Towards General Equilibrium in a Technology-Rich Model with Empirically Estimated Behavioural Parameters

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Abstract

Most energy-economy policy models offered to policy makers are deficient in terms of at least one of technological explicitness, microeconomic realism, or macroeconomic completeness. We herein describe CIMS, a model which starts with the technological explicitness of the "bottom-up" approach and adds the microeconomic realism and macroeconomic completeness of the "top-down" CGE approach. This paper demonstrates CIMS' direct utility for policy analysis, and also how it can be used to better estimate the long run capital-for-energy substitution elasticity (ESUB) and autonomous energy efficiency index (AEEI) technology parameters used in top-down models. By running CIMS under several possible energy price futures and observing their effects on capital and energy input shares and energy consumption, we estimate an economy-wide ESUB of 0.26 and an AEEI of 0.57%, with significant sectoral differences for both parameters.

1. Introduction

Policy makers need to forecast the responses of businesses and consumers to policy signals meant to influence the uptake of more environmentally benign energy supply and demand technologies. Two types of policy models attempt to provide this service. Conventional bottom up models describe current and prospective technologies in detail, but lack a realistic portrayal of microeconomic decision-making by businesses and consumers when selecting technologies, and fail to represent potential macroeconomic equilibrium feedbacks. Conventional top-down models, in contrast, address these deficiencies by representing macroeconomic feedbacks in a general equilibrium framework and, where feasible, by estimating parameters of technological change from observations of aggregate market responsiveness to cost changes and non-price autonomous trends. Without technological detail, however, these models are unable to help policymakers assess how future market responses and autonomous trends might differ from the past as technology-specific regulations and new expectations interact with market incentives over long time periods. Frustration with this methodological dichotomy has led a growing number of researchers around the world to explore hybrid modelling approaches that combine the technological explicitness of bottom-up models with the microeconomic realism and macroeconomic feedbacks of top-down models.

In this paper, we briefly describe the conventional top-down and bottom-up modelling approaches, and then describe our efforts to produce a hybrid model by adding supply and demand equilibrium feedbacks to a technologically rich and behaviourally realistic model. Section 2 compares the strengths and weaknesses of the traditional model structures. Section 3 describes the main streams of hybrid model development, how we added supply and demand equilibrium feedbacks to our hybrid model, and the significance of these feedbacks for policy analysis. Section 4 describes how the model can be used to improve the estimation of two parameters critical to top-down models' depiction of technology, the input elasticities of substitution and the autonomous energy efficiency index. Section 5 concludes and provides a brief summary of future methodological directions.

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2. The Limitations of Traditional Modeling Approaches

Historically, policy makers have faced the dilemma of choosing between bottom-up or top-down models to assess policies to influence energy-related technology choices (Jaccard et al., 2003). Bottom-up analysis, applied frequently by engineers, physicists and environmental advocates, estimates how changes in energy efficiency, fuel use, emission control equipment, and infrastructure might influence energy use and thus environmental impacts. When their financial costs are converted into present value using a social or financial cost-of-capital discount rate (3-12%), many emerging technologies available for abating various emissions appear to be profitable, or just slightly more expensive relative to existing stocks of equipment and buildings. These models show, therefore, that environmental improvement can be profitable or low cost. Many economists criticize this approach, however, for its assumption that a single, *ex ante* estimate of financial cost indicates the full *ex post* social cost of technological change. New technologies present greater risks, as do the longer paybacks associated with investments like energy efficiency. A broad literature indicates that revealed discount rates, which include anticipation of extra cost and failure risk, are 20-50% for industrial applications and as high as 80% for residential applications (Nyboer, 1997).

The alternative, top-down analysis, usually applied by economists, estimates aggregate relationships between the relative costs and market shares of energy and other economic inputs, and links these to sectoral and total economic output in a broader equilibrium framework. Two key parameters generally describe the capacity for technological change in the face of policy in these models: elasticities of substitution (ESUBs) and the autonomous energy efficiency index (AEEI). ESUBs indicate the substitutability between any two pairs of aggregate inputs (capital, labour, energy, materials), and between the different forms of usable secondary energy (electricity, processed natural gas, gasoline, diesel, methanol, ethanol, hydrogen) as their relative prices change. The higher the capital-for-energy and inter-fuel ESUBs, the lower will be the cost of policies to reduce energy use or greenhouse gas (GHG) emissions. AEEI indicates the rate at which price-independent technological evolution improves energy productivity, and is a function of technology improvement and capital stock turnover. The higher AEEI is, the faster the economy is becoming more efficient at using energy (and by implication reducing GHG intensity). When analyzing any type of policy that involves long run technological adjustment, it is critical that both types of parameters accurately reflect the underlying system dynamics.

We conducted a survey to improve our understanding of how ESUBs and AEEI are typically estimated and used in climate change policy models. While not comprehensive, the survey provides a sample of various approaches to capital-for-energy substitution (Table 1) and AEEI (Table 2), their parameter values, and how they were estimated.

Table 1 and Table 2 show that most of the parameters in general use are guessed using expert judgment, based on estimates from historic data in the case of ESUBs, or used as tools to calibrate to base-year statistics or a growth forecast in the case of AEEI; data seems to be more available for ESUBs than AEEI. ESUBs and AEEI would preferably be estimated from historical data; this, however, is a substantial challenge because there is often insufficient variability in the historical record, insufficient disaggregation of data, or the necessary data are missing to estimate statistically valid parameters. As a result, most top-down modellers set their ESUBs and AEEI judgmentally, based on the best historical data they can find. Additionally, while parameters based on historic data would usually hold more credence, Griffin (1977) suggested that it may be impossible to calculate the long run capital-for-energy ESUB from past data because the future production possibility frontier is constantly adjusting in response to input prices, technological advances, and energy and environment policy (Grubb et al., 2002). The emergence of hybrid gasoline-electric vehicles, for example, will probably increase the transportation sector's AEEI, because it allows for improved energy efficiency, and increase ESUB, because it will enhance the consumer's ability to choose between capital and energy in response to their relative input prices. On a larger scale, until recently there was little incentive to design and commercialize technologies with zero or near-zero GHG emissions; today, such technologies are under development worldwide. Top-down models are unable to help policy makers assess this dynamic. Increasingly concerned with these long-term parameterization problems, some top-down modellers are exploring ways of treating technological change endogenously. However, there has been little success in linking real-world evidence to the estimation of aggregate parameters of technological change in these models (Löschel, 2002).

Model with sample references	Relationship between Capital and Energy	Parameter Sources
SGM MacCracken et al (1999), Sands (2002)	For most sectors a non-nested, single level constant elasticity of substitution (CES) production function is used to represent substitution between capital, labour, energy and other intermediate inputs. A short-run elasticity of 0.1 is used for all sectors except electricity, refining and gas distribution, which use 0. A long run elasticity of 0.28 is used for all but electricity, refining, and gas distribution (0.1), agriculture (0.3), and services (0.4). In recent versions the equivalent of Leontief production functions are used to represent explicit generating and producing technologies in electricity and iron and steel, which are competed based on lifecycle cost.	A mixture of values from the literature and expert judgment.
MIT-EPPA Babiker et al (2001) and McFarland et al. (2004)	For each sector the top-level relationship is a Leontief production function between intermediate inputs and capital, labour and energy. At the second level it uses a CES production function with capital and labour nested against energy ((K:L):E) with an elasticity of 0.5 (0.4 for electricity). Recent versions compete discrete electricity technologies using a similar approach to SGM.	“
G-Cubed McKibben and Wilcoxen (1999)	The top-level relationship is a CES with capital, labour and energy and materials sub-nests. Top-level elasticities range from 0.2556 to 1.703; estimated elasticities in the energy nest range from 0.1372 to 1.14. Estimation of the elasticities for electricity, refining and transportation produced nonsensical values that were replaced with 0.2.	Most elasticities are estimated from historic data, with some set using expert judgment.
AIM Kurosawa et al. (1999)	The top-level relationship is a CES between energy, primary factors (capital, labour) and intermediate inputs (σ =0.3). At the second level it uses CES relationships which substitute capital against labour and electricity against fossil fuel energy, which are substituted on a 3rd level.	Set using expert judgment
MS-MRT Bernstein et al. (1999)	The top-level relationship is a Leontief production function between intermediate inputs and capital, labour and energy. At the second level it a uses a CES capital and labour nested together against energy ((K:L):E) with an elasticity of 0.25-0.5 depending on the country.	“
McKitrick (1998)	The relationships in this model were set econometrically, and so are not uniformly structured. The top-level relationship is a nested CES, usually but not always non-energy vs. energy. Non-energy breaks down into various sub-components that usually include capital and labour. Manufacturing (0.23), Services (0.09), Mining (1.15), Utilities (0.15), Refining (0).	Most elasticities are estimated from historic data, with some set using expert judgment.
CASGEM Iowerth et al. (2000)	The relationship between energy and the primary factors is indirect; energy is treated as an intermediate good. CASGEM first substitutes primary and intermediate goods (0.2-0.7), and then stationary energy and other intermediate goods (0.2-1.45), and on the third level non-fuel intermediate goods and motive fuels (0.1-0.83), as well as splitting stationary energy between electricity and fossil fuels (0.6-2.25).	Based on the Canadian econometrics literature and Natural Resources Canada’s Interfuel Substitution Demand model.
AMIGA Hanson and Laitner (2004)	A nested CES production function with vintaged capital stock for both energy-related and non-energy related capital. For energy-related services from 1 to j (in buildings, for example, ranging from heating and cooling to lighting and equipment), the third level provides a trade-off between energy-related capital to energy flows. Elasticities, determined by a comparison of actual technologies (e.g., an array of natural gas or electric heating systems, each with different requirements for capital and energy), range from 0.4 to 0.8.	The parameters sources are from a mixture of detailed technology characterizations, historic time series data, and expert judgment.

Table 1. Summary of the relationship between capital and energy in various models (ESUB)

Griffin (1977) suggested a different method to estimate long run ESUBs; instead of looking to past data for the production possibility frontier, he suggested that one could instead use a bottom-up model as a production function and subject it to a broad range of input prices. The resulting input share data could then be utilized as “pseudo” or “future-historical” data, which could be subjected to standard econometric regression techniques to find an estimate of long run ESUBs. Jaccard and Bataille (2000) reported results from such an exercise using a technologically rich and behaviourally realistic bottom-up model of 10 sectors of the Canadian economy.[1] The average capital-for-energy substitution elasticity was estimated to be one of mild substitutability (an Allen partial elasticity of 0.24), with significant sector differences. Inter-fuel elasticities were generally significantly more elastic. An AEEI for the same 10 sectors was also calculated, with an average rate of 0.69% per year, by comparing a technologically frozen future to a business-as-usual reference case.

The ESUB and AEEI research described above was conducted with a Canadian version of the ISTUM technology simulation model (Nyboer, 1997); it did not include feedbacks for energy prices, cost driven changes in prices and

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[1] Jaccard and Bataille (2000) included the following sectors: Pulp and Paper, Industrial Minerals, Commercial and Institutional, Residential, Iron and Steel, Chemical Products, Other Manufacturing, Metal Smelting, Mining and Petroleum Refining.

demand, or more general macroeconomic feedbacks common in standard top-down models. To test the hypothesis that the ESUB and AEEI estimates may be sensitive to these feedbacks, we needed to add them to ISTUM and re-do the estimates. This direct requirement opened a broader line of inquiry: is it possible to build a full general equilibrium model starting with a behaviourally realistic bottom-up model?

Model	AEEI (%)	Source
SGM	Used primarily for calibration	Energy efficiency is used to calibrate against a base case.
MS-MRT	"	"
AMIGA	"	".
MIT-EPPA – US Note: AEEI decreases with time as producers exhaust the technical potential for saving energy. Primary energy sectors are unaffected.	1.301	Expert elicitation and literature
MIT-EPPA – Other OECD	1.210	"
MIT-EPPA – China	1.980	"
MIT-EPPA – India	1.430	"
MIT-EPPA – Rest of World	1.100	"
G-Cubed	1	Expert judgment
CASGEM	Not applicable	"
AIM	Not applicable	"
McKitrick (1998)	0.5	"

Table 2 Treatment of energy productivity over time (AEEI)

3 A New Hybrid Approach to Energy Modeling

While it is impossible for any policy model to be completely accurate in its representation of current conditions or its characterization of future dynamics, the previous section suggests criteria by which we can judge the ability of an energy-economy model to be more useful to policy makers. It would be technologically explicit, including an ability to assess how policies to promote technology commercialization and diffusion might affect the future financial costs of acquiring new technologies. It would be behaviourally realistic, including an ability to assess how policies to increase market share might affect the future intangible costs of acquiring new technologies. Finally, it would have equilibrium feedbacks linking the production cost of final and intermediate input goods and services to their supply and demand, as well as more general macroeconomic feedbacks, including long term balancing of the government budget and labour and investment market equilibrium.

Several modelling teams have explored the development of hybrid models that endeavour to meet these criteria. There are two general approaches. The first is to add technological explicitness to a top-down computable general equilibrium (CGE) or neo-classical growth model.[2] This is usually done by representing explicit technologies as Leontief fixed input share production functions and allocating market share amongst these technologies using life-cycle-cost competitions (e.g., Sands, 2002), or by advanced mathematical techniques, e.g. by solution of a mixed complementarity problem (Böhringer, 1998). Work in this area has generally been confined to the energy supply side of the economy, with Sands (2002) also using it in the iron and steel sector. The second approach is to add economic equilibrium feedbacks to a bottom-up model; developments with the MARKAL optimization model have been particularly noteworthy. The original MARKAL integrated the energy supply chain (Fishbone and Abilock, 1981), MARKAL-MACRO (Manne and Wene, 1992) introduced a basic growth model and economy-wide production function, MARKAL-ED (Loulou and Lavigne, 1996) added demand elasticities for key products, and 15-Region MARKAL (Labriet et al., 2004) integrated MARKAL models for 15 world regions. In terms of behavioural realism, however, linear programming models such as MARKAL suffer from an inherent emphasis on financial cost minimization.

Jaccard et al. (1996) suggested using a technologically rich and behaviourally realistic bottom-up model instead of an optimization model as the foundation for a general equilibrium model: this project became the energy-economy model now known as CIMS. We pursued the first two requirements, technological richness and behavioural realism,

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[2] Authors in this area include: Jacobsen, 1998; Koopmans and te Velde, 2001; Morris et al., 2002; Frei et al., 2003; Babiker et al., 2001; McFarland et al., 2004; Hanson and Laitner, 2004; and Schäfer and Jacoby, 2005.

by building the necessary sector sub-models (Nyboer, 1997; Jaccard et al., 2003) and empirically estimating key behavioural parameters for technology competitions (Rivers and Jaccard, 2005; Horne et al. 2005). A brief description of the scope and function of these aspects of CIMS is described below and in Appendix A.

Starting with an initial exogenous forecast of physical output, CIMS' sector sub-models track the evolution of all energy-using capital stocks over a 35 year time horizon, including individual technology level accounting for base year stock, new purchases, retrofits, and retirement. When making new purchases and performing retrofits, consumers and firms make decisions with limited foresight based on financial and intangible costs. These include: financial capital, labour, energy, material and emissions costs; intangible risk, time preference, option value costs; and individual and firm level positive and negative externalities. The model also includes two functions for simulating endogenous change in individual technologies' characteristics in response to policy: a declining capital cost function to represent economies-of-scale and learning-by-doing, and a declining intangible cost function for new technologies that may be unfamiliar to firms and consumers.

Approximately 2800 technologies are competed in CIMS in hundreds of final and intermediate goods and services competitions. These competitions are organized by sector; the most important final and intermediate goods and services are described in Table 3, but there are hundreds of intermediate end-uses that are also competed, e.g., space heating and cooling, pumping, compression, conveyance, steam, air displacement, etc. Appendix A describes the technology competition and endogenous technological change algorithms in CIMS.

Sector Models	**Final and intermediate goods and services produced by the sector models***
Commercial / Institutional	Refrigeration, cooking, hot water, and plug load
Transportation	Freight (marine, road, rail and rail), Personal (intercity and urban, which splits into single and high occupancy vehicles, public transit and walking and cycling) and off-road
Residential	Refrigeration, dishwashers, freezers, ranges, clothes washers/dryers.
Iron and Steel	Slabs, blooms and billets
Pulp and Paper	Newsprint, linerboard, uncoated and coated paper, tissue and market pulp.
Metal Smelting	Lead, copper, nickel, titanium, magnesium, zinc and aluminium
Chemical Production	Chlor-alkali, sodium chlorate, hydrogen peroxide, ammonia, methanol, and polymers
Mining	Open-pit, underground and potash
Industrial Minerals	Cement, lime, glass and bricks
Other Manufacturing	Food, tobacco, beverages, rubber, plastics, leather, textiles, clothing, wood products, furniture, printing, machinery, transportation equip., electrical and electronic equipment
Petroleum Refining	Gasoline, diesel, kerosene, naphtha, aviation fuel, and petroleum coke
Electricity Prod.	Electricity
Natural Gas Production	Natural gas and natural gas liquids
Coal Mining	Lignite, sub-bituminous, bituminous and anthracite coal
Crude Oil Production	Light/medium and heavy crude oil, bitumen and synthetic crude oil

* All include space heating and cooling, pumping, compression, conveyance, hot water, steam, air displacement, and motor drive as applicable.

Table 3 CIMS sub-sectors

Technological adjustment through available options (ESUB), over time with new technological development independent of policy (AEEI), or as a consequence of policy (also known as "induced technological change"), is only part of the economy's response to energy policy. A further adjustment may occur in the demands for final and intermediate goods and services as their relative costs change under the influence of policy, leading to structural change in the economy. For example, a rising cost for domestic steel production may lead to a declining competitive position for domestic producers relative to foreign producers in domestic and export markets. A rising cost for using personal vehicles may lead to a decline in the demand for mobility as well as shifts to public transit or walking. The addition of micro and macro-economic equilibrium feedbacks to include these kinds of dynamics in CIMS is described in the next section.

The addition of economic equilibrium feedbacks to the CIMS hybrid model

CIMS estimates the effect of a policy by comparing a business-as-usual market equilibrium with one generated by a policy. The model operates by iteration of two sequential phases in each five year period, with as many iterations as necessary to arrive at a new policy equilibrium in each period. The scope of a policy can range from one that affects a single technology, such as a subsidy to a specific technology, to a technology competition, where one might apply an efficiency standard applying to a single market, all the way up to an economy-wide carbon tax or emissions permit trading system.

The first phase, equilibrium of energy supply and demand, is described schematically in Figure 1. In this first phase, the models representing the final goods and services producing sectors of the economy are run first (the transportation, residential, commercial and industrial models on the left side of Figure 1). The firms and consumers in these sectors choose capital stocks based on CIMS' technological choice algorithms, which minimize financial and intangible expenditure on capital, labour, energy and emissions charges based on an initial set of input prices. Based on this, the model then calculates the demand and cost of delivery for electricity, refined petroleum goods and primary energy commodities, including any policy effects (the middle and right side of Figure 1). If the cost of producing any of these commodities has changed by a threshold amount (normally 5%) from the business-as-usual case, the model is considered to be in disequilibrium and is re-run based on prices calculated from the new production costs. Prices are adjusted using multipliers of the base case absolute values. The model will iterate until a new equilibrium set of energy prices and demands is reached, i.e., all prices change by less than 5% between iterations, which usually occurs within three iterations.[3]

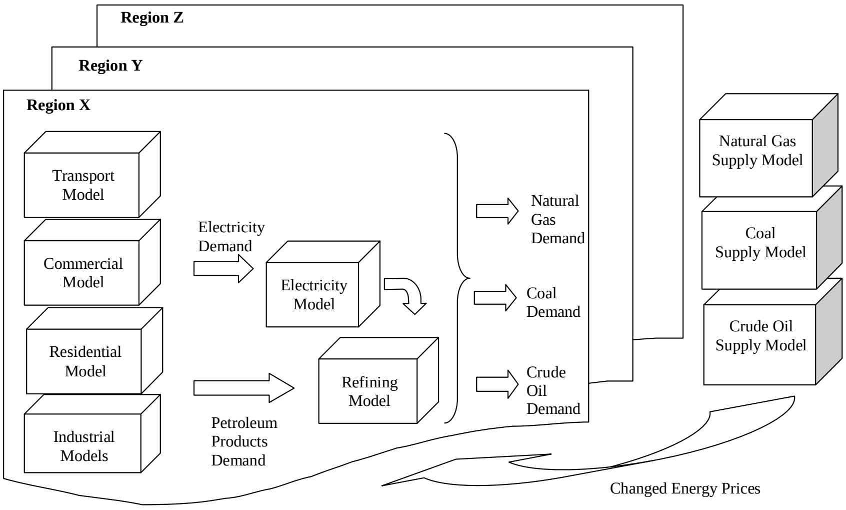

Figure 1 **CIMS' energy supply and demand flow model**

In the second phase, once a new equilibrium set of energy prices has been reached, the model then calculates the degree to which the costs of producing traded goods and services have changed; assuming perfectly competitive markets, these changes translate directly into prices. These new prices are used to adjust demand for internationally traded goods using price elasticities which follow the Armington specification, which provides a demand response that blends domestic and international demand for these goods.[4] Demand for freight transportation is linked, using a cross price elasticity of 0.95, to the combined value added of the industrial sectors, while personal transportation is adjusted using an own-price personal kilometres traveled elasticity (-0.02; Michaelis and Davidson, 1996). Residential and commercial floorspace are adjusted by a sequential substitution of home energy consumption vs. other goods ($\sigma = 0.5$), consumption vs. savings (1.29) and goods vs. leisure (0.82) in response to the new cost of service (McKitrick, 1998; Iowerth et al., 2000).[5] If demand for any good or service has shifted more than a threshold amount, typically 5%, the model is considered to be in disequilibrium and re-runs both the energy supply

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[3] An energy trade function, based on Armington price elasticities applied to changes in the cost of producing energy commodities, can also be included.

[4] CIMS' Armington elasticities are derived from Wirjanto (1999), who estimated them econometrically based on the 1960-1990 period. If a policy were to cause a response outside the 1960-1990 experience, it may be desirable to set these elasticities judgmentally.

[5] We have also used a method whereby CIMS adjusted demand for residential households and commercial floorspace using an econometric relationship between these variables and value added in the traded sector. For various reasons, this method was adequate for small policy shocks, but not for large ones.

and final demand phases using the last set of prices and the new demands. The model continues re-iterating until supply and demand for all goods and services comes to a new equilibrium, and repeats this convergence procedure every five years until the end of the run, which can last from 5-35 years.[6]

Figure 2 shows the effect of including progressive levels of macroeconomic structural feedbacks in CIMS on the predicted cost of GHG reductions in Canada over a 10-year period, starting in 2005. The marginal cost of GHG abatement in on the vertical axis, and the corresponding levels of GHG reductions on the horizontal axis.

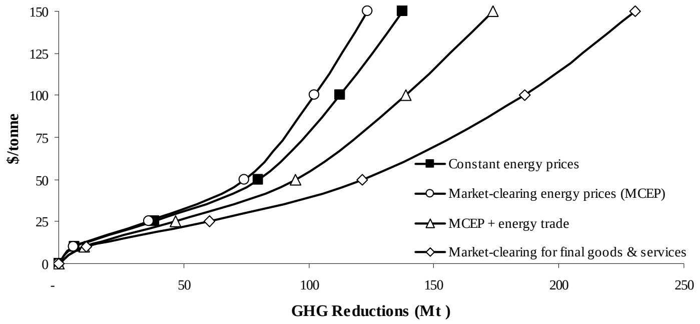

Figure 2 GHG reductions (Mt CO_2e) in Canada after 10 years of GHG pricing ($ Cdn.)

The "Constant energy prices" scenario, where each sector is run independently with no goods or services linkages between them, is an example of the common practice of sector specific analyses that assume constant fuel prices under business as usual and policy; a $150 per tonne CO_2e charge generates 140 Mt of GHG emissions reductions. When feedbacks for "Market clearing energy prices" are included, demands for all fuels are forced to balance with supply at the prevailing cost of production; in other words, the supply sectors are forced to produce as much energy as demanded, and charge the consumer the requisite price. Because of this, the marginal GHG abatement curve is shifted up in relation to the constant energy prices case; a $150 per tonne price generates 124 MT in reductions, 16 Mt less than the constant energy prices case.

Including energy trade has a significant effect on GHG emissions. At the $150 per tonne GHG price reductions increase to 173 Mt. Canada's exports of natural gas and crude oil to the United States produce significant domestic GHG emissions. Key amongst these are combustion emissions from producing bitumen and synthetic crude oil, venting emissions from heavy crude oil production, leakage from natural gas pipelines, and combustion emissions from natural gas pipeline compressors. Export demand for natural gas and crude oil is somewhat elastic (Armington own price elasticities of -0.67 and -0.92 respectively represent responsiveness over a broad range of prices) and application of GHG pricing to the production and transmission of natural gas and crude oil increases their cost, reduces their demand, and thus reduces their associated emissions.

Introducing market clearing for final goods and services increases GHG emissions reductions at all prices, because the increased cost of production associated with carbon costs raises prices and reduces final demand, thus reducing overall emissions. At $150 per tonne price, GHG reductions increase to 230 Mt. The sectors that are most affected are the industrial minerals and chemicals sectors, both of which produce significant process emissions. Demand reductions in this analysis were limited to 50% of initial demand: industrial minerals declines to this level by $50 per tonne CO_2e and chemicals by $75 per tonne CO_2e.[7] Most other sectors do not significantly reduce output (defined as more than 3-5%) until the GHG price is well above $75 per tonne CO_2e.

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[6] In the current version of CIMS Canada is treated as a small, open and highly traded economy (e.g., McKitrick, 1998; Iowerth et al., 2000). The domestic interest rate is effectively exogenous as it is assumed to be determined by the US prime rate, and foreign savings are assumed to be available elastically; the foreign sector automatically clears any surplus or deficit in the domestic savings market. The wage rate is also currently exogenous. In ongoing work, we are adding to CIMS a household and a sector to represent the economically important sectors that use little energy. Once these projects towards a more general equilibrium are complete, we will be able to optimize the discounted utility of household consumption as the fundamental driver in the model, link the supply of capital to the domestic savings rate, equilibrate the labour market and wage rate, and endogenize overall growth.

[7] Limits on output changes were included judgmentally to represent the feasible range for which the own-price elasticities could be relied upon without more elaborate structural feedbacks.

In summary, macroeconomic structural change and demand feedbacks have little effect on GHG emissions reductions under small carbon charges for most sectors, and by analogy on energy policies that cause only small changes in energy prices, but become increasingly significant with the strength of policy.

4. Generating Long Run ESUB and AEEI Values for Top-down Models

We calculated capital-for-energy and inter-fuel elasticities using CIMS by running simulations under a broad range of energy and capital prices and under three different equilibrium conditions, and used the results to estimate input substitution elasticities. The price for each input was adjusted by -50%, -25%, +25%, +50%, +75%, and for each range of prices we ran three different simulation conditions: no economic equilibrium feedbacks, just energy supply and demand feedbacks, and full goods and services supply and demand feedbacks. 35 year simulations were run to capture the long run turnover of the capital stock. The simulation shares of the inputs as a proportion of total production costs were used as data in a translog production function; see Appendix B for a description of this regression process. This process, under full feedback conditions, generated a long run capital-for-energy ESUB value for Canada of 0.26 and inter-fuel ESUB values ranging mostly from 0.95 to 2.0. The sector values differed widely, suggesting that future structural changes between sectors' shares of total production could change the overall Canadian capital for energy ESUB. Detailed results for the capital-for-energy ESUB are presented in Table 4.

Sector / Regions		**Capital (K) for (E)nergy ESUB**		
		All goods and services feedbacks	**Energy supply and demand feedbacks**	**No feedbacks**
Canada		0.26	0.10	0.21
Energy Demand Sectors				
Residential		0.30	0.28	0.36
Commercial & Institutional		0.27	0.20	0.21
Transportation		0.31	0.02	0.24
Industry	Total	0.13	0.10	0.09
	Chemical Products	0.04	0.03	0.03
	Industrial Minerals	0.33	0.26	0.38
	Iron and Steel	0.12	0.01	0.01
	Metal Smelting	0.02	0.03	0.06
	Mining	0.18	0.14	0.15
	Other Manufacturing	0.03	0.04	0.05
	Pulp and Paper	0.32	0.24	0.17
Energy Supply Sectors				
	Crude Oil Extraction	-0.07	-0.09	-0.07
	Electricity	0.33	0.31	0.20
	Coal Mining	0.39	0.38	0.39
	Petroleum Refining	-0.09	-0.11	-0.15
	NG Extraction	-0.26	-0.29	-0.28

Table 4 Long run Allen partial capital-for-energy substitution elasticities by sector

Table 4 shows that the capital-for-energy ESUB estimates for many of the sectors are sensitive to the inclusion of equilibrium feedbacks: Canada overall rises from 0.21 to 0.26 with full feedbacks, the residential sector falls from

0.36 to 0.3; the commercial and institutional sector rises from 0.21 to 0.27; transportation, which consumes half the energy in Canada by value, rises from 0.24 to 0.31, and industry as a whole rises from 0.09 to 0.13. The electricity sector rises from 0.2 to 0.33, while the rest of the energy supply sectors are relatively unaffected.

The individual capital-for-energy ESUBs for each of electricity, oil products, natural gas and coal varied considerably. The aggregate capital-for-electricity estimate with full feedbacks was 0.32, capital-for-natural gas -0.05, capital-for-oil products 0.13, and capital-for-coal 0.09. These estimates indicate most of the potential for capital-for-energy substitution, a partial proxy for energy efficiency, is between capital and electricity.[8]

The aggregate inter-fuel substitution elasticity estimates from CIMS, with the exception of electricity-for-coal (0.01), ranged from 0.95 to 1.91. Electricity-for-oil products was 1.73, electricity-for-natural gas 1.91, oil products-for-natural gas 1.27, natural gas-for-coal 0.95, and coal-for-oil products 1.29.

AEEIs were calculated by comparing two simulations of CIMS, one in which economic structure and the mix of technologies were held constant at their year 2000 states, while in the other technological and structural development proceeded normally. The difference in energy use between the two futures in 2035 was then used to calculate the yearly increase in autonomous energy efficiency (Equation 1).

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

AEEI is the autonomous change in energy efficiency (%/year), *TF* is energy consumption in the (T)echnically (F)rozen universe, *BAU* is energy consumption in the (B)usiness (A)s (U)sual universe, and *n* is the number of compounding periods, which was 35 years. This process, under full feedback conditions, generated an AEEI of 0.57% per year for Canada and sector AEEIs ranging from -2.07 to 1.53 %, with the majority in the range of 0.15-0.85%. This compares to 0.25-0.5% for top-down estimates in the literature, and 0.75-1.5% for bottom-up estimates. Detailed results are presented in Table 5.

The AEEI estimates for many of the sectors are sensitive to the inclusion of equilibrium feedbacks: Canada in aggregate rises from 0.53 to 0.57 with full feedbacks; the residential sector rises from 0.19 to 0.46; the commercial and institutional sector rises from 0.82 to 1.59; transportation rises from 0.32 to 0.53, and industry as a whole rises from 0.16 to 0.27. The electricity sector rises from -0.27 to -1.09 and petroleum refining rises from 0.34 to 0.46, while the rest of the energy supply sectors are relatively unaffected by feedback levels.

The commercial and institutional sector AEEI estimate is significantly higher than that for the other sectors, which perhaps reflects a potential for efficiency increases as older, less efficient stock is replaced. Crude oil extraction’s decrease in efficiency (-2.07%) reflects business-as-usual structural change in the Canadian crude oil production industry over the next generation; conventional oil production is declining at the same time as energy intense oil sands production is increasing. Electricity production’s decrease in efficiency is also reflective of structural change; while a large majority of existing equipment is hydroelectric or nuclear, most new capacity is uses fossil fuels in the simulations.

The ESUB and AEEI estimates generally confirm the judgmentally estimated values used in top-down models, with a couple of important caveats. A single production function with one capital-for-energy substitution elasticity representing the entire production side of the economy is not sufficient to capture the full breadth of possible responses to energy policy; top-down models must incorporate sufficient sector and sub-sector technological disaggregation to capture the full potential for fuel switching and energy efficiency improvements. A single AEEI for the entire economy is also insufficient; the aggregate AEEI will shift with the shares of sectors of total economic activity, and a model’s level of disaggregation must be sufficient to reflect this.

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[8] Energy efficiency can, in general, can be increased by either substituting capital for energy, e.g. by using compact fluorescent light bulbs in place of incandescent ones, or by more directly applying primary energy to an end-use, e.g. by using natural gas directly for space heating instead of using it to make electricity for space heating purposes.

Sector / Regions		AEEI % / year		
		All goods and services feedbacks	Energy supply and demand feedbacks	No feedbacks
Canada (Energy Demand - analogous to that used in macro models)		0.57	0.38	0.53
Canada (Energy Supply)		-0.73	-0.34	-0.37
Canada (Demand and Energy Supply)		0.16	0.13	0.22
Energy Demand Sectors				
Residential		0.46	0.31	0.19
Commercial & Institutional		1.59	0.85	0.82
Transportation		0.53	0.18	0.32
Industry	Total	0.27	0.16	0.16
	Chemical Products	0.33	0.20	0.20
	Industrial Minerals	0.84	0.17	0.17
	Iron and Steel	0.15	0.06	0.06
	Metal Smelting	0.52	0.39	0.39
	Mining	0.37	0.35	0.35
	Other Manufacturing	0.17	0.15	0.15
	Pulp and Paper	0.16	0.01	0.01
Energy Supply Sectors				
	Crude Oil Extraction	-2.07	-2.07	-2.07
	Electricity	-1.09	-0.21	-0.27
	Coal Mining	0.65	0.65	0.65
	Petroleum Refining	0.46	0.33	0.34
	NG Extraction	0.22	0.20	0.20

Table 5 : Long run AEEI results by sector

5. Conclusions

The conventional top-down and bottom-up energy-economy models offered to policy makers are deficient in terms of at least one of technological explicitness, behavioural realism or completeness of equilibrium feedbacks. Awareness of this limitation has motivated the recent drive to design and apply hybrid models that combine these features. CIMS is a hybrid model that incorporates progress along all three dimensions, and this paper demonstrates the utility of the model for direct analysis of policies that combine top-down and bottom-up requirements, and for improving the parameterization of CGE models for long term analysis.

Analysis of CIMS' equilibrium feedbacks indicates the importance of technological adjustment to GHG pricing at all tax levels, but also the increasing importance of macroeconomic structural adjustment with increasing price. CIMS may also be used to help improve the key long term ESUB and AEEI technology parameters used in top-down models. Based on the underlying structure and data in the Canadian CIMS model, we estimated an economy-wide long run (35 year) capital-for-energy ESUB of 0.26, and AEEI of 0.57%. Estimates for both parameters showed a wide variance in individual sector values, indicating that top-down models should have a sufficiently disaggregated production structure to reflect this sectoral heterogeneity.

The CIMS model continues to be actively developed, including its application to other jurisdictions (e.g., CIMS China, CIMS North America), the inclusion of new technologies to model conversion of fossil fuels into electricity, hydrogen and petrochemical feed-stocks while using carbon capture and storage technologies, and the addition of features necessary to make CIMS into a more complete general equilibrium model.

Appendix A: Simulation of Capital Stock Turnover, Parameter Estimation and Endogenous Technological Change in CIMS.

CIMS simulates the competition of technologies at each energy service node in the economy based on a comparison of the technologies' life-cycle-costs (LCCs) and some technology-specific controls, such as a maximum market share limit in the cases where a technology's market share is constrained by physical, technical or regulatory means. CIMS applies a definition of LCC that includes intangible costs that reflect consumer and business preferences and the implicit discount rates revealed by real-world technology acquisition behaviour. Equation 2 presents how CIMS determines technology market shares for new capital stocks.

$$MS_j = \frac{\left[CC_j * \frac{r}{1-(1+r)^{-n_j}} + OC_j + EC_j + i_j\right]^{-v}}{\sum_{k=1}^{k}\left\{\left[CC_k * \frac{r}{1-(1+r)^{-n_j}} + OC_k + EC_k + i_k\right]^{-v}\right\}} \tag{2}$$

MS_j is the market share of technology *j*, CC_j is its capital cost, OC_j is its maintenance and operation cost (labour), EC_j is its energy cost, which depends on energy prices and energy consumption per unit of energy service output – producing a tonne of steel, heating a m^2 of a residence, transporting a person one kilometre. The *r* parameter represents the weighted average time preference of decision makers for a given energy service demand; it is the same for all technologies at a given energy service node, but can differ between nodes according to empirical evidence. The i_j parameter represents all intangible costs and benefits that consumers and businesses perceive, additional to the simple financial cost values used in most bottom-up analyses, for technology *j* as compared to all other technologies *k* at a given energy service node. n_j is the lifetime of the technology in question.

The *v* parameter represents the heterogeneity in the market, whereby different consumers and businesses experience different LCCs. It determines the shape of the inverse power function that allocates market share to technology *j*. A high value of *v* means that the technology with the lowest LCC captures almost the entire new market share. A low value for *v* means that the market shares of new equipment are distributed fairly evenly, even if their LCCs differ significantly. A traditional linear programming optimization model would have $v = \infty$, equivalent to a step function where the cheapest technology captures 100% of the market (Jaccard et al., 2003).

Technical and market literature provide the conventional bottom-up data on the costs and energy efficiency of new technologies. Because there are few detailed surveys of the annual energy consumption of the individual capital stocks tracked by the model (especially smaller units), these must be estimated from surveys at different levels of technological detail and by calibrating the model's simulated energy consumption to real-world aggregate data for a base year. The goal is to ensure that the energy use simulated by the model is within 5% of real-world energy use at whatever level of disaggregation these data are available.

Estimation of behavioural parameters is more complicated. In previous applications of CIMS, the three key behavioural parameters – *i*, *r* and *v* – were estimated through a combination of literature review, judgment, and meta-analysis. However, the available literature usually provides only separate estimates for the three parameters, often using the discount rate to account for several factors, such as time preference and risk aversion to new technologies. This creates problems for predicting the costs and effects of policies that focus on only one of these factors. More recent estimation of these three behavioural parameters involves the use of discrete choice surveys for estimating models whose parameters can be transposed into the *i*, *r* and *v* parameters in CIMS (Rivers and Jaccard, 2005; Horne et al., 2005). In general, industry and energy supply sectors have lower discount rates, lower and in some cases zero intangible values, and less market heterogeneity compared to household energy consumption, personal transportation and some commercial energy uses.

CIMS includes two functions for simulating endogenous change in individual technologies' characteristics in response to policy: a declining capital cost function and a declining intangible cost function. The declining capital cost function links a technology's financial cost in future periods to its cumulative production, reflecting economies-of-learning and scale (Equation 3).

$$C_j(t) = C_j(0)\left(\frac{N_j(t)}{N_j(0)}\right)^{\log_2(PR_j)} \tag{3}$$

In this algorithm, *C(t)* is the financial cost of a technology *j* at time *t*, *N(t)* is the cumulative production of a technology at time *t*, and *PR* is the progress ratio, defined as the percentage reduction in cost associated with a doubling in cumulative production of a technology. Researchers have found empirical evidence of this relationship, with *PR* values typically ranging from 75% to 95% depending on the maturity of the technology and any special characteristics such as scale, modularity, thermodynamic limits, and special material requirements (McDonald and Schrattenholzer, 2001).

The declining intangible cost function links the intangible costs of a technology in a given period with its market share in the previous period, reflecting improved availability of information and decreased perceptions of risk as new technologies become more broadly adopted. Attraction to a new technology can increase as its market share increases and information about its performance becomes more available. The parameters of this function are currently estimated from literature review, but a series of discrete choice surveys are underway to estimate how changes in key attributes, such range and fuel availability for alternatively fuelled vehicles, might affect their evolution over time. Intangible costs for technology *j* decline according to Equation 4, where $i_j(t)$ is the intangible cost of a technology at time *t*, MS_{t-1} is the market share of the technology at time *t-1*, and *A* and *k* are estimated parameters reflecting the rate of decline of the intangible cost in response to increases in the market share of the technology.

$$i_j(t) = \frac{i_j(0)}{1 + A_j e^{k_j * MS_{j_{t-1}}}} \tag{4}$$

Appendix B: Estimation of ESUBs from CIMS input share data

Equation 5 describes the production function used for estimating ESUBS;

$$q = f(K, E, N, O, C) \tag{5}$$

where *q* is output, *K, E, N, O* and *C* are expenditure for each of capital, electricity, natural gas, refined petroleum products, and coal. While labour was not included directly in the estimation, partly because it would introduce co linearity with capital, labour costs directly influence the technology competitions in CIMS through the operations and maintenance variable (Appendix A), and thus the estimated substitution elasticities.[9]

We used the transcendental logarithmic production function (Equation 6) to regress the pseudo data because it is a highly general functional form that places no a priori restrictions on the Allen elasticities of substitution (Christensen et al. 1973: Berndt and Wood 1975);

$$\ln q = \alpha_0 + \sum_{i=1}^{n} \alpha_1 \ln x_i + 0.5 \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} \ln x_i \ln x_j \tag{6}$$

where *q* is output, the *α*'s and *β*'s are parameters to be estimated, $x_i \ldots n$ are the inputs (*K,E,N,O,C*). Bilateral symmetry of substitution between inputs ($\beta_{ij} = \beta_{ji}$) is imposed.

Logarithmic differentiation in the translog and application of Sheppard's Lemma produces the following set of cost share equations that can then be directly estimated as a system, with symmetry restrictions ($\beta_{ij} = \beta_{ji}$) (Equation 7).

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[9] The cost of labor is represented in CIMS as a percentage of capital cost for individual technologies; it is therefore an *a priori* Leontief style complement to machinery and buildings.

$$
\begin{aligned}
S_{(K)} &= \alpha_K + \beta_{KK}\ln(P_K) + \beta_{KE}\ln(P_E) + \beta_{KN}\ln(P_N) + \beta_{KO}\ln(P_C) + \beta_{KC}\ln(P_O) \\
S_{(E)} &= \alpha_E + \beta_{KE}\ln(P_K) + \beta_{EE}\ln(P_E) + \beta_{EN}\ln(P_N) + \beta_{EO}\ln(P_C) + \beta_{EC}\ln(P_O) \\
S_{(N)} &= \alpha_N + \beta_{KN}\ln(P_K) + \beta_{EN}\ln(P_E) + \beta_{NN}\ln(P_N) + \beta_{NO}\ln(P_C) + \beta_{NC}\ln(P_O) \\
S_{(O)} &= \alpha_O + \beta_{KO}\ln(P_K) + \beta_{EO}\ln(P_E) + \beta_{NO}\ln(P_N) + \beta_{OO}\ln(P_C) + \beta_{OC}\ln(P_O) \\
S_{(C)} &= \alpha_C + \beta_{KC}\ln(P_K) + \beta_{EC}\ln(P_E) + \beta_{NC}\ln(P_N) + \beta_{OC}\ln(P_C) + \beta_{CC}\ln(P_O)
\end{aligned}
\tag{7}
$$

Each of $S_{(K,E,N,O,C)}$ are the input cost shares of each input, each of $P_{(K,E,N,OC)}$ are the input prices, each of $\alpha_{(K,E,N,O,C)}$ are base estimated cost shares, and the β's are estimated coefficients that relate the log of the price of capital and each energy type to the cost share of the relevant input. Homogeneity of degree 1 in input prices is enforced.

Following the norm in the literature for comparability, Allen partial elasticities of substitution were calculated for the translog function. Allen partial elasticities represent the input elasticities of substitution adjusted for cost share, and as such allow comparison between inputs with different cost shares. Equation 8 and 9 provide the formulas for the own and cross price elasticities of demand using the cost shares (S_{ij}) and estimated coefficients (β_{ij}) from Equation 7.

Cross Price Elasticity of Demand

$$\sigma_{ij} = \frac{\beta_{ij} + S_i S_j}{S_i S_j} \qquad \text{i,,j =1, . . ., n but } i \neq j \tag{8}$$

Own-price Elasticity of Demand

$$\sigma_{ii} = \frac{\beta_{ii} + S_i^2 - S_i}{S_i^2} \qquad \text{i = 1, . . . , n} \tag{9}$$

Application of these estimates to other models may require consideration of the other model's nesting structure and input cost shares; the β parameters estimates are available from the authors.

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