period is sufficient to capture the majority of long-term response.

Allen-Uzawa elasticity of substitution

The Allen-Uzawa (or simply Allen) elasticity of substitution (AES, represented by σ) (Allen 1938, Uzawa 1962) is a partial elasticity of substitution, meaning that it does not factor in effects of any factors of production other than the 2 that any given AES is based on. The AES is the most common elasticity of substitution measure, and in the current paper, I focus on calculating AES values. Shown in an alternate form from Allen's initial 1938 definition, the Allen elasticity of substitution between two inputs Q_i and Q_j, with prices P_i and Q_j is described as:

$$\sigma_{ij} = \frac{\partial(Q_i/Q_j)}{\partial(P_j/P_i)} \times \frac{P_j/P_i}{Q_i/Q_j}$$

Interpreting AES values is fairly straightforward. AES values are symmetrical, applying in both directions; that is, the value of i for j substitution is equivalent to that of j for i. Negative values suggest that input pairs are compliments, while positive values suggest that pairs are substitutes. A value of 1 for a pair of inputs (or for an own-price elasticity), for example, indicates that a 1% rise in the relative price of one, will yield a 1% rise in the relative demand for the other – and vice versa. An own-price value of -1, means that a 1% rise in the own-price of an input will lead to a 1% decrease in consumption of that input. Values between 0 and 1, or between 0 and -1 indicate an inelastic relationship and values greater than 1 or less than -1 indicate an elastic relationship. Note that special cases are 0 (perfectly inelastic - a fixed proportion relationship), 1 or -1 (unit elastic), and positive or negative infinity (perfectly elastic – indicating perfect compliments/substitutes). As a guide to interpreting quantitative ESUB results qualitatively, the following list is useful:

• 0 to 0.3	or	0 to -0.3	Highly inelastic
• 0.3 to 0.6	or	-0.3 to -0.6	Fairly inelastic
• 0.6 to 0.9	or	-0.6 to -0.9	Slightly inelastic
• 0.9 to 1.1	or	-0.9 to -1.1	(Roughly) unit elastic
• 1.1 to 1.4	or	-1.1 to -1.4	Slightly elastic
• 1.4- to 2.0	or	-1.4 to -2.0	Fairly elastic
• 2.0 and above	or	-2.0 and below	Highly elastic

There are a number of alternate specifications that have different uses, which some argue can be superior to the AES.

Alternate specifications of ESUB values

Though ESUBs in the form of the AES are fairly standard in the literature (and are focused upon in this report) there are a number of alternate elasticity of substitution specifications that have unique definitions, interpretations, and usages. There is extensive debate about the appropriateness of the various alternate elasticity metrics in different contexts (Blackorby and Russel 1989, Frondel 2011). Commonly employed alternate specifications include:

1. **Own and cross-price elasticity of demand**

While the AES is the dominant ESUB metric, own/cross price elasticities of demand (PED) are also good indicators of substitutability. They account for a given input's share, s_i, and as such are directional. I report own- and cross-price elasticities of demand (along with cost shares of the various inputs) in Appendix D. From the AES, cross-price elasticities of demand, PED_{ij}, are given by:

$$PED_{ij} = s_j \sigma_{ij}$$

which gives the relative percentage change in the Q_i resulting from an increase in P_j (but not vice-versa, since the inputs usually have different cost shares (Serletis, Timilsina and Vasetsky 2011). Own-price elasticities of demand are given by:

$$PED_{ii} = s_i \sigma_{ii}$$

2. **Morishima elasticity of substitution**

Like the price elasticity of demand, the Morishima elasticity of substitution (MES) is a directional (asymmetric) measure of substitution. The distinguishing feature of this metric is that it indicates how changes in the price of input *j* impact the ratio of Q_i:Q_j. Like the PED, the MES can be derived from the AES, as follows (Serletis, Timilsina and Vasetsky 2011):

$$MES_{jj} = s_j(\sigma_{ij} - \sigma_{jj})$$

The specification of elasticities has proven important in debates over ESUB values (Jaccard 2008). There are a few things to note concerning these alternate measures. While the AES is the dominant measure of the elasticity of substitution in the literature, there are cases where the PED or MES elasticities may be preferable, since, being asymmetric, they are arguably more representative of true economic behaviour (Broadstock, Hunt and Sorrell 2007). Frondel (2011) argues that price elasticities of demand are the preferable metric for many practical purposes. Blackorby and Russell (1989) are critical of the AES in cases with more than two inputs, and discuss the relative merits of the Morishima elasticity. In this research project, I chose to use the AES specification, since it is the most widespread in the literature, and thus easiest to compare.

Definition of the AEEI

ESUB values guide price-induced changes in energy usage. However, some energy-efficiency improvements are not price driven; as the name implies, the autonomous energy efficiency index (AEEI) indicates a rate of price-independent improvements in energy-efficiency (Jaccard 2009, Paltsev, et al. 2005) and it is used to capture these dynamics in energy-economy models. It is possible that modeling limitations prevent certain types of energy-efficiency gains from being captured by substitution between fuels, other inputs and technologies, and thus there is a need to capture these changes in energy-economy models. The AEEI is typically represented as an annual percentage improvement in overall energy-efficiency, and tends to vary by sector (though models will often use a single value across the economy). The methodology for calculating AEEI values from CIMS is described in section 3.5.

Role of ESUB and AEEI values

ESUB and AEEI values are key parameters in general equilibrium models – and in particular in the CGE class of models mentioned above. ESUB and AEEI parameters simulate price dependant and price independent energy use responses to changes in technology, respectively. Since, in response to price changes, ESUB values indicate the degree of substitutability between any two pairs of production inputs, as well as between different forms of energy/fuels, ESUB values govern how demand adjusts to price changes within many economic models. For example, they indicate how easily one can buy energy-efficient equipment when energy prices rise. The AEEI is a parameter that guides improvements in energy productivity that result from price-independent technological advances. Calibrating these parameters is vital to the accuracy of the simulations, and is thus an important part of model design.

More generally, ESUB and AEEI values are useful in a stand-alone context since they allow one to assess the relative opportunities for fuel switching, and the decoupling of energy use from output, across sectors or across regions. For example, if one observes a higher value for the ESUB between energy and capital in the residential sector as compared to the commercial sector, then one could expect that there will be greater potential for price induced improvements in energy efficiency in the residential sector. Additionally, ESUBs are a useful tool for understanding and estimating the magnitude of the rebound effect. The next section explores the debate over energy-capital substitutability, and discusses how this relates to the rebound effect.

The debate over energy-capital ESUB values

The periods of oil price volatility that began in 1973 motivated many energy economists to study the empirical relationship between energy inputs and economic output in greater depth (Jaccard 2008). The idea that we can substitute capital (for example, in the form of the monetary value of more efficient equipment) for energy is widespread, and the debate over the extent to which we can substitute the two inputs is a very complicated - and divisive - topic (Jaccard 2008).

Engineers and environmentalists often argue that we can make considerable reductions in energy consumption while maintaining economic output levels, even with possible economic benefits (McKinsey&Company 2009, Lovins 1977). However, by employing more energy-efficient capital, economists note several possible complicating factors. First, the savings brought on by energy efficiency gains are realized in the future, and if returns on capital would be higher for investments on things other than energy efficiency, economic output would decrease. As well, the energy efficiency increase may require more expensive capital (equipment), which may not be entirely offset by energy cost savings, thus causing a reduction in economic output (Jaccard 2008). Finally, and perhaps most important among the risks of energy-efficiency investment, is concern over the rebound effect. There is evidence of both a direct and indirect rebound effect (Sorrell 2008). An example of a direct rebound is that when investing in a higher efficiency television, one might purchase a larger television, offsetting some of the efficiency gain. Indirect rebound effects refer to phenomena such as a consumer or firm using cost savings from energy efficiency improvements to acquire additional goods or services that in themselves use energy. As compared to ESUBs suggesting long-term substitutability between energy and capital, ESUBs indicating a complimentary relationship suggest a greater influence of rebound effects upon shifts to more energy-efficient capital.

Whether capital and energy factors of production serve as compliments or substitutes, and to what extent, is highly debated. Seminal papers on the extent of energy-capital (E-K) substitution found conflicting results. This debate is often expressed via elasticity values. Berndt and Wood (1975) initially reported complementarity between capital and energy. However, Griffin and Gregory (1976) argued that the time series data set employed by Berndt and Wood could only elicit short-run elasticities, and that their new work using pooled, inter-country data in fact revealed capital and energy to be substitutes. Griffin and Gregory argued that time-series data did not contain enough price variation to capture long-run dynamics, and that the pooled data, with it's greater price-variation, was more representative of potential long-term response. In trying to determine other factors that might explain the conflicting results throughout the literature, researchers have looked into the effects of alternate functional forms other than the commonly employed translog (described in section 3.3), the effects of alternate ESUB specifications from the standard Allen values, and the importance of relative input share size on the elasticity estimates (Jaccard 2008).

Upon observing the extensive literature on E-K substitution, it quickly becomes clear that there is no consensus on the values, despite decades of intensive research on the subject - so much so, that many values seem nearly impossible to reconcile (and are even arbitrary). As reinforced by Broadstock, Hunt and Sorrell's comprehensive review of E-K relationships in the literature (2007), the debate on E-K complementarity/substitutability has not been solved.

The debate over AEEI values

Given their exogenous nature, variations in AEEI values are highly influential over model forecasts. Similar to the debate over ESUB values, it is impossible to accurately predict the rate of technological energy efficiency improvement on the basis of historical data. As with ESUB values, there is a fair degree of expert elicitation and 'guesstimation' in addition to historical information used for AEEI estimation. This was reinforced by exchanges that I had with a well-known CGE modeller who mentioned in a personal communication that for some studies AEEI values might need to be changed for some periods in order to reflect observed world developments. This is necessary, since there is no way to observe responses to new developments (and thus no hard data upon which to base the numbers), but nimble adjustments highlight the occasionally soft terms upon which the numbers are based.

A survey of ESUB and AEEI parameters in models used for energy and climate policy analysis and related studies

The goal of this section is to explore various ways in which ESUB and AEEI parameters are estimated and used in the literature, and to show some numerical examples drawn for sources comparable to my study. The following is an overview of both the specification and treatment of the parameters in a brief survey of top-down models and other elasticity of substitution studies. There is a fairly wide body of literature available on aggregate factor substitution between capital, labour, and materials/energy (though for energy-economy modeling, energy-capital aggregate factor substitution relationships are most important), with less research on inter-fuel relationships.

The complete findings from the survey can be found in Appendix B, but tables Table 2-Table 4 below shows some of the key values.

In Table 2 I give an overview of key energy for capital ESUB values, beginning with the seminal finding of complementarity by Berndt and Wood (1975) – the study listed in the top-row. The next study listed is that of Griffin and Gregory (1976) which showed energy-capital substitutability using pooled inter-country data. From the survey, it appears that time-series data seems to lead to findings of complementarity, while pooled data show substitutability. I also included the ESUB within MIT's EPPA model, a value generated from CIMS-CANADA in a previous study, as well as estimates from a recent comprehensive review by Broadstock, Hunt and Sorrell in the last two rows. Elasticity values ranging from -3.25 to 1.7 indicate the high variation among estimates.

Table 2 Energy-Capital ESUB Key Models/Studies

ENERGY-CAPITAL ESUBs

Model/Survey	Sector	Elasticity of Substitution
Time series data (Berndt and Wood 1975)	U.S. Manufacturing	-3.25
Pooled data (Griffin and Gregory 1976)	U.S. National	1.07
Time series data (Fuss 1977)	CAN Manufacturing	-0.10
Pooled data (Pindyck 1979)	U.S. National	1.77
Time series data (Hunt 1984)	UK Industrial	-1.6
MIT-EPPA (Paltsev, et al. 2005)	U.S. National	0.4 to 0.5
Generated from CIMS-CANADA (Bataille 2005)	CAN National	0.13
Comprehensive review (Broadstock, Hunt and Sorrell 2007)	National	-0.39
	Industrial	-0.23

A brief overview of inter-fuel ESUBs drawn from various sources is given in Table 3. Note that NG and RPP indicate natural gas and refined petroleum products, respectively. For the purpose of this comparison, I include only electricity sector values across select sources – values for other sectors (and including additional sources) are in Table 13 of Appendix B. As with capital for energy ESUB values, there is a very wide range in values, with certain notable trends across sources. Given the very minor role (~1%) that RPPs play in electricity generation (mostly for peaking generation) in the US and Canada, RPP own-price ESUB values indicate a highly elastic response, as expected.

Table 3 Inter-fuel ESUB for Electricity in Key Models/Studies

Model/Survey	Sector	Input pair (or own-price)	Elasticity of Substitution
U.S. Translog inter-fuel model (Serletis, Timilsina and Vasetsky 2011)	Electricity Generation	NG own-price	-0.482
		NG-RPP	-0.071
		NG-COAL	0.227
		RPP own-price	-4.553
		RPP-COAL	0.671
		COAL own-price	-0.196
U.S. Translog inter-fuel model (Griffin 1977)	Electricity Generation	NG own-price	-0.90
		NG-RPP	0.58
		NG-COAL	0.16
		RPP own-price	-3.46
		RPP-COAL	0.50
		COAL own-price	-0.66
MIT-EPPA (Paltsev, et al. 2005)	Electricity	COAL – RPP/NG bundle	1.00
		RPP – NG	0.30
CIMS-Canada (Bataille 2005)	Electricity	NG own-price	-0.99
		NG-RPP	Na
		NG-COAL	2.13
		RPP own-price	-2.49
		RPP-COAL	N.A.
		COAL own-price	-1.34

Table 4 summarizes AEEI values from various sources. The first two sources listed – the MIT-EPPA and MERGE models – use 1% and 0.8%, respectively for economy-wide AEEI values (though MIT uses 0.35-0.40% for electricity generation), while the corresponding CIMS-CANADA derived value is a far lower 0.16%. Moreover, while the MIT-EPPA and MERGE AEEI values are positive across all sectors, those derived from CIMS-CANADA (shown in the bottom part of the table) indicate decreasing energy efficiency in electricity, as well as the aggregate of energy supply sectors.

Table 4 AEEI Values in Key Models/Studies

Model/Study	Sector	AEEI Value (%/yr)
MIT-EPPA (Paltsev, et al. 2005; personal communication)	Electricity	0.35-0.40
	All sectors except electricity	1.00
MERGE (Richels and Blanford 2008)	All sectors - technology as usual scenario	0.80
	All sectors - advanced technology path	1.00
CIMS-Canada (Bataille 2005, Bataille et al. 2006)	Canada (All Sectors)	0.16
	Energy supply	-0.73
	Energy demand	0.57
	Electricity	-1.09

As was previously alluded to, given the importance of ESUB and AEEI parameters, it is somewhat surprising- and troubling - that such a broad range of opinions and values exists, with little agreement over values or the procedures used for estimation. Trying to model a true-life process of course requires simplifying assumptions, which can help to explain the variety of approaches and values. Furthermore, empirically estimating such values from time-series data is challenging since we desire long-term ESUB and AEEI valus, yet there are always confounding short-term effects occurring in the economy, and thus the long term is difficult to estimate with confidence.

2.3. Estimation of ESUB and AEEI Parameters in Top-Down Models

Traditional approach

Given that top-down energy-economy model forecasts rely on aggregated representations of an economy, external information is required in order to guide how energy consumption might change in the future, and to parameterize the equations by which sectors interact as time progresses. The intuitive sources for this data are historical records about energy consumption and energy prices. In many developed countries, this information is extensive, and often available to the public. For example, the U.S. Department of Energy 's Energy Information Administration, or Natural Resource Canada are two examples of organizations that keep and make public extensive records about historical energy usage, data from utilities, and provide analysis of trends. Historical records can reveal important behavioural and technological information about consumer and producer energy dynamics.

Most top-down modellers analyze historical data using econometric techniques to derive the key parameters that drive their models. While the historic record is the best (because it is the only) true data that a modeller has upon which to base parameters, the past does not fully encapsulate the future possibility. Thus, the data may be obscuring true future price and non-price induced energy responses.

An important caveat for parameter estimation is that ESUB and AEEI values are often model dependent; in other words, if an econometric study was done for a specific sectoral or regional aggregation that is different from the one used in the intended model, it can lead to inconsistencies. Consequently, most of the time it is necessary to estimate values that are to inform a specific production structure/model.

An alternate approach to estimating ESUB and AEEI parameters

A major and persistent critique of the top-down approach (such as in CGE models) concerns the values of key ESUB and AEEI parameters. Misspecification of ESUB parameters can have a very large influence on the outcomes of model simulations, estimates of policy costs, and accordingly on emissions reduction potential in an economy. Much of the historical data used for parameter estimation dates back to the decades following World War II (Jorgenson, et al. 2000). Does historical data carry enough information to accurately portray *future* substitution potential? The future – with different technologies and fuels may differ from the past in terms of price response. For example, ESUB values between electricity and gasoline, or between ethanol and electricity in personal vehicles are important for understanding future substitution possibilities, however those possibilities were non-existent in the past (and there was not a clear incentive for low emission technologies). Relying solely on revealed preferences from past markets is dubious when we know that market options are changing. There is a lack of empirical evidence concerning our behaviour when faced with emission reduction issues.

While estimated from historical data in most cases, there is wide use of expert elicitation, and subjective 'guesstimation' in informing models. A modeller might have a quantitative basis to assume a particular level of price responsiveness for an input pair – for example, electricity and natural gas in the residential sector, though oftentimes they will simply assume a value that is in accordance with their qualitative observations.

Incorporating technological change in top-down models using ESUB parameters enables modellers to capture substitution responses despite relying on highly aggregated data (Jaccard 2009). While bottom-up models excel at modeling endogenous technological change, top-down CGE models are not ideal for this purpose, though they remain essential for understanding the macro-economic effects of climate policies. There is a need to overcome the shortcomings of using historical data, and to incorporate future possibilities in elasticity estimation. But we do not have a counterfactual – there is no way to know what would have happened under a different set of circumstances with any certainty.

Given the shortcomings of using historical records to derive top-down model ESUB and AEEI parameters, some researchers have explored an alternative approach. Griffin (1977) created a simulated set of future 'pseudo-data' based on a highly varied range of input prices to derive elasticity of substitution estimates. Griffin used a technologically explicit optimization model of the U.S. petroleum refining sector that can solve for optimal input quantities given a set of input prices. Via repetitive solution of the model, varying the input prices between simulations, Griffin was able to generate an artificial data set of model outputs corresponding to a range of input values, and thereby estimate the shape of the production possibility frontier. In other words, he could assess the substitution potential within the sector; he used the data on how input quantities change relative to input prices to derive elasticities of substitution for statistical estimation of ESUB parameters based on a flexible functional form. Griffin obtained results that were arguably more indicative of potential future responsiveness and substitution possibilities than those obtained by analyzing historical data, because (1) statistical estimation can be problematic given all the confounding historic effects and (2) technology and fuel choices differ in the future versus the past to and this impacts the economic response to price change.

While Griffin found a way to avoid using historical data to estimate elasticities, he derived forecasted pseudo-data using a linear programming/optimization model – a bottom-up energy-economy model. As discussed in section 2.1, conventional bottom-up models fail to capture behaviourally realistic responses to price and technology changes. Griffin's optimization modeling approach might be inappropriate for estimating the likely real-world substitution response in the market to price change. Jaccard et al. (1996) suggested that replacing the optimization model used by Griffin with CIMS, a hybrid model that incorporates behavioural realism might offer a more faithful portrayal of substitution responses. Thus, Bataille (2005), and Bataille, Jaccard et al. (2006) used CIMS to generate the future 'pseudo-data' set based on sectors of the Canadian economy. The method creates ceteris paribus conditions by freezing all variables but a price change for one input in a given scenario, which allows one to avoid problems of confounding short-term effects apparent in historical data. With historical data, one can never see such isolated responses – one of the main reasons people have at-times been suspicious of the significance of values issuing from econometric studies. The same methodology has not been used since those studies from 2005 and 2006, and the methodology has not yet been applied to any other regional versions of CIMS. Given the particular interest in, and importance of climate policy developments within the U.S., using a U.S. application of CIMS can provide a check on the values emanating from conventional econometric estimation of historical data.

2.4. Research Objectives

In summary, my research objectives are to:

1. Provide estimates of elasticity of substitution and autonomous energy efficiency index, which, by being derived from historical data (revealed preference) but also future likely market conditions (stated preference research which estimates CIMS values), offer extra and perhaps better information than typical estimates based on time-series historical data alone.

2. Use the CIMS ESUB generating methodology for estimating long-run values for the U.S., which has never been done before.

To achieve these objectives, I will:

- Apply the price-shocking technique to generate a suite of pseudo-data from CIMS-US.
- From this pseudo-data, estimate transcendental logarithmic production functions, and thereby calculate long-run ESUB parameter values for the U.S.
- Investigate inter-fuel substitutability between the major fossil-fuel categories at both the economy-wide and sectoral levels.
- Investigate aggregate-factor substitutability between capital and energy at economy-wide and sectoral levels.
- Calculate AEEI values by comparing a technologically frozen CIMS simulation with a CIMS Business-as –usual (BAU) simulation.
- Elicit and outline remaining challenges in using the price shocking, pseudo-data estimation methodology.
- Discuss potential applications for ESUB and AEEI results.
- Describe ideas for model and methodological improvement.

3. Methods and Data

3.1. Overview

My principal objective was to calculate a suite of sectoral and national elasticity of substitution (ESUB) values for the United States, based on a set of ‘pseudo data’ generated from simulated scenarios in which prices of key energy inputs and capital varied. I followed the method set out by Griffin (1977), using the ‘pseudo-data’ to estimate transcendental logarithmic (translog) production functions. I also calculated sectoral and national autonomous energy efficiency index (AEEI) values from the pseudo-data.

Bataille (2005) as well as Bataille, Jaccard et al. (2006) adapted the methodology set out by Griffin (1977) to estimate ESUB parameters by simulating a contrasting range of input prices in CIMS, treating the model output as a set of pseudo-data. The methodology for this study is closely based on this work, but my research is for the first time applying a United States application of CIMS, which was developed in recent years. The use of ‘pseudo-data’ generated with hybrid models such as CIMS is an adaptation to Griffin’s methodology since it pursues behavioural realism while allowing for technological developments not predictable from historical records. In addition to differences related to applying the CIMS methodology to a new region, the base CIMS model has improved significantly in recent years in terms of its ability to show response to new prices in the energy-economy system, especially in transportation and in technologies that prevent carbon emissions via capture and storage. These advancements could have a significant effect on ESUB estimates.

Price shocking an energy-economy model can be seen as testing out the model’s *response surface.* This refers to assessing and exploring potential for technological development in multiple directions, pushing the model towards its response limits.

As noted in chapter 1, ESUBs such as the values resulting from my work, can serve to inform CGE models, though choice of production function would most often be of the constant elasticity of substitution (CES) form rather than translog. However, in the case of this empirical work, I wanted to focus on exploring the price-shocking methodology, and generating a suite of values useful for comparison to other values in the literature.

For this project, I price-shocked the CIMS-US model for 45-year periods to estimate long-run inter-factor and inter-fuel ESUBs from the data set produced from these simulations at both sectoral and national levels. In addition, I calculated AEEI values for each sector by comparing BAU runs with 'technologically frozen' runs, to establish the energy-efficiency improvement that is embedded in the baseline technology evolution within the model. The following sections provide more detail on how I went about each of the steps involve in estimating the ESUB and AEEI values.

3.2. Price-shocking CIMS to Generate a Suite of Pseudo-data

Model run methodology

I generated a script[1] to automate CIMS simulations with input price variations. I considered a range of prices for each fuel input as well as capital that include four unique price levels per input: -30%, starting price, +30%, and +60%. Thus, with four price levels for each of five inputs, there are 1024 unique price combinations, each representing an individual model simulation. The script outlined the price combinations in each of the 1024 pricing scenarios, and generated code that instructs CIMS to run each

[1] For the script, I used a script-generating tool initially developed by Jotham Peters, member the Energy and Materials Research Group where I am based, and which developed CIMS. For more information on the Energy and Materials Research Group at Simon Fraser University in Vancouver, Canada, and to access past publications and model documentation, visit www.emrg.sfu.ca

scenario at the correct price combination scenario, in a sequence that resets the fuel prices between simulations in order to model every possible pricing combination. Using a simulation period of 45 years from 2005-2050, prices were set to immediately go to the specified level in 2005, and remain at that level through the end of the simulation, 2050. I chose this time horizon since it is the standard run-time in CIMS (though the model can theoretically run indefinitely). Given my goal to calculate long-run ESUB values, the 45-year simulation period is more than sufficient to elicit full capital stock turnover in all sectors (with notable exceptions being very long-lived capital such as hydroelectric dams and nuclear power plants in the electric generation sector). The initial price changes are imposed at the simulation outset in 2005. Though price adjustments are gradual in real world situations, for the purposes of gauging production responsiveness to price changes, it is not necessary to mimic this. In fact, maintaining constant prices throughout may yield superior representations of an economy's absolute responsiveness by imposing the price shock immediately. Nevertheless, the rationale for using gradual price changes has merit. This is discussed in section 5.3.

The price range I used is similar (though not identical) to that used in the antecedent work employing Canadian data (Bataille 2005) and captures a broad range of possible prices, revealing the majority of the simulation model's price response surface. Absent carbon pricing policy, this range is likely to show the majority of the possible price variation for the long-term real prices from 2005 to 2050, the current standard simulation period in CIMS. It is worth noting that in the presence of significant carbon pricing policies (for example, in the range of \$200/ton of CO_2e, the fuel prices could rise significantly higher than the maximum +60% variation that I consider (with coal prices rising the most drastically given the notably high emissions associated with coal combustion). Nevertheless, carbon price elasticities should be analyzed in future studies since many researchers view stringent carbon pricing as the most efficient mechanism to curtail GHG emissions in regional and supra-regional economies. This is discussed in greater detail in section 5.3 on future work.

The 'pseudo data' that results from the price-shocking simulations represents 1024 alternate pricing situations that are roughly comparable to individual data points on a time series or in a cross-section, in terms of the way that they are used to estimate production functions.

I aggregated the resulting 2050 data for each sector into spreadsheets that show data on prices and quantity of each of the five inputs in a single file, and then summed each sector into national level data. From the price and quantity data, I could calculate expenditure on each fuel input up, and accordingly the cost share for each input, which is what the parameter regressions for the translog regression are based on. This formed the set of pseudo-data used to estimate translog production functions.

3.3. Estimation of a Transcendental Logarithmic (Translog) Production Function Based on Pseudo-data

While there are various functional forms studied and applied to estimate production functions, the transcendental logarithmic cost function (Christensen, Jorgenson and Lau 1975) is the common choice among researchers wishing to look at substitution elasticities. This is because, as a fully flexible functional form, the translog cost function allows one to look at the relationship between any pair of inputs with relative ease, since it places no a priori restrictions on specification of the Allen elasticities of substitution that one can calculate from production function parameter estimates. The translog production function is:

$$\ln q = \alpha_0 + \sum_{i=1}^{n} \alpha_1\, lnx_i + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij}\, lnx_i lnx_j$$

in which q is output, α's and β's are the parameters to estimate by regression, and x_i and x_j are inputs (for this study: capital, electricity, natural gas, refined petroleum products, and coal).

Using logarithmic differentiation, and applying Shephard's Lemma (Shephard 1953) to the translog function above yields a system of cost share equations, representing the demand for each individual energy type in terms of its share of aggregate energy expenditure. The system of cost share equations has several unique attributes that facilitate parameter estimation (and subsequent ESUB calculation). The system of cost share equations that applies to sectors in which every input category that

I chose to represent is included is as follows. Note that E=electricity, N=natural gas, O=refined petroleum products, and C=coal. Section 2.3 describes how the parameters are regressed from the set of pseudo-data.

$$\begin{cases} S_E = \alpha_E + \beta_{EE}\ln(P_E) + \beta_{NE}\ln(P_N) + \beta_{OE}\ln(P_O) + \beta_{CE}\ln(P_C) \\ S_N = \alpha_N + \beta_{EN}\ln(P_E) + \beta_{NN}\ln(P_N) + \beta_{ON}\ln(P_O) + \beta_{CN}\ln(P_C) \\ S_O = \alpha_O + \beta_{EO}\ln(P_E) + \beta_{NO}\ln(P_N) + \beta_{OO}\ln(P_O) + \beta_{CO}\ln(P_C) \\ S_C = \alpha_C + \beta_{EC}\ln(P_E) + \beta_{NC}\ln(P_N) + \beta_{OC}\ln(P_O) + \beta_{C}\ln(P_C) \end{cases}$$

An assumption that the translog function is homogenous of degree one (this is related to having constant returns to scale) requires the following symmetry and parameter restrictions be imposed, which allow the cost share equations to be estimated as a system:

$$\beta_{ji} = \beta_{ij}$$

$$\sum_{i=1}^{n} \alpha_i = 1$$

$$\sum_{i=1}^{n} \beta_{ij} = \sum_{i=1}^{n} \beta_{ji} = 0$$

The first restriction above implies that cross-price elasticities are symmetric. In order to estimate the parameters of the system, any one of the share equations needs to be removed by deleting any one cost share equation, as shown by Barten (1969). As a result of the symmetry restrictions above, the system of cost share equations can then be written as below, where I drop the coal equation (though any share equation can be dropped equivalently) to yield a resulting system of the form:

$$\begin{cases} S_E = \alpha_E + \beta_{EE}\ln(P_E/P_C) + \beta_{NE}\ln(P_N/P_C) + \beta_{OE}\ln(P_O/P_C) \\ S_N = \alpha_N + \beta_{EN}\ln(P_E/P_C) + \beta_{NN}\ln(P_N/P_C) + \beta_{ON}\ln(P_O/P_C) \\ S_O = \alpha_O + \beta_{EO}\ln(P_E/P_C) + \beta_{NO}\ln(P_N/P_C) + \beta_{OO}\ln(P_O/P_C) \end{cases}$$

Regression of pseudo-data to estimate production model parameters

Regression of the parameters for the production model's system of cost share equations was done using the "STATA" statistical software package (StataCorp. 2009), using Zellner's Seemingly Unrelated Regression (SUR) technique (Zellner 1962). SUR estimation is a variety of linear regression across a system of equations, in which the error terms across the equations are seemingly unrelated, but in reality are correlated. In terms of translog cost share equations, since the equations' error terms exhibit non-zero covariance, the cost share equations for each input are in fact related, and as such SUR estimation is the appropriate regression tool (Griffin 1977). For energy-capital relationships, however, since there are only two cost-share equations, SUR regression was not necessary – and as such I used linear regression for estimating these relationships.

The output from each of the 1024 price-combination scenarios/simulations represented a single data point for regression. This output, a set of prices and quantities across each scenario, was used to calculate input cost shares, which along with the natural logarithm of the prices formed the basis for the SUR /linear regression of this data, which yielded the parameter estimates for the system of cost share equations for each sector (or national aggregations). The multiple pricing scenarios formed the basis for a regression of the parameter estimates for the system of cost share equations. The remaining parameter estimates for the omitted cost share equation can be calculated by virtue of the parameter restrictions outlined above.

Note that in CIMS, not every fuel is represented in every sector. (For example, it is assumed that there is no coal consumption in the residential sector.) As a result, in sections where certain fuel classes are not represented, there will be one fewer cost share equation in the system per excluded fuel category. The following section describes the inter-fuel production models used in this study by sector, and Table 5 indicates which fuel categories are included by sector.

Inter-fuel production models

For this study, as indicated in the system of equations above, I have distinguished energy types into four categories: (1) Electricity; (2) Natural Gas; (3) Refined Petroleum Products; and (4) Coal. Each individual fuel has specific and unique attributes – notably in terms of GHG and particulate emissions intensity, energy density, cost, and availability by sector. However, bundling them into the four categories makes both logical and computational sense.

1. **Electricity** – Includes electricity only. (The electricity generation sector within CIMS accounts for the various primary forms of energy used for generation, including fossil fuels, nuclear, and renewable fuels.)
2. **Natural Gas** – Includes methanol natural gas and process natural gas.
3. **Refined Petroleum Products** – Includes aviation fuel, biodiesel, diesel, ethanol, gasoline, heavy (residual) fuel oil, light (distillate) fuel oil, liquefied petroleum gas, petroleum coke, petroleum pitch, propane, refinery fuel gas and still gas. (All products are generated from crude oil, which is represented by a separate sector within CIMS.)
4. **Coal** – Includes regional varieties of anthracite, bituminous, sub-bituminous and lignite coal, coke, and coke oven gas.

Table 5 below is a summary of the fuel categories included in CIMS by sector, where shaded cells indicate that a particular sector includes the given fuel category:

Table 5 Fuel Categories Consumed/Represented in CIMS by Sector

Fuel Category / Sector	Electricity	Natural Gas	Refined Petroleum Products	Coal
Residential				
Commercial/Institutional				
Personal Transportation				
Freight Transportation				
Industry				
Chemical Products				
Industrial Minerals				
Iron and Steel				
Non-Ferrous Metal Smelting				
Metals and Mineral Mining				
Other Manufacturing				
Pulp and Paper				
Energy Supply				
Coal Mining				
Electricity Generation				
Natural Gas Extraction				
Petroleum Crude Extraction				
Petroleum Refining				
Biofuels				
Agriculture				
Waste				

It is important to note my production functions do not include every fuel/energy-type that is represented in the CIMS model; I only include electricity, along with fossil fuel categories. While this is logical in regard to GHG emissions and constituency of the U.S. energy-system, there are also reasons that one would explicitly include other major (and high future potential) energy types such as hydroelectric, other renewables, and nuclear. (However, these are primary inputs in electrical generation with little to no direct energy consumption, and as such represented indirectly in electricity.) Reasons for choosing what is included in this study include the fuels' roles in GHG emissions reduction, and the limited role for omitted fuels outside of the electricity generation sector. I discuss the rationale and drawbacks to only including electricity and fossil fuel energy types in Section 5.3 (future research).

The following is a list of fuels/energy-types that, while represented and demanded by technologies in CIMS-US, are omitted from my analysis (note that some of the fuels serve as primary inputs for electricity generation): bio-gas, black liquor, by-product gas, crude oil (though crude oil is processed into RPPs, which themselves are subject to price changes), flare gas, geothermal, hazardous waste, hog fuel, hydrogen, landfill gas, solar, uranium (nuclear), walking, waste fuel, water (hydro), wind, wood, and iron process gases. That said, the simulations I conducted include the information needed to infer the effect of substitution between fossil fuels and renewables in the electricity sector, since this substitution is embodied in the K-E elasticity (since the cost of renewable generation is virtually entirely capital.)

Aggregate factor energy and capital production model

The energy price aggregator function

Using the translog cost function approach, I analyzed inter-fuel substitution using the model specification described above in2.3. However, calculating substitutability between the two aggregate factors of production included in this study – capital (K) and energy (E) – required data on price and quantity of each factor. The model output from each of the 1024 simulation scenarios yielded this information only for K. Obtaining the required price and quantity information on the energy aggregate required aggregating price information for the individual energy sub-types. One might initially attempt weighting each energy price by its share – however this is appropriate only if all ESUBs are zero. Since this is not the case, I needed to calculate an overall energy price index.

Following the methodology initially set out by Fuss (1977), and used in subsequent studies (Serletis, Timilsina and Vasetsky 2011, Bataille, Jaccard, et al. 2006) I calculated an aggregate energy price index using an energy price aggregator function. The energy price aggregator has a similar form to the translog production function:

$$\ln P_E = \alpha_0 + \sum_{i=1}^{n} \alpha_1 \, lnP_{E\,i} + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \, lnP_{E\,i} lnP_{E\,j}$$

In which P_E is the price of the energy aggregate, $P_{Ei,}$, and P_{Ej} represent prices of individual energy types (thus each possible fuel pair figures in to the equation), and the alpha and beta values are parameters estimates from the inter-fuel production model. In essence, I could insert inter-fuel parameter estimates along with disaggregate energy prices to the translog price aggregator function to generate an aggregate energy cost estimate for each price-shocking scenario.

Calculating the energy price-index involves treating the inter-fuel energy production function as a sub-model and recognizing the implicit assumption of homothetic, weak separability – that aggregate inputs (in my case, capital and energy) can be disaggregated, and that the sub-function(s) are monotonically increasing, such that the two stage regression procedure yields valid results (Fuss 1977). In this study I am treating RPP, ELEC, NG and COAL as making up a separable and homogenous energy aggregate. This essentially allows modeling of the production function to occur in 2 stages, beginning with energy types, and then feeding an aggregate energy price index into the two-input capital-energy model. The assumption of separability is required in order to able to analyze inter-fuel relationships (as described in the previous section), such that total output can be 'separated' into a capital (K) component, and an energy (E) bundle. The simplified form of the production function illustrates this:

$$Q = f(K, E(E_{ELEC}, E_{NG}, E_{RPP}, E_{COAL}))$$

Value-added compensation and data source for comparison

Since the focus of CIMS is on energy supply and demand aspects of production, the model does not fully capture the amount of value-added (VA) provided by productive capital and labour inputs within each sector. Moreover, energy is the only intermediate input that CIMS explicitly represents (other materials are excluded in CIMS). CIMS sub-models cover fuel costs, capital costs associated with consuming energy, and some labour costs (operation and maintenance costs, which are often represented as a fixed proportion of capital costs). Thus, the sub-models omit costs for installing capital that are not associated with energy and raw materials. The extent of costs covered by each sector varies from very low (~5%) to nearly full coverage. For example, within the commercial sector of CIMS, the sub-model covers only the equipment that uses energy and the building shells, and not activity that occurs within the shells. Similarly, in the other manufacturing sector, the model only represents energy using and consuming activity, and as such does not capture the majority of capital provided by the sector. I measured the missing costs by comparing CIMS' capital cost output with historical data, and the CIMS output was adjusted accordingly by a compensation factor proportional to the size of the gap. In my study, I did not consider labour costs; thus I only needed to account for capital costs not covered by CIMS in order to yield meaningful estimates of capital for energy substitutability. It was necessary to apply compensation factors to the capital levels reported by CIMS simulations to do so.

In order to determine appropriate compensation factors, I utilized input-output data from the 2002 benchmark data provided by the U.S. Bureau of Economic Analysis (BEA) (US Bureau of Economic Analysis 2011) and aggregated the reported VA values into aggregations that matched with CIMS sector composition to yield a valid comparison. As in Griffin and Gregory (1976), I then separated out wages and salaries - the labour cost component (listed by the BEA as "compensation to employees") - from the BEA VA values, since I desired capital values. Though CIMS does not account for all categories that the BEA data reports, in aggregating BEA sectors to match those from CIMS, I accounted for 88% of all capital reported by BEA for the U.S. economy, and thus included the majority of capital expenses (the BEA reports certain categories such as government expenditures which are not accounted for in CIMS, explaining why I could only account for 88% of total BEA reported capital expenditures). After compensation for consumer price adjustments and growth to make the 2002 BEA data comparable with the 2005 CIMS data which I was assessing, I determined the proportion of capital that was captured in each sector of CIMS.

At the national level, CIMS captures 49% of the capital as reported by the BEA. Excluding transportation sectors, this number drops to 25%, presumably due to CIMS accounting for a relatively high share of capital in the transportation sectors – a logical finding since a large part of capital in the transportation sectors is energy using, and as such is represented in CIMS.

Individual sectors showed considerable variation as expected. For example, the other manufacturing sub-sector of CIMS captured 6.4% of BEA reported K, which is sensible since much of the other manufacturing capital stock is excluded from CIMS analysis. This translated into a 1/0.064, or ~15.6 compensation factor for CIMS' K values. Similarly, my finding of ~78% and ~100% of K captured by electricity and refinery sectors, respectively, is logical since the majority of activity in energy supply sectors is energy-intensive. On the other hand, in certain sectors, I found that CIMS was ostensibly indicating greater than the full K indicated by the BEA, suggesting either methodological or model issues. For these sectors, I applied a decreasing compensation factor to reduce K estimates from CIMS.

Though I would not expect CIMS to capture the full extent of value added/capital in most sectors, the problem sectors should be assessed in future work. This is discussed further in Section 5.3.

3.4. Calculation of ESUBs Based on Regressed Production Function Parameters

From the parameter estimates for the translog system of cost share equations, Allen elasticities of substitution can be calculated as follows:

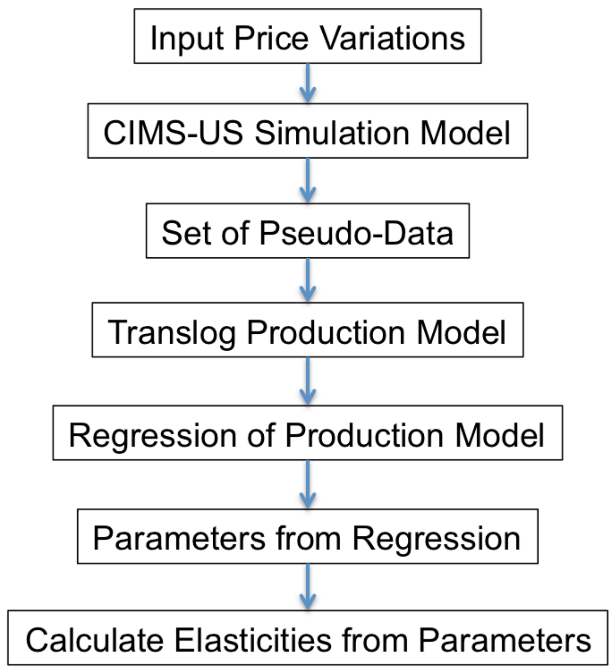
$$Cross-Price: \qquad \sigma_{ij} = \frac{\beta_{ij} + S_i S_j}{S_i S_j}$$

$$Own-Price: \qquad \sigma_{ii} = \frac{\beta_{ii} + S_i^2 - S_i}{S_i^2}$$

For all resulting ESUB values, I followed Bataille (2005) in using +/- 3.00 as a maximum cut-off point for ESUB values calculated. The ESUB estimation process can, in theory, yield a response surface implying elasticity values from negative to positive infinity. For certain inter-fuel values, when the price-shocking technique takes the model and pseudo-data out of the realm of reality – and especially in sectors in which a particular fuel has a very low cost share – the model can yield elasticities of an unrealistically high magnitude. The limiting elasticity values of +/- 3.00 are cut-off points that constrain my estimates within reasonable bounds (comparable to what is found in external literature). The +/- 3.00 range has the potential to indicate highly elastic substitution response, but prevents values that suggest infinitely/very highly elastic responses, which are likely unrealistic.

Figure 3 below shows an overview of the ESUB estimation methodology:

Figure 3 ***Graphic Overview of Elasticity Calculation Method***



As shown, the process of generating elasticities from CIMS pseudo-data is a multi-step procedure, in which the outputs from the various steps are soft-linked (for example, I manually took the pseudo data output and entered it into the regression model). Beginning with the desired range of input prices, I ran a series of simulations. I then assembled a set of pseudo data so that it would be compatible with the translog structure, and used regression software to calculate the coefficients of the cost-share equations. Finally, I used the coefficient estimates to calculate elasticity values.

3.5. Calculation of AEEI values using CIMS

Autonomous energy efficiency index (AEEI) values were calculated by comparing energy consumption in the year 2035 between a technologically frozen (TF) simulation and a BAU reference simulation. Running a model under technologically frozen conditions entails freezing market shares and technology attributes within CIMS. The formula used to determine the annual rate of change in energy consumption in the model is:

$$AEEI = 10^{\left[\left(\log\left(\frac{TF}{BAU}\right)\right)/n\right]} - 1$$

which outputs a rate of AEEI in %/year, in which n refers to the number of compounding periods, TF refers to energy consumption in the technologically frozen simulation, and BAU the energy consumption in the reference case (Luciuk 1999, Bataille 2005). I considered AEEI values at both national and sectoral levels of aggregation.

I chose a to use a 30-year simulation period for AEEI calculations (n = 30), as opposed to the 45-year period used for ESUB calculation. It made sense to use this shorter timeframe for calculating AEEI values due to concern about CIMS reaching a maximum in terms of technical development, and as such compounding energy consumption changes over an unreasonably long-period, causing erroneously lowered AEEI estimates. On the other hand, even if certain aspects of the model achieved their maximum technical potential ahead of 2050 (the end of the ESUB simulation period), I would not expect the additional run time to have a significant effect on ESUB values.

3.6. Challenges

One of the main challenges associated with the elasticity generation technique outlined above is the coordination of all steps, as well as deciding on time frames, price deviations, sectoral aggregations and other such decisions that might have an influence upon the results. Quantifying the impact of methodological variations is a separate challenge – one that I did not explore in any depth given the large number of price variations I was already studying in the model. That said, by the large number of price combinations, I am already doing somewhat of a sensitivity analysis, since the ESUB values represent an 'average' of responses to multiple changes in price. I discuss some of these considerations in greater detail at the end of this report, where I consider potential methodological improvements and sensitivity analyses for future studies (see Section 5.3).

4. Results and Discussion

This section outlines the ESUB and AEEI results that I calculated from the set of simulated pseudo-data generated by CIMS. Note that I present national level results both with and without the personal and freight transportation sectors included. This is mainly due to low price responses that I found in the transportation sectors (discussed further in later sections) which I thought might unduly distort national level data.

When interpreting the results, the reader should keep in mind the following: (1) as noted previously, the Allen elasticity of substitution values are symmetrical between any 2 inputs, and as such I do not present the duplicate data – i.e. a capital for energy ESUB is equivalent to energy for capital; and (2) the following abbreviations apply: E = electricity or energy (depending upon context – energy if aggregate results, electricity if interfuel results), NG = natural gas, RPP = refined petroleum products, K = capital.

4.1. ESUB results

National ESUB estimates are presented first, with inter-fuel values listed in Table 6, and aggregate (E-K) values presented in Table 8. Following this, I present sub-sector ESUB results, with inter-fuel values given in Table 7, and aggregate values in Table 9[2].

[2] Most regressions, on which the ESUBs are based, yielded coefficients of variation (R^2) values that indicate the majority of variation within the pseudo-data set being explained by the production model. For many sectors the values are 0.9 or higher. P-values are generally under 0.05 indicating that the dependent variables were strongly significant. This makes sense since the CIMS simulation algorithm is designed to respond to changes in prices in (usually) predictable and expected ways.

Interpretation

At the national scale, inter-fuel ESUBs, as shown in Table 6, exhibited a wide range of values, and seemed to be influenced to a varying degree by the inclusion or exclusion of the transportation sector in the national aggregate. Natural gas and coal own-price values in both cases were highly elastic, each with a value of -3. According to the result, at the national scale, a 1% rise in the relative price of either input will result in in a 3% decline in its relative demand. Electricity and refined petroleum product own-price values, on the other hand, indicate lower elasticity and greater influence from the inclusion of transportation sectors. The calculated own-price elasticity for electricity became less elastic with the exclusion of transport, going from -1.02 to −0.60.

Table 6 National Inter-fuel Elasticities of Substitution

Substitution Relationships	**U.S.**	**U.S. w/out Transport**
ELEC own-price	-1.02	-0.60
ELEC:RPP	0.36	0.47
ELEC:NG	1.27	1.04
ELEC:COAL	-0.73	-0.69
NG own-price	-3.00	-3.00
NG:RPP	1.10	2.83
NG:COAL	3.00	2.59
RPP own-price	-0.77	-3.00
RPP:COAL	-0.16	-1.06
COAL own-price	-3.00	-3.00

Between individual fuels, I found the electricity for RPP relationship to be moderately inelastic (0.36 with transport sectors, 0.47 without), and electricity for NG to be close to unit elastic. Electricity's more elastic relationship with NG (1.27 with transport sectors, 1.04 without) reflects the many instances across the U.S. economy in which electricity and NG can offer similar services – for example for space heating, and providing heat for industrial processes – instances in which RPPs have limited applicability. A result that is somewhat surprising, and seemingly counterintuitive is the complimentary relationships that I found between coal and electricity (-0.73 with, and -0.69 without transport sectors), and coal and RPPs (-0.16, and -1.06). I speculate that these interesting coal-electricity results are strongly influenced by the predominance of coal in the U.S. electric generation sector, which, consuming nearly the entire share of coal in the economy, may experience a rise in electricity output price and/or decline in output in response to higher coal input prices. However, these national level results also show that aggregating sectors and end-uses can lead us to estimate complementary relationship between two inputs, when in fact they may be substitutes at a sectoral/end-use level.

In interpreting the national level results, note that the values are not simply the mean of ESUB (and AEEI) values across all sectors, but are calculated from national level pseudo-data and production models. In effect, the national aggregates are weighted by costs/expenditures. It is important to keep this in mind when interpreting national aggregate results, since for certain measures, a given sector may hold significantly more influence on the elasticity value. For example, since the majority of expenditures on petroleum products are in the transportation sector, transportation price responses dominate the calculation of the national values involving RPPs. As shown in Table 7 below, measured RPP own-price elasticities in personal and freight transportation were -0.04 and -0.15, respectively, or very inelastic, and in general for other sectors the ESUB was more elastic, and in many cases -3. This is reflected by the national aggregate measures given in Table 6. With the transportation sector included, the RPP own-price value is -0.77, whereas with the transport sector excluded, the value is -3.

Table 7 Inter-fuel Elasticities of Substitution by Sector

	Note: * = not applicable; _p = own-price elasticities; E = electricity, N = natural gas, O = refined petroleum products, and C = coal)					
Substitution Relationships:	**E:N**	**E:O**	**E:C**	**N:O**	**N:C**	**O:C**
Demand Sectors						
Commercial	0.69	1.17	*	3.00	*	*
Residential	1.80	1.20	*	2.26	*	*
Personal Trans.	-3.00	1.06	*	3.00	*	*
Freight Trans.	*	*	*	3.00	*	*
Waste	*	*	*	*	*	*
Agriculture	0.76	0.02	*	-0.18	*	*
Industry						
Chemical Products	1.50	1.11	-3.00	3.00	-3.00	3.00
Industrial Minerals	0.64	3.00	0.13	-0.12	0.18	0.40
Iron and Steel	0.18	0.20	-0.07	3.00	0.19	0.17
Metal Smelting	0.26	0.61	-0.23	3.00	1.68	0.75
Mining	0.11	0.33	0.36	1.68	-3.00	0.36
Other Manufacturing	0.82	0.77	-1.00	3.00	3.00	3.00
Pulp and Paper	0.57	0.48	-1.33	3.00	1.41	-0.37
Supply Sectors						
Crude Extraction	-0.26	0.09	1.86	0.42	3.00	-0.54
Electricity	*	*	*	3.00	2.26	0.29
Coal Mining	-0.26	0.17	-3.00	-0.35	3.00	-1.11
Petroleum Refining	-3.00	-1.87	-3.00	1.47	-3.00	0.04
NG Extr. and Trans.	1.29	-3.00	*	0.12	*	*
Biofuels	2.46	0.16	1.26	0.72	3.00	-3.00

	Table 7 Continued			
Substitution Relationships:	**Ep**	**Np**	**Op**	**Cp**
Demand Sectors				
Commercial	-0.20	-3.00	-3.00	*
Residential	-0.34	-3.00	-3.00	*
Personal Trans.	-3.00	-3.00	-0.04	*
Freight Trans.	*	-3.00	-0.15	*
Waste	2.64	*	*	*
Agriculture	-0.26	-1.07	0.01	*
Industry				
Chemical Products	-2.89	-1.30	-3.00	3.00
Industrial Minerals	-0.63	-0.84	-3.00	-0.83
Iron and Steel	-0.12	-3.00	-3.00	-0.17
Metal Smelting	-0.12	-3.00	-3.00	-3.00
Mining	-0.22	-3.00	-0.76	3.00
Other Manufacturing	-0.78	-1.44	-3.00	-3.00
Pulp and Paper	-0.09	-3.00	-3.00	3.00
Supply Sectors				
Crude Extraction	-0.35	-1.57	-0.19	-3.00
Electricity	*	-1.47	-3.00	-3.00
Coal Mining	-0.09	2.87	-0.12	3.00
Petroleum Refining	-3.00	-3.00	-0.36	3.00
NG Extr. and Trans.	-3.00	-0.43	3.00	*
Biofuels	-3.00	-1.08	-1.02	-3.00

Own price elasticities across the four fuel categories revealed notable differences. As seen in Table 7, NG, RPP and coal values often reached the cut-off of +/- 3.00, while electricity values were by comparison modest, and with greater variability. One would normally expect negative values indicating reductions in the quantity of a fuel used in response to price increases, but this was not always observed. While this makes sense for the waste sector's own-price electricity value (since cogeneration causes waste's electricity output to increase in light of higher electricity prices), for own-price coal responses some values are difficult to explain. In the industrial and supply sectors, coal own-price ESUBs indicated highly elastic responses across all sectors, and in both positive and negative directions. The seemingly strange own-price coal responses may be due in part to the low cost share of coal in most sectors, which can cause exaggerated results, since elasticity estimates are directly affected by the cost share of a given fuel. As such, while some elasticities don't make sense for coal, they are not particularly important results. In light of its low price and low use, coal has a very low (0.2% - ~3%) cost share in five out of 7 industrial sectors. (Table 16 in Appendix D gives an overview of each fuel categories' cost share across sectors.) The two sectors that use significant shares of coal, and accordingly displayed inelastic own-price coal ESUBs were industrial minerals and iron and steel – indicating very limited substitution possibilities. For example in a scenario that had coal prices inflated by 60%, with all other fuels unchanged, adoption of coal consuming technologies was relatively unchanged, given that metallurgical coal is an essential input in the manufacturing of steel. Also, while relative price changes are the same across all fuels, since coal has such a low price to begin with changes to coal prices may get buried in model noise, and thus a greater range of coal prices could help to more fully determine the effect of coal price change.

Capital-energy relationships indicate the potential for switching away from energy, and are shown in Table 8 below. National capital for energy ESUB calculations resulted in fairly inelastic measures of 0.21 with and 0.15 without the inclusion of the transportation sector, indicating only modest potential for long-term substitution between the input pair. This difference suggests that a good portion of energy-efficiency price based response occurs in the transportation sector. Notably, personal transportation had the highest E-K ESUB of all demand sectors at the national level, 0.28, surpassed only by certain supply sectors - electricity (0.62) and biofuels (1.56). Chemical products was the only demand sector showing a negative relationship, albeit negligible at -0.02. Residential and commercial sectors yielded values of 0.09 and 0.13, respectively. Amongst energy supply sectors, coal mining and petroleum refining were the only two that exhibited complimentary relationships, as indicated by the negative E-K ESUB values - potentially a result of demand feedbacks that cause reductions in output as a consequence of higher energy prices.

Table 8 National Inter-factor Capital (K) for Energy (E) Elasticities of Substitution

Substitution Relationships	**U.S.**	**U.S. w/out Transport**
K:E	0.21	0.15
K own-price	-0.06	-0.02
E own-price	-0.66	-1.00

Even with results suggesting only slight potential for long-term substitution between energy and capital, the future ability to produce energy with low or zero emissions may reduce the importance of the debate over E-K ESUB values (Jaccard 2008).

From Table 9 below, we see that own-price energy responsiveness was generally low, with notable exceptions in the residential sector (-3.00), waste sector (2.64 – a positive value due to cogeneration possibilities), electrical generation sector (-1.63) and biofuels sectors (-3.00). Inelastic own-price energy elasticities show the relative susceptibility of those sectors to fluctuations in energy prices. The relatively high response to energy prices in the residential sector reflects the adoption of efficient varieties of space and water heating and electrical appliances (notably refrigeration technologies). In scenarios with high natural gas and electricity prices, the more energy-efficient technologies in a technology node captured significant portions of new market share. Likewise, under high fuel prices in the electrical sector, I observed energy-efficient (though relatively costly) combined cycle generators gaining the majority of new market share over the course of the simulation period. Nationally, the values for own-price energy elasticity were -0.66, and -1.00 both with and without transportation, implying inelastic and unit elastic complementary relationships, respectively.

Table 9 Inter-factor Capital (K) for Energy (E) Elasticities of Substitution by Sector

Substitution Relationships:	K:E	Kp	Ep
Demand Sectors			
Commercial	0.09	-0.01	-1.29
Residential	0.13	0.00	-3.00
Personal Trans.	0.28	-2.37	-0.03
Freight Trans.	0.07	-0.02	-0.20
Waste	0.17	0.01	2.64
Agriculture	0.05	-0.03	-0.09
Industry			
Chemical Products	-0.02	0.00	0.08
Industrial Minerals	0.07	-0.05	-0.11
Iron and Steel	0.07	-0.16	-0.03
Metal Smelting	0.06	-0.28	-0.01
Mining	0.08	-0.16	-0.04
Other Manufacturing	0.07	-0.01	-0.41
Pulp and Paper	0.11	-0.04	-0.31
Supply Sectors			
Crude Extraction	0.07	-0.07	-0.06
Electricity	0.62	-0.24	-1.63
Coal Mining	-0.31	1.06	0.09
Petroleum Refining	-0.05	0.02	0.09
NG Extraction and Trans.	0.25	-0.10	-0.66
Biofuels	1.56	-3.00	-0.51

Table 15 in Appendix C gives an overview of all ESUB values.

Comparison to literature

While initial work by Berndt and Wood (1975) found complementarity between E and K, Griffin and Gregory (1976) found divergent evidence of substitutability, and argued that the time-series data used by Berndt and Wood could only elicit short-run elasticities. Berndt and Wood (1979) wrote that early contradictory results on E-K substitution were the result of differing data sets, treatments of excluded inputs, and distinctions between short-run and long-run elasticities. Thus, without sufficient time for adjustment to price changes deducible from time-series data sets, findings of complementarity might make sense. Nevertheless, Griffin and Gregory’s seminal findings of E-K substitutability reflected their use of data that represented greater variation in prices, and which they argued could, as such, better elicit long-run E-K relationships. In addition to the issues of eliciting long-term effects from short-term data, there are too many confounding effects over time to be able to elicit the long-term effect of price changes from historical data – and of course this is made all the more difficult during periods of no price change. My calculations indicated substitutability, however with only a slight opportunity for the long-term substitution between capital and energy. This suggests that increases in price-induced energy-efficiency have less potential for the reduction of energy consumption and GHG emissions than some claim (and in particular, less then many engineers and environmentalists believe).

In comparison to the elasticity study done by Bataille (2005) using a Canadian application of CIMS, certain results stand out. In particular, E-K ESUBs responded in the opposite direction with the exclusion of transport sectors. In Bataille's work, the value rose from 0.13 to 0.27, whereas in my U.S. study, it declined from 0.21 to 0.15 with the exclusion of personal and freight transportation. Note that in my unreported preliminary results, however, in which my price-shocking scheme involved more drastic price changes (relative to embodied emissions in the different fuel categories) I found a result similar to that of Bataille – E-K National ESUBs went from 0.14 to 0.29 – nearly identical to Bataille's result. I believe that this is due to my finding of relatively high E-K substitution in the personal transportation sector (0.28) as compared to Bataille's transportation result of 0.08 (noting again that Bataille's model did not disaggregate personal and freight transportation). Also note that Bataille's study was done roughly 8 years ago (published in 2005), and several key models of efficient vehicles are now in the CIMS model now (in both Canadian and U.S. versions). This may help to explain the reversal of the effect of including/excluding transport between newer and older models.

An earlier article which utilized a price-shocking methodology comparable to my own in order to derive ESUBs from the NEMS hybrid energy-economy model (Wade 2003) appears to have found significantly less responsiveness in the U.S. residential and commercial sectors, as compared to my results (see Table 7). Though the reason is not clear, it is interesting to note that the Wade study used a simple price shocking scheme that involved two price scenarios (base and doubled prices), whereas in the CIMS study, I employed a less extreme, and more gradated price-shocking scheme. Additionally, I consider price increases and decreases, whereas Wade looks only at price increases, and this might help explain the lower responsiveness that he found. Wade discusses how an earlier round of elasticity estimates from NEMS was obtained using a 10% increase in prices, as opposed the subsequent approach of doubling energy prices. The use of higher prices was motivated by higher than anticipated energy prices, though the change of price shocking scheme did not have a significant impact on elasticity estimates. Despite differences in price shocking schemes, the higher price responsiveness in my study using CIMS as compared to Wade's NEMS study might simply reflect greater technical efficiency potential embedded in CIMS model options.

4.2. AEEI Results

Interpretation

Comparing 30-year simulations of CIMS with and without technological development revealed a varying response across sectors. As shown in Table 10 below, nationally, the U.S. AEEI was estimated to be 0.96%/year with all sectors included. The exclusion of the transport sector raised the measure of energy-efficiency improvement to 1.07%/year, largely due to the impact of removing freight transportation, which exhibited a low 0.25%/year AEEI, and is a high energy consuming sector.

Table 10 AEEI Results: National

Sector/Region	AEEI % / year
U.S.	0.96%
U.S. w/out transportation sectors	1.07%

Table 11 indicates that the residential sector showed the highest potential for price-independent energy-efficiency improvement, with an AEEI value of 1.99%/year – due in part to energy efficient HVAC options gaining market share as relatively long-lived older equipment is retired. The commercial sector on the other hand exhibited a lower AEEI value of 0.56%/year, potentially reflecting the greater initial efficiency of some commercial sector technologies. With the exception of the chemical products sector that exhibited a slightly negative AEEI of -0.02%/year, AEEI values ranged from 0.26-0.79%/year across the industrial sectors. Electricity generation experienced relatively high improvements in energy-efficiency when technology development was unhindered, with an AEEI value of 1.39%/year.

Table 11 AEEI Results: Sectoral

Sector	AEEI % / year
Demand Sectors	
Commercial	0.56%
Residential	1.99%
Personal Trans.	0.73%
Freight Trans.	0.25%
Waste	-1.73%
Agriculture	0.74%
Industry	
Chemical Products	0.43%
Industrial Minerals	0.33%
Iron and Steel	0.41%
Metal Smelting	0.79%
Mining	0.26%
Other Manufacturing	0.26%
Pulp and Paper	-0.02%
Supply Sectors	
Crude Extraction	-0.82%
Electricity	1.39%
Coal Mining	1.37%
Petroleum Refining	1.31%
NG Extraction and Trans.	-0.68%
Biofuels	-80.53%

Sectors with negative AEEI values include waste (-1.73), natural gas extraction and transportation (-0.68) and crude extraction (-0.82). AEEI is a function of of both technical efficiency and sub-structural change (i.e. energy intensity). Note that the energy intensity of a sector can be increasing even though the technologies are in general becoming more efficient. This can happen if the more energy-intensive sub-sectors are gaining in importance relative to the less energy-intensive sectors. A negative AEEI value suggests price-independent increases in energy consumption over time, and reflects decreases in sectoral energy-intensity. As for the negative AEEI values that occur in energy supply sectors – the crude oil and natural gas extraction sectors - the negative value I obtained is the result of a shift to more energy intensive extraction/processing techniques in the BAU run (compared to the technologically frozen case), including shale/tight natural gas extraction using hydraulic fracturing in the natural gas sector. In natural gas extraction, both tight gas, and shale gas technology groups obtain significant market share over the course of simulation. These shifts to unconventional, energy intensive forms of primary energy reflect the exhaustion of conventional extraction techniques.

Comparison to literature

The most direct comparison that I can make for my AEEI results is to Bataille (2005). One interesting and notable difference between my AEEI results for the U.S. and Bataille's (2005) results for Canada is for electric generation, in which I found a positive value, indicating improvements in price-independent energy efficiency, while Bataille found a negative value. Bataille reported that the negative values might be the result of the exhaustion of technologies in the BAU simulation, such as available hydroelectric sites, which do not require primary energy input, and thus a shift in generation to thermal sources. As for the positive value that I found, I cannot pinpoint the cause since the sectors differ considerably between countries. Possibly this is in part due to the high amount of inefficient single-cycle coal generation in the U.S., and evolution away from these technologies. Otherwise, natural gas extraction evolves in the opposite direction from the Canadian data. This is logical, because when the Canadian numbers were calculated (in 2005), CIMS models did not incorporate the development of shale/tight gas, along with their higher energy inputs resulting from the energy-intensive nature of fracking extraction techniques.

Aside from Bataille's results, values presented in Table 4 do not tend to reveal AEEI values at as high a level of disaggregation as presented in the present work. The MERGE model simply uses an overall value for the entire economy of 0.8-1.0%/yr. The EPPA model uses different values for electric and non-electric sectors. My national value (0.96%/year) was slightly lower than in MITs EPPA model (~1.3%/year). However, for the electric sector in particular, I found significantly higher energy-efficiency improvement of 1.39%/year as compared to EPPA's 0.35-0.40%/year. The variation in AEEI values in the literature suggests that the methodology for estimation has a significant impact on parameter values, and indicates a potential value from further research to explore the reasons for the divergence.

5. Conclusions and Future Research

5.1. Key conclusions

The ESUB experiments suggested various conclusions about potential energy substitutability in the U.S., the U.S. version of CIMS, and the methodology that I used to elicit the elasticities of substitution. While I found modest potential for energy-efficiency changes as a response to varied energy costs, in general, potential for inter-fuel switching seems to be more significant. In addition, I found AEEI and ESUB parameters to differ considerably between model sub-sectors.

While the model and method I used to estimate the likely response of sectors of the economy to changing prices produced many plausible results, it also produced some that appeared less plausible. In some cases, it is possible that unexpected or illogical results reflect issues within the CIMS model. For example, the model suggested low price elasticities in transportation. I am suspicious of this because there are many alternative technology options that I expect to outcompete conventional transportation technologies. This is due in part to the aggregation of all RPPs into one fuel category (thus masking shifts to biofuels, for example), however there was still less shifting to efficient varieties of internal combustion engines than I expected in a scenario with RPP prices elevated by 60%. An additional example of a result that seems implausible is the low electricity price response in the commercial sector. In this case, the lack in electricity response was partly the result of the high take up of an HVAC natural gas cogeneration technology that was capturing roughly 10% of the HVAC market share under high electricity prices, thus increasing the available electricity to be consumed within the sector.

5.2. Remaining issues with results and methodology

Some implausible values may reflect areas that need improvement within CIMS, inadequate specification of production functions, problems with my estimation of production function parameters, or issues with the calculation and reporting of ESUB values based on the production function estimates. In this chapter, I outline what I view as remaining issues with my results and methodology and offer ideas for improving upon them.

5.3. Future research, and improvements to results and methods

Ideas for model improvement and further CIMS technology development

Some of the results which seemed illogical or otherwise stood out caused me to look into underlying reasons in greater detail. As such, I have made a few observations that relate to potential CIMS model improvement.

1. Cogeneration adoption in the commercial sector:

My finding of low own-price electricity ESUBs in the commercial sector (-0.20) appeared low, since there are many available energy-efficient technologies running on electricity, any of which would be adopted in those simulations I ran which entailed inflated electricity prices. Technologies such as improved appliances, building shells/construction, and lighting were readily available. From investigating technology shares in the commercial sector, once a sufficiently high electricity price exists in the market, I found that there was a significant shift to a specific natural gas fuelled cogeneration HVAC technology. This appears to be the principal cause of the low electricity elasticity in the sector. The extent of cogeneration in the sector is not plausible and needs to be addressed within CIMS-US, for example by restricting cogeneration technologies to the types of commercial buildings that are more likely to be initial adopters (e.g. hospitals, schools, etc.).

2. Low responsiveness of RPPs in transportation sectors

My finding of low own-price values for RPPs may indicate that the transportation sectors are overly resistant to changes in fuel prices. Bataille (2005) noted similar findings in his Canadian study. However, it is also possible that by aggregating all fuels consumed in transport (other than natural gas and electricity) into a single category, I am masking some opportunities for switching from gasoline to diesel engines, and more importantly switching to vehicles that run on biofuels, since biofuels can be made from renewable resources, and offer reductions in GHG emissions. In further price-shocking studies, I would recommend disaggregating individual RPPs to better portray the substitution possibilities in transportation.

3. Value added in sub-sectoral models

Certain sub-sector models appeared to be showing unreasonably high levels of value-added from labour and capital as compared to comparable data from the U.S. Bureau of Economic Analysis (US Bureau of Economic Analysis 2011). In some cases CIMS sub-sectors appeared to be showing greater than 100% of the capital reported by the BEA, whereas one should expect CIMS to capture less than 100% in most sectors since CIMS focuses only on energy-using capital stocks. Though this may not point to a model problem, and may in fact be the result of inappropriate comparison, or other factors such as flaws in unit conversion, it is possible that this finding points to some calibration problems within CIMS-US. The at times drastic and/or negative compensation factors that I needed to apply again highlight the diagnostic benefits of the elasticity calculation work in this paper, which may have additional benefits for not only future elasticity studies, but for any work involving CIMS-US. The fact that CIMS does not account for non-energy related capital, and does not incorporate full labour costs is not a problem with CIMS, since CIMS is focused on energy by design. Adjusting capital values reported by CIMS is not an issue in terms of elasticity estimation, however I would recommend investigating the calibration (in particular the technology specification, initial technology splits, and base year stocks) in the sectors which appeared to capture an implausible amount of capital. I did not look at the model calibration since it is an extensive process that is beyond the scope of my project.

Ideas for methodological improvement

The effect of the magnitude of input-price level variation

For future studies, there may be value in testing the responsiveness of the long-run price elasticity estimates to the size of the price-shocks in CIMS. Based on the differences in ESUB values that I observed between my first round results, involving carbon intensity price changes, and the final results presented in this paper, it is clear that the effect of having more levels per input (the gradation of the price changes), and of changing the magnitude of relative price changes has a significant impact on elasticities generated, and potentially a drastic effect. Carbon intensity price variations involve varied input prices for each fuel category relative to the average embodied emissions for each fuel category. Thus, in my first round of results, coal prices were changed by greater proportions than natural gas. There is not much of a precedent against which to judge price shock levels. The four levels per input scheme I employed (-30%, standard, +30%, +60%) was relatively similar to that of Bataille (2005) who used 6 levels (-50%, -25%, standard, +25%, +50% and +75%). Once I can quantify the impacts of price-levels, and assess the influence that this factor has on simulation outputs and ESUB results, it may be easier to determine the most logical price-shocking scheme. It is possible that the most appropriate price-shocking scheme depends on intended use for results (i.e. for comparison to other values vs. the intent of informing a CGE model). It is also possible that the scheme may involve a more detailed gradient of price-levels.

It is worth noting that generating a consistent data set for production function parameter regression involves capturing every possible input price combination, with each being the basis of a unique model simulation. Consequently, increasing the number of price-levels per input increases the number of CIMS simulations required to generate a full suite of price-shocking data exponentially. At the four level per input (-30%, base prices, +30%, +60%) 5 input (K, ELEC, NG, RPP, COAL) scale that I used, capturing every input price combination requires 4^5 = 1024 simulations. Five price levels per input instead of four implies 3125 simulations, while 6 inputs instead 5 requires 4096 simulations. It is possible to complete approximately 100 simulations per hour using CIMS-US running on a standard personal computer, thus run-time can be an issue with greater price-levels or additional inputs. Run-time would increase if I had disaggregated CIMS-US into distinct regions. The price-shocking scheme I employed represents a good balance of run-time and gradation of price-shocks. However, for future studies I would suggest using lower number of price-levels (3) for initial tests and trials, so as to quickly gauge initial problem areas, and then increasing to 5-7 price-levels per fuel once any initial issues have been addressed.

The importance of capturing every possible price level combination is another point to consider. In Bataille (2005), the price shocking scenarios were slightly different. Rather than analyze every possible price combination, for his 6 price variations on each of the 5 inputs analyzed, other inputs were held constant at their normal levels. Bataille looked at every possible price per input with other inputs held constant and thus had a drastically lower number of simulations. The tools that I used to price-shock the model, however, were designed to look at every possible combination. While it may seem otherwise, it is in fact not more work to include a far higher number of simulations – though it does require several hours/days to run a complete price-shocking suite.

The study of price shock size brings about another related, albeit quite different, point to consider. In my study, the primary goal was to assess the *response surface* of the model. Put otherwise, I wanted to push the model to its limits to see what is technically feasible in terms of simulated technology development. However, the price changes that I used are arguably unrealistic.

In terms of capital price modifications, I looked at a very extreme range compared to what might occur in reality. Capital price variations on the order of 5-10% are already significant, and would serve as better ranges, should my goal be to study realistic capital price changes. However, the responsiveness to the model may be very slight. This is an unfounded prediction, and the only way to know if the model would show much response to these comparatively minor changes would be to test it.

Including other energy inputs

In my study, I only looked at four different energy inputs: refined petroleum products, natural gas, electricity, and coal. These are the fuels that cover the majority of energy use in the U.S. and are responsible for the majority of CO_2 emissions. However, including different fuels (renewables for industry), and/or disaggregating fuel categories (splitting biofuels from RPPs) may reveal critical substitution information, in particular for the electricity generation and transportation sectors. The ability of economies and sectors therein to switch between emitting energy-types, and non-emitting energy types such as nuclear, hydroelectric, and renewables may be highly informative.

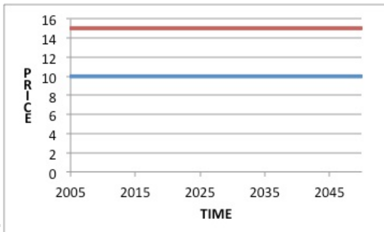
Dynamic effects

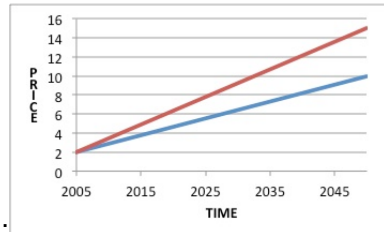
1. Endogenous change: Learning by doing and the neighbour effect functions in CIMS

Simulation period length may have a significant impact on outputs from price-shocking, given the functioning of the declining capital cost (DCC) and declining intangible cost (DIC) functions of CIMS (section 2.1 gives a brief description of these functions, and Appendix A), which were operating for my simulations. The longer a model is set to run for, the greater the potential impact of the DCC and DIC functions on technologies that initially play a relatively minor role. Across the economy, many of the technologies which have low starting market shares entail relative increases in energy-efficiency or consume lower emissions fuels. Given the low initial market shares, they are likely to be the most influenced by the effects of DCC and DIC functions. As such, a longer run time in many cases will imply greater adoption of such technologies. Thus, longer run times might result in higher values for capital-energy substitutability, and/or greater fuel switching represented by higher inter-fuel elasticities, should the DIC and DCC function exert a greater influence on technology evolution. I did not look at the impact of changing DCC and DIC settings (or turning them off entirely) on ESUB results, and in future research using the same price-shocking method, I recommend looking into the sensitivity of results to changes in these behavioural parameters.

2. Gradual price changes

Figure 4 Sudden and Rising Price Shocks

Sudden: 

Gradual: 

In my simulations, input prices were set immediately at the desired level, and remained constant throughout. It may be worthwhile to implement the price-shocking technique using a gradually changing price (as shown in the right panel of Figure 4). Gradual price changes would be helpful if one is to estimate short-run elasticities (for simulating years before all capital stock has turned over). Gradual changes will help to more realistically simulate the initial technology competition dynamics, and will have effects over the rate of price-responsive technology switching, and the resulting technology mix and levels of inputs (energy and sub-types, and capital),.

3. Using actual/present input cost shares to calculate ESUBs

The standard practice for calculating ESUBs from translog cost function parameter estimates is to use the mean of the cost shares across the data set. (Translog functions are locally flexible, meaning that elasticities can be calculated at any single point across possible input mixes.) However, since the 'pseudo-data' set I generated is not of time-series or true cross-sectional types, the average does not necessarily have much meaning. An alternative is to use actual cost shares from the current year (i.e. today's cost shares) since the pseudo-data is not real-world data. In this regard, using real cost shares, along with estimated production function coefficients to calculate ESUBs may yield more accurate results, since the average cost share across a series of simulations may not be the same as the present cost shares. I chose to follow the norm of using the mean within the data, in accordance with standard elasticity estimation literature, and as in Bataille (2005), though the differences in cost shares obtained by either method do not differ significantly in my study. For future work with the price-shocking methodology, it is worthwhile to compare cost shares based on the average across scenarios, with real/current cost shares. Should they differ considerably, I would suggest using those based on current cost shares.

Applying the methodology to inform specific top-down models

While the intent of my study was to provide a scholarly exploration of the price-shocking methodology to generate ESUBs, in other instances, the intent may be to produce values that can inform a top-down, CGE model. Doing so would require a number of changes to the approach.

Most likely, rather than estimating translog production functions, one would need to estimate constant elasticity of substitution (CES) production functions, since CGE models are designed using specific nesting structures to represent how an economy functions, and how the model solves. Note, however, that it is necessary to know the nesting structure of a particular CGE model prior to elasticity estimation, since this changes the way one would aggregate fuels, regions, and sub-sectors in the CIMS model prior to production function estimation.

The variation between my ESUB results across individual fuels, as shown by this study, brings into question the validity and potential drawbacks of the standard approach of using CES production functions and elasticities to inform CGE models. While a CGE model would use a single value (a “constant elasticity”) to represent substitutability between fuels (i.e. all non-electricity energy inputs) and electricity, according to my findings this would obscure true substitution potential. Being fully flexible, the translog function has this advantage of enabling the modeller to specify the relationship between any two factors of production. For example, Rivers and Sawyer (2008) use an ESUB of 0.66 between fuels and electricity, whereas my results, in which I analyze the relationships between each of the 5 inputs that I chose to include, show differing ESUBs for electricity paired with each other fuel. Thus, I found the electricity for natural gas elasticity to be 1.27, whereas electricity for refined petroleum products was estimated at 0.36. While I am not suggesting that translog models are inevitably superior for informing CGE models, given the significant computational advantages of using CES functions, rather I am highlighting the fact that the simplifying advantages of CES functions may mask some of the more nuanced substitution responses that may exist in an economy.

5.4. Final words

Energy-economy modeling has played, and continues to play an important role in helping to understand the dynamics of energy substitution. The methodology which I presented and applied in this research project offers a potentially beneficial approach to estimating elasticity of substitution parameters for production analysis and for informing top-down models. This overcomes some of the shortcomings of the standard use of parameters estimated from time-series data. While the methodology yielded interesting parameter results, it also serves to assist in CIMS model improvement and diagnostics, exposing potential areas for improvement via unexpected and outlying parameter estimates.

The debate over ESUB and AEEI parameter values for the United States remains unresolved, with a notable lack of consensus in the literature. In estimating parameters for top-down models, there is always a degree of subjectivity at play, and despite the uncertainty involved with price-shocking technique, traditionally estimated top-down model parameters appear to be more arbitrary and less informative than the numbers that can be produced by price-shocking a hybrid model such as CIMS. Given that that the price-shocking pseudo-data methodology overcomes some of the shortcomings of the more common time-series and cross-sectional methods for estimating ESUBs, it merits serious consideration and further study.

References

Allen, R. *Mathematical Analysis for Economics.* London: Macmillan, 1938.

Axsen, J., D. Mountain, and M. Jaccard. "Combining Stated and Revealed Choice Research to Simulate the Neighbor Effect: The Case of Hybrid Electric Vehicles." *Resource and Enrgy Eocnomics* 31, no. 3 (2009): 221-238.

Barten, A. "Maximum likelihood estimation of a complete system of demand equations." *European Economic Review* 1 (1969): 7-73.

Bataille, C. *Application of a Technologically Explicit Hybrid Energy-Economy Policy Model with Micro and Macro Economic Dynamics.* Vol. PhD Dissertation. Vancouver: Simon Fraser University, 2005.

Bataille, C., M. Jaccard, J. Nyboer, and N. Rivers. "Towards General Equilibrium in a Technology-Rich Model with Empirically Estimated Behavioral Parameters." *The Energy Journal* Special Issue #2, no. Hybrid Modelling (2006): 93-112.

Berndt, E., and D. Wood. "Engineering and Econometric Interpretations of Energy-Capital Complementarity." *American Economic Review* 69, no. 3 (1979): 342-354.

Berndt, E., and D. Wood. "Technology, Prices, and the Derived Demand for Energy." *Review of Economics & Statistics* 57 (1975): 259-268.

Blackorby, C., and R. Russel. "Will the Real Elasticity of Substitution Please Stand Up? (A Comparison of the Allen/Uzawa and Morishima Elasticities)." *American Economic Review* 79, no. 4 (1989): 883-888.

Broadstock, D., L. Hunt, and S. Sorrell. "UKERC Review of Evidence for the Rebound Effect - Technical Report 3: Elasticity of substitution studies." *UK Energy Research Center Working Paper*, 2007.

Christensen, L., D.W. Jorgenson, and L.J. Lau. "Transendental logarithmic utility functions." *American Economic Review* 65 (1975): 367-383.

Energy Information Administration. "The National Energy Modeling System: An Overview 2009." Wahington, DC, U.S. Department of Energy, 2009.

Frondel, M. "Modeling Energy and Non-energy Substitution - a survey of elasticities." *Ruhr Economic Papers* 256 (2011).

Fuss, M. "The Demand for Energy in Candian Manufacturing." *Journal of Econometrics* 5 (1977): 89-116.

Goettle, R., M. Ho, D. Jorgenson, D. Slesnick, and P. Wilcoxen. "Analyzing Environmental Policies with IGEM, an Intertemporal General Equilibrium Model of U.S. Growth and the Environment Part 2." 2011. http://www.igem.insightworks.com/docs/247/part2chap1.pdf (accessed November 2011).

Griffin, J. "The Econometrics of Joint Production: Another Approach." *The Review of Economics and Statistics* 59, no. 4 (1977): 389-397.

Griffin, J., and P. Gregory. "An Intercountry Translog Model of Energy Substitution Responses." *The American Economic Review* 65, no. 5 (1976): 845-857.

Hicks, J.R. *Theory of Wages.* London: Macmillan, 1932.

Hoffert, M., et al. "Energy implications of future stabilization of atmospheric CO2 content." *Nature* 395 (1998): 881-884.

Horne, M., M. Jaccard, and K. Tiedemann. "Improving behavioral realism in hybrid energy-economy models using discrete choice studies of personal transportation decisions." *Energy Economics* 27, no. 1 (2005): 59-77.

Hourcade, J.-C., M. Jaccard, C. Bataille, and F. Ghersi. "Hybrid modeling: new answers to old challenges - Hybrid Modeling of Energy–Environment Policies: Reconciling Bottom-up and Top-down)." *The Enrgy Journal* 27 (2006): 1-12.

Hunt, L. "Energy and capital: substitutes or complements? Some results for the UK industrial sector." *Applied Economics* 16, no. 5 (1984): 783-790.

Jaccard, M. "Combining top down and bottom up in energy economy models." In *International Handbook on the Economics of Energy*, by Joanne Evans and Lester Hunt, 311-331. Chetlingham, UK: Edward Elgar, 2009.

Jaccard, M. "Modeling Energy Use and Technological Change for Policy Makers: Campbell Watkins' Contribution as a Researcher-Practitioner." *The Energy Journal* Special Issue (2008): 31-42.

Jaccard, M., A. Bailie, and J. Nyboer. "CO2 Emission Reduction Costs in the Residential Sector: Behavioural Parameters in a Bottom-Up Simulation Model." *The Energy Journal* 17, no. 4 (1996): 107-134.

Jaccard, M., J. Nyboer, C. Bataille, and B. Sadownik. "Modeling the Cost of Climate Policy: Distinguishing between Alternative Cost Definitions and Long-Run Cost Dynamics." *The Energy Journal* 24, no. 1 (2003): 49-73.

Jorgenson, D., R. Goettle, P. Wilcoxen, and M. Ho. "The Role of Substitution in Understanding the Costs of Climate Change Policy." *Pew Center Report* (Pew Center on Global Change), 2000.

Loschel, A. "Technological change in economic models of environmental policy: a survey." *Ecological Economics* 43 (2002): 105-126.

Lovins, A. *Soft Energy Paths: Toward a Durable Peace.* Friends of the Earth International, San Francisco and Ballinger Publishing, Cambridge, USA, 1977.

Luciuk, D. "The Price-Independent Trend in Energy Efficiency in Canada and the Potential Influence of Non-Price Policies." *Research Project - Simon Fraser University*, 1999.

McKinsey&Company. "Reducing US Greenhouse Gas Emissions: How Much at What Cost." 2007.

McKinsey&Company. "Unlocking Energy Efficiency in the US Economy." 2009.

Murphy, R., and M. Jaccard. "Energy efficiency and the cost of GHG abatement: A comparison of bottom-up and hybrid models for the US." *Energy Policy* 39, no. 11 (2011): 7146-7155.

Oreskes, N. "The role of quantitative models in science." In *Models in Ecosystem Science*, by Charles Canham, Jonathan Cole and William Lauenroth, 13-31. Princeton: Princeton University Press, 2003.

Paltsev, S., et al. "The MIT Emissions Prediction and Policy Analysis (EPPA) Model: Version 4." *MIT Joint Program on the Science and Policy of Global Change* Technical Report 125 (2005).

Pindyck, R. "Interfuel Substitution and the Industrial Demand for Energy: An International Comparison." *The Review of Economics and Statistics* 61, no. 2 (1979).

Ramskov, J., and J. Munksgaard. "Elasticities – a Theoretical Introduction." *Balmorel Project.* February 2001. www.balmorel.com/Doc/B-ElastTheory0201.pdf (accessed December 2010).

Richels, R., and G. Blanford. "The value of technological advance in decarbonizing the U.S. economy." *Energy Economics* 30 (2008): 2930-2946.

Rivers, N., and D. Sawyer. "Pricing carbon: saving green - a carbon price to lower emissions, taxes and barriers to green technology." *David Suzuki Foundation*, 2008.

Rivers, N., and M. Jaccard. "Combining top-down and bottom-up approaches to energy-economy modeling using discrete choice methods." *The Energy Journal* 26, no. 1 (2005): 83-106.

Roy, J., A. Sanstad, J. Sathaye, and R. Khaddaria. "Substitution and price elasticity estimates using inter-country pooled data in a translog cost model." *Lawrence Berkeley National Laboratory Report* LBNL55306 (2006).

Serletis, A., G. Timilsina, and O. Vasetsky. "Interfuel substitution in the United States." *Energy Economics* 32 (2011): 737-745.

Shephard, R. *Cost and production functions.* Princeton, NJ: Princeton University Press, 1953.

Sorrell, S. "The rebound effect: a review." *Current Affairs - Perspectives on Electricity Policy for Ontario.* University of Toronto, 2008.

StataCorp. "Stata Statistical Software: Release 11." *College Station, TX.* StataCorp LP, 2009.

US Bureau of Economic Analysis. "BEA : Benchmark Input-Output Data." *US Bureau of Economic Analysis.* May 23, 2011. http://www.bea.gov/industry/io_benchmark.htm (accessed January 2011).

Uzawa, H. "Production Functions with Constant Elasticities of Substitution." *Review of Economic Studies* 29 (1962): 291-299.

Wade, S. "Price Responsiveness in the AEO2003 NEMS Residential and Commercial Buildings Sector Models." *Energy Information Administration*, 2003.

Zellner, A. "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias." *Journal of the American Statistical Association* 58, no. 2 (1962): 348-368.

Appendices

Appendix A

Description of CIMS Algorithms

In CIMS simulations, technologies compete for a market share of new capital stock at each energy service node based on a comparison of their life cycle costs. CIMS also includes several technology specific physical, technical, or regulatory controls that provide means to constrain a technology from capturing the entire market share, but which are not shown in the market share equation below (Jaccard 2009, Murphy and Jaccard 2011)

$$MS_j = \frac{\left[CC_j * \frac{r}{1-(1+r)^{-n_j}} + MC_j + EC_j + i_j\right]^{-v}}{\sum_{k=1}^{K}\left\{\left[CC_k * \frac{r}{1-(1+r)^{-n_k}} + MC_k + EC_k + i_k\right]^{-v}\right\}}$$

In the above formula, market share for a technology j MS_j is given by the ratio of the life cycle cost of *j* to the total life-cycle cost of every competing technology *k* and where for each technology, *CC* is the capital cost, *MC* is the maintenance and operation cost, and *EC* is the energy cost, which depends on energy prices and service demands. As mentioned in the main text of this paper, microeconomic behavioral parameters in CIMS are informed by a combination of revealed and stated preference research. *i*, *r*, and *v* represent the three behavioral parameters in the market share algorithm:

The *i* parameter denotes intangible costs and benefits, which represent option value costs and/or consumer surplus losses for a given technology compared to its competitors. Intangible costs are a means of embedding consumers' and businesses' perceptions of costs and benefits that do not figure into the simple financial costs used in traditional bottom-up analyses. They represent aspects such as the perception of risk for a new technology and the social benefits or drawbacks of a given technology. For example, plug-in hybrid electric cars are often perceived as a risky purchase to consumers, since there is high uncertainty as to how the electrical infrastructure for vehicles will develop. As well, some consumers feel that they will 'stand-out' in either desirable or undesirable ways for owning such vehicles, thus changing the intangible costs and benefits of such a technology.

The *r* parameter represents the weighted average time preference of decision makers for a particular energy service demand, and is generally set higher than social discount rates (whereas traditional bottom-up analyses typically use the social discount rate). *r* is the same across all technologies at a given service node, however differs between the various energy service nodes in accordance with market observations. Along with a technologies lifespan, *n*, one can calculate a capital recovery factor, which can be used to annualize the up-front capital cost of a technology, and then added to the annual *MC* and *EC* costs to obtain annualized estimates of technology cost (Jaccard 2009, Murphy and Jaccard 2011).

Last, the *v* parameter indicates the degree of heterogeneity in a particular market, by which firms and consumers experience differing costs for the same technology due to varying locations, perceptions, and preferences. Conventional bottom-up models depict homogenous markets, ignoring such variation, and thus the technology with the lowest cost captures 100% of the market. Modifying the *v* parameter in CIMS changes the shape of the inverse power function that assigns market share to technology *j*. Low values for *v* mean that competing technologies obtain fairly distributed market share, even if life-cycle costs differ. High values, on the other hand, will result in the technology with the lowest cost capturing most of the market share (up until v = ∞ at which point the model operates as a conventional bottom-up model, with the cheapest technology capturing the entire market. At a value of v = 10, if technology A becomes 15% more expensive than B, B will capture 85% of the new market share (this is typically the starting value prior to market-specific parameter calibration).

Aside from the central market share algorithm, CIMS contains two key functions for simulating endogenous technological change, as briefly described in the main text:

First, the declining capital cost (DCC) function (often referred to as a learning curve) is described as:

$$C(t) = C(0)\left[\frac{N(t)}{N(0)}\right]^{log_2(PR)}$$

in which the financial cost of a technology at a time *t* is adjusted from its initial cost *C(0)* as a function of cumulative production and assumed progress ratios. *N(t)/N(0)* represents cumulative production at time *t* relative to initial production, and *PR* represents the percentage reduction in a technology's cost given a doubling in cumulative production. This formulation enables CIMS to capture economies of scale and economies of learning.

Second, the declining intangible cost (DIC) function reflects the 'neighbour' effect, whereby the intangible cost of a technology in a given period is linked to its market share in the previous period. This function reflects improved information, and decreased perceptions of risk by firms and consumers as technologies gain market presence. The formulation in CIMS is:

$$i_j(t) = \frac{i_j(0)}{1 + A_j e^{k_j * MS_{j_{t-1}}}}$$

in which $i_j(t)$ is the intangible cost of technology *j* at time *t*, MS_{jt-1} is the market share of technology *j* at time *t-1*, while *A* and *k* are estimated parameters that indicate the rate at which intangible costs decline in response to increases in market share.

Appendix B

Survey of ESUB and AEEI values

Table 12, Table 13 and Table 14 below give an overview of values and methods used for E-K ESUBs, inter-fuel ESUBs, and AEEI values in various models/studies, respectively.

Table 12 Summary of Energy-Capital ESUBs in Various Models/Studies

Model/Survey	Notes/Parameter Source	Sector	Elasticities of Substitution
Time series data (Berndt and Wood 1975)	Translog cost function approach. Authors present E-K ESUB at 5 points in time – I report the mean of values.	U.S. Manufacturing	-3.25
Pooled data (Griffin and Gregory 1976)	Griffin and Gregory respond to perceived shortcomings of using time-series data in estimating long run elasticities. Also translog approach.	U.S. National	1.07
Time series data (Fuss 1977)	Using two-stage approach, estimating separable fuel sub-model. I estimated AES from price elasticities given.	CAN Manufacturing	-0.10
Pooled data (Pindyck 1979)	Similar approach to Griffin and Gregory.	U.S. National	1.77
Time series UK data (Hunt 1984)	A time-series approach with translog cost function method. Notably, data-set reflects the oil price-shocks of the early 1970s.	UK Industrial	-1.6
MIT-EPPA (Paltsev, et al. 2005)	A dynamic CGE model. Since there is a specific nesting structure using CES production functions, one can only find ESUB values as per the model's aggregations. As such, note that the value indicated here is between energy and value added (thus including labour in addition to capital). It is nevertheless worthy of comparison.	U.S. National	0.4 to 0.5
Generated from CIMS-CANADA (Bataille 2005)	Translog cost function approach, using similar methodology to the current study.	CAN National	0.13
Time series U.S. data for paper sector (Roy, et al. 2006)	A translog cost function study for several countries. The authors present results for pooled, cross sectional data across countries, and using time series data for the individual countries. Here I present U.S. time series data for paper, the only sector reported for the U.S. in this study.	Paper	5.27
Comprehensive review (Broadstock, Hunt and Sorrell 2007)	Mean of studies reporting AES U.S. values.	National	-0.393
		Industrial	-0.23

Table 13 Summary of Inter-Fuel ESUBs in Various Models/Studies

Model/Survey	Notes	Sector	Input pair (or own-price)	Elasticities of Substitution
NEMS Residential and Commercial models (Wade 2003)	A hybrid model from the U.S. Department of Energy, similar in nature to CIMS. Values obtained by running the sub-models with doubled energy prices from 2005-2025 (thus not capturing longest lived capital) and comparing adjustments with base price scenarios. I consider distillate fuel equivalent to RPP for residential and commercial sectors. Wade reports directional, share adjusted cross-price elasticities (not AES).	Residential	ELEC own-price	-0.49
			ELEC-NG	0.01
			ELEC-RPP	0.00
			NG-own-price	-0.41
			NG-ELEC	0.13
			NG-RPP	0.02
			RPP own-price	-0.60
			RPP-ELEC	0.01
			RPP-NG	0.05
		Commercial	ELEC own-price	-0.45
			ELEC-NG	0.01
			ELEC-RPP	0.00
			NG own-price	-0.40
			NG-ELEC	0.86
			NG-RPP	0.01
			RPP own-price	-0.39
			RPP-ELEC	0.08
			RPP-NG	0.75
U.S. Translog interfuel model (Serletis, Timilsina and Vasetsky 2011)	Includes electricity, natural gas, crude oil and coal using data from the U.S. Energy Information Administration. Similar specification of fuels and production model to my study.	National	ELEC own-price	-0.287
			ELEC-NG	0.326
			ELEC-RPP	0.185
			ELEC-COAL	0.283
			NG own-price	-3.258
			NG-RPP	0.344
			NG-COAL	1.050
			RPP own-price	-0.299
			RPP-COAL	-0.028
			COAL own-price	-3.335
		Residential	ELEC own-price	-0.382
			ELEC-NG	0.675
			ELEC-RPP	-1.385
			NG own-price	-2.903
			NG-RPP	-1.385
			RPP own-price	-7.146
		Commercial	ELEC own-price	-0.158
			ELEC-NG	0.497
			ELEC-RPP	1.280
			NG own-price	-3.565
			NG-RPP	-1.697
			RPP own-price	-12.981
		Electricity Generation	NG own-price	-0.482
			NG-RPP	-0.071
			NG-COAL	0.227
			RPP own-price	-4.553
			RPP-COAL	0.671
			COAL own-price	-0.196

		Industrial	ELEC own-price	-0.914
			ELEC-NG	1.693
			ELEC-RPP	0.024
			ELEC-COAL	2.824
			NG own-price	-3.719
			NG-RPP	0.331
			NG-COAL	-6.589
			RPP own-price	-0.222
			RPP-COAL	0.638
			COAL own-price	-10.642
U.S. Translog inter-fuel model (Griffin 1977)	Focus on the electricity generation sector, using OECD data, reporting for several countries – here I report the U.S. values.	Electricity Generation	NG own-price	-0.90
			NG-RPP	0.58
			NG-COAL	0.16
			RPP own-price	-3.46
			RPP-COAL	0.50
			COAL own-price	-0.66
MIT-EPPA (Paltsev, et al. 2005)	I report for fuel aggregations that are relevant to my study.	Electricity	COAL - RPP/NG bundle	1.00
			RPP - NG	0.30
		All sectors	Electricity - fuels bundle	0.50
		All except electricity	Among fuels	1.00
CIMS-Canada (Bataille 2005)	Translog cost function approach, using similar methodology to the current study.	National	ELEC own-price	-1.95
			ELEC-NG	1.91
			ELEC-RPP	1.73
			ELEC-COAL	.01
			NG own-price	-1.69
			NG-RPP	1.27
			NG-COAL	0.95
			RPP own-price	-0.35
			RPP-COAL	1.29
			COAL own-price	-1.16
		Electricity	NG own-price	-0.99
			NG-RPP	Na
			NG-COAL	2.13
			RPP own-price	-2.49
			RPP-COAL	Na
			COAL own-price	-1.34

Table 14 Summary of AEEI Values in Various Models/Studies

Model/Study	Notes	Sector	AEEI Value (%/yr)
MIT-EPPA (Paltsev, et al. 2005; personal communication)	Somewhat subjective/guesstimated it appears. Dr. Paltsev at MIT reported that in combination with price-induced changes, the AEEI and ESUB aggregate effect usually implies improvements in energy efficiency of about 1.2-1.3% for non-energy sectors and about 0.4-0.45% for electricity.	Electricity	0.35-0.40
		All sectors except electricity	1.00
MERGE (Richels and Blanford 2008)	MERGE model of U.S. Includes advanced technology scenario in which efficiency advances more quickly. I report both scenarios.	All sectors - technology as usual scenario	0.80
		All sectors - advanced technology path	1.00
CIMS-Canada (Bataille 2005, Bataille et al. 2006)	Calculated using the same methodology that I present in the next chapter, but with a Canadian application of CIMS, dating back 6 years. I use the results Bataille presents under conditions of all markets clearing).	Canada (Energy Demand)	0.57
		Canada (Energy Supply)	-0.73
		Canada (Demand and Energy Supply)	0.16
		Energy Demand Sectors	
		Residential	0.46
		Commercial & Institutional	1.59
		Transportation	0.53
		Industry	
		Total	0.27
		Chemical Products	0.33
		Industrial Minerals	0.84
		Iron and Steel	0.15
		Metal Smelting	0.52
		Mining	0.37
		Other Manufacturing	0.17
		Pulp and Paper	0.16
		Energy Supply Sectors	
		Crude Oil Extraction	-2.07
		Electricity	-1.09
		Coal Mining	0.65
		Petroleum Refining	0.46
		NG Extraction	0.22

Appendix C

Overview of ESUB Results

Table 15 Summary of Substitution Relationships

Region/Sector	**Substitution Relationships (K:EN = Capital for Energy; * = not applicable; _p = own-price elasticities)**												
	K:EN	**K-p**	**EN-p**	**E:N**	**E:O**	**E:C**	**N:O**	**N:C**	**O:C**	**Ep**	**Np**	**Op**	**Cp**
U.S. (w/ Trans.)	0.21	-0.06	-0.66	1.27	0.36	-0.73	1.10	3.00	-0.16	-1.02	-3.00	-0.77	-3.00
U.S. (w/o Trans.)	0.15	-0.02	-1.00	1.04	0.47	-0.69	2.83	2.59	-1.06	-0.60	-3.00	-3.00	-3.00
Demand Sectors													
Commercial	0.09	-0.01	-1.29	0.69	1.17	*	3.00	*	*	-0.20	-3.00	-3.00	*
Residential	0.13	0.00	-3.00	1.80	1.20	*	2.26	*	*	-0.34	-3.00	-3.00	*
Personal Transportation	0.28	-2.37	-0.03	-3.00	1.06	*	3.00	*	*	-3.00	-3.00	-0.04	*
Freight Transportation	0.07	-0.02	-0.20	*	*	*	3.00	*	*	*	-3.00	-0.15	*
Waste	0.17	0.01	2.64	*	*	*	*	*	*	2.64	*	*	*
Agriculture	0.05	-0.03	-0.09	0.76	0.02	*	-0.18	*	*	-0.26	-1.07	0.01	*
Industry													
Chemical Products	-0.02	0.00	0.08	1.50	1.11	-3.00	3.00	-3.00	3.00	-2.89	-1.30	-3.00	3.00
Industrial Minerals	0.07	-0.05	-0.11	0.64	3.00	0.13	-0.12	0.18	0.40	-0.63	-0.84	-3.00	-0.83
Iron and Steel	0.07	-0.16	-0.03	0.18	0.20	-0.07	3.00	0.19	0.17	-0.12	-3.00	-3.00	-0.17
Metal Smelting	0.06	-0.28	-0.01	0.26	0.61	-0.23	3.00	1.68	0.75	-0.12	-3.00	-3.00	-3.00
Mining	0.08	-0.16	-0.04	0.11	0.33	0.36	1.68	-3.00	0.36	-0.22	-3.00	-0.76	3.00
Other Manufacturing	0.07	-0.01	-0.41	0.82	0.77	-1.00	3.00	3.00	3.00	-0.78	-1.44	-3.00	-3.00
Pulp and Paper	0.11	-0.04	-0.31	0.57	0.48	-1.33	3.00	1.41	-0.37	-0.09	-3.00	-3.00	3.00
Supply Sectors													
Crude Extraction	0.07	-0.07	-0.06	-0.26	0.09	1.86	0.42	3.00	-0.54	-0.35	-1.57	-0.19	-3.00
Electricity	0.62	-0.24	-1.63	*	*	*	3.00	2.26	0.29	*	-1.47	-3.00	-3.00
Coal Mining	-0.31	1.06	0.09	-0.26	0.17	-3.00	-0.35	3.00	-1.11	-0.09	2.87	-0.12	3.00
Petroleum Refining	-0.05	0.02	0.09	-3.00	-1.87	-3.00	1.47	-3.00	0.04	-3.00	-3.00	-0.36	3.00
NG Extraction and Trans.	0.25	-0.10	-0.66	1.29	-3.00	*	0.12	*	*	-3.00	-0.43	3.00	*
Biofuels	1.56	-3.00	-0.51	2.46	0.16	1.26	0.72	3.00	-3.00	-3.00	-1.08	-1.02	-3.00

Appendix D

Cost Shares, and Own- and Cross-Price Elasticities of Demand

Table 16 Average Cost Shares of Aggregate and Fuel Inputs

	K	ENER	ELEC	NG	RPP	COAL
U.S. (w/ Trans.)	76.3%	23.7%	35.5%	18.7%	42.4%	3.4%
U.S. (w/o Trans.)	87.0%	13.0%	53.6%	28.8%	12.3%	5.3%
Demand Sectors						
Commercial	93.4%	6.6%	80.5%	14.3%	5.2%	*
Residential	96.3%	3.7%	82.0%	9.8%	8.2%	*
Personal Transportation	10.4%	89.6%	3.0%	0.0%	97.0%	*
Freight Transportation	75.0%	25.0%	*	2.7%	97.3%	*
Waste	107.0%	-7.0%	100.0%	*	*	*
Agriculture	63.4%	36.6%	25.9%	7.1%	67.0%	*
Industry						
Chemical Products	81.8%	18.2%	32.9%	57.7%	9.2%	0.2%
Industrial Minerals	59.4%	40.6%	45.8%	38.1%	0.6%	15.5%
Iron and Steel	30.0%	70.0%	44.9%	17.8%	18.7%	18.7%
Metal Smelting	16.6%	83.4%	75.7%	11.4%	10.6%	2.2%
Mining	33.5%	66.5%	58.5%	4.6%	36.0%	0.9%
Other Manufacturing	86.2%	13.8%	50.4%	45.8%	3.3%	0.5%
Pulp and Paper	74.1%	25.9%	77.3%	14.0%	5.8%	3.0%
Supply Sectors						
Crude Extraction	47.5%	52.5%	13.6%	27.3%	55.5%	3.6%
Electricity	72.4%	27.6%	*	62.3%	1.8%	35.9%
Coal Mining	22.8%	77.2%	48.2%	8.1%	43.6%	0.1%
Petroleum Refining	67.3%	32.7%	-4.1%	16.5%	87.6%	0.0%
NG Extraction and Trans.	72.4%	27.6%	25.1%	74.8%	0.0%	*
Biofuels	24.8%	75.2%	6.9%	63.1%	22.2%	7.8%

Cost shares are expressed as a percentage of expenditures on given aggregate factor or fuel, calculated from average expenditure across the 1024 simulation scenarios. Negative values for electricity in refining, and for energy in Waste sectors result from cogeneration of electricity. * indicates not-applicable.

Table 17 Own- and Cross-Price Elasticities of Demand

	Substitution Relationships (K:EN = Capital for Energy; * = not applicable; _p = own-price elasticities)											
Region/Sector	**K:EN**	**EN:K**	**K-p**	**EN-p**	**N:E**	**O:E**	**C:E**	**Ep**	**E:N**	**O:N**	**C:N**	**Np**
U.S. (w/ Trans.)	0.05	0.16	-0.05	-0.16	0.45	0.13	-0.26	-0.36	0.24	0.20	1.21	-1.13
U.S. (w/o Trans.)	0.02	0.13	-0.02	-0.13	0.56	0.25	-0.37	-0.32	0.30	0.82	0.75	-1.04
Demand Sectors												
Commercial	0.01	0.09	-0.01	-0.09	0.55	0.94	*	-0.16	0.10	1.97	*	-1.27
Residential	0.00	0.12	0.00	-0.12	1.47	0.99	*	-0.28	0.18	0.22	*	-1.66
Personal Transportation	0.25	0.03	-0.25	-0.03	-3.00	0.03	*	-0.80	-0.23	0.01	*	-0.03
Freight Transportation	0.02	0.05	-0.02	-0.05	*	*	*	3.00	*	0.12	*	-3.00
Waste	-0.01	0.18	0.01	-0.18	*	*	*	2.64	*	*	*	*
Agriculture	0.02	0.03	-0.02	-0.03	0.20	0.00	*	-0.07	0.05	-0.01	*	-0.08
Industry												
Chemical Products	0.00	-0.02	0.00	0.02	0.49	0.37	-2.03	-0.95	0.87	1.93	-3.00	-0.75
Industrial Minerals	0.03	0.04	-0.03	-0.04	0.29	2.27	0.06	-0.29	0.24	-0.05	0.07	-0.32
Iron and Steel	0.05	0.02	-0.05	-0.02	0.08	0.09	-0.03	-0.06	0.03	0.69	0.03	-0.84
Metal Smelting	0.05	0.01	-0.05	-0.01	0.20	0.46	-0.18	-0.09	0.03	0.36	0.19	-0.57
Mining	0.05	0.03	-0.05	-0.03	0.06	0.19	0.21	-0.13	0.00	0.08	-0.38	-0.60
Other Manufacturing	0.01	0.06	-0.01	-0.06	0.41	0.39	-0.51	-0.40	0.38	3.00	1.77	-0.66
Pulp and Paper	0.03	0.08	-0.03	-0.08	0.44	0.37	-1.03	-0.07	0.08	2.60	0.20	-1.56
Supply Sectors												
Crude Extraction	0.04	0.03	-0.04	-0.03	-0.04	0.01	0.25	-0.05	-0.07	0.11	1.75	-0.43
Electricity	0.17	0.45	-0.17	-0.45	*	*	*	*	*	3.00	1.40	-0.92
Coal Mining	-0.24	-0.07	0.24	0.07	-0.12	0.08	-3.00	-0.04	-0.02	-0.03	2.71	0.23
Petroleum Refining	-0.01	-0.03	0.01	0.03	1.07	0.08	3.00	3.00	-3.00	0.24	-3.00	-2.06
NG Extraction and Trans.	0.07	0.18	-0.07	-0.18	0.32	-3.00	*	-0.89	0.96	0.09	*	-0.32
Biofuels	1.17	0.39	-1.17	-0.39	0.17	0.01	0.09	-1.69	1.55	0.45	2.89	-0.68

Table 17 Own- and Cross-Price Elasticities of Demand (Continued)

Region/Sector	N:E	O:E	C:E	Ep	E:N	O:N	C:N	Np
U.S. (w/ Trans.)	0.15	0.46	-0.07	-0.33	-0.02	0.22	-0.01	-0.88
U.S. (w/o Trans.)	0.06	0.35	-0.13	-1.01	-0.04	0.14	-0.06	-0.25
Demand Sectors								
Commercial	0.06	0.71	*	-2.91	*	*	*	*
Residential	0.10	0.19	*	-1.21	*	*	*	*
Personal Transportation	1.03	3.00	*	-0.04	*	*	*	*
Freight Transportation	3.00	3.00	*	-0.15	*	*	*	*
Waste	*	*	*	*	*	*	*	*
Agriculture	0.01	-0.12	*	0.01	*	*	*	*
Industry								
Chemical Products	0.10	0.31	0.36	-2.30	-0.01	-0.05	0.01	3.00
Industrial Minerals	0.03	0.00	0.00	-2.28	0.02	0.03	0.06	-0.13
Iron and Steel	0.04	0.73	0.03	-0.81	-0.01	0.03	0.03	-0.03
Metal Smelting	0.06	0.34	0.08	-0.84	-0.01	0.04	0.02	-0.10
Mining	0.12	0.61	0.13	-0.27	0.00	-0.07	0.00	0.04
Other Manufacturing	0.03	0.23	0.13	-3.00	-0.01	0.02	0.02	-1.40
Pulp and Paper	0.03	1.07	-0.02	-2.95	-0.04	0.04	-0.01	0.85
Supply Sectors								
Crude Extraction	0.05	0.23	-0.30	-0.11	0.07	0.23	-0.02	-1.70
Electricity	*	0.11	0.01	-3.00	*	0.81	0.10	-1.41
Coal Mining	0.07	-0.15	-0.48	-0.05	-0.01	0.05	0.00	1.11
Petroleum Refining	-1.64	1.29	0.03	-0.32	-0.20	-0.30	0.00	3.00
NG Extraction and Trans.	-0.08	0.00	*	3.00	*	*	*	*
Biofuels	0.04	0.16	-0.69	-0.23	0.10	0.36	-0.24	-2.29