THE ROAD AHEAD FOR ENERGY-ECONOMY POLICY MODELS: INTEGRATING MARKET DYNAMICS, EXPECTATIONS AND WELFARE COSTS

by

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Abstract

Energy-economy models have emerged to provide policy makers with information on the effect of their policies. These models are used to forecast the responses of businesses and consumers, and the costs of these responses may be estimated using a cost accounting method. In this paper, I suggest three improvements that can be made to energy-economy models and cost accounting techniques. First, I outline a method of simulating the obsolescence of technologies when they become uncompetitive. Second, I develop a method to simulate the behaviour of businesses and consumers when they have expectations of their future emissions costs. Finally, I develop a method of cost accounting that can estimate the social costs caused by policies, and that can estimate the costs caused by regulations.

Keywords: energy-economy modeling, obsolescence, price expectations, welfare costs

Dedication

To my parents – Don and Elaine Peters.

Your support over the past 27 years is the main reason I completed this research project.

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1. Project Rationale

1.1. Introduction

Over the centuries, industrial economies have relied on fossil fuels to meet the demand for energy services. While energy services have improved people's standards of living, the combustion of fossil fuels emits greenhouse gases (GHGs), which are believed to cause climate change. Policy makers in Canada and elsewhere have become increasingly aware of the link between the combustion of fossil fuels and climate change, and recognize that energy consumption must be decoupled from GHG emissions. Thus, technologies must emerge that provide equivalent services, but that do so while emitting less or no GHGs.

There is considerable optimism about the role of technical change in strategies to reduce GHGs. Jaffe and Stavins's (1995) views on technical change are echoed throughout the literature: "in the long run, the development and widespread adoption of new technologies can greatly ameliorate what, in the short run, sometimes appears to be overwhelming conflicts between economic well-being and environmental quality" (pg. S-44). The invention, innovation and diffusion of technologies that provide energy services with low or no emissions could substantially reduce GHG emissions. Additionally, as technical expertise and familiarity with these technologies improves, the costs associated with their adoption and operation are expected to decrease, thus reducing the costs of abating emissions (McDonald and Schrattenholzer, 2001). Over the long run, technical change could reduce emissions to sustainable levels while maintaining a high standard of living in industrialized countries.

Despite the optimism about the role of technical change in efforts to reduce GHG emissions, emerging technologies have so far mostly enabled businesses and consumers to increase, not decrease, their emissions. Energy efficiency and emissions per unit of economic output improved during the 20th century, but those improvements were offset by a substantial increase in production (Smil, 2000). Azar and Dowlatabadi (1999) explain that, in the absence of any constraints or incentives, technical change is focused on maximizing the total productivity of the economy. Improvements in energy efficiency or GHG intensity occur because energy has a cost, or because energy efficiency improves autonomously as a result of other structural changes to the economy. Historically, these improvements have not offset the increase in emissions caused by increasing output; nor are not expected to do so in the absence of any incentives or constraints (Azar and Dowlatabadi, 1999). Policy makers are, thus, faced with the challenge of directing technical change to ensure that the rate at which technologies emerge to reduce GHGs exceeds the increase in emissions that results from increases in production.

While policy makers must implement policies to induce technical change, they are hesitant to do so, in part because of uncertainty about the impacts of those policies. In order to make appropriate decisions, policy makers require accurate information on how their policies may influence technical change, and future trends in emissions. They also require information on the economic costs of those policies as the economy diverts from its unconstrained path. Energy-economy models have emerged as tools to provide policy makers with the information they need. In the following sections, I introduce and discuss some of the challenges in energy-economy modeling. I then discuss how some of the challenges associated with energy-economy modeling can be resolved.

1.2. Energy-economy models

Energy-economy models are used to forecast the effects and economic costs of policies to induce technical change. All such models represent the interaction between economic activity, energy consumption, and the resulting GHG emissions, but differ with respect to methodology and purpose. Energy-economy models can be classified into two general groups: top-down models and bottom-up models.

Top-Down models are intended to describe or predict the actual responses of businesses and consumers to changes in prices when making energy-related decisions. In their conventional form, these models use historical market data to estimate aggregate relationships between economic output and energy consumption. Two main categories of top-down models exist – macroeconometric models and computable general equilibrium (CGE) models. Macroeconometric models are econometrically (i.e., statistically) estimated from time series data; and they may be simple one-equation models or they may employ an input-output matrix to capture intra-sectoral transactions. They are then used to assess the responsiveness of GHG emissions and energy consumption to changes in emissions charges or energy prices (Löschel, 2002).[1] CGE models, on the other hand, include multiple sectors, each with a representative production function. The production function relates the output from each sector to its inputs, such as capital, labour, materials and energy. Energy inputs can be further disaggregated into different forms of energy, such as coal or electricity. The willingness to substitute amoung the various inputs, and amoung the outputs of the different sectors, is measured by econometrically estimated elasticities of substitution.[2] After all elasticities have been calculated, the CGE model solves for a set of relative prices that bring all sectors into equilibrium. Therefore, CGE models represent the feedbacks that can occur between sectors when policies are implemented (Bergman and Henrekson, 2003; Bohringer, 1998).

In contrast, **bottom-up** models are intended to prescribe the optimal path to meeting a given constraint, such as reducing emissions to a specified quantity. In their conventional form, they include a detailed list of technologies and model the penetration of these technologies based on costs, performance characteristics and any constraints placed upon the model. Bottom-up models usually determine the technology mix that minimizes the financial cost of the total energy system over time. These models can assess the effects of technology specific regulations, in addition to price-based policies, by placing a constraint on aggregate emissions (Löschel, 2002, Berger et al, 1992).

Each classification of model has advantages and disadvantages when providing information to policy makers. Particularly, their performance differs with respect to: behavioural realism, the inclusion of equilibrium feedbacks and their representation of technical change.

Behavioural realism

Models vary in their ability to predict the decisions that businesses and consumers actually make when faced with a policy to induce technical change. Businesses and consumers undoubtedly consider financial costs when purchasing technologies, but they

[1] Emissions charges may be an emissions tax or the price of emissions permits
[2] Elasticities of substitution measure the responsiveness of the demand for various inputs to changes in the relative prices for those inputs.

may also be influenced by: 1) non-financial costs (called "intangible costs") or preferences towards adopting specific technologies; 2) risks associated with adopting different technologies; 3) "option value" derived waiting for more information before making a risky and potentially irreversible investment; 4) information about a technology or its substitutes; 5) whether the person purchasing a technology incurs all its costs, or whether the person can pass some of the costs onto someone else; and 6) individual differences in the costs of adopting the same technologies (Pindyck, 1991; Jaffe and Stavins, 1994; Jaffe et al, 2002 Sutherland, 1991; Jaccard et al, 2003b). Top-down and bottom-up models vary in their ability to incorporate these factors when predicting or prescribing a technology mix that results from a policy.

Conventional top-down models may be more behaviourally realistic than conventional bottom-up models because they use parameters estimated from historical market data. Market data are said to "reveal" preferences and costs of adopting technologies because it was, presumably, those preferences and costs that influenced past technology choices (Jaccard et al, 2003b). Despite the top-down models' strong performance on behavioural realism, some challenges remain. CGE models may not perform as well as macroeconometric models because they often fail to obtain statistically significant estimates of the elasticities of substitution. Rather, the estimates are generally mere guesses because modelers lack data to ensure statistical significance (Bergman and Henrekson, 2003; Carraro and Hourcade, 1998). Additionally, while top-down models are likely to be behaviourally realistic over the short and medium term, there is no way of ensuring that preferences revealed from historic data will remain the same over the long-term (Jaccard et al, 2003b).

Conventional bottom-up models are not designed to be behaviourally realistic, but rather to prescribe an optimal technology mix. In many applications of bottom-up models, the optimal technology mix is based on financial costs alone (Lovins and Lovins, 1991; Brown et al, 2001). As discussed above, businesses and consumers may also base their purchasing decisions on factors other than financial costs, and conventional bottom-up models may not accurately forecast how they respond to policies. An additional criticism of bottom-up models is that, in the absence of any constraints, they prescribe the cheapest technology to gain one hundred percent of the market for a service while other technologies gain none. Due to the heterogeneity of businesses' and consumers' costs and preferences, a variety of different technologies may be purchased (Jaccard et al, 2003a).

Equilibrium feedback

The inclusion of equilibrium feedbacks is important because policy makers are often interested in a policy's effect on the output of the whole economy, or its effect on individual sectors such as the labour market. Models vary in their ability to equilibrate the various sectors of the economy. Some models attain a general equilibrium in which all prices are adjusted to ensure that supply and demand are consistent for all products in the economy. However, other models attain a partial equilibrium because they equilibrate one or several sector(s), but omit a policy's impact on other sectors.

Top-down models often perform better than bottom-up models with respect to equilibrium feedback. CGE models are most effective because they adjust relative prices until all sectors are in equilibrium (Bergman and Henrekson, 2003). Macroeconometric models are demand driven and do not include equilibrium assumptions; however, they may be reasonably effective at representing equilibrium conditions if they are estimated from data when the economy was in equilibrium. In contrast, conventional bottom-up models are partial equilibrium models. They do not account for the feedback that can occur if a policy affects the demand for certain types of energy, and, thus, alters energy prices (Löschel, 2002). As a result, bottom-up models perform poorly with respect to equilibrium feedbacks.

Representation of technical change

Models vary in their ability to accurately represent technical change. Technical change is a dynamic process in which new technologies are invented, innovated and diffused, and old technologies eventually become obsolete (Azar and Dowlatabadi, 1999; Malcomson, 1975). Models may include an exogenous specification of technical change, in which no relationship exists between technical change and other economic variables, or an endogenous specification, in which policies or changes in prices may influence technical change. An exogenous specification prevents models from predicting how policies influence the rate and direction of technical change. Therefore, an endogenous specification of technical change is necessary to model long-term responses to policies (Carraro and Hourcade, 1998; Grubb et al, 2002; Dowlatabadi, 1998).

While conventional top-down models perform better with respect to behavioural realism and equilibrium feedbacks, conventional bottom-up models perform better with respect to their representation of technical change. The detailed list of technologies included in bottom-up models enables them to reflect the diffusion of new technologies, and the replacement of old technologies with new ones. Bottom-up models may also predict how technologies are innovated or commercialized by allowing new technologies to penetrate the market in future years. Although bottom-up models generally perform strongly with respect to their representation of technical change, they perform poorly with respect to research and development and the invention of new technologies (Löschel, 2002). Conventional top-down models, however, usually represent technical change as an exogenous process. They generally use two measures of technical change: the autonomous energy efficiency index (AEEI) – which refers to non-price induced changes in energy efficiency – and elasticities of substitution (ESUB) – which represent the degree to which capital and labor inputs will be substituted for energy, or the degree to which low GHG intensive energy inputs will be substituted for high GHG intensive inputs when relative prices change (Löschel, 2002). If both the AEEI and ESUB parameters are estimated from historical data, they are assumed to remain the same in the future. Therefore, conventional top-down models indicate how the substitution for various inputs is affected by changes in relative prices, but substitution occurs among technology options already available. They provide little insight into how the available set of technology options may change in response to a policy or other economic dimensions. In other words, the fixed values for the AEEI and ESUB parameters provide an inflexible picture of technical change (Grubb et al, 2002).

Summary of energy-economy models

Figure 1.1 summarizes the performance of top-down and bottom-up models with respect to behavioural realism, equilibrium feedbacks and representation of technical change. A model that performs well on all three criteria would be situated in the far, top right-hand corner of Figure 1.1. None of the conventional top-down or bottom-up models performs well on all three criteria, because they are incomplete representations of reality. As a result, they are flawed at providing policy makers with accurate information about the effects of policies to induce technical change.

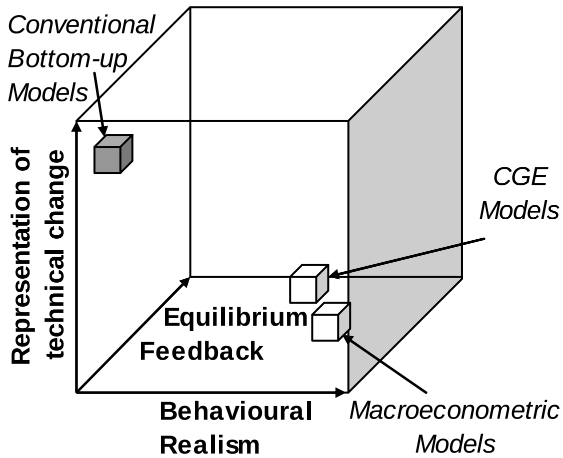

Figure 1.1: Characterization of energy-economy models

1.3. Emissions forecasts and cost estimates using top-down and bottom-up models

The problem with not performing well on all three criteria discussed above is highlighted by the respective policy forecasts and the economic costs estimated from the two types of models. Conventional top-down and bottom-up models use different methodologies to predict the willingness to reduce emissions and, in consequence, they predict different costs of reducing emissions. Costs are generally estimated from top-down models by determining the level of effort, or the implicit price of the GHG reduction, required to attain a specific GHG emissions reduction (ERG/MKJA, 2000).[3] After the implicit price for different levels of emissions reductions is determined, it can be graphed to estimate the marginal cost of abatement curve. Figure 1.2 illustrates a

[3] The implicit price of an emissions charge is the value of the charge. However, the implicit price of an emissions reduction can also be calculated for non-price based policy instruments, such as technology specific regulations.

hypothetical marginal abatement curve and the resulting costs caused by a \$50/tonne CO_2e emissions charge, using the output from a top-down model.

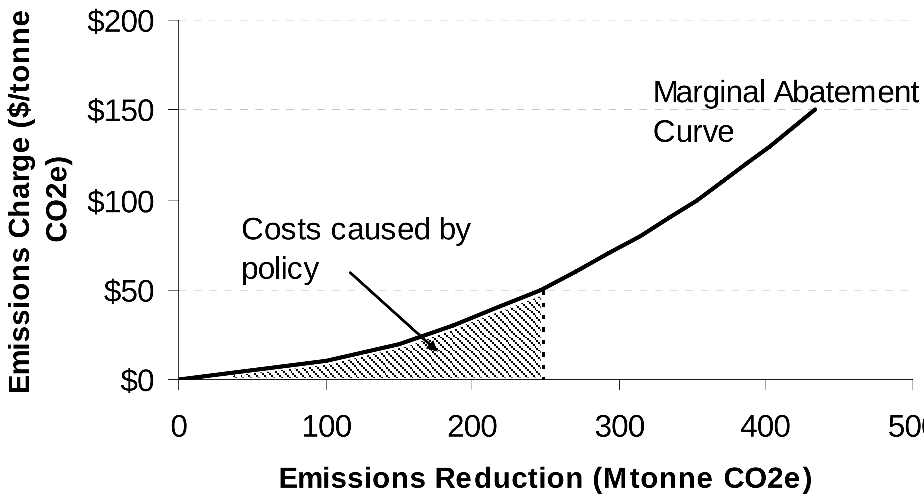

Figure 1.2: Cost estimation using top-down models

After the marginal abatement curve has been determined, the economic costs of an emissions reduction are equal to the area under the marginal abatement curve:

$$\text{Economic Costs caused by Policy} = \int MAC(ER)\,dER \qquad \textbf{(Equation 1.1)}$$

where *ER* is the emissions reduction; *MAC* is the marginal abatement cost, which is a function of *ER*. In Figure 1.2, a \$50/tonne CO_2e emissions charge reduces 250 Mtonnes of CO_2e, resulting in a cost equal to the area between the MAC curve and the x-axis.[4] The area under the marginal cost of abatement curve represents what businesses and consumers "perceive" to be their cost of reducing emissions. At a \$50/tonne CO_2e emissions charge, businesses and consumers only undertake actions to reduce one tonne of CO_2e that they think will cost \$50 or less.

In many applications of bottom-up models, the model minimizes the total net present cost of the energy system over the planning horizon. The costs caused by a

[4] CO_2e refers to "carbon dioxide equivalents" and it can include the greenhouse effect of CH_4, N_2O and other GHGs.

policy are then estimated by comparing the costs of the energy system in the business-as-usual (BAU) forecast to the costs in the policy forecast. If the costs from the BAU forecast exceed the costs from the policy forecast, the policy is believed to cause a financial benefit to the economy.

Due to their method of parameter estimation, conventional top-down models generally predict high costs of reducing emissions. The behavioural and technical change parameters used in top-down models were estimated from historical data, periods when there was little social or political interest in reducing GHGs. These parameters suggest that energy consumption, and the resulting GHGs, are relatively unresponsive to changes in energy costs or GHG costs, and the models imply that a large price signal is required to attain an emissions reduction. However, there is no guarantee that these parameters will remain valid into the future, when there is a greater social and political will to reduce emissions (Jaccard et al, 2003b).

A further criticism of conventional top-down models is that people's purchasing decisions do not always reveal their preferences towards specific technologies. Moxnes (2004) suggests that people often make decisions in an environment with imperfect information and other market failures. Market failures prevent people from making decisions they would consider optimal if they were perfectly informed and, consequently, market data may not reveal people's true preferences. It is important to note that excluding the effect of market failures does not affect the behavioural realism of top-down models – if people made poor market decisions in the past, they may continue to do so in the future. However, the persistence of market failures does affect the cost estimates. The cost estimates using conventional top-down models rest upon strong assumptions about optimizing behavior; and if people do not always make optimal decisions, a deviation from their initial technology choice does not necessarily imply a reduction in welfare (Bergman and Henrekson, 2003). As a result, the cost estimates from top-down models may be incorrect.

Conventional bottom-up models may be better at representing technical change, but they are less behaviourally realistic and lack equilibrium feedbacks. In such models, technology selection is based on financial costs alone, and does not include measures of intangible costs, risk or the heterogeneity of consumers. As a result bottom-up models may overestimate people's willingness to adopt new energy saving technologies, because many of those technologies are riskier and have characteristics that some people view unfavourably (Jaffe et al, 1994; Jaffe et al, 2002). For example, a fluorescent light bulb provides the same service as an incandescent light bulb, and it is financially cheaper over its lifespan. However, people may avoid buying fluorescent light bulbs because the cost of premature failure or accidental breakage is greater; or because they do not like the hue (an intangible cost). By basing cost estimates on financial costs alone, bottom-up modelers may omit some of the real costs of their prescribed technology mix, and, thus, underestimate the costs of an emissions reduction (Jaffe and Stavins, 1994).

Many bottom-up models also lack feedbacks that equilibrate the various sectors of the economy, such as energy supply and demand. As a result, the models may predict that a policy will decrease the demand for GHG intensive energy, but that energy prices will remain unchanged. In reality, such a policy is likely to have a "rebound effect", where its effectiveness is partially offset when the decrease in the cost of GHG intensive energy stimulates its consumption. As a result, bottom-up models may underestimate the level of effort required to attain an emissions reduction (Jaccard et al, 2003b). Conventional bottom-up models also fail to account for the costs associated with reductions in the demand for services, which may occur when a policy changes costs. If businesses or consumers forgo or reduce their demand for a service in response to higher service costs, they incur a cost equal to the net benefit they derived from the service before costs change. For example, a household may forgo a road trip due to a policy that causes higher fuel prices. In this case, the cost of the forgone service is equal to the net benefit the household would have derived from the road trip when fuel prices were lower.

Overall, conventional top-down models tend to overestimate the costs of policies to induce technical change because they underestimate technical responsiveness. Conventional bottom-up models ignore or underestimate financial risks and preferences, as well as equilibrium feedbacks, and therefore tend to overestimate the willingness to adopt energy-efficient technologies, resulting in an underestimation of costs.

1.4. Hybrid energy-economy models – an introduction to CIMS

In response to the respective weaknesses of conventional top-down and bottom-up models, modelers have tried to add endogenous technical change to top-down models, and behavioural realism and equilibrium feedbacks to bottom-up models (Bohringer, 1998; Koopmans and Velde, 2001). The CIMS model, used for the present paper, is the latter of the two approaches, which can be referred to as a “hybrid energy-economy” model (Jaccard et al, 2003b). This section performs two tasks: it clarifies CIMS’s position in the top-down vs. bottom-up debate, and it highlights aspects of CIMS that are important for the later chapters.

Technology selection in CIMS

Similar to bottom-up models, CIMS includes several sectors of the economy, each with substantial technological detail. CIMS simulates technical change by mimicking capital cycles where new equipment stocks replace retired stocks and meet any growth in service demand. New stocks compete for a share of new equipment sold with other technologies that provide the same or similar service. The competitiveness of a technology is based on its life-cycle cost, which includes capital, operating, energy costs and intangible costs. The annual life-cycle cost of a technology is:

$$LCC_{kt} = \frac{\left[\left(CC_{kt} + ip_k\right) \times CRF\left(r_k\right)\right] + \left(O_{kt} + io_k\right) + E_{kt}}{SO_k} \qquad \textbf{(Equation 1.2)}$$

where LCC_{kt} is the annual life-cycle cost of technology k at time t per unit of service output; CC_{kt} is the capital cost of technology k at time t; ip_k is the intangible cost of purchasing technology k; CRF is the capital recovery factor used to annualize capital and the intangible costs of purchasing a technology, and it is a function of the revealed discount rate of technology k (r_k); SO_k is the annual service output of technology k; O_{kt} is the annual operating cost of technology k at time t; io_k is the intangible cost of operating technology k; and E_{kt} is the annual energy cost of technology k at time t (Jaccard et al, 2003b; ISTUM manual, 2004).

After the life-cycle costs of each technology have been calculated, CIMS allocates a share of total new stock to each technology available for competition. Market share is determined by relative life-cycle costs, and is allocated using a technology competition algorithm. The most common competition algorithm in CIMS is illustrated in Equation 1.3.[5]

$$NMS_{kt} = \frac{LCC_{kt}^{-v}}{\sum_{j=1}^{J} LCC_{jt}^{-v}} \qquad \textbf{(Equation 1.3)}$$

where NMS_{kt} is the market share of technology k in year t; LCC_{kt} is the annual life-cycle cost of technology k in year t; v is a variance parameter representing cost heterogeneity; and J is the number of technologies that compete to provide the same service as technology k. Equation 1.3 allocates the greatest amount of new stock to the technology with the lowest life-cycle cost, while technologies with higher life-cycle costs gain less market share. The exact market share will depend on the variance parameter v, which is analogous to the standard deviation of a normal distribution. For low values of v (example: $v = 1$), the standard deviation for different people's costs of adopting a technology is large, and all technologies gain roughly the same market share regardless of their relative LCC values. As v increases the standard deviation decreases and technologies with lower LCCs gain a greater amount of market share (Jaccard et al, 2003b).

CIMS's allocation of the market share for new stocks differs from a conventional bottom-up model in several respects. The LCC of a technology include intangible costs associated with its adoption and operation. CIMS uses a revealed discount rate, instead of a social discount rate, to annualize the capital costs of a technology, in order to reflect the time preference businesses and consumers appear to have when choosing investments. Intangible costs and the revealed discount rates have been estimated from market data in order to ensure a behaviourally realistic simulation of technology choice.

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[5] CIMS also includes another option for simulating technology choice, by random sampling from a Weibull distribution. This option is used less frequently, and is not discussed here.

Furthermore, the competition algorithms account for the heterogeneity of different consumer's costs by allowing more than one technology to gain a share of new equipment stocks sold in the market.

Equilibrium feedbacks

After the market share for new stock has been allocated, CIMS adds the new stock to the stock that remained from the previous year. CIMS then calculates the total amount of energy demanded and the amount of energy supplied. If energy demanded does not equal the energy supplied for a given set of energy prices, the model recalculates the LCCs of all technologies with a new set of energy prices. CIMS iterates this process until the energy demand-supply reaches an equilibrium.

In addition to ensuring that energy supply-demand are in equilibrium, CIMS also simulates a reduction in demand for services if the costs of those services increase. CIMS calculates the average costs of all technologies in a sector before and after a policy has been implemented. If those costs increase, the demand for services from that sector is reduced using an elasticity function. Finally, CIMS determines the total technology mix that occurs, and calculates the resulting emissions.

Representations of technical change

CIMS's representation of technical change is similar to a conventional bottom-up model. It reflects the turnover of equipment stocks by simulating the adoption of new technologies in order to replace retiring technologies and to meet any growth in service demand. In many instances, CIMS also reflects the expected innovation of new technologies by simulating their competition when they become available in the future.

In addition to simulating the innovation and diffusion of new technologies, CIMS includes a measure of endogenous technological learning – where the capital costs of technologies decline as manufacturers gain experience (McDonald and Schrattenholzer, 2001; Löschel, 2002). CIMS simulates technological learning by reducing capital costs in Equation 1.2 by a given rate when the production of a technology doubles.

Policy simulation in CIMS

CIMS can simulate several policies, such as emissions charges, subsidies, technology specific regulations, environmental standards (which require the market share of a class of technologies to increase), and information programs. Emissions charges are simulated by adjusting a technology's energy costs (E_{kt}) to reflect the costs of an emissions charge:

$$E_{kt} = \left[\sum_{j=1}^{J} \left(P_{jt} \times Q_{kjt} \right) \right] + \left(Charge_t \times EMISSIONS_k \right) \qquad \textbf{(Equation 1.4)}$$

where P_{jt} is the price of energy type j (coal, electricity, etc) at time t; Q_{kjt} is the quantity of energy type j consumed by technology k at time t per unit of service output; $Charge_t$ is the emissions charge at time t measured in \$/tonne of CO_2e; $EMISSIONS_k$ is the total emissions emitted by technology k per unit of service output.

CIMS simulates technology specific regulations or environmental standards by constraining the new stock market share of a specific technology or the total market share for a class of technologies. CIMS may simulate a subsidy by adjusting the capital costs of select technologies. Finally, CIMS may simulate information programs by adjusting the revealed discount rates or the intangible costs of technologies.

Evaluating CIMS

The figure below places CIMS in the box used to evaluate the conventional top-down models and bottom-up models in Figure 1.1. As a hybrid energy-economy model, CIMS is closer to the far top right-hand corner of the box than conventional bottom-up or top-down models. CIMS performs similarly to bottom-up models in terms of its representation of technical change. CIMS includes the technological detail of a bottom-up model; therefore, it explicitly simulates the innovation and diffusion of technologies under various conditions. It also includes a measure of endogenous technological learning. CIMS seeks to perform similarly to top-down models in terms of behavioural realism because it includes revealed discount rates and intangible costs. It also accounts for market heterogeneity by allowing more than one technology to gain a share of the market. Finally, CIMS incorporates equilibrium feedbacks by equilibrating energy supply/demand and by allowing for energy service demand adjustments when the costs of these services increase or decrease. However, CIMS does not have the full equilibrium potential of a CGE model because it does not endogenize feedbacks with other sectors, such as the service sector, investment and savings, or international trade.

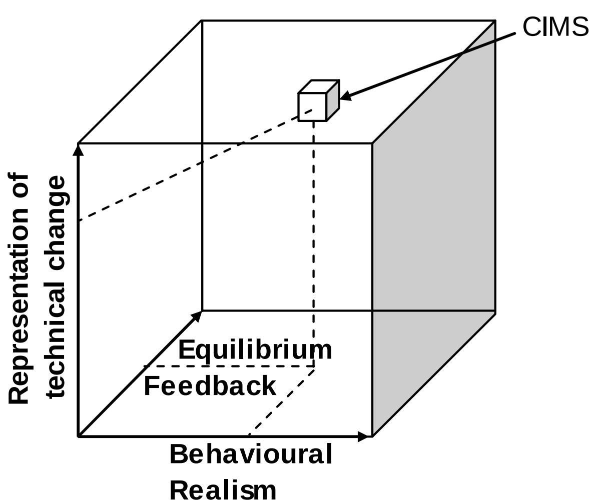

Figure 1.3: Characterization of CIMS

1.5. New requirements of CIMS

Simulating obsolescence in CIMS

CIMS reflects the innovation and diffusion of new technologies by simulating their competition when they become available in future periods. New technologies often provide services at lower financial or intangible costs than older vintages, and they can gain a large portion of market share for new equipment stocks. As a result, older vintages begin to lose their ability to compete in the market, and their market share declines.

Regardless of their decline in competitiveness, CIMS simulates that older vintages will continue to compete and gain a minimum market share. In reality, the decline in competitiveness of older vintages may induce manufacturers to shift their expertise and capital to a newer technology. As a result, older vintages may become obsolete (Katz and Rosen, 1998; Christensen, 1999). The first purpose of this paper is to simulate the obsolescence of old technologies in CIMS, after their competitiveness declines below a given threshold.

Simulating a rising emissions charge with a clear schedule for charge increases

Several policy analysts advocate using a rising emissions charge to induce technical change towards low emissions technologies. One approach is a rising emissions tax; and another is an emissions cap-and-trade (ECT) system with a ceiling on the price of emissions permits. An ECT with a rising ceiling would place an aggregate limit on emissions and distribute the rights to those emissions by auctioning or freely distributing permits, but government would then sell additional emissions permits at a fixed price. As a result, the price of permits would not exceed the price set by the government (Jacoby and Ellerman, 2004; McKibbin and Wilcoxsen, 2002).

An ECT with a price ceiling combines the advantages of an emissions tax and a conventional emissions cap-and-trade system. Similar to both policies, an ECT ensures that the marginal cost of abating emissions is equalized across all emitters, because all emitters can purchase emissions permits if the costs of abating their emissions exceed the cost of permits. This is the necessary condition to ensure that an emissions reduction is attained at the lowest costs to society (Ekins and Barker, 2001; Field and Olewiler, 2002). Similar to a tax, businesses are assured that their marginal abatement costs will not exceed a politically determined amount. However, the politically unpopular redistribution of income from businesses and consumers to government caused by emissions taxes is avoided because most redistribution occurs between businesses as they trade emissions permits (Ekins and Barker, 2001; Pizer, 1999). An ECT with a price ceiling is also an advantageous policy instrument when there is uncertainty over the marginal cost of abatement. By placing a price ceiling on emissions permits, policy makers are assured that the economic costs of a policy will not reach politically unacceptable levels (Pizer, 1999; McKibbin and Wilcoxen, 2002).

The emissions tax or the price of emissions permits is likely to be set low initially, but scheduled to rise over time. A rising emissions charge is required to address the projected increase in emissions (Ekins and Barker, 2001). Furthermore, if government has a clear schedule for increasing charges, people may anticipate the future trend in emissions charges, and government could avoid the equivalent of an "emissions charge shock". A clear schedule for rising charges could enable businesses and consumers to prepare for higher future emissions costs by encouraging them to preemptively purchase technologies with lower emissions (Mork and Olstein, 1994; Boucekkine and Pommeret, 2004).

CIMS cannot currently simulate such a policy because it does not simulate the way businesses and consumers form expectations of their future emissions costs. Its method of calculating the emissions costs, as illustrated in Equation 1.4, is consistent with myopic expectations, where businesses and consumers use the emissions charge at the time of purchase to calculate emissions costs over the life-cycle of a technology. This paper develops a method to introduce businesses' and consumer's expectations of future emissions charges into CIMS.

New method of cost accounting

A hybrid energy-economy model like CIMS may resolve several of the problems inherent in conventional top-down or bottom-up models. However, an analyst using CIMS is still faced with the dilemma over how to define the cost of actions, because conventional top-down and bottom-up analyses provide alternative definitions. Bottom-up analyses are meant to prescribe the path with the lowest financial costs to an emissions reduction. Cost estimates using a conventional bottom-up definition compare the financial costs of the technology mix that results from a policy to the financial costs of the technology mix in a business-as-usual forecast. This method represents businesses' and consumers' financial costs of adjusting to a policy. In contrast, top-down analyses aim to describe how businesses and consumers will actually respond to a policy. The costs estimates from this approach represent the perceived costs of reducing emissions (Löschel, 2002; Jaccard et al, 2003b).

The cost estimates using either definition may not be an accurate reflection of the social costs caused by a policy. Costs from bottom-up analysis often exclude any non-financial costs that influence technology decisions (i.e., intangible costs, risk or cost heterogeneity). By ignoring non-financial costs, bottom-up analyses may underestimate the social cost of actions to reduce emissions. Conventional top-down analyses, however, are believed to reveal people's non-financial costs from historic market data. However, this approach rests on strong assumptions about optimizing behaviour and the absence of market failures. If any of these assumptions do not hold, market data may fail to reveal people's costs and preferences; and the resulting cost estimates may not reflect full social costs.

The final purpose of this paper is to develop a methodology that uses the simulations from CIMS to estimate the cost of actions to reduce GHG emissions. The method is designed to accommodate a top-down or a bottom-up definition of costs, and it can estimate the costs for a mid-point between the definitions.

1.6. Overview of paper goals

The first goal of this paper is to develop a method to simulate the obsolescence of old, uncompetitive technologies in CIMS. This method should complete CIMS's representation of the capital cycle so that technologies are innovated, diffused, and eventually become obsolete. The obsolescence function improves CIMS's representation of technical change, and moves CIMS further along the "representation of technical change" axis in Figure 1.4.[6]

The second goal of this paper is to improve CIMS's behavioural realism when it simulates an emissions cap-and-trade system with a rising price ceiling for emissions permits or a rising emissions tax. Businesses and consumers are likely to anticipate future rises in emissions charges if government has a clear schedule for charge increases. As a result, expectations of higher emissions charges may influence people's decisions regarding technology acquisition. Including expected future emissions costs moves CIMS along the "behavioural realism" axis in Figure 1.4.

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[6] Figure 1.4: Characterization of CIMS before and after the contributions of this paper excludes the "equilibrium feedback" axis because the present paper does not discuss any improvements made to CIMS in this category.

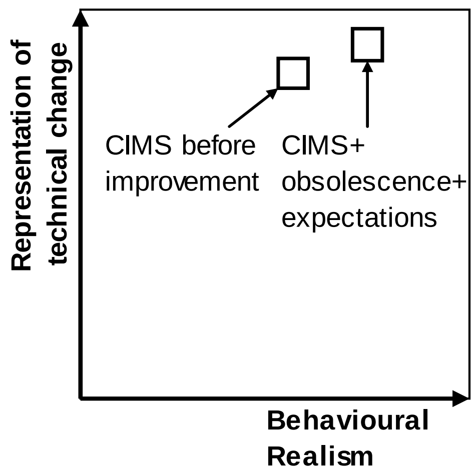

Figure 1.4: Characterization of CIMS before and after the contributions of this paper

The final purpose of this paper is to develop a new method of accounting the costs caused by policies to induce technical change. This method does not affect the CIMS's simulation of technological evolution, but it improves the cost estimates attained using CIMS. The cost accounting model I develop in this paper accommodates alternative definitions of the costs caused by policies.

This paper is organized as follows. In chapter 2, I discuss a method to remove obsolete technologies from CIMS's capital stock. I present the results from using a function to simulate obsolescence. In chapter 3, I present three algorithms to represent the expected emissions costs of a technology. Each algorithm represents a different assumption about how businesses and consumers form expectations of their future emissions costs. In chapter 4, I outline a cost accounting model that calculates the costs caused by policies to induce technical change. In chapter 5, I present the results from policy simulations, which use the additions to CIMS, and I present cost estimates for those policies using the new cost accounting method.

2. Simulating Obsolescence in a Hybrid Energy-Economy Model

2.1. Introduction

CIMS simulates technological evolution through the innovation and diffusion of new technologies, but it does not include an option for simulating the obsolescence of old technologies. Obsolescence is an important component of technical change, because the innovation and diffusion of new technologies may displace older vintages from the market. Newer technologies often provide services at lower costs or greater benefits than older vintages, and as more new technologies emerge, the ability of older vintages to compete in the market declines. Eventually, the manufacturers of old vintages may find that their capital and expertise would be better used by producing a new technology, and old vintages become obsolete (Katz and Rosen, 1998; Cardullo, 1999).

Obsolescence may also be influenced by economic dimensions and policies to induce technical change. Boucekkine and Pommeret (2004) argue that the rate and direction of obsolescence may be influenced by energy prices. When energy prices increase, technologies that require fewer energy inputs become more competitive, and some energy-intensive technologies may become obsolete. Accordingly, a policy to induce technical change towards technologies that emit less GHGs may also induce the obsolescence of GHG intensive technologies.

Although technological obsolescence is an important aspect of technical change, CIMS does not currently simulate obsolescence. CIMS' competition algorithm ensures that all technologies, regardless of their vintage and competitiveness, capture a minimum amount of market share. The competition algorithm used most frequently in CIMS is illustrated in Equation 2.1:

$$NMS_{kt} = \frac{LCC_{kt}^{-v}}{\sum_{j=1}^{J} LCC_{jt}^{-v}} \qquad \textbf{(Equation 2.1)}$$

where NMS_{kt} is the market share of technology k for new equipment stocks in year t; LCC_{kt} is the annual life-cycle cost of technology k in year t; v is a variance parameter representing cost heterogeneity; and J is the number of technologies that compete to provide the same service as technology k. The competition algorithm simulates technology choice based on the LCC of technologies. When new technologies with lower LCCs become available for competition, they may reduce the market share of older technologies with higher LCCs. However, the competition algorithm simulates that old technologies will continue competing and winning some portion of new equipment sold. Consequently, old uncompetitive technologies retain a small but positive share of active stocks. Figure 2.1 illustrates an example of two technologies, which experience large declines and then an asymptote in their share of active stocks. The figure illustrates the technologies' share of active stock as a percent of its share of active stock in year 2000.

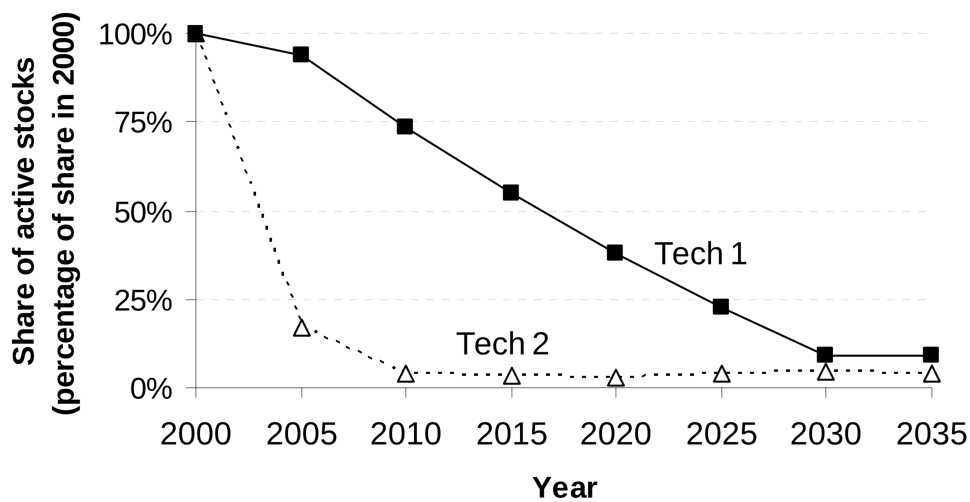

Figure 2.1: Market share evolution of two old technologies[7]

Both technologies illustrated in Figure 2.1 experience large declines in their share of active stocks. When new technologies are introduced into the market, old technologies maintain their previous market share. As a result, the share of old technologies in all active stocks declines as stocks are gradually retired. Despite their lower

[7] Technology 1 is a low efficiency ammonia synthesis technology; and technology 2 is a low efficiency natural gas-fired boiler, both in Ontario's chemical products sector.

competitiveness, old technologies retain a minimum share of active stocks and do not become obsolete.

2.2. The algorithm for simulating obsolescence

The algorithm for simulating the obsolescence of uncompetitive old technologies (henceforth called the “obsolescence algorithm”) prevents technologies from competing for new market share after their share of active stocks declines below a threshold. Equation 2.1 illustrates the revised competition algorithm that simulates the obsolescence of old, uncompetitive technologies:

$$NMS_{kt} = \begin{cases} \dfrac{LCC_{kt}^{-v}}{\sum_{j=1}^{J} LCC_{jt}^{-v}} & if\ SAS_{k(t-5)} \geq n \times SAS_{k\,base} \\ \\ 0 & if\ SAS_{k(t-5)} < n \times SAS_{k\,base} \end{cases} \qquad \textbf{(Equation 2.2)}$$

were NMS_{kt}, LCC_{kt}, J, and v have been defined above; SAS_{kt} is technology k’s share of active stocks in year t; and n is the obsolescence parameter. Using the algorithm, a technology competes for a share of new equipment as long as its share of active stocks does not decline below a percentage of its initial share. For an obsolescence parameter (n) of 0.5, a technology that captures 80% of active stocks in the base year (year 2000 many applications of the model) will not be available for competition if its share of active stocks declines below 40%. The algorithm is dependent on a technology’s share of active stocks in the base year, rather than a specific share of active stocks, to allow for differences between technologies’ peak market shares. Some technologies attain a peak share close to 100% of the market, while others may only attain 25%. Additionally, the algorithm only simulates the obsolescence of old technologies – technologies that have stock in the base year. New technologies may not become obsolete in the simulation because they only attain a share of active stocks after the base year.

The value of the obsolescence parameter is left to the discretion of the analyst. The parameter should be set high enough to simulate the obsolescence of technologies that experience rapid declines in their share of active stocks. However, the parameter should not be set so high that it simulates the obsolescence of technologies that experience only a temporary or small decline in competitiveness (caused by periodic changes in energy prices for example). Such technologies should remain eligible for competition.

As a default value in the absence of empirical data, I suggest a value of 0.5, which simulates the obsolescence of technologies experiencing extreme declines in their share of active stocks, but does not affect technologies with declines of less than 50%. Figure 2.2 illustrates a technology's share of active stocks with and without the obsolescence algorithm. The solid line indicates the technology's share of active stocks without the algorithm and the broken line indicates the technology's share with the algorithm. The obsolescence parameter (*n*) is 0.5.

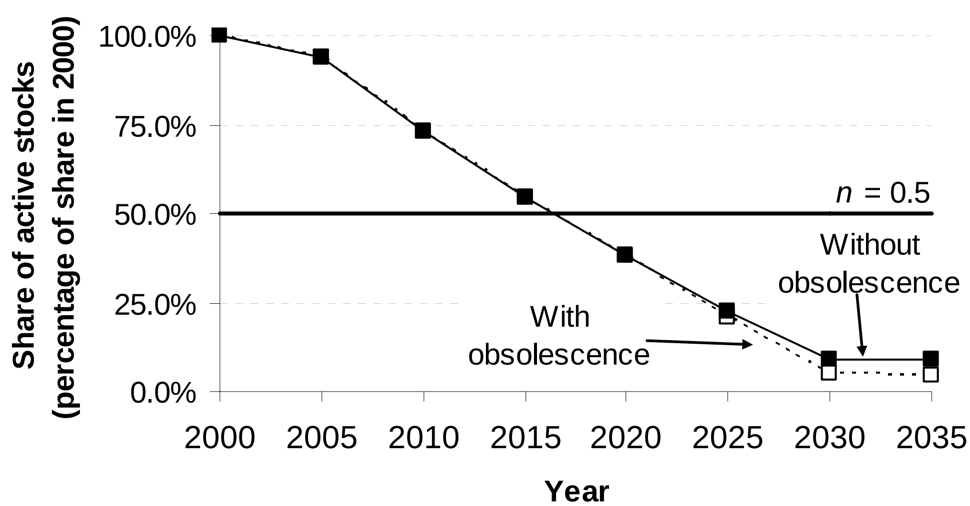

Figure 2.2: A technology's share of active stocks, with and without simulating obsolescence

An obsolescence parameter of 0.5 prevents the technology from competing for a share of new equipment after its share of active stocks falls below the threshold (in year 2020). After the technology falls below the threshold, a technology's share of active stocks trends towards zero, because its stock is no longer replaced with new stocks and its active stock is gradually retired. Using a lower obsolescence parameter, say 0.25, the technology would stop competing for a share of new equipment later in the simulation (2030). A higher parameter, say 0.75, would stop the technology from competing earlier in the simulation (2010).

Finally, it is important to note that obsolescence is not a policy lever. The algorithm is simply designed to improve CIMS's simulation of capital stock turnover; therefore the threshold should always be the same in both the business-as-usual and the policy simulations.

2.3. Results

Figure 2.3 illustrates the decline in energy consumption and GHG emissions from simulating obsolescence over a 35 year simulation (2000 to 2035). The results are reported as the percent difference between a simulation with obsolescence and a simulation without.

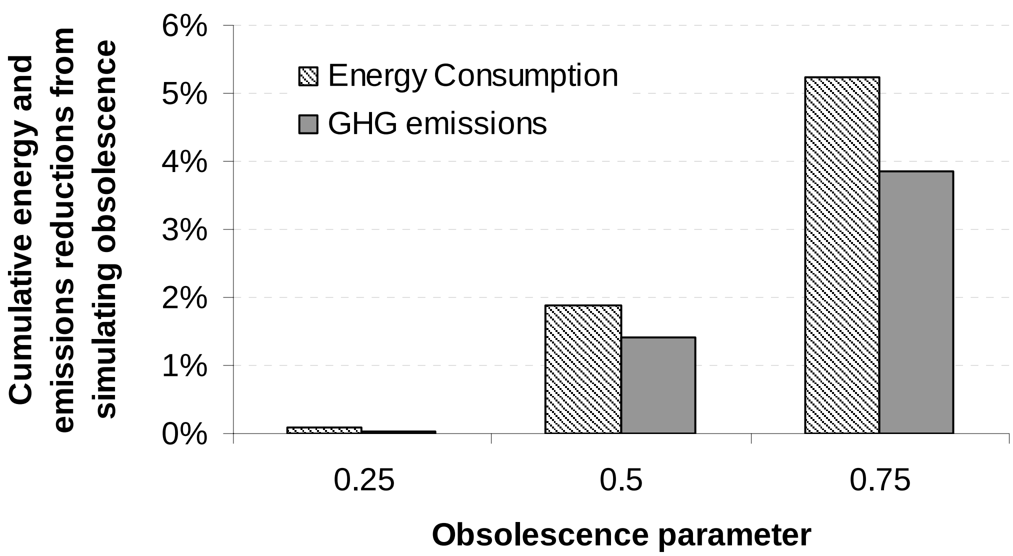

Figure 2.3: Decline in energy consumption and emissions when simulating obsolescence

When simulating obsolescence using an obsolescence parameter of 0.5, CIMS predicts that stocks will become 2% more energy efficient, and 1.5% less GHG intense. The obsolescence of old technologies enables new technologies – which in the data set tested here were generally more efficient and less GHG intense – to capture a greater share of active stocks. At a high threshold (*n* = 0.75), the active stock of equipment becomes approximately 5% more energy efficient and 4% less GHG intense over a 35 year simulation. At low thresholds (*n* = 0.25), the results from the simulation are not substantially different from a simulation without obsolescence.

Concerns with the obsolescence algorithm

An analyst should be aware of two problems that may arise when simulating the obsolescence of technologies. First, in rare occasions, an error may arise due to the interaction between the market constraints on certain technologies and the obsolescence algorithm. If a technology is no longer available for competition and the remaining technologies have constraints on their market share, the demand for a service may not be met. This problem can be resolved by adjusting the market constraints of the technologies prior to running the simulation. In practice, the maximum market share constraint may be replaced with a minimum market share constraint on the technology that becomes obsolescent.

The second problem is that the algorithm occasionally simulates the obsolescence of technologies that are unlikely to become obsolete, such as walking or transit in the transportation sector. While this outcome may be plausible, it is not the intention of the obsolescence algorithm to allow certain technologies to become obsolete. If the algorithm is incorporated into the model, it will be necessary to include a means for the user to indicate which technologies should be excluded from its application.

2.4. Discussion

If policy makers wish to direct technical change towards technologies with low or zero emissions, their policies may also induce the obsolescence of technologies with high emissions. The obsolescence algorithm introduced into CIMS prevents technologies from competing for a share of new equipment sold if their share of active stocks falls below a threshold. The threshold can be set by the user, or it may be informed with further research.

3. Simulating a Rising Emissions Charge Using Expectations

3.1. Introduction

Policy makers may be concerned about the economic effect of rapid and unexpected increases in emissions charges. In order to implement a policy that enables businesses and consumers to have foresight into their future emissions costs, government could have a clear schedule for increases in emissions charges. Kaufmann (1994) argues that people's expectation of future costs influences their technology choice, but the accuracy of their expectations is dependent on the information available to them. In other words, if charge signals are not clear, people may anticipate the wrong emissions charge and make poor technology acquisitions. A widely advertised schedule for rises in emissions charges may enable businesses and consumers to form accurate expectations, and policy makers may avoid an emissions charge shock.

CIMS's current methodology does not account for expectations of future emissions costs. CIMS's calculation of a technology's energy and emissions costs is illustrated in Equation 3.1:

$$E_{kt} = \left[\sum_{j=1}^{J} \left(P_{jt} \times Q_{kjt} \right) \right] + \left(Charge_t \times EMISSIONS_k \right) \qquad \textbf{(Equation 3.1)}$$

where E_{kt} is the energy and emissions costs of technology k at time t: P_{jt} is the price of energy type j (coal, electricity, etc) at time t; Q_{kjt} is the quantity of energy type j consumed by technology k at time t per unit of service output; $Charge_t$ is the emissions charge at time t measured in \$/tonne of CO_2e; $EMISSIONS_k$ is the total emissions emitted by technology k per unit of service output; and t is the year the technology is purchased. CIMS current methodology assumes myopic expectations, because emissions costs over a technology's lifespan are calculated using only the emissions charge in the year the technology is purchased. Therefore CIMS only simulates an accurate outcome if emissions charges remain the constant throughout the lifespan of a technology, or if people are in fact myopic.

Expectations in other energy-economy models

Before discussing how expectations of future emissions charges may be introduced into CIMS, I review other modeling efforts to include expectations. Two models are discussed: the Market Allocation model (MARKAL), which is a bottom-up model, and the National Energy Modeling System (NEMS), which is a hybrid model like CIMS.

MARKAL solves across time to calculate the technology mix that minimizes the net present cost of the total energy system. Therefore, technology selection occurs with perfect foresight into all the future costs of a technology, including the energy and emissions costs. This representation of people's expectations may not be behaviourally realistic, given the evidence for some degree of myopia in technology acquisition decision making (Wirl, 1991). Additionally, MARKAL does not differentiate between expectations of emissions charges and energy prices. Therefore, MARKAL may not accurately simulate a policy with a clear schedule for increases in emissions charges because those increases are likely to be foreseen, while changes in energy prices, which are highly volatile, are not (Wirl, 1991, Kaufmann, 1994; DOE, 2005b).

NEMS includes three options for simulating foresight of future energy prices. In the first option, expectations are assumed to be "myopic". In the second option, expectations are formed "adaptively" by extrapolating from past trends in energy prices to form expectations about future prices. In the final option, technology selection occurs with "perfect foresight" into the future costs of a technology (DOE, 2005a). Despite its flexibility, NEMS cannot simulate a situation where people have foresight into their future emissions costs, but do not have foresight into their future energy costs. Emissions charges are simulated in NEMS by adjusting the price of a fuel to reflect the cost of its emissions; therefore, emissions charges and energy prices cannot be separated (DOE, 2005a).

Neither MARKAL's nor NEMS's method of simulating expectations is appropriate for the objectives of this study. Ideally, the method developed for CIMS would allow for alternative assumptions about expectations in order to simulate policies with and without a clear schedule for increases in emissions charges. Additionally, CIMS's method of simulating expectations should apply to emissions charges and exclude expectations of energy prices. Historical trends in energy prices are highly volatile, and there is no indication that they are becoming less volatile. Therefore, expectations of future energy prices are likely to be characterized by myopia, whereas expectations of future emissions charges may not. Furthermore, estimating the influence of alternative energy price trends is not an expected application of the model. In the following sections, I develop and discuss three options for generating expectations of future emissions costs in CIMS.

3.2. The emissions costs expectations functions

In order to include expectations of future emissions costs into CIMS, the energy cost equation must be redefined as follows:

$$E_{kt} = \left[\sum_{j=1}^{J} \left(P_{jt} \times Q_{kjt} \right) \right] + \left(E\left(Charge_n\right)_k \times EMISSIONS_k \right) \qquad \textbf{(Equation 3.2)}$$

where E_{kt}, P_{jt}, Q_{kjt} and $EMISSIONS_k$ have the same definition as in Equation 1.4; and $E\left(Charge_n\right)_k$ is the expected emissions charge over the lifespan of technology k. The expected emissions costs of the technology are equal to the expected emissions charge multiplied by the emissions of technology k $\left(E\left(Charge_n\right)_k \times EMISSIONS_k \right)$. Expected emissions costs are specific to individual technologies, because a technology's lifespan determines how far into the future people will form expectations. Energy costs, however, are calculated using the price of energy in the year the technology is purchased (P_{jt}) in order to reflect myopic expectations of future energy costs.

The first option for generating expectations represents myopic expectations, where the expected emissions charge is completely weighted on the emissions charge at the time a technology is purchased.

$$E(Charge_n)_k = Charge_t \quad \textbf{(Equation 3.3)}$$

where the expected emissions charge over the lifespan of technology k $\left(E(Charge_n)_k\right)$ is equal to the emissions charge at the time the technology is purchased $\left(Charge_t\right)$. The myopic option may be used to simulate a rising emissions charge when charge increases are unanticipated. The myopic option may also be used when there is substantial uncertainty about the future trend in emissions charges. Research by Wirl (1991) indicates that people's expectations are best characterized by myopia when there is substantial uncertainty about future events.

The second option can be used to simulate situations where businesses and consumers have a high degree of confidence in future emissions charges, and they give equal weight to all future charges.

$$E(Charge_n)_k = \frac{\sum_{n=t}^{N+t-1} Charge_n}{N} \quad \textbf{(Equation 3.4)}$$

where $Charge_n$ is the emissions charge that occurs in year n; t is the year technology k is purchased; and N is the lifespan of technology k. This option calculates the average emissions charge over the lifespan of a technology, and it may be used to simulate an emissions charge with a clear schedule for increases in emissions charges.

The third option can also be used to simulate situations where businesses and consumers have a high degree of confidence in future emissions charges. However, it gives greater weight to emissions charges in the near future, than to emissions charges later in the lifespan of a technology.

$$E(Charge_n)_k = \left(\sum_{n=t}^{N+t-1} \frac{Charge_n}{(1+r_k)^{n-t+1}}\right) \times \left(\frac{r_k}{1-(1+r_k)^{-N}}\right) \quad \textbf{(Equation 3.5)}$$

where $Charge_n$, t and N have the same definition as in Equation 3.3; and r_k is the revealed discount rate of technology k. This option discounts future emissions charges to calculate the present value of emissions charges over the lifespan of a technology. It then annualizes the present value using a capital recovery factor (the second half of the equation). The present value of all emissions charges must be annualized, because Equation 3.2 requires an annual value for expected emissions charges. The discounted option gives greater weight to emissions costs closer to the present because it discounts future emissions charges.

Either the average expectations option or the discounted expectations option may be used to simulate a rising emissions charge with a clear schedule. In both options, the emissions charge that occurs in year *n* ($Charge_n$) is assumed to be known by businesses and consumers, thus reflecting perfect foresight. The key difference between the options is that the discounted option gives less weight to emissions charges in the future.

Expected emissions charges in years following the final simulation year

In the current version of CIMS, an analyst may only input the value of emissions charges up to the final simulation year (year 2035 in many applications of the model). However, technologies with lifespans that extend beyond the final simulation year require further inputs for emissions charges when using either of the foresight options. Emissions charges beyond the final simulation year are set to the emissions charge in the final simulation year:

$$Charge_n = \begin{cases} Charge_n & \text{if } 2000 < n \leq fsy \\ Charge_{(fsy)} & \text{if } n > fsy \end{cases} \qquad \textbf{(Equation 3.6)}$$

where $Charge_n$ has the same definition as above, and *fsy* is the final simulation year. This method of generating emissions charges beyond the final simulation year reduces the data requirements of the model, because additional emissions charges are not required. However, it may not simulate a behaviourally realistic outcome if emissions charges are expected to change after the final simulation year.

Comparison of the options

When an emissions charge remains the same over the lifespan of a technology, the expected emissions cost calculated by the three options is the same. Table 3.1 illustrates the expected emissions cost of a hypothetical technology calculated using the myopic, average and discounted expectations options. The emissions charge remains at $10/tonne CO_2e for three years, and the technology has a lifespan of three years, a revealed discount rate of 15%, and emits one tonne of CO_2e per year.

Table 3.1: Expected emissions cost of a technology when emissions charges remain constant

Myopic Expectations

	Year 1	Year 2	Year 3
Emissions Cost in year n	$10	$10	$10
Expected Cost (Myopia)	**$10.00**		

Average Expectations

	Year 1	Year 2	Year 3	Total Costs
Emissions Cost in year n	$10	$10	$10	$30.00
Expected Cost (Average)				**$10.00**

Discounted Expectations

	Year 1	Year 2	Year 3	PV of Costs
Emissions Cost in year n	$10	$10	$10	
Present Value of Costs	$8.70	$7.56	$6.58	$22.83
Expected Cost (Discounted)				**$10.00**

When CIMS simulates a constant emissions charge, the expected emissions cost remains the same regardless of the option used. However, when CIMS simulates a rising emissions charge, the expected emissions costs depend on the analyst's assumptions about expectations. Figure 1.1 illustrates a comparison between the myopic, average and discounted expectations options for a technology. Emissions charges rise in $10/tonne of CO_2e increments every five years. The technology has a lifespan of thirty years, a revealed discount rate of 15%, and it emits one tonne of CO_2e per year.

The solid line in Figure 3.1 illustrates the annual emissions costs of a technology with a lifespan of thirty years; the top horizontal line represents the expectations of future emissions costs using the average expectations option; the middle line represents expectations using the discounted option; and the bottom line (which overlays the x-axis) represents expectations using the myopic option. The myopic expectations option calculates expected emissions costs from the emissions charge in the year the technology is purchased. Therefore, its value is zero in the example above, and has the lowest value for all expectations options. The options based on average expectations and discounted expectations allow for foresight into future emissions costs. However, the discounted option gives less weight to emissions costs in the future, and therefore has a lower expected emissions charge.

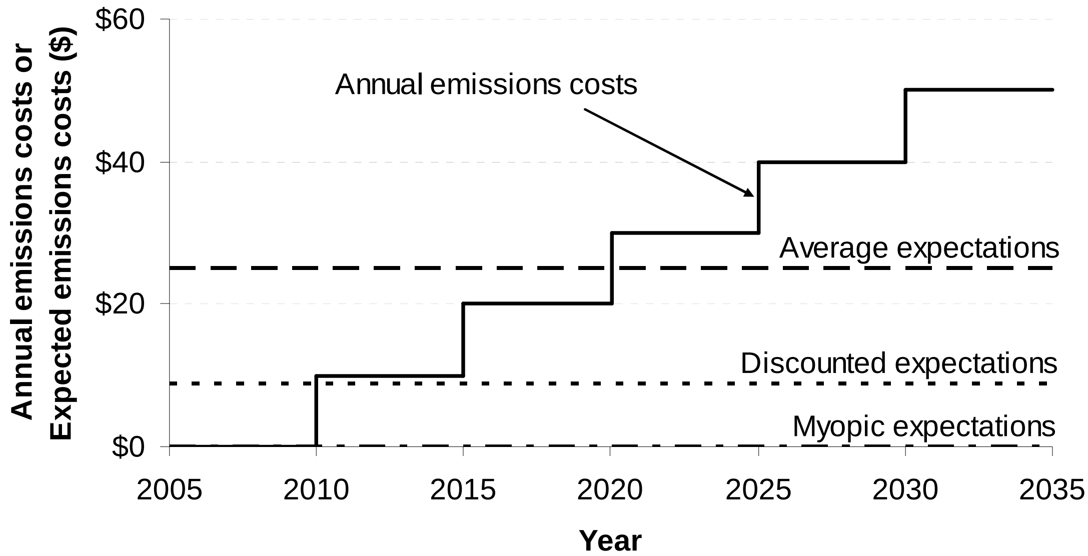

Figure 3.1: Expected emissions costs of a technology when emissions charges rise

3.3. Results

Emissions reductions using the three options for generating expectations

The three options for generating expectations simulate different quantities of emissions reductions for a rising emissions charge. Figure 3.2 illustrates a forecast of the annual emissions reductions caused by a rising emissions charge. The emissions charge remains at \$0/tonne CO_2e until 2005, and rises by \$10/tonne CO_2e increments every five years thereafter. The time period, and the emissions charge in each period are labeled on the x-axis.

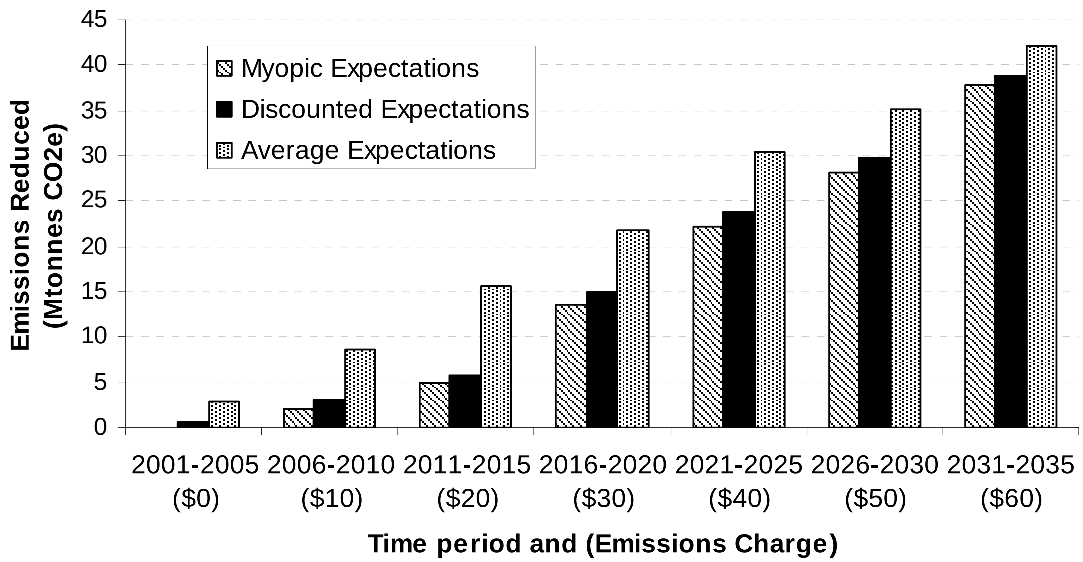

Figure 3.2: Annual emissions reductions caused by a rising emissions charge, using alternative options for simulating expectations

For both foresight options (the discounted and average expectations options), emissions reductions occur before an emissions charge is implemented (before 2006). These reductions occur because expected future costs are incorporated in technology choices in the earlier periods. The average expectations option simulates the greatest emissions reductions because it places equal weight on all future emissions costs.

3.4. Possible extensions to the expectations options

People's expectations of rising emissions charges may fall somewhere between perfect foresight and myopic. Perfect foresight and myopia are the least restrictive assumptions and the easiest to model, but are not always behaviourally realistic. For example, people may expect government to waiver on its schedule for rising emissions charges, or another political party with different environmental policies could be elected. In these situations, people may foresee more than one possible emissions charge and their expected emissions costs will be based on the perceived probability of each event occurring (Morgan and Henrion, 1990). At a later date, CIMS could accommodate uncertainty in government policy by simulating expected emissions costs based on multiple emissions charges.

A fourth option to represent adaptive expectations could also be added to CIMS. This option would simulate expectations when people extrapolate from past trends in emissions costs to form expectations about future costs. In my view, however, this option is not necessary because expectations of future emissions charges are likely to be heavily dependent on information provided from government (Kaufmann, 1994). Therefore, people are unlikely to look at past information when they form expectations about future emissions charges.

3.5. Discussion

Prior to introducing expectations, CIMS may have underestimated the emissions reductions caused by a policy with a clear schedule for increases in emissions charges. Previous applications of the model could only simulate myopic expectations of future emissions costs. However, a clear schedule for rises in emissions charges may enable businesses and consumers to have foresight into their future emissions costs because it sends a clear signal that emissions charges will be higher in the future. As a result, businesses and consumers may preemptively select technologies that emit fewer emissions.

I have developed three options for generating expectations in CIMS. The myopic expectations option simulates situations where businesses and consumers do not have foresight into their future emissions costs. This option should be used when government does not have a clear schedule for increases in emissions charges or when there is extreme uncertainty about future charges. The average expectations option represents complete information of future emissions charges, and businesses and consumers place equal weight on all emissions charges across the lifespan of a technology. The discounted expectations option also represents complete information, but people place less weight on emissions costs further in the future. Either the average or the discounted expectations options may be used when simulating a policy with a clear schedule for increases in emissions charges.

4. Estimating the Costs Caused by Policies to Induce Technical Change

4.1. Introduction

Alternative definitions of costs

One of the main purposes for modeling a policy's effect on technical change is to estimate the economic costs of actions to reduce greenhouse gas emissions.[8] However, policy analysts can generate very different cost estimates for similar policies because they use alternative definitions for the cost of actions. The alternative definitions can be categorized into two extremes – a conventional bottom-up definition and a conventional top-down definition.

Policy analysts that use a conventional bottom-up definition of costs generally assume that technologies (e.g., vehicles) that provide the same energy service (e.g., personal mobility) are perfect substitutes, except for differences in their financial costs. The financial cost of a technology is estimated as the sum of its capital costs and the present value of its operating costs over its lifespan (discounted using a social discount rate). Conventional bottom-up analysts also assume that a technology's financial cost is deterministic. In other words, all technologies are used until the end of their engineering lifespans, and every person experiences the same cost of adoption. Conventional bottom-up analysts recognize that many technologies that appear to be cost-effective on a financial cost basis only enjoy limited market success. The divergence between the "optimal" penetration of energy efficient technologies predicted by bottom-up models, and their actual penetration is called the "energy-efficiency gap" (Jaffe and Stavins, 1994). Bottom-up analysts explain that market barriers, such as imperfect information, prevent the wider adoption of such technologies, and argue for public policy to offset market barriers. Bottom-up modelers commonly conclude that policies to close the energy-efficiency gap reduce expenditures on energy, so that the overall cost caused by

[8] An action is a change in equipment choice, equipment use rate, lifestyle or resource management practice that changes GHG emissions from what they otherwise would be (Jaccard et al, 2003b)

the policy is low, or even negative (Lovins and Lovins, 1991; Brown et al, 1998; Jaffe and Stavins, 1994).

Policy analysts that use a conventional top-down definition of costs provide an opposing insight into why technologies that may appear cost effective only enjoy limited success. They emphasize that there are costs of adopting technologies that are not captured by a deterministic, *ex ante* estimate of financial costs. People may prefer the qualitative attributes of some technologies over others (e.g., some lower efficiency vehicles may be associated with greater social status); they may perceive some technologies to be riskier than others (e.g., a hybrid-electric vehicle may be perceived to have a greater chance of premature failure because it employs technology that has only been developed recently); and they may have different costs of adopting the same technologies (e.g., some people may require larger vehicles for work purposes). Conventional top-down analysts attempt to "reveal" people's non-financial costs and preferences from historic market data. They use market data to estimate aggregate relationships between energy consumption and relative factor prices. They argue that these relationships reveal people's costs and preferences because it was presumably these costs and preferences that induced them to make past technology choices. A conventional top-down analyst would attribute the energy-efficiency gap to costs and preferences that are not captured by financial costs alone. When people deviate from their initial choice of technology due to a policy, they are usually assumed to incur greater financial or non-financial costs (Jaffe and Stavins, 1994; Jaccard et al, 2003b; Azar and Dowlatabadi, 1999).[9]

The conventional bottom-up and top-down definitions of costs represent the two extremes on a continuum of cost definitions, and both definitions may misrepresent the social cost of altering people's technology choice. The conventional bottom-up approach associates the energy-efficiency gap with market barriers. However, if market barriers arise due to real non-financial costs of adopting technologies, the conventional bottom-up

[9] Most policy analysts that follow a top-down approach recognize that market failures and existing market distortions prevent an efficient allocation of resources. Therefore, the relationship between energy consumption and relative input prices does not always reveal people's preferences. I refer to the conventional top-down approach as an extreme position where market data is assumed to reveal the full social cost of adopting or switching technologies; and deviations from the business-as-usual allocation of resources necessarily causes a cost.

approach will misrepresent the social cost of people's actions. The conventional top-down approach rests upon strong assumptions about optimizing behaviour, the absence of market failures, and the permanence of people's preferences over time. Should any of these assumptions prove to be incorrect, the relationships estimated from market data will not reveal people's social costs of altering their future technology choice. As a result, the conventional top-down definition may also misrepresent the social cost caused by policies to induce technical change (Jaffe and Stavins, 1994; Bergman and Henrekson, 2003).

A mid-point between the conventional bottom-up and top-down definitions may be a more accurate reflection of the social costs caused by policies that induce technical change. In such an approach, the costs of adopting or switching technologies should represent their *ex poste* costs to businesses and consumers. The *ex poste* cost of a technology is what businesses and consumers would expect it to cost over its lifespan, if there were no market failures (i.e., businesses and consumers are fully informed with all the available information, and there are no market distortions that affect their technology selection). *Ex poste* costs include a technology's financial costs, but also include a risk premium (required to compensate people for undertaking risky investments), a measure of people's preferences (measured as intangible costs or benefits) and the heterogeneity of people's costs. At first glance, the *ex poste* costs of a technology may appear to be the same as a technology's cost revealed from market data. However, the risk premium, intangible costs, and the heterogeneity of people's costs may be different from their revealed values, if their revealed values are partially the result of market failures. A policy that induces people to purchase technologies with lower *ex poste* costs would cause a social benefit; otherwise, the policy causes a social cost. Figure 4.1 illustrates an example of the difference between the perceived and *ex poste* costs of a hybrid car.

A person is deciding whether he should purchase a hybrid car. The *ex poste* costs of the hybrid car include its financial costs (i.e., capital and operating costs). In addition to considering the hybrid car's financial costs, the person prefers larger vehicles with leather interiors. Hybrid cars are not available in the size he likes; therefore, the hybrid imposes a real intangible cost on the person. Hybrid vehicles are available with leather interiors, but the person does not think they are. Therefore, the person has a perceived intangible cost of adopting a hybrid which is caused by a market failure (imperfect information). The cost associated with the size of the vehicle represents an *ex poste* cost to the person, while the perceived cost associated with the leather interior does not.

In addition to the financial and intangible costs of adopting a hybrid, the person is also concerned that the hybrid may fail before the end of its engineering lifespan. Hybrid cars have been thoroughly tested by several consumer organizations, and the results indicate that there is a 20% chance that the hybrid will fail prematurely. By purchasing a hybrid car, the person incurs an *ex poste* cost associated with undertaking a risky investment. The person, however, is unfamiliar with this research and believes that the chance of premature failure is much greater. Therefore, the perceived costs associated with risk is greater than the *ex poste* cost.

Figure 4.1: Example of the *ex poste* costs of a hybrid car

Estimating the costs caused by a policy

The costs caused by a policy can be estimated using a hybrid energy-economy model, like CIMS, and a cost accounting tool. Market behaviour is simulated in CIMS to determine the relative market shares for different technologies in both a policy and a business-as-usual simulation. After CIMS determines market shares for alternative technologies, the costs caused by the policy can be estimated using a cost accounting tool and the analyst's definition of costs.

To mimic a conventional top-down definition of costs, the costs caused by a policy are estimated by simulating several emissions charges, and by estimating the emissions reductions caused by each charge. Emissions charges and emissions reductions are graphed to yield a marginal cost of abatement curve, and the cost of each emissions charge is equal to the area under the curve at that emissions charge (refer to Figure 4.2).

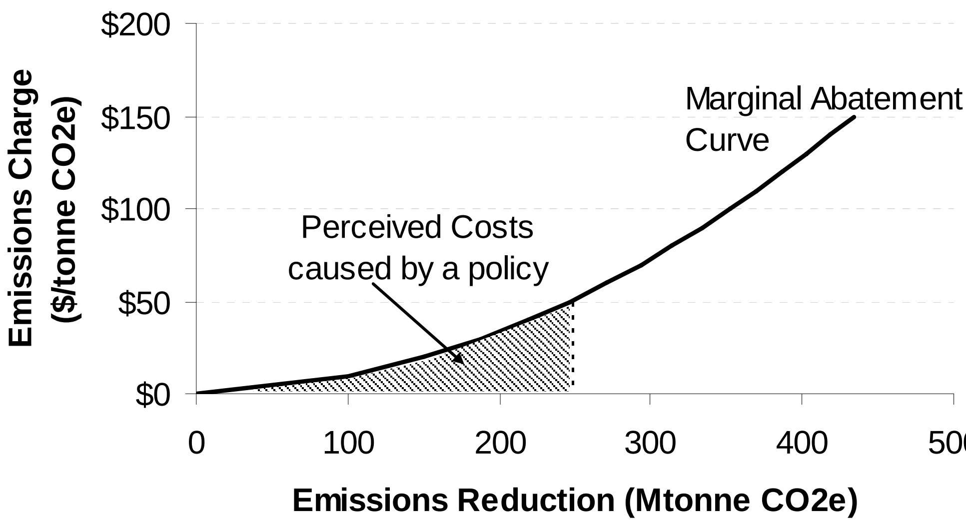

Figure 4.2: Perceived costs caused by an emissions charge (hypothetical example)

After the marginal cost of abatement curve has been estimated, the perceived cost of reducing emissions is equal to the area under the marginal abatement curve:

$$\textit{Perceived costs caused by policy} = \int MAC(ER)\,dER \qquad \textbf{(Equation 4.1)}$$

where *ER* is the emissions reduction; *MAC* is the marginal abatement cost, which is a function of *ER*. The area under the marginal cost of abatement curve represents what businesses and consumers "perceive" to be their cost of reducing their emissions. At a \$50/tonne CO_2e emissions charge, people only undertake actions to reduce one tonne of CO_2e that they think will cost \$50 or less, after accounting for perceived intangible costs and risk. The total perceived cost caused by a \$50/tonne CO_2e emissions charge is equal to the shaded area in Figure 4.2.

The costs caused by a policy can also be estimated using a bottom-up definition. After CIMS determines the technology mix that results from a policy, a cost accounting tool may be used to estimate the *ex ante* financial costs of active technologies. The costs caused by a policy are then calculated by subtracting the *ex ante* financial costs of the technology mix selected in the policy simulation from the *ex ante* financial costs of the technology mix selected in the business-as-usual simulation. Costs from the bottom-up approach may be positive or negative, because policies that induce investment in energy efficiency or technologies that emit fewer GHGs can reduce *ex ante* financial costs.

One effort to reconcile the top-down and bottom-up cost definitions assumes that the social cost caused by a policy lies between the perceived and financial costs caused by the policy. The financial costs caused by a policy set a lower bound; and 25% of the difference between the perceived and financial costs caused by the policy is the result of inefficient resistance to a policy. In previous studies, this arbitrary value has been used by some users of CIMS to calculate the expected resource costs (ERC) caused by a policy. This method of estimating ERC is summarized in Equation 4.1 (MKJA, 2002).

$$ERC = \Delta FC + \left(\left(PC - \Delta FC\right) \times 75\%\right) \qquad \textbf{(Equation 4.2)}$$

where ΔFC is the difference between the *ex ante* financial costs of the technology mix selected due to a policy and the *ex ante* financial costs of the technology mix selected in business-as-usual; *PC* is the perceived costs caused by the policy; and only 75% of the difference between the perceived and financial costs caused by the policy is considered to represent a social cost. The remaining 25% represents perceived costs that are assumed to arise from market failures. The 75% difference is an expert judgment which lacks strong empirical basis, and is therefore highly uncertain (MKJA, 2002). Figure 4.3 illustrates a hypothetical cost estimate using the perceived and financial costs of altering the technology mix to calculate ERC.

The method of calculating ERC represents a mid-point between the two definitions. However, it assumes that 25% of the difference between the perceived cost and the financial cost is always due to inefficient technology choices. In reality, the difference between the perceived cost and financial cost will depend on each action to reduce emissions. Therefore, a cost accounting method based on the *ex poste* costs of individual technologies may provide a more accurate representation of the social costs caused by a policy. Furthermore, financial costs set a lower bound and perceived costs set an upper bound to an array of possible expected resource costs. A cost accounting method that accommodates any array of definitions about costs would allow analysts to use their own assumptions to estimate the ERC caused by a policy.

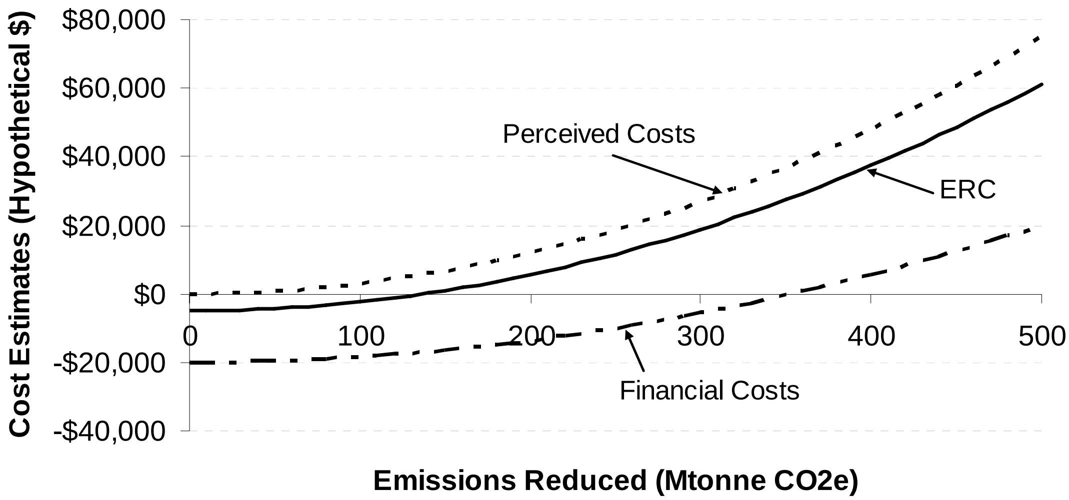

Figure 4.3: Comparison of hypothetical cost estimates

Cost estimates of regulations

An additional requirement of the new method of cost accounting is that it must estimate the costs caused by regulations. The previous method of estimating ERC requires an estimate of the perceived and financial costs caused by a policy. As described above, the perceived costs caused by a policy can only be estimated for emissions charges, or policies for which the marginal cost of abatement (*MAC(ER)* in Equation 4.1) can be estimated. It is impossible to determine the marginal cost of abatement for regulations from CIMS simulations, therefore the previous method of cost accounting cannot be used for regulations.

In the sections that follow, I outline a cost accounting model that accommodates alternative definitions of the costs caused by policies, and that can calculate the costs caused by regulations in addition to emissions charges.

4.2. The cost accounting model

Policies may induce businesses or consumers to take two types of actions that alter the *ex poste* costs of the active technology mix. Both actions may incur a cost or a benefit to businesses or consumers.

1) *Switching technologies*. In order to avoid an emissions charge or abide by a regulation, people may purchase a different technology than they would have purchased in the absence of a policy. People generally have different *ex poste* costs for adopting different technologies, and a policy that induces them to change their technology mix will cause a cost or benefit.
2) *Changes in the demand for a service*. A policy may induce businesses and consumers to change their demand for a service. If the policy increases the cost of attaining a service, businesses and consumers may be unwilling to participate in a market at higher costs. The cost of a reduction in the demand for a service is the net benefit (i.e., benefit minus cost) people derived from the service before they reduced their demand. The demand for a service may also increase due to a subsidy. Such a policy also causes a cost, because the people who attain the additional services require a transfer payment greater than the net benefit they derive from the service.

The cost accounting model estimates the costs of switching technologies and the costs of changes in demand separately. I first introduce the method for estimating the costs of switching technologies.

Reproduction of CIMS's market share simulation

The cost accounting model functions by reproducing CIMS's technology competition. The market share for new equipment stocks is reproduced by simulating the technology selection of one thousand businesses or consumers, where each agent experiences a unique cost of adopting each technology. Technology choice is based on the "perceived" costs that have been revealed from market data, to ensure a behaviourally realistic outcome. Each agent's perceived cost of adopting each technology is randomly drawn from a normal distribution with a mean equal to the technology's average perceived cost, and a variance that represents observed market heterogeneity.[10] After a unique cost has been allocated to each agent in the cost accounting model, each agent adopts the technology with the lowest perceived cost. Figure 4.4 illustrates how the model reproduces CIMS's technology competition (for simplicity, the figure illustrates a market with three people).

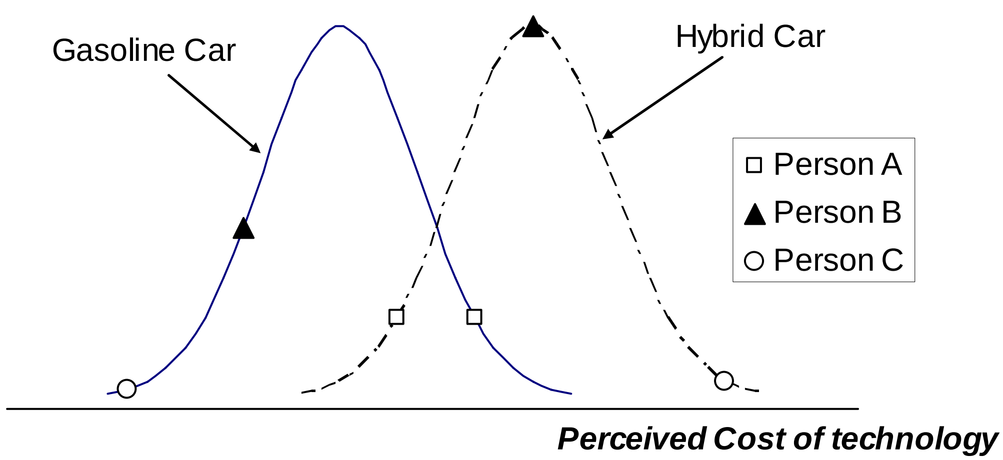

Figure 4.4: Allocation of market share for new equipment

The average perceived cost of the gasoline car is lower than that of the hybrid car, however the model allocates some market share to the hybrid car. Person A (represented by the square) adopts the hybrid because his/her perceived cost of adopting a hybrid car is lower than that of adopting the gasoline car. Person B (the triangle) and C (the circle) select the gasoline car, and the model adds up the number of people who select each technology to determine relative market shares. In this case, the hybrid car receives 33% and gasoline cars receive 67%.[11]

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[10] The cost accounting model can also accommodate other distributions, such as a Weibull distribution.
[11] The reproduction of market share from the cost accounting model results in approximately the same market share as observed from CIMS. For a comparison between the market shares of CIMS and the market shares from the model, refer to the Appendix.

Market share reproduction for a regulation

The cost accounting model reproduces the market outcome of a regulation by simulating how people switch technologies to meet the regulation.[12] Figure 4.5 illustrates the market share simulation for new vehicles before and after a regulation has been imposed. The regulation requires that the market share for hybrid cars must be greater than 60% of all hybrid and gasoline cars sold.

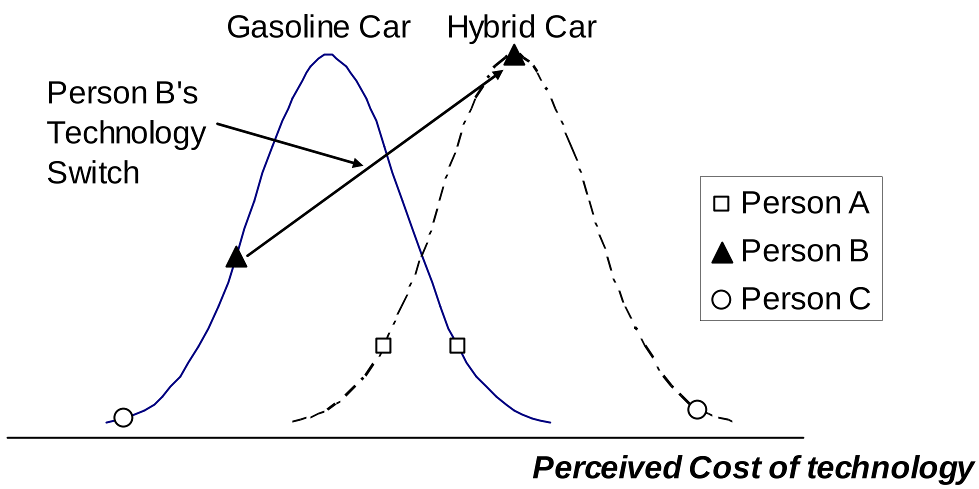

Figure 4.5: Market share simulation for a regulation

In order to attain the aggregate market outcome stipulated by the regulation, either person B or C must switch to the hybrid car. Assuming there is a market for businesses and consumers to trade their responsibilities to meet the regulation, person B and C will reach an agreement for person B to switch to the hybrid car. Person C perceives his/her cost of switching to the hybrid to be greater than person B, therefore, their combined perceived costs of meeting the regulation are lower if person B switches. After person B switches to the hybrid, the market share for hybrid cars is 67%, the market share for gasoline cars in 33%, and the market outcome stipulated by the regulation is met.

[12] A regulation may require all people to switch technologies; or it may require a portion of people to switch technologies.

Market share reproduction of an emissions charge

If an emissions charge is implemented, the mean perceived cost of technologies that emit GHGs increases, and the curve representing those costs, shifts to the right. (For simplicity, I assume that hybrid cars are exempt from all emissions charges).

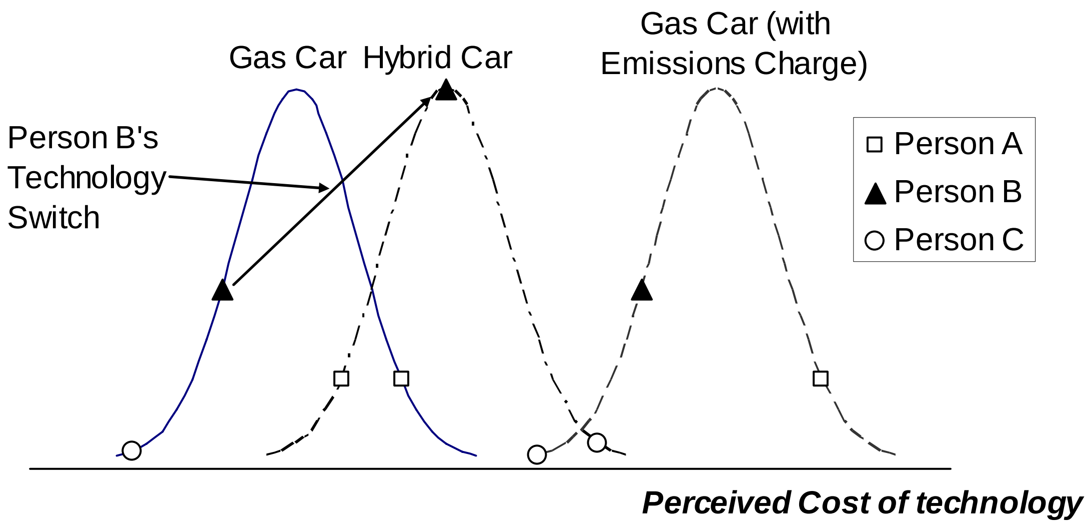

Figure 4.6: Market share simulation for an emissions charge

After the emissions charge is implemented, the curve representing the perceived costs of the gasoline car shifts from the curve labeled "Gas Car" to the curve labeled "Gas Car (with Emissions Charge)". Again, person B switches to the hybrid car as a result of the policy because his/her perceived costs of adopting and paying the emissions charges for the gasoline car exceed his/her costs of adopting the hybrid car. Despite the emissions charge, person C purchases the gasoline car because his/her perceived costs of adopting and paying the emissions charge for the gasoline car are lower. Person C incurs an additional cost by paying for the emissions charge, but this payment represents a transfer of income to government or elsewhere, and it does not represent a cost to society.

Estimating costs of switching technologies using alternative cost definitions

The main goal of the cost accounting model is to accommodate alternative definitions of the costs of actions to reduce emissions. The assumption behind the top-down approach is that people's costs and preferences towards alternate technologies may be revealed from market data. Accordingly, the *ex poste* cost of a technology is calculated using a discount rate, intangible costs and a variance parameter that have been revealed from market data. This approach represents what businesses and consumers perceive to be their costs of altering their initial technology mix. Figure 4.7 illustrates the perceived cost of person B's switch from the gasoline car to the hybrid car.

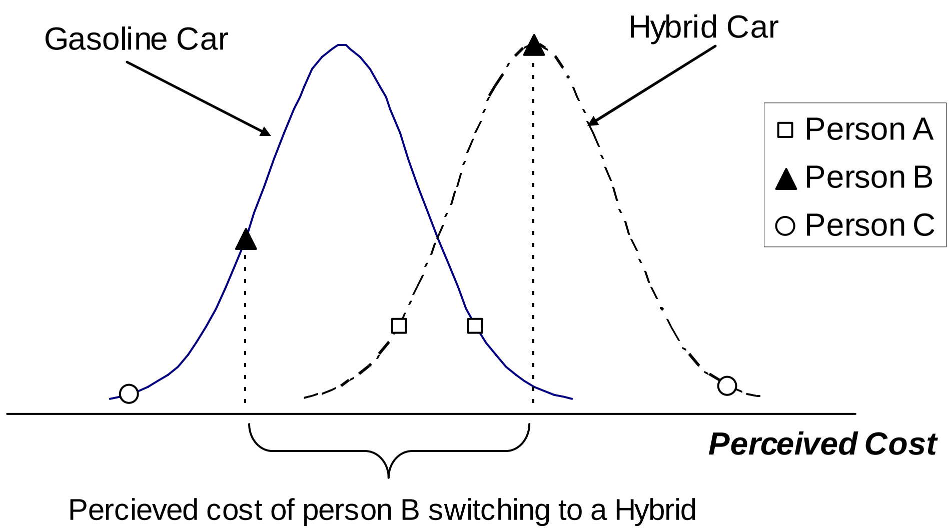

Figure 4.7: Cost of a technology switch, using a top-down definition

The perceived cost of a person's technology switch is the horizontal distance between the perceived cost of the technology they select due to the policy and the perceived cost of the technology they select in business-as-usual. Neither person A or C experience a change in their perceived costs because they select the same technology regardless of the policy. Person B, however, switches to the hybrid car as a result of the regulation or emissions charge, and he/she experiences an increase in perceived costs.

The conventional bottom-up approach, in contrast, suggests that revealed market data do not necessarily represent the true cost of technology adoption. Rather, the cost of a technology is captured by a deterministic, *ex ante* estimate of financial costs. These costs are calculated using a social discount rate, no intangible costs and no cost heterogeneity. When person B switches to the hybrid, the financial costs of the switch are equal to the difference between the financial costs of the hybrid car and the financial costs of the gasoline car. The financial cost of the switch may be negative if the hybrid car is financially cheaper to purchase and operate over its lifespan.

Regardless of the definitions of costs, the ERC of technology switches is calculated using the following equation.

$$ERC_a = EPCost_{Pol.,a} - EPCost_{BAU,a} \quad \textbf{(Equation 4.3)}$$

where the ERC of person *a*'s technology switch is the difference between the *ex poste* cost of the technology he/she selects in due to a policy ($EPCost_{Pol,a}$) and the *ex poste* cost of the technology he/she selects in business-as-usual ($EPCost_{BAU,a}$). ERC_a may be negative for some technology switches because the *ex poste* cost of the technology purchased due to a policy may be less than the *ex poste* cost of the technology purchased in BAU. Finally, the cost accounting model is primarily designed to measure the social costs caused by policies. Therefore, *ex poste* costs generally exclude a measure of a technology's emissions charges, which represent a transfer of income.

After ERC_a has been calculated for each of the one thousand people in the cost accounting model, the average *ERC* of each person who switched to technology *k* is calculated and multiplied to the increase in the stock of technology *k* that results from switching.

$$ERC_k = \left(\frac{\sum_{a=1}^{A} ERC_{ka}}{A} \right) \times SwitchNS_k \quad \textbf{(Equation 4.4)}$$

Where ERC_k is the total expected resource cost of all people who switched to technology *k*; ERC_{ka} is the expected resource cost person *a* incurs by switching to technology *k*; *A* is the number of people in the cost accounting model who switched to technology *k*; and $SwitchNS_k$ is the increase in the stock of technology *k* that results from technology switching. Equation 4.4 only calculates the costs of people who switch to technology *k*, and it excludes the costs associated with changes in the stock of technology *k* that result from a change in demand. The costs from a change in demand are discussed later in this chapter. The equation also helps illustrate the connection between CIMS and the cost accounting model. The cost accounting model calculates the average cost of switching technologies (the first part of the equation), and the increase in the stock of technology *k* that results from technology switching is calculated from the CIMS simulation of equipment stocks. $SwitchNS_k$ has the following formulation:

$$SwitchNS_k = NS_{kPol} - \left(MS_{kBAU} \times TNS_{Pol}\right) \qquad \textbf{(Equation 4.5)}$$

where NS_{kPol} is the new stock of technology *k* from the Policy simulation; MS_{kBAU} is the market share for technology *k* from the business-as-usual simulation; and TNS_{Pol} is the total new stock of all technology competing to provide the same service as technology *k* in the Policy simulation. All the variables in Equation 4.5 are obtained directly from CIMS's output. The equation calculates the increase (or decrease) in the stock of technology *k* that results from technology switching, and it excludes changes in stock that result from changes in demand. The second part of the equation $\left(MS_{kBAU} \times TNS_{Pol}\right)$ calculates the new stock of technology *k* in business-as-usual that will remain in the market after a policy has been implemented.

Estimating costs for a mid-point between the conventional definitions of cost

While the cost accounting model can estimate the costs of technology switches using either a conventional top-down or bottom-up definition, it can also estimate costs using a mid-point between the definitions. To calculate a mid-point, the *ex poste* costs of technologies are recalculated using discount rates, intangible costs and variance parameters between their revealed and financial values.[13] To ensure that the *ex poste* costs of technologies represent their true social cost, the parameters should only reflect real costs to businesses and consumers, and exclude the effect of market failures. If a technology's high revealed discount rate corresponds to real risks of adopting the technology, the discount rate used to calculate the *ex poste* costs of a technology should equal the revealed discount rate (Jaffe and Stavins, 1994). However, if the high revealed

[13] It is important to note that market shares are allocated using the perceived costs of technologies, regardless of the definition of cost.

discount rate corresponds to perceived risks that arise from market failures, such as imperfect information about the energy costs of a technology, the revealed discount rate may be high because people place more weight on the up-front capital costs of a technology than is privately optimal (Moxnes, 2004). In this case, the discount rate used to calculate the *ex poste* costs of a technology should be lower than the revealed discount rate. Similarly, the values of intangible costs may fall between their revealed and financial values. The revealed intangible costs may be the result of imperfect information about the attributes of a technology. Therefore, the actual value of intangible costs may be lower than the implicit value from market research. Finally, people's individual costs of adopting technologies may be more or less heterogeneous if there were no market failures. The variance parameter representing cost heterogeneity may be different when calculating people's individual *ex poste* costs.

The selection of parameters to calculate the *ex poste* costs of technologies is left to the discretion of the analyst, the result of empirical research or expert judgment. A prescription of what the values of these parameters should be is beyond the scope of this paper, but several authors have conducted empirical research in the area (Rivers, 2003; Mau, 2005; Moxnes, 2004).

Costs of technology switches over time

The cost of switching technologies may extend beyond the year when the switch occurs. When people are induced to switch to a specific technology, they experience the cost of switching to that technology until it retires. For example, if a person who requires a large truck for work purposes is forced to purchase a hybrid car, he/she experiences the extra cost of adopting that car until the car is retired. Therefore, the ERC of a technology switch is added to all future time periods within the lifespan of the technology.

Costs caused by a reduction in demand

Another potential action to a policy is that businesses or consumers may reduce their demand for a service instead of incurring the costs of emissions charges or the costs of switching technologies. For example, if an emissions charge is implemented, a person may decide to reduce his/her demand for personal mobility, rather than adopting a vehicle with lower emissions or paying the emissions charge associated with their mobility. The cost of this person reducing his/her personal mobility is the net benefit (i.e., the benefit they would have derived from personal mobility minus the costs associated with their mobility) they would have attained from the service before its cost increased. The ERC caused by a reduction in demand is illustrated in Figure 4.8.

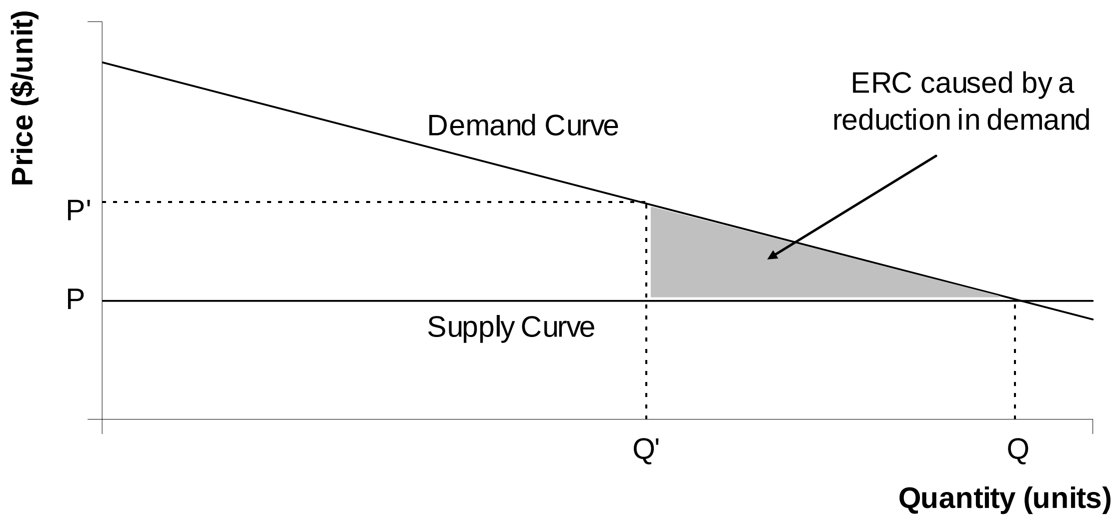

Figure 4.8: ERC from a reduction in demand

A reduction in demand from Q (the service demanded in BAU) to Q' (the service demanded in policy) causes an ERC equal to the shaded area. While the net benefit of people who remain in the market is reduced by the higher price of the service, their loss is offset by an associated gain to government. Therefore this reduction in net benefit does not represent a net loss to society or an ERC. The increase in the price of the service (P' – P) is calculated from the average increase in the perceived costs of attaining the service for each person.

$$(P' - P) = \frac{\sum_{i=1}^{I=1000} \left(PC_{Pol,i} - PC_{BAU,i}\right)}{I} \qquad \textbf{(Equation 4.6)}$$

where $PC_{Pol,i}$ is the perceived cost of the technology person *i* purchased in the policy simulation (including emissions costs); $PC_{BAU,i}$ is the perceived cost of the technology person *i* purchased in the business-as-usual simulation; and *I* is the number of people in the cost accounting model.

After the average increase in perceived costs of all people participating in the market is calculated, the ERC from a reduction in demand (the triangular area in Figure 4.8) is calculated using the following equation:

$$\textit{ERC from a reduction in demand} = \frac{1}{2} \times (Q' - Q) \times (P' - P) \qquad \textbf{(Equation 4.7)}$$

Costs caused by an increase in demand

While policies such as emissions charges usually increase the perceived costs of technologies, other policies, such as subsidies, reduce the costs of specific technologies. Such a policy may increase the demand for a service because people are encouraged to participate in the market due to lower costs. Lower costs increase the net benefit of people participating in the market, but they do so at the expense of taxpayers. Taxpayers must compensate the people who enter the market by a greater amount than the increase in net benefit, causing an ERC.

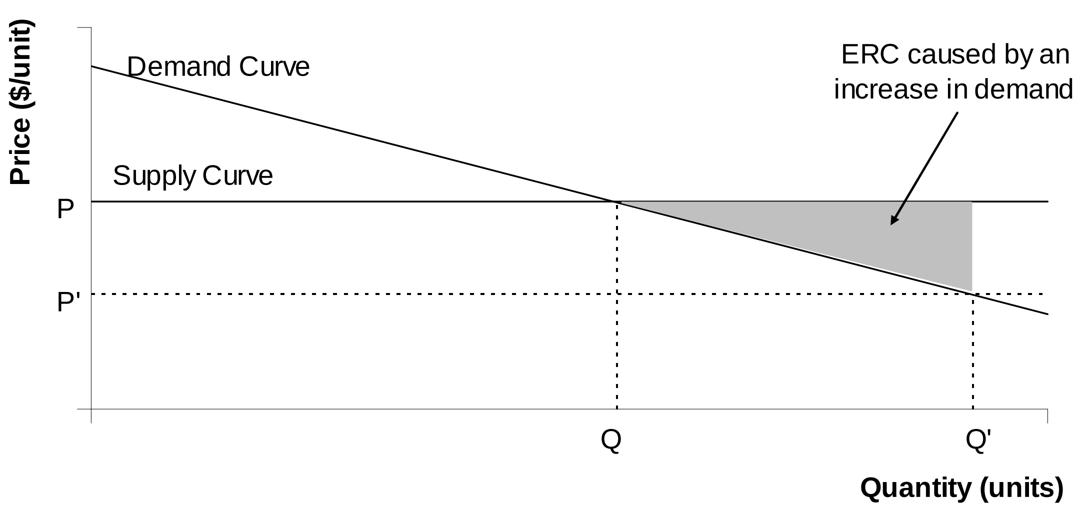

Figure 4.9: ERC from an increase in demand

Taxpayers compensate businesses or consumers by P – P' for every unit of service they demand, even though some do not need this amount of compensation to take action. This amount is greater than the gain in net benefit for quantities Q to Q'; therefore, the subsidy causes a net cost to society (equal to the shaded area).

Costs caused by changes in demand for alternative definitions of costs

The process described above for calculating the cost of a change in demand is best used when the analyst uses a top-down definition of costs. The costs for a reduction in demand are based on what people perceive their net benefit to be from participating in a market. The cost of attaining the service is based on the perceived costs of attaining the service, and the demand for the service is determined by price elasticities of demand. These elasticities, which measure the change in demand that results from a change in price, have been revealed from market data, and represent the perceived benefit from the service.

As discussed above, the perceived cost or benefit of a service does not necessarily equal its *ex poste* cost or benefit. Ideally, the increase in the price of the service (P' – P in Equation 4.6) would be calculated from the *ex poste* costs of technologies instead of the perceived costs. However, to estimate the price for a service from *ex poste* costs would substantially increases the data requirements of the model. The model would require an estimate of the *ex poste* costs of each technology with emissions costs, in addition to the *ex poste* costs without emissions costs. Furthermore, the benefits of this method are small. I developed a model that accommodates alternative definitions of costs when calculating the costs of a change in demand, and the cost only varied by 7% when using alternative definitions. Therefore, a method to accommodate alternative definitions when estimating the cost of a change in demand would increase the complexity of the model without a substantial effect on the results. In the current version of the cost accounting model, the cost of a change in demand for all cost definitions is approximated from the cost when using a top-down definition.

Technologies that supply services to other technologies

The model does not calculate the cost of changes in demand for services that are provided to another technology. Examples of these services are steam, which is provided to other industrial processes, or all services provided by the energy supply sector, which provides energy to the energy demand sectors. A change in the demand for these services is caused by a change in services upstream; and including the costs of a change in demand for services provided to other technologies would double count costs.

4.3. Summary

A cost accounting tool can be used with a hybrid energy-economy model (in this case CIMS) to estimate the costs caused by a policy to induce technical change. The cost accounting model accommodates alternative definitions of the cost of people's actions to reduce emissions. To produce a cost estimate consistent with a conventional bottom-up definition, the costs of technologies are set to their deterministic, *ex ante* estimate of financial costs. A policy may cause a financial benefit to businesses and consumers if it induces them to purchase technologies with lower financial costs. To produce a cost estimate consistent with a conventional top-down definition, the costs of technologies are set to their revealed costs, which have been estimated from observed market behaviour. Under this definition, the costs caused by a policy are strictly positive because people are assumed to be efficient in their allocation of resources in the absence of a policy. The cost accounting model may also generate a cost estimate that represents a mid-point between the top-down and the bottom-up definition of costs.

The cost accounting model can also generate an estimate of the costs caused by regulations. Each business or consumer simulated in the model experiences a unique cost of adopting each technology; and the costs of switching technologies is estimated from the difference between the *ex poste* costs of the technology selected due to a policy and the technology selected in business-as-usual.

5. Results from the Cost Accounting Model and the Additions to CIMS

5.1. Introduction

The cost accounting model, the option for including expectations and the obsolescence algorithm are designed to improve the information an energy-economy model can provide to policy makers. The cost accounting model uses the results from an energy-economy model to estimate the cost of actions to reduce greenhouse gas (GHG) emissions. It accommodates alternative definitions of costs, as well as intermediates between these definitions. The cost accounting model can also estimate the costs caused by regulations, in addition to emissions charges. The options for including expectations of future emissions charges may be used to simulate a rising emissions charge with a clear schedule for charge increases. The obsolescence algorithm is designed to improve CIMS's representation of technical change.

In this chapter, I estimate the costs caused by several policy instruments using the cost accounting model. In section 5.1, I introduce the policy instruments analyzed later in the chapter, and highlight the reasons why each policy instrument may be used to induce technical change. In section 5.2, I discuss the methodology used to simulate policies in CIMS, and to generate the cost estimates. And in section 5.3, I present estimates of the costs of several policies to induce technical change. I begin by comparing the cost accounting model to the previous method used to estimate costs of actions simulated in CIMS . The purpose of this section is to illustrate that the two methods yield similar results. I then illustrate an estimate of the Expected Resource Costs (ERC) caused by emissions charges. Furthermore, I compare the ERC of reducing one tonne of carbon dioxide or equivalent (CO_2e) using several different policy instruments. Finally, I compare cost estimates of a rising emissions charge under different assumptions about the way people form expectations of their future emissions costs.

5.2. Policy instruments available to induce technical change

For this chapter, I simulate various policy instruments in CIMS. I then use the results from the simulations to estimate the costs caused by each policy. Each policy is simulated over the period between 2006 and 2020, with cost estimates reported for the same period. I introduce the policy instruments below.

Emissions charges

To compare the new and old methods of cost accounting, I simulate several constant emissions charges in order to estimate the costs at different levels of emissions charge. Each constant emissions charge ranges from \$10/tonne CO_2e to \$150/tonne CO_2e. While it is unrealistic to assume that policy makers will set an emissions charge to \$150/tonne CO_2e in the near future, the purpose of this exercise is to generate and compare the cost estimates from the cost accounting model to the estimates from the previous method.

For the later sections of the chapter, I estimate the costs caused by a rising emissions charge. I simulate two rising emissions charges, of varying aggressiveness. In the "less aggressive" version, the emissions charge is set to \$10/tonne CO_2e in 2006, and rises by \$10/tonne CO_2e increments every five years until 2016. In the "more aggressive" version of the policy, the emissions charge is set to \$10/tonne CO_2e in 2006, and rises by \$20/tonne CO_2e increments every five years until 2016. Table 5.1 summarizes the values for the rising emissions charges.

Table 5.1: Values for the rising emissions charge

Policy Aggressiveness	Value of Emissions Charge (\$/tonne CO_2e)			
	2000-2005	2006-2010	2011-2015	2016-onwards
Less Aggressive	\$0	\$10	\$20	\$30
More Aggressive	\$0	\$10	\$30	\$50

While emissions charges may be an attractive policy option because they send a uniform signal to all emitters, other policy instruments may be adopted for a number of reasons. First, emissions charges may be judged to fall outside federal jurisdiction, and other policies may be easier to implement at a federal level. Second, government may want to encourage technical change in niche markets where reductions in GHG emissions have co-benefits, such as a reduction in urban air pollution. Third, emissions charges may be less politically feasible than other policy instruments because businesses and consumers may oppose emissions taxes or any policy similar to a tax (Hahn and Stavins, 1992; Pizer, 1999; Jaccard et al, 2002).

Vehicle Emissions Standard

A Vehicle Emissions Standard (VES) is a niche market regulation that requires manufactures to sell a minimum percentage of low or zero emissions vehicles (Jaccard et al, 2004c). The VES stipulates an aggregate market outcome, and allows manufacturers to trade among themselves to achieve the required market share. The main reason for using a VES is that it may be more effective than a price based policy at encouraging technical change in the transportation sector. Research has shown that consumers are relatively insensitive to small increases in fuel prices (Espey, 1997; Hirschman et al. 1995; Kirby et al 2000). Additionally, consumers oppose the use of strong price increases as a transportation policy (Horne, 2003). Therefore, emissions charges may not be a practical option for inducing technical change in the transportation sector, whereas a VES directly forces the adoption of low or zero emissions vehicles.

The VES I simulate for this paper classifies vehicles into three types based on their tailpipe GHG emissions:

Table 5.2: Vehicle classification

Emissions class	Example	Emissions range (tonnes CO_2e/vkt)*	
		Minimum	Maximum
Zero Emissions (ZEV)	Hydrogen fuel-cell car	0.000000	0.000000
Low Emissions (LEV)	Hybrid or efficient gasoline	0.000001	0.000200
Standard Emissions (SEV)	Inefficient gasoline	0.000201	0.000500

* *vkt* stands for vehicle-kilometre-traveled

In the business-as-usual simulation, zero emissions vehicles gain a negligible amount of market share up to 2020, while low emissions vehicles gain approximately a 60% market share of new vehicles sales. In the “less aggressive” VES, 3% of new cars must have zero emissions by 2020, and 70% of new cars must have low emissions. In the “more aggressive” VES, 6% of new cars must have zero emissions by 2020, and 80% of new cars must have low emissions. Table 5.3 illustrates the goals of the less and more aggressive policies.

Table 5.3: Minimum market share requirements for class of vehicles

Emissions Class	Minimum New Market Share					
	Less Aggressive			More Aggressive		
	2010	2015	2020	2010	2015	2020
ZEV	1%	2%	3%	2%	4%	6%
LEV	63%	67%	70%	67%	73%	80%

Renewable Portfolio Standard

Policy makers may also wish to promote the generation of electricity from energy sources that have additional social and environmental benefits that markets undervalue. A Renewable Portfolio Standard (RPS) requires electricity producers to deliver a minimum amount of electricity that has been produced from renewable energy sources, such as wind, solar or biomass. But a RPS may also include other energy sources, such as generation from fuel cells, which does not produce direct GHG emissions. In order to implement a RPS, policy makers must establish which energy sources comply with the standard (Jaccard, 2004b). For the purpose of this study, electricity produced from solar, wind, biomass, geothermal or fuel-cell energy sources are eligible in the RPS. Hydroelectric generation is excluded from the RPS because it has already been highly commercialized.

In the business-as-usual forecast from CIMS, less than 1% of electricity is produced from the specified energy sources by 2020. In the “less aggressive” RPS, 6% of electricity must be produced from the specified sources by 2020; and in the “more aggressive” RPS, 9% of electricity must be produced from the specified sources by 2020.

Table 5.4: Electricity acquired from the sources specified in the RPS

Policy Aggressiveness	Electricity Acquired from the Specified Energy Sources (% of Total Electricity generation)		
	2010	2015	2020
Less Aggressive	2%	4%	6%
More Aggressive	3%	6%	9%

Regulation of household appliances

Another option for policy makers is to remove the least efficient household appliances from the market. Empirical research by Moxnes (2004) suggests that such a regulation may improve people's welfare, because people often make imperfect decisions due to high search costs and imperfect product information. Moxnes (2004) found that people tend to overemphasize the initial purchasing costs of appliances and overlook the subsequent energy costs. As a result, households may purchase appliances that do not maximize their welfare. A regulation on household appliances may improve welfare if it prevents people from making poor market decisions.

I simulate two versions of a regulation to phase out new sales of inefficient appliances. In the "less aggressive" version, the least efficient 10% of appliances are removed from the market; in the "more aggressive" version, the least efficient 30% appliances are removed.

Table 5.5: Percent of least efficient appliances removed from market

Policy Aggressiveness	Least efficient appliances removed from market (% of new appliances sold)		
	2010	2015	2020
Less aggressive	10%	10%	10%
More aggressive	30%	30%	30%

5.3. Assumptions

This section describes the key assumptions used to simulate policies in CIMS, and to estimate the costs caused by those policies using the cost accounting model. I begin by discussing the settings used in CIMS, and later I discuss the parameters and settings used in the cost accounting model.

Obsolescence function

As recommended in chapter 2, the obsolescence parameter is set to 0.5 in all simulations. An obsolescence parameter of 0.5 simulates that a technology will no longer compete for a share of new equipment sales after its share of active stock declines below 50% of its share of active stock in year 2000.

Expectations of emissions charges

For the first two sections – comparing the new and previous cost accounting methods, and the section that reports the cost estimates for regulations – I simulate myopic expectations of future emissions charges. In the later section, where I compare the costs of a rising emissions charge with and without a clear schedule for increases in charge, I use the three options for generating expectations – myopic, average and discounted expectations.

Sectors included in simulations

CIMS represents the residential, transportation, commercial and major industrial sectors in all provinces. All sector-region pairs are included in all simulations, unless otherwise noted. Therefore, the results represent all the major sectors and regions in Canada.

Inclusion of equilibrium feedbacks

Most of the simulations in CIMS include several feedbacks to equilibrate the different sectors of the economy. Unless otherwise noted, the prices for electricity and refined petroleum products are set endogenously by the model to equilibrate energy supply and demand. The demand for the output can also decline (or increase) if the costs of services increase (or decrease).

Ex poste costs of technologies

After the policies have been simulated in CIMS, the cost accounting model estimates the cost of actions to reduce emissions. In order to estimate the costs caused by policies, the cost accounting model requires an estimate of the *ex poste* costs of technologies. *Ex poste* costs vary according to the definition of cost. When generating cost estimates using a conventional top-down definition, *ex poste* costs reflect the costs businesses and consumers appear to use when making market decisions. They are calculated using discount rates, intangible costs and cost heterogeneity that have been revealed from market data. When generating cost estimates using a conventional bottom-up definition, the *ex poste* costs of technologies are equal to their deterministic, *ex ante* financial costs. They employ a social discount rate (10%), exclude intangible costs and assume complete cost homogeneity among different businesses and consumers.

Additionally, I generate a cost estimate for a mid-point between the two definitions. *Ex poste* costs for estimating the mid-point employ discount rates between their financial and revealed values (between 20% and 25% in most sectors). Discount rates are set below their revealed values because research indicates that the implicit discount rate businesses and consumers appear to use may be too high due to market failures (Moxnes, 2004; Jaffe and Stavins, 1994). However, the discount rates are set above the social rate to include a measure of the real risk people incur when purchasing technologies (Jaffe and Stavins, 1994). In all sectors except transportation, intangible costs are reduced to 75% of their revealed values. The reduction reflects that some of the revealed intangible costs may arise due to market failures, such as imperfect product information. In the transportation sector intangible costs are left unchanged because they are the product of stated preference research (Mau, 2005; Ezyguirre, 2004). The variance parameter representing cost heterogeneity is set to the same value as when generating costs for the conventional top-down definition.

In most cases, the selection of behavioural parameters to calculate *ex poste* costs is arbitrary, and lacks empirical backing. However, the purpose of this exercise is to illustrate that the cost accounting model *can* generate a mid-point between the two definitions of costs. To generate a more accurate estimate of the ERC caused by policies, more empirical research is required to determine the approximate discount rate, intangible costs and cost heterogeneity that simulate outcomes people would prefer.

Cost accounting methodology

The methodology for calculating costs using the cost accounting model has mostly been explained in Chapter 4. However, the model reports the annual costs that businesses and consumers incur as a result of a policy for several years over the time period (i.e., 2010, 2015 and 2020). In order to report a single estimate of costs over the entire time period, I discount all future costs to 2005 using a social discount rate (10%). Therefore, all cost estimates are reported as the present value of costs from 2006 to 2020. Costs have also been adjusted for inflation, and are reported in 1995 Canadian dollars.

The previous method for estimating the perceived costs (a conventional top-down definition) from CIMS' simulation requires an estimate of the emissions reductions at several emissions charges. Emissions charges and emissions reductions are then graphed to yield a marginal cost of abatement curve, and the cost of an emissions charge is the area under the curve at that charge level. This method is called the "area under the curve" method, and it measures what businesses and consumers perceive to be their costs of altering their technology choices.[14]

The previous method for estimating costs using a conventional bottom-up definition requires an estimate of the deterministic *ex ante* financial costs of a technology. The method of calculating these costs is illustrated in Equation 5.1:

$$FC_{kt} = CC_k \times p + \sum_{n=t} \frac{O\&M_k + EC_{kn}}{(1+R)^{n-t}} \qquad \textbf{(Equation 5.1)}$$

where FC_{kt} is the present value of a technology's financial costs that are paid off over a specific time period (in this case from 2005 to 2020); t is the year technology k is purchased; CC_k is the capital cost of technology k; p is the portion of the capital cost that has been paid off by the end of the time period; $O\&M_k$ are the annual operating and

[14] This method of calculating the perceived costs caused by a policy has already been discussed in chapters 1 and 4.

maintenance costs of technology *k*; EC_{kn} are the energy costs of technology *k* in year *n*; *R* is the social discount rate (10%); and *n* is years, up to a maximum of the end of technology *k*'s lifespan or the end of the time period (which ever comes first). Equation 5.1 only includes the financial costs of a technology that are paid off over the planning horizon (i.e., before 2020). Businesses or consumers may take several years to pay off the capital costs of a technology, and some of these payments may fall outside the time period (i.e., payments after 2020). Payments beyond 2020 are excluded from the financial costs of a technology when generating cost estimates for 2005 to 2020.

The previous method for estimating the financial costs caused by a policy subtracts the *ex ante* estimate of financial costs of the technology mix selected in business-as-usual from the *ex ante* estimate of financial costs of the technology mix selected due to a policy. This estimate measures businesses' and consumers' anticipated financial cost of adapting to the policy. It may be negative for some policies, because policies can induce or force people to purchase technologies with lower financial costs.

When generating a cost estimate using a bottom-up definition, analysts must be careful not to double count costs caused by increases in energy prices. When the energy supply sector experiences increases in financial costs or emissions charges, they generally pass some of those costs on to the energy demand sectors in the form of higher energy prices. As a result, the energy demand sectors pay for some or all of the costs in the energy supply sector. In order to eliminate any possibility of double counting costs when I generate a cost estimate using a bottom-up definition, I prevent CIMS from adjusting energy prices to equilibrate energy supply / demand.

Finally, the emissions reductions occur over several years. In order to calculate a single estimate of the emissions reductions caused by a policy, I discount future emissions reductions to 2005 using a social discount rate. Emissions reductions are a surrogate measure of the benefits of reducing emissions, therefore they may be discounted in a similar fashion to costs. By discounting future emissions costs I can also estimate the costs caused by reducing a tonne of GHGs over the entire time period.

5.4. Analysis of the policy instruments

Comparison of the cost accounting model to the previous accounting method

The cost accounting model and the area under the curve method yield similar estimates of the costs caused by emissions charges. Figure 5.1 compares the cost estimate for the two methods. The cost estimates represent the present value of people's perceived costs of adjusting to an emissions charge, over the period between 2006 and 2020.

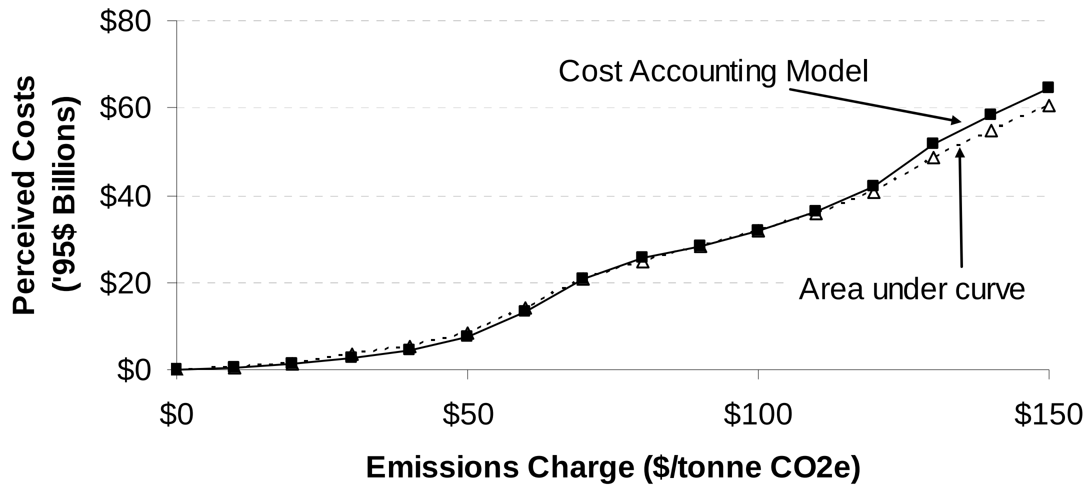

Figure 5.1: Comparison of the perceived costs caused by an emissions charge using the cost accounting model and the area under the curve method

The solid line represents the perceived costs estimated using the cost accounting model, and the dashed line represents the perceived costs estimated using the area under the curve method. The figure illustrates that the cost accounting model performs similarly to the area under the curve method. The slight differences between the two methods arise for two reasons. First, the cost accounting model uses random sampling to estimate the cost of actions, whereas the estimate of emissions reductions from CIMS is deterministic. Therefore, there are random differences between the results from the cost accounting model and the area under the curve method. Second, the greater cost estimate by the cost accounting model at high emissions charges is probably because the area under the curve method slightly underestimates the perceived costs of an emissions charge. The area under the curve method accounts for actions that increase emissions as a negative cost, because they offset actions that reduce emissions.[15] However, the perceived cost of all technology switches should be strictly positive. When the cost accounting model replicates a top-down definition, the cost of all technology switches is strictly positive, causing a higher estimate of cost.

The cost accounting model also approximates the results from the previous method for estimating cost from CIMS when using a bottom-up definition. Figure 5.2 compares the cost estimates from the cost accounting model and the previous accounting method. The results do not include the effect of equilibrium feedbacks in CIMS, which were turned off for these simulations.

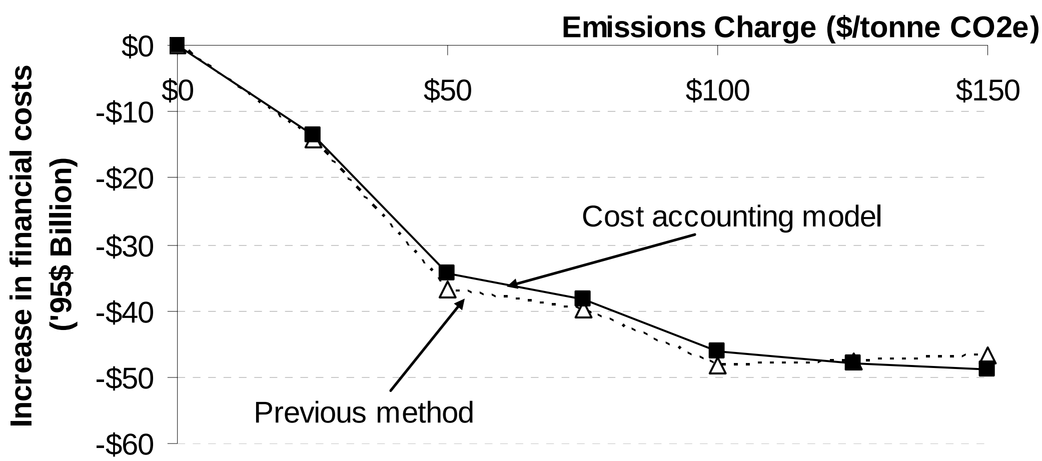

Figure 5.2: Comparison of the financial costs caused by an emissions charge using the cost accounting model and the previous method

Again, the results between the two methods are reasonably similar. The slight difference between the methods arises for two reasons. First, in order to simplify the calculation of the financial costs of a technology, I estimated of the portion of capital costs that are paid off during the time period (*p* in Equation 5.1) for an entire sector, and I assumed this portion would remain the same across the same sectors in all provinces.

[15] When energy prices change to equilibrate energy supply and demand, some technology switches may increase emissions. For example, if an emissions charge increases the price of electricity, industrial sectors have a greater incentive to cogenerate electricity and steam. However, the cogeneration of electricity and steam requires more fuel than the generation of steam alone, and technology switches towards cogeneration generally increase emissions.

This estimate is likely to be approximately correct, but it is not a perfect measure of the *p* parameter. Second, the cost accounting model double counts the capital costs of technologies in a few instances. Some technologies represented in CIMS have capital amortization periods which are shorter than the lifespan of the technology. For example, all personal transportation vehicles represented in CIMS have capital amortization periods of four years, but lifespans of sixteen years. For such technologies, the annual cost in the year it is purchased overstates its cost in later years. The cost of switching technologies estimated by the cost accounting model is based on the annual cost of technologies in the year they are purchased. The cost of switching is then added to all subsequent years within the lifespan of the technology, and capital costs can be double counted. This problem has been addressed in the transportation sector, where it has serious effects on the cost estimates from the model, but it has not been addressed in other sectors. Therefore, the results from the cost accounting model may be slightly incorrect.

The continuous financial gains from higher emissions charges is solely attributed to the transportation sector, where people experience a substantial reduction in financial cost when taking cheaper forms of transportation (high efficiency vehicles, walking or transit). When the transportation sector is removed, the other sectors initially experience a decline in financial costs, but eventually experience positive financial costs as result of higher emissions charges. Figure 5.3 excludes the cost estimate from the transportation sector.

When the transportation sector is removed, the estimate remains negative up to approximately $25/tonne CO_2e, and becomes positive thereafter. Figure 5.3, again, illustrates that the results from the cost accounting model are reasonably close to the results from the previous method, indicating that both methods yield similar results.

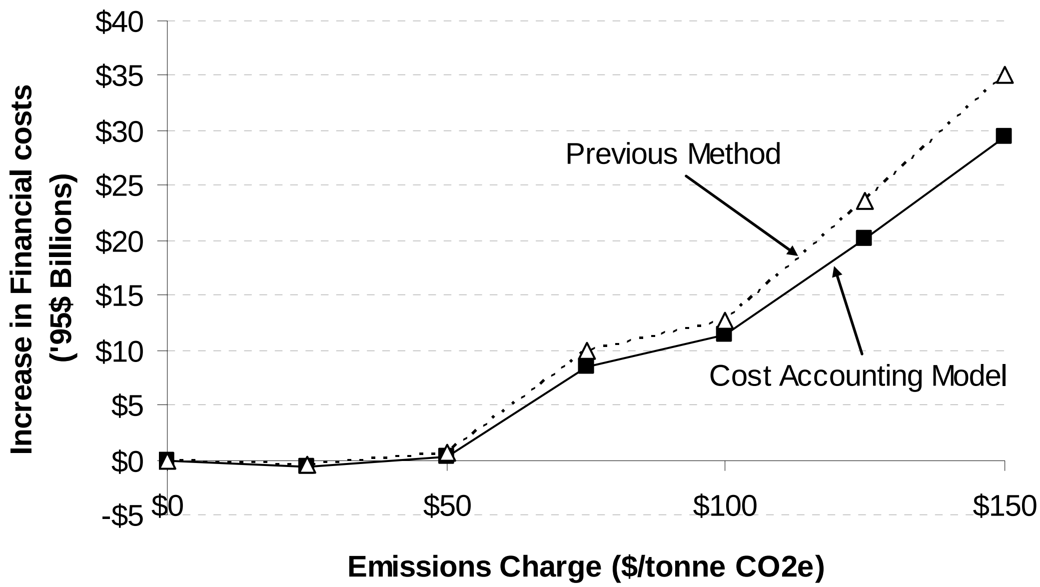

Figure 5.3: Comparison of cost estimates using alternative cost definitions (excluding transportation)

The cost accounting model can also be used to generate intermediate values between the top-down and bottom-up definitions of costs. Figure 5.4 compares the perceived costs caused by an emissions charge to the expected resource costs. The estimate of expected resource costs have been calculated using a mid-point between the two definitions.

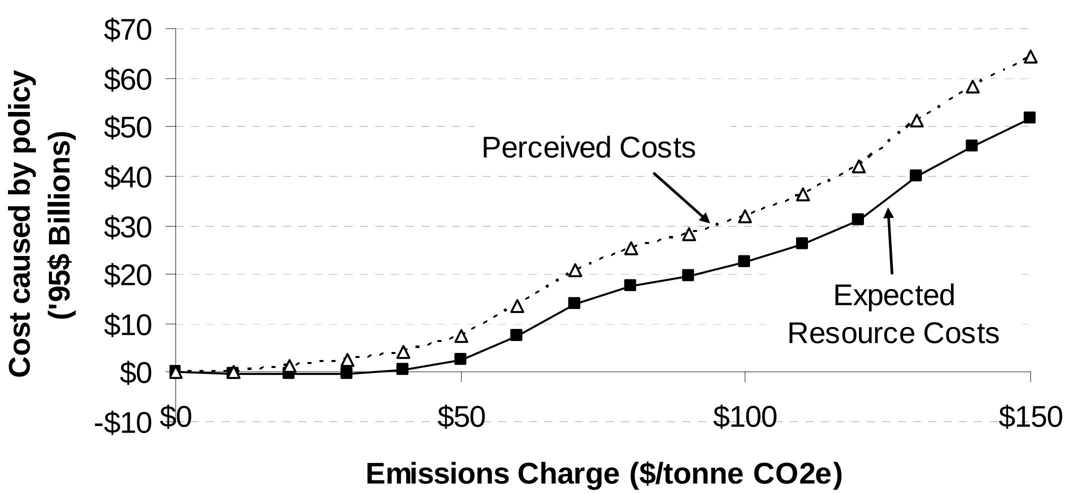

Figure 5.4: The Expected Resource Costs caused by an emissions charge

The purpose of this exercise is not to make a claim about the actual ERC caused by an emissions charge. My calculation of the *ex poste* costs of technologies lacks strong empirical grounds, and is therefore uncertain. If the *ex poste* costs are accurate, however, the estimate of ERC indicates that emissions charges up to \$30/tonne CO_2e cause a social benefit. In other words, emissions charges below \$30/tonne CO_2e induce people to purchase technologies that have lower *ex poste* costs. Above \$30/tonne CO_2e, the costs of emissions charges are positive, and generally follow the same path as the perceived costs of an emissions charge.

In summary, the cost accounting model can be used to generate cost estimates that accommodate either a top-down or bottom-up definition of costs. This section also illustrates that the cost accounting model yields similar results to the previous method of cost accounting. In the remaining sections of this chapter, I only report the ERC caused by the policy instruments simulated in CIMS.

Estimating the costs of reducing a tonne of GHGs using alternative policy instruments

As illustrated above, the cost accounting model can be used to estimate the costs caused by an emissions charge. A further benefit of the model is that it can be used to estimate the costs caused by regulations, and it can do so while accommodating alternative definitions of costs. The cost accounting model can also generate a cost estimate of policy packages – policies that include more than one policy instrument. Figure 5.5 illustrates the average ERC of reducing one tonne of GHGs when using the policy instruments introduced above. The figure also illustrates the average ERC of reducing one tonne of GHGs when using a policy package, which combines an emissions charge, a renewable portfolio standard, a regulation on household appliances, and a vehicle emissions standard. The VES in the policy package excludes the requirement to increase the market share of zero emissions vehicles.

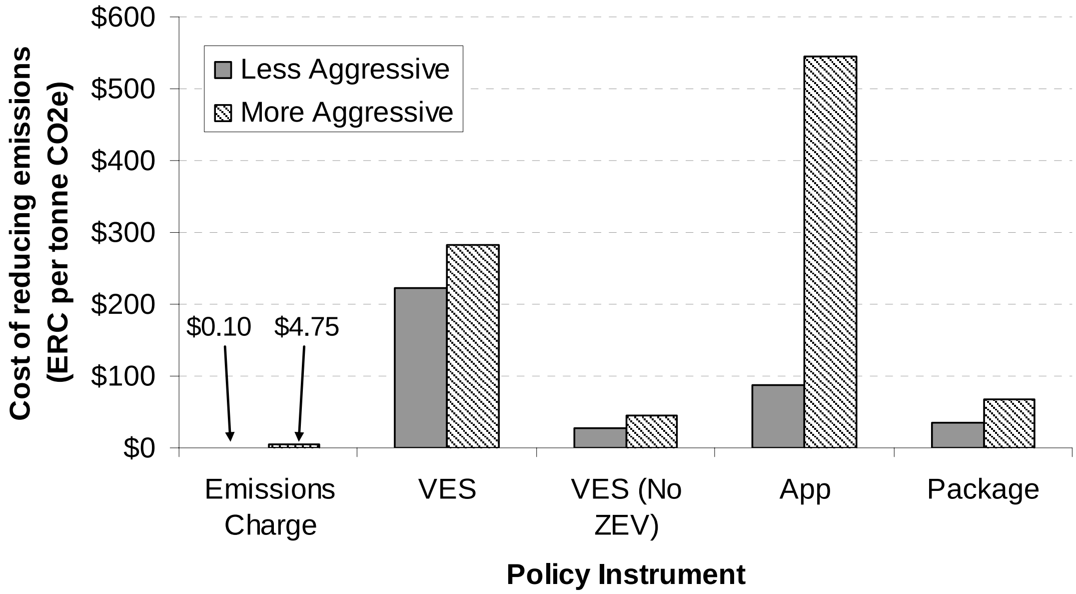

Figure 5.5: Average cost of reducing a tonne of CO_2e emissions, using different policy instruments

Figure 5.5 illustrates that the cost accounting model can be used to compare the costs caused by emissions charges to the costs caused by regulations. The cost estimates indicate that the emissions charge is the least costly policy instrument at reducing emissions. The greater cost associated with the other instruments is partially because they do not directly target emissions. The cost estimate of the renewable portfolio standard is not illustrated because its simulation produced an increase in emissions. In provinces where electricity generation is not GHG intense, such as Quebec and Manitoba where most electricity generation is from hydroelectric power plants, the RPS does not have a great effect on the emissions from the electricity sector. However, the policy increases the price of electricity because technologies specified in the RPS generate electricity at higher costs than conventional technologies. The higher electricity prices encourage the residential, commercial and industrial sectors to reduce their electricity consumption by purchasing technologies that consume more fossil fuels; and aggregate emissions from all sectors increase. The regulation on appliances also emerged as a costly method of reducing emissions. Such a regulation is effective at reducing electricity consumption, but it does so in provinces where electricity production has low emissions. The inefficiency of the vehicle emissions standard is mostly the result of the requirement to increase the market share of zero emissions vehicles. The zero emissions vehicles represented in CIMS have high capital and intangible costs, and a policy that forces their adoption causes consumers to incur greater *ex poste* costs. When the requirement to increase the market share of zero emissions vehicles is removed, the cost effectiveness of the VES improves substantially. The remaining inefficiency of the VES occurs because it forces people to incur higher intangible costs when switching from a low efficiency car to a high efficiency car, transit or walking.

Although the other policy instruments may be more costly than emissions charges, they also have advantages. A VES may be more effective at reducing emissions in the transportation sector, which is the single largest source of GHG emissions in Canada. As discussed above, empirical research indicates that the transportation sector is not very sensitive to changes in prices. A VES overcomes the ineffectiveness of emissions charges by directly forcing the adoption of low emissions vehicles. A RPS may be more effective at increasing the production of electricity from specified sources, and a regulation on appliances directly forces an improvement in household energy efficiency.

As an interesting side note, the cost estimate for the regulation on household appliances is inconsistent with the research of Moxnes (2004). Moxnes suggests that a regulation on household appliances may be welfare improving, whereas Figure 5.5 illustrates a positive cost estimate for a moderate regulation on household appliances. The differences between the findings of Moxnes (2004) and the cost estimates reported here have three possible explanations. First, my calculation of the *ex poste* costs of appliances may be incorrect. It is possible that the actual *ex poste* costs of appliances are closer to their financial costs. If this is the case, the discount rate and intangible costs may be reduced further to calculate the *ex poste* costs of appliances. Second, CIMS may misrepresent the financial costs of appliances with different efficiencies. For example, the financial life-cycle cost of the least efficient refrigerator in CIMS is cheaper than the closest alternative. The result from CIMS's simulation is that any policy that forces people to purchase a more efficient refrigerator will cause an increase in their financial costs. CIMS may need to represent additional appliances that are less efficient to simulate accurate outcomes. Third, the life-cycle costs of appliances in the country where Moxnes (2004) conducted his research may be different from the life-cycle costs of appliances in Canada. For example, another country may have higher electricity prices than Canada, resulting in a greater incentive to purchase a higher efficiency appliance.

Cost estimates when simulating expectations of future emissions charges

A rising emissions charge with a clear schedule for charge increases is likely to have a different effect on the technology mix than an emissions charge without a clear schedule. The policy with a clear schedule is designed to send a clear signal to businesses and consumers that their future emissions cost will be higher, and people may preemptively undertake actions to reduce their emissions. As a result, businesses and consumers are likely to experience the cost or benefit of their actions before emissions charges actually rise. Figure 5.6 illustrates the cost estimates of policies where people are either myopic or have foresight into their future emissions costs. Both the average and discounted expectations options represent situations where people have foresight into their future emissions costs. In the average expectations option, they give equal weight to all future emissions costs, and in the discounted option, they give less weight to their emissions costs further in the future.

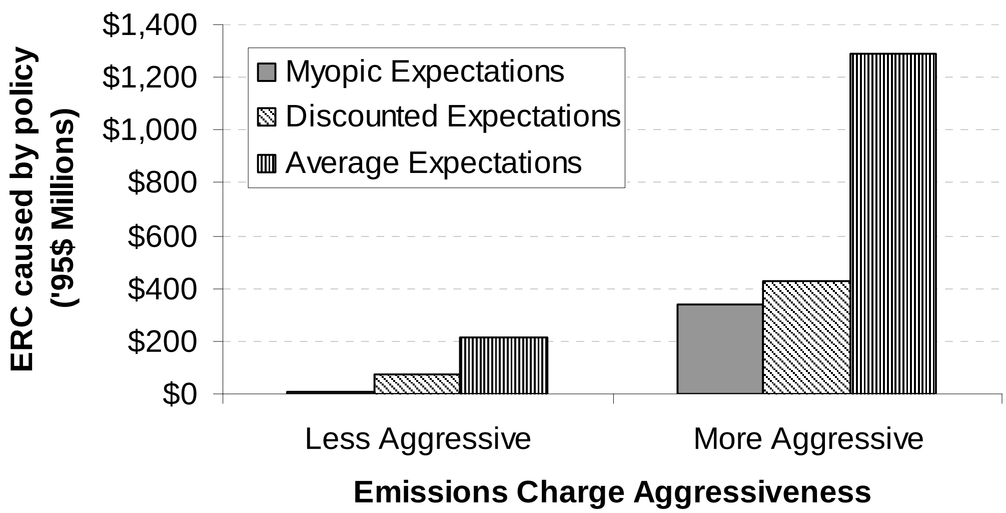

Figure 5.6: Cost estimates of a rising emissions charge under different assumptions about expectations

Figure 5.6 illustrates that the foresight options yield greater cost estimates than the myopic option. The cost estimate for the foresight options indicate that businesses and consumers are willing to purchase technologies with greater financial, intangible or risk costs in order to avoid their expected future emissions costs. It is also important to note that the estimate of ERC represents the social costs of a policy and excludes the cost imposed on businesses and consumers from the payment of emissions charges. The payment of emissions charges represents a transfer from the payer to government or seller of emissions permits, and it therefore causes a gain elsewhere in society. If emissions charge payments were included in the *ex poste* cost of technologies, the cost estimate from the expectations options would be lower than the myopic option.

When comparing the foresight options, the cost estimate for the discounted expectations option is much lower than the estimate for the average option. The discounted option places less weight on emissions charges further in the future, while the average option places equal weight on all future emissions charges. When emissions charges rise, the average option will place greater weight on the higher emissions charges in the future than the discounted option. If the average expectations option accurately depicts businesses' and consumers' expectations, people are more willing to undertake more expensive actions to reduce their emissions in order to avoid their future emissions costs. As a result, the cost accounting model predicts that people incur greater *ex poste* costs when the average option is simulated in CIMS.

5.5. Summary

This chapter illustrates several examples of the cost estimates from the cost accounting model. All policies were first simulated in CIMS, and the cost accounting model then determines the cost caused by each policy. The first section of the chapter compares the cost accounting model to the previous method of estimating costs from CIMS simulations. As shown, both methods produce similar cost estimates for the same policies. Additionally, the cost accounting model can generate cost estimates using mid-points between a top-down and a bottom-up definition of costs. The mid-point is designed to represent all the social costs that businesses and consumers incur when a policy influences their technology choice. Policy analysts will have different assumptions about the cost of people's actions to reduce emissions, and the *ex poste* cost of technologies used to generate the mid-point may be adjusted to reflect an analyst's assumptions. Therefore, the cost accounting model can accommodate any point between a top-down and a bottom-up definition of costs.

The cost accounting model can also be used to generate cost estimates for regulations, whereas the previous method could only be used for emissions charges. Therefore, the cost accounting model may be used to provide information on a greater number of policies to policy makers. The cost accounting model can also accommodate alternative definitions of costs while estimating the costs caused by regulations.

6. Summary and Conclusion

The contributions of this paper – the option for simulating obsolescence, the option for including expectations, and the cost accounting model – are designed to improve the information a hybrid energy-economy model can provide to policy makers. The option for simulating the obsolescence of old technologies improves the representation of technical change in technologically explicit models. Obsolescence is a consequence of technical change because the development of new technologies can render old technologies uncompetitive. As a result, the manufacturers of uncompetitive old technologies may shift their capital and expertise to the manufacture of a newer technology. By simulating obsolescence, hybrid models are better suited to simulate technology evolution.

The option for simulating expectations enables an analyst to specify whether CIMS simulates technology choice when businesses and consumers have foresight into their future emissions costs. Businesses and consumer foresight is likely to be contingent on government policy. If policy makers set a widely known schedule for future increases in emissions charges, businesses and consumers are likely to have a high degree of confidence in the future emissions costs of technologies. However, if policy makers do not provide a reliable schedule, expectations of future emissions costs are likely to be characterized by myopia. By introducing expectations, CIMS may provide a more accurate simulation of technology choice when policy makers provide a widely known schedule for rising emissions charges. It can also be used, however, to simulate a policy without a clear schedule.

The option for simulating obsolescence and the option for simulating expectations push energy economy models along the “representation of technical change” and “behavioural realism” axes in Figure 6.1.

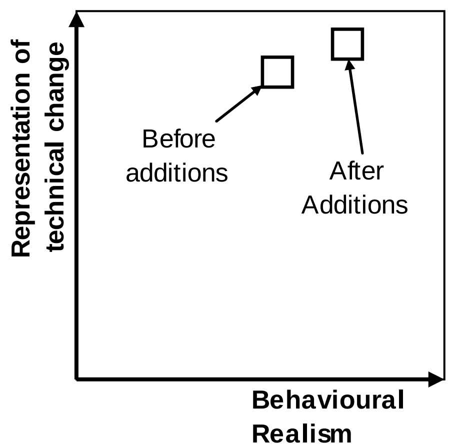

Figure 6.1: Contributions of the obsolescence algorithm and the option for simulating expectations

In my view, the cost accounting model is the most important contribution of this paper. After actions to reduce greenhouse gas emissions have been simulated in a hybrid energy-economy model, the cost of those actions may be estimated using a method of cost accounting. However, different methods of cost accounting use competing definitions of the cost of actions. A conventional bottom-up definition measures the cost of actions in strictly financial terms; whereas a conventional top-down definition measures the cost of actions in terms of what businesses and consumers perceive their costs to be. Both definitions provide useful information to policy makers – a bottom-up definition indicates the *ex ante* financial costs of adjusting to a policy and the top-down definition indicates the strength of a policy that is necessary to induce the desired actions to reduce emissions. However, either definition may fall short of estimating the social costs caused by a policy. The *ex ante* financial costs of adjusting to a policy excludes any non-financial or risk-related costs businesses and consumers may have when altering their technology mix; and the perceived costs of altering the technology mix may not equal the social cost if market failures prevent the adoption of technologies that businesses and consumers would consider optimal if they were perfectly informed.

The social costs caused by a policy may be better represented by some point between the two definitions of costs. The cost accounting model enables an analyst to set the *ex poste* costs of technologies to reflect their social cost of adoption and operation; and it then estimates the social costs of altering the technology mix. I have not made any *a priori* assumptions about the *ex poste* costs of technologies; however these costs may be informed using the research of others (e.g., Rivers, 2003; Mau, 2005). After the *ex poste* costs of technologies have been estimated, the cost accounting model may be used to prescribe policies that induce actions to reduce emissions at low social costs.

Another important contribution of the model is that it can estimate the social costs caused by regulations. Policy makers may consider regulations to induce technical change in niche markets, such as electricity generation, transportation or household appliances. Despite the importance of regulations, the previous cost accounting method could only calculate the cost caused by emissions charges. Therefore, the new cost accounting model can provide information on a greater number of policy instruments; and it can do so while accommodating alternative definitions of costs.

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Appendix: Comparison between the Market Shares from CIMS and the Cost Accounting Model

In order to calculate the costs of policies to induce technical change, the cost accounting model must recreate CIMS's market shares. The simulations from the cost accounting model and CIMS yield roughly the same market shares. Figure A.1 compares the market shares simulated by the cost accounting model and the market shares simulated by CIMS. In CIMS, a *v* parameter of 10 is used, and the standard deviation of the normal curves used in the cost accounting model is adjusted accordingly. The differences between the market shares predicted by the two models are small – with 86% of samples drawn from the cost accounting model result in market shares that are within ±1.5% of the market shares predicted by CIMS.

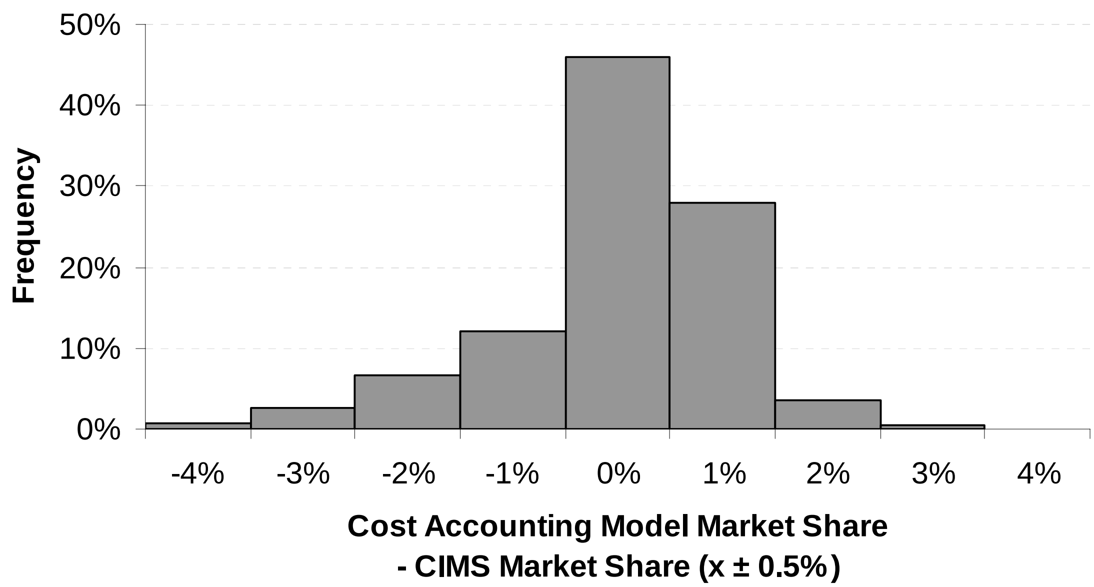

Figure A.1: Comparisons of market shares between the cost accounting model and CIMS (*v* = 10)

The cost accounting model is also effective at recreating the market shares from CIMS for different *v* parameters. Figure A.2 and A.3 illustrate a comparison between market shares from the cost accounting model and CIMS for $v = 5$ and $v = 50$ respectively:

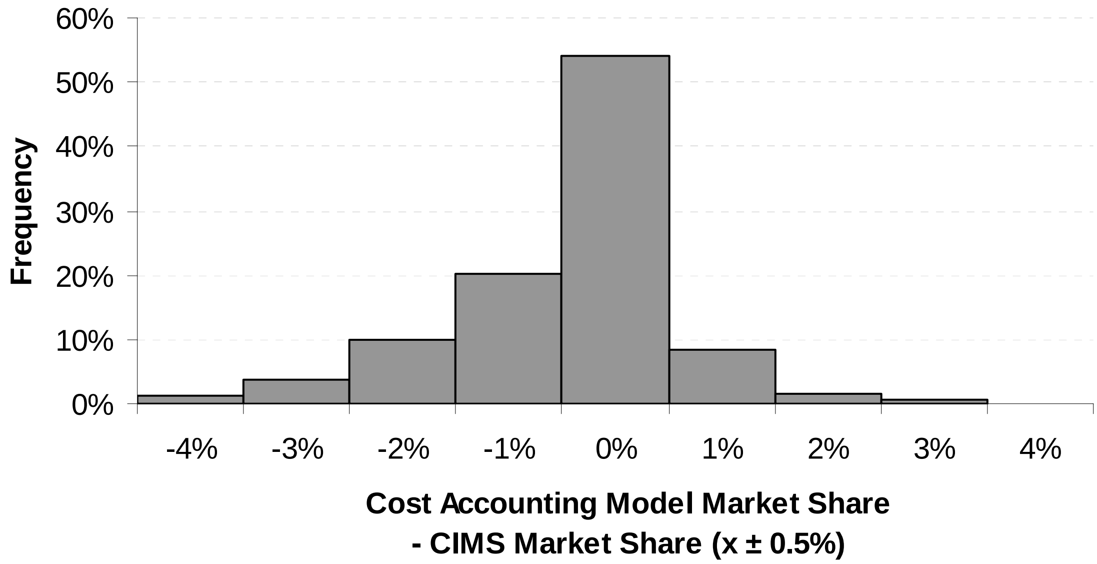

Figure A.2: Comparisons of market shares between the cost accounting model and CIMS (*v* = 5)

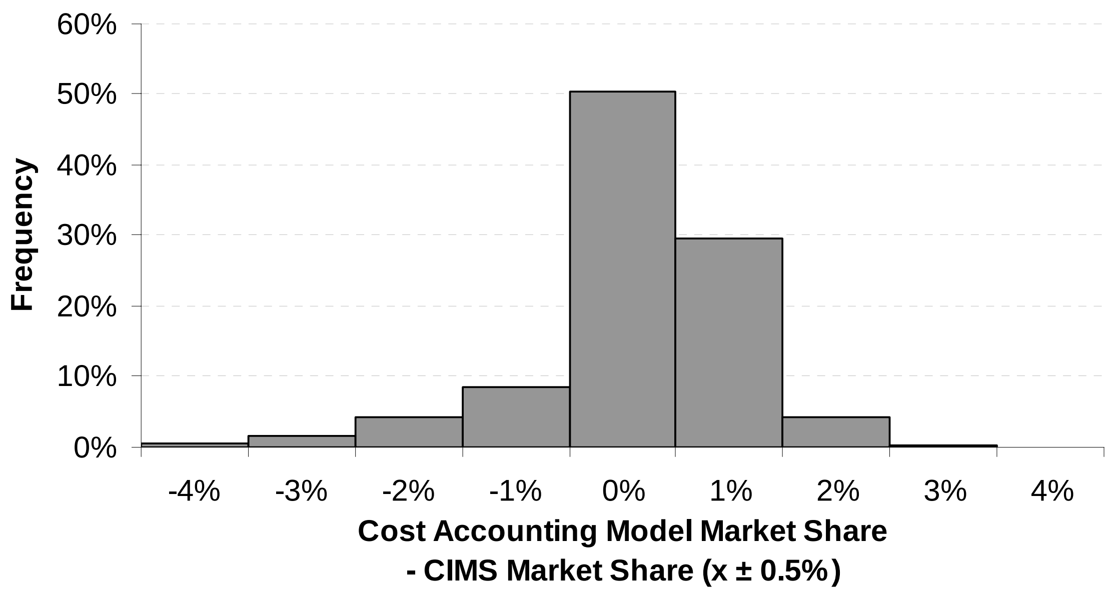

Figure A.3: Comparisons of market shares between the cost accounting model and CIMS (*v* = 50)

The cost accounting model yields similar market shares when *Tech Compete Sample* is used as the competition type. However, these results are more difficult to display graphically.