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Useful models for simulating policies to induce technological change

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Abstract

Conventional top-down and bottom-up energy–economy models have limitations that affect their usefulness to policy-makers. Efforts to develop hybrid models, that incorporate valuable aspects of these two frameworks, may be more useful by representing technologies in the energy–economy explicitly while also representing more realistically the way in which businesses and consumers choose between those technologies. This representation allows for the realistic simulation of a wide range of technology-specific regulations and fiscal incentives alongside economy-wide fiscal incentives and disincentives. These policies can be assessed based on the costs required to reach a goal in the medium term, as well as on the degree to which they induce technological change that affects costs over long time periods.

Ke d : Hybrid model; Endogenous technical change

1. Introduction

Policy-makers are interested in better understanding the prospects for policies to shift energy systems towards more environmentally desirable technology paths over a long-term trajectory. Two types of policy models attempt to provide this service. Conventional bottom-up models describe technologies (current and prospective) in detail, but lack a realistic portrayal of micro-economic decision-making by businesses and consumers when selecting technologies, and fail to represent potential macro-economic equilibrium feedbacks. Conventional top-down models, in contrast, address these deficiencies by representing macro-economic feedbacks in a general equilibrium framework and by estimating

2. Conventional energy–economy models

2.1. B tt - de

Conventional bottom-up models are disaggregated models of the energy–economy that contain a detailed representation of current and emerging technologies that can be used to satisfy demands for energy services. Technologies are characterized in terms of capital and operating costs, as well as performance attributes such as fuel consumption and emissions profile. When their financial costs in different time periods are converted into present value using a social discount rate (opportunity cost of capital), many emerging technologies available for abating various emissions appear to be profitable or just slightly more expensive relative to existing stocks of equipment and buildings. Conventional bottom-up models suggest, therefore, that substantial environmental improvement related to energy use can be profitable or low cost if these low-emission technologies were to achieve market dominance.

Many economists criticize the conventional bottom-up approach, however, for its assumption that a simple financial cost estimate indicates the full social cost of technological change. New technologies present greater financial risks, as do the longer paybacks associated with irreversible investments—such as most energy efficiency investments. Some low-cost, low-emission technologies are not perfect substitutes for their competitors, requiring a substantial, ongoing subsidy before businesses or consumers will adopt them. To the extent they ignore some of these costs, conventional bottom-upngs.igmaions339.4i[t10(the7s.)-96io1(em4tt)-9.i4.9(4(Tooi(or).ion)-324.5(emis)-)-8.3ment)-2852.8(if)-281.5(.)-96io1((long reduction could be achieved domestically through a tax on carbon emissions of no more than \$25/t C as well as a host of other policies.

Top-down analyses have also been used to assess the potential cost to the US of meeting its Kyoto commitments. Weyant and Hill (1999) summarized the results of a multi-model comparison of the costs of meeting the US Kyoto Protocol commitments; most of the models in their study were of the computable general equilibrium (top-down) variety. Of the 11 participating models, eight found that a tax of at least \$150/t C would be required to meet Kyoto commitments, and of these, four required a tax of at least \$250/t C. GDP impacts ranged from modest levels to the loss of over 3% of economic growth.

Policy-makers see results from both of these types of studies and do not know whom to believe, and what policies to apply. On the one hand, conventional bottom-up models suggest that environmental goals can be reached at low cost, and require only mild policies. On the other hand, conventional top-down models suggest that achieving environmental goals is costly, and that more stringent policies are required.

3. A hybrid modelling approach

The challenges with conventional bottom-up and top-down models suggest that an energy–economy model that is useful to policy-makers should have strength in each of the three attributes shown in Fig. 1. Such a model would contain a disaggregated representation of the technologies available in the energy–economy system. To simulate the manner in which consumers choose between those technologies, the model would use real market data and surveys to estimate not only

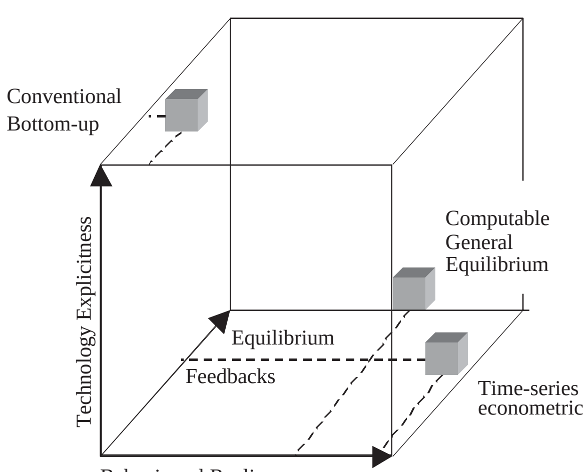

Fig. 1. Representation of top-down and bottom-up energy–economy models. *N t:* Computable general equilibrium models and time-series econometric models are both considered top-down.

financial costs, but also key intangible decision factors that reflect more fully the costs of adopting alternative technologies. It would also capture the relationship between the energy system and the rest of the economy in a broader macro-economic framework. We call this type of model a *h b id* model, because it incorporates the important features of both top-down and bottom-up models.

Efforts towards hybrid modelling usually involve either incorporation of technological detail into a top-down framework (Bohringer, 1998; Jacobsen, 1998; Koopmans and te Velde, 2001; Frei et al., 2003) or incorporation of behavioural realism and/or macro-feedbacks into a bottom-up framework (Jaccard et al., 1996; Sanstad et al., 2001; Morris et al., 2002). In this paper, we present a specific hybrid model, called CIMS, that started as a bottom-up simulation model, but has evolved to include macro-economic feedbacks and empirically estimated behavioural parameters for simulating technological adoption. Because a large challenge for this type of approach involves estimating how businesses and firms might choose among future technology options, we focus our description on this dimension of the model—in terms of model structure and parameter estimation. Our particular goal is to explore how such a model might be more useful to policy-makers in terms of linking immediate policy initiatives to future financial costs and adoption rates of new technologies. In this sense, a key objective for using this model is the endogenous modelling of policies to induce technological change.

3.1. The CIMS h b id de

The CIMS hybrid model is an integrated, energy–economy equilibrium model that simulates the interaction of energy supply demand and the macro-economic performance of key sectors of the economy, including trade effects. Unlike most computable general equilibrium models, however, the current version of CIMS does not equilibrate government budgets and the markets for employment and investment. Also, its representation of the economy's inputs and outputs is skewed towards energy supply, energy-intensive industries, and key energy end-uses in the residential, commercial/institutional, and transportation sectors.

As a technology vintage model, CIMS simulates the evolution of capital stocks over time through retirements, retrofits, and new purchases, in which consumers and businesses make sequential acquisitions with limited foresight (Jaccard et al., 2003). The model calculates energy costs (and emissions) at each energy service demand node in the economy, such as heated commercial floor space or person-kilometres-travelled. In each time period, capital stocks are retired according to an age-dependent function (although retrofit of unretired

which businesses and consumers are presented with hypothetical choices between well-known technologies and emerging technologies. The most common approach to provide consumer and business values is through discrete choice surveys and analysis. Fig. 2 is an example of the discrete choice survey that was used to assess consumer preferences for alternative types of vehicles. Respondents to the survey were asked to indicate which of the four types of vehicles they would choose, given attributes shown in Fig. 2. The attributes were based on respondents's current vehicle situation (i.e., how much they spent on the last vehicle purchased, how far they commute daily, what type of vehicle they currently own) and were varied up and down from these levels according to an experimental design to provide the variation in attribute levels needed to estimate regression parameters.

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Table 1
Discount rates from discrete choice studies

Study	Implicit discount rate (%)
Choice of vehicle types	22.6
Choice of commuting mode types	N/A
Choice of home renovation	26.3
Choice of home heating system	9.0
Choice of industrial steam generation system	34.7

resulted in highly statistically significant models with all estimated parameters taking on the expected signs.

Table 1 shows the implicit discount rate (parameter in CIMS) calculated from the studies described above.[2] For most of the experiments reported, the implicit discount rate is significantly higher than that used in bottom-up analyses. The higher values in our research are consistent, however, with the implicit discount rates in revealed preference research. This research suggests that the high implicit discount rates found in empirical studies are likely a reflection of the challenges of obtaining information in the market, the high perceived risk of those energy efficiency investments which involve long payback periods, the scepticism of some business decision makers to a priori claims of high rates of return on energy efficiency investments, and the option value of waiting for more information before making a decision, among other factors (de Groot et al., 2001; Dixit and Pindyck, 1994; Harris et al., 2000; Hasset and Metcalf, 1994; Sassone and Martucci, 1984). Train (1985) summarizes several studies on implicit discount rates and finds results ranging from 15% to 70% in the residential and transportation sectors.

In each of the studies described above, intangible costs (i parameter in CIMS) were also calculated from the regression results to reflect non-financial preferences in the choices made by consumers. Table 2 briefly outlines the intangible costs estimated from surveys for different technologies in each study. The results in Table 2 imply, for example, that the average consumer would require compensation of $5913 + $4599 = $10,512 annually in order to be indifferent to purchasing an electric vehicle instead of a high efficiency gasoline vehicle. While this may seem high, it should be noted that the low range and current performance of electric vehicles has confined their market share to a very small niche. Improvements in these characteristics would reduce the intangible costs felt by consumers.

[2]The discount rate was calculated from $CRF = \ /(1-(1+\ )^{-}\ ) = B_{CC}/B_{AC}$, where CRF

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Table 2
Intangible costs from discrete choice studies[a]

Study	Intangible costs ($/yr)
Ch ice f ehic e t e	
Methanol	8058
Ethanol	1457
Electric	5913
Hybrid-electric	12,224
Fuel cell	270
Propane	5527
Diesel	−2242
Natural gas	937
Efficient gasoline	−4599
Inefficient gasoline	−7363
Ch ice f c t g de t e	
Single occupancy vehicle	6352
High occupancy vehicle	7828
Transit	12,394
Walk/cycle	11,947
Ch ice f h e e a t	
Standard renovation	—
Efficient renovation	614
Ch ice f h e hea t g t	
Standard natural gas	499
Efficient natural gas	28
Electric baseboard	308
Heat pump	271
Oil furnace	—
Ch ice f i d t ia t a ge e a t t	
Standard efficiency boiler	500,000
High efficiency boiler	−137,000
Cogeneration system	—

[a]Intangible costs presented in Table 2 are based on 'baseline' assumptions about non-cost variables. For example, to calculate the intangible cost for public transit, we used data on average commuting times, number of transfers required, cost of public transit, etc. If any of these variables were to change (due to policy for example), the intangible cost for public transit would also change. All of these costs are presented in $CDN.

Table 3
Market heterogeneity parameter from discrete choice studies

Study	Market heterogeneity
Choice of vehicle types	2.9
Choice of commuting mode types	2.2
Choice of home renovation	0.7
Choice of home heating system	3.0
Choice of industrial steam generation system	1.4

In each of the studies we conducted, we also calculated the degree of market heterogeneity (the   parameter in CIMS). Table 3 shows results for our calculation of this parameter. Our empirical estimates for the   parameter reveal that there is significant preference and behaviour heterogeneity in the market, so basing model predictions on an ‘‘average’’ consumer or producer may lead to misleading results.

With these parameters calculated and integrated into the CIMS market share function (Eq. (1)), we conduct policy simulations that entail a portfolio of technology-specific and economy-wide instruments. For example, we have simulated the change in the market share of industrial cogeneration systems when a subsidy is provided to encourage the uptake of industrial cogeneration. We have also simulated the increase in transit ridership as the transit service is improved by reducing bus wait times and number of transfers required for average commuting trips. We have likewise estimated the response in the residential sector to a tax on GHG emissions of different levels.

In addition, because our analysis is based on empirical research, we are able to integrate an empirical portrayal of uncertainty into our results. For example, in addition to calculating the most likely market share for different technologies in a policy scenario, we also generate probability distributions around those market shares. This enables us to test for the robustness of different policies in the face of uncertainty about parameter values, and also points the way forward to fruitful new research.

This type of analysis is possible with any discrete choice model, and indeed other researchers are applying sophisticated discrete choice methods to evaluate choices of many different energy-using (and other) technologies, and to evaluate how those choices change under the influence of policies.

The analysis presented in this paper differs in that discrete choice research sets the parameters in a hybrid price-responsiveness, are what we call ‘‘preference dynamics’’. There are many potential explanations for changes in consumer preferences, some rational and some seemingly irrational to the analyst. Not all can be captured in a simple energy-economic model. Instead, we focus on one source of preference dynamics that has been identified in the literature—preference changes due to the influence of what other people in the economy are doing (Hautcsh and Klotz, 2002).

Using a discrete choice framework, we have attempted to empirically estimate how preferences can change. In particular, we examine how our estimates of the *i* parameter, which reflects intangible, or non-financial costs associated with adoption of a particular technology, change in response to a change in the surrounding environment. For our analysis, we have measured the change in preferences for alternative types of vehicles as information about these becomes more diffused in the economy, and as alternative types of vehicles themselves become more adopted in the market. We consider this an analysis of the ‘neighbourhood effect’ whereby consumer preferences for alternative types of vehicles are influenced by the types of vehicles owned by neighbours, friends, and family. Our preliminary discrete choice research has shown that as more neighbours own a certain type of vehicle, consumers begin to exhibit stronger preferences for that type of vehicle.

3.4. Sa e ic i a t i g he CIMS h b id de

With empirically determined parameters and an empirical representation of endogenous technical change, we are able to use CIMS to conduct integrated analysis of broad fiscal policierebinteg fiscal eno5(fisol*[n in many conventional bottom-up studies, where it is assumed that the economy is not currently economically efficient, and that appropriate policies can remove barriers that move the economy closer to efficiency. This definition of costs allows for the possibility of ‘‘no regrets’’ policies, which can improve environmental outcomes while increasing economic output.

In our policy simulations, we can also generate cost estimates more akin to those of the top-down approach. We use the empirical data on consumer preferences to determine the financial incentive that would be required by a business or individual in order to shift their technology choice. The implicit assumption is that the economy may not be that far from an economically efficient outcome, although change would be beneficial as the expected costs of climate change risks are internalized into prices.

Jaccard et al. (2003) provide a more thorough review of these cost concepts and their application to CIMS. Although a priori assumptions will inevitably play a role in estimating costs, empirical research into how consumers and businesses view the risks and quality differences of competing technologies can provide valuable information to policy-makers in assessing the likely response to a policy package, and this in turn will help assess the ultimate costs.

4. Conclusions

The hybrid modelling framework presented in this paper is designed to be useful to policy-makers. It includes a detailed representation of the technologies available in the energy system, so it allows for simulation of technologically oriented policies, and for measurement of the technological response of specific end-use and supply sectors to policy changes. It also incorporates an empirical depiction of behavioural response to policies using a series of technology adoption models developed from survey data and discrete choice analysis. Further, it incorporates equilibrium feedbacks: the energy supply and demand sectors are linked via physical energy volumes and prices derived from the cost of energy production, while equilibrium feedbacks between the energy supply and demand sectors and the rest of the economy are represented using empirically derived demand and trade elasticities, which adjust demand for a product based on its cost of production. Finally, it includes a detailed and empirically based portrayal of endogenous technological change.

These features allow the model to simulate the types of policies that policy-makers are interested in, and to give confidence to policy-makers that the results are not a feature of ad hoc assumptions regarding human behaviour, but instead a result of empirical measurements of stated policy response by economic actors in response to changing economic conditions. This hybrid approach incorporates some of the important features of both top-down and bottom-up models, and thereby transcends some of their weaknesses in providing a useful tool to policy-makers seeking to induce long-run technological change for energy–environment objectives.

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