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.

Keywords: 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 parameters of technological change from observations of aggregate market responsiveness to cost changes and non-price autonomous trends. Without technological detail, however, these models are unable to help policy-makers assess how future market responses and autonomous trends might differ from the past as technology-specific regulations, research and development, and new expectations interact with market incentives over long time periods. Frustration with this methodological dichotomy has led a growing number of researchers around the world to explore hybrid modelling approaches that combine the technological explicitness of bottom-up models with the micro-economic realism and macro-economic feedbacks of top-down models.

In this paper, we describe briefly these alternative approaches, and then describe in detail the challenges and possible solutions for estimating micro-economic behavioural parameters for a hybrid model. Section 2 compares the strengths and weaknesses of the traditional model structures. Section 3 outlines the general structure of a specific hybrid model and discusses how the behavioural parameters for this model can be estimated using empirical data collected from surveys and other studies. It also outlines how endogenous technological change can be captured in a hybrid modelling framework, and finishes by presenting sample policy analyses to demonstrate the usefulness of this type of approach to policy-makers. Section 4 concludes.
2. Conventional energy–economy models

2.1. Bottom-up models

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-up models may suggest the wrong technological options and the wrong policies (or policy intensities) for policy-makers.

Another challenge with the conventional bottom-up approach is that its technology-specific focus hinders its ability to portray broader macro-economic effects of policies, notably the trade and structural repercussions from changes in energy prices and costs throughout the economy. In this sense, conventional bottom-up models only provide a “partial equilibrium analysis” of the response to policies.

2.2. Top-down models

Top-down analysis, which is usually applied by economists, estimates aggregate relationships between relative costs and market shares of energy and other inputs to the economy, and links these to sectoral and total output in a broader equilibrium framework—full equilibrium models are referred to as computable general equilibrium models. Elasticities of substitution (ESUB) indicate the substitutability between any two pairs of aggregate inputs (capital, labour, energy, materials) and between energy forms (coal, oil, gas, renewables) within the energy aggregate. Most top-down models also have a parameter called the autonomous energy efficiency index (AEEI), which indicates the rate at which price-independent technological evolution improves energy productivity. Because these parameters are estimated from real market behaviour, as energy prices and energy consumption have changed historically, they are said to reveal the actual preferences of consumers and businesses—and therefore implicitly incorporate losses or gains in non-financial consumer welfare, as well as reflect the market heterogeneity of real-world financial cost conditions.

Top-down models can also be criticized however. The key parameters in conventional top-down models, ESUB and AEEI, are usually estimated from historical data. Even if the confidence intervals of these estimated parameters are narrow, there is no guarantee that values derived from past experience will remain valid into the future (Grubb et al., 2002). For example, AEEI and ESUB could change dramatically in the future as financial costs of technologies change due to economies of scale in production or accumulated experience, and as consumers become more accepting of emerging technologies as these are established in the market. Because AEEI and ESUB are fixed parameters in conventional top-down models, these may not show the full adaptation of firms and households to policies that significantly affect economic conditions. This can in turn lead to high cost estimates for policies to abate energy-related emissions.

Another problem for the top-down approach is that the constraints of policy development often push policy-makers towards technology- and building-specific policies in the form of tax credits, subsidies, regulations, and information programmes. With their abstract depiction of technologies, top-down models have considerable difficulty in simulating the effects of this type of technology-oriented policy.

2.3. Results from conventional models

Because of their different approaches, top-down and bottom-up models often predict divergent costs, and consequently suggest different policies, for meeting environmental goals. Analyses of the costs of achieving the US Kyoto Protocol commitments provide an example.

After signing the Kyoto Protocol in 1997, the US government commissioned studies on the potential costs of meeting its Kyoto obligations by five national research laboratories. These studies used a bottom-up modelling approach and found that a 30% reduction in greenhouse gas (GHG) emissions from business-as-usual levels could be achieved at no net cost to the economy (Brown et al., 1998; Interlaboratory Working Group, 2000). They suggested that this level of
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 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 hybrid 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 hybrid model

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
stocks is possible if warranted by changing economic conditions), and demand for new stocks grows or declines depending on the initial exogenous forecast of economic output, and then the subsequent interplay of energy supply and demand and the macro-economic feedbacks between the energy sector and the rest of the economy. A model simulation iterates between energy supply and energy demand until energy price changes fall below a threshold value, and repeats this convergence procedure in each subsequent 5-year period of a complete run, which usually extends 30–35 years. A similar iterative convergence procedure is followed to equilibrate the markets for goods and services.

CIMS simulates the competition of technologies at each energy service node in the economy based on a comparison of their life cycle cost (LCC) mediated by some technology-specific controls, such as a maximum market share limit in the cases where a technology is constrained by physical, technical, or regulatory means from capturing all of a market. Instead of basing its simulation of technology choices only on financial costs and social discount rates, CIMS applies a formula for LCC that allows for divergence from that of conventional bottom-up analysis by including intangible costs that reflect revealed and stated consumer and business preferences with respect to specific technologies and time. The following equation shows how CIMS assigns market share to K different technologies competing to provide the same service at a node (for example, the node could be residential lighting, and the technologies could be incandescent, compact fluorescent, and halogen light bulbs):

\[ MS_j = \frac{\left[ CC_j \left( \frac{1}{1 + (r \cdot v)} \right) + MC_j + EC_j + ij \right]^{-v}}{\sum_{k=1}^{K} \left[ CC_k \left( \frac{1}{1 + (r \cdot v)} \right) + MC_k + EC_k + ik \right]^{-v}}. \]  

(1)

MS\(_j\), is the market share of technology \(j\), CC\(_j\) is its capital cost, MC\(_j\) is its maintenance and operation cost, \(n_j\) is the average lifespan of the technology, EC\(_j\) is its energy cost, which depends on energy prices and energy consumption per unit of energy service output—producing a tonne of steel, heating a m\(^2\) of a residence, transporting a person 1 km. The \(r\) parameter represents the weighted average time preference of decision makers for a given energy service demand; it is the same for all technologies competing to provide a given energy service, but can differ between different energy services according to empirical evidence. The \(i_j\) parameter represents all intangible costs and benefits that consumers and businesses perceive, additional to the simple financial cost values used in most bottom-up analyses, for technology \(j\) as compared to all other technologies \(k\) at a given energy service node. For example, public transit and single occupancy vehicles compete to provide the service of personal transportation. Empirical evidence suggests that some consumers place an intangible, non-financial cost on public transportation to reflect their perceptions of its lower convenience, status, and comfort. These costs are captured in CIMS using the \(i_j\) parameter.

The \(v\) parameter represents the heterogeneity in the market, whereby different consumers and businesses experience different LCCs. It determines the shape of the inverse power function that allocates market share to technology \(j\). A high value of \(v\) means that the technology with the lowest LCC captures almost the entire new market share. A low value for \(v\) means that the market shares of new equipment are distributed fairly evenly, even if their LCCs differ significantly. At \(v = 10\), when technology A becomes 15% more expensive than B, B captures 85% of the market. At \(v = 1\), when technology A becomes 15% more expensive than technology B, B only captures 55% of the market. We consider this second case a more heterogeneous market, and the first case a more homogeneous market. A conventional bottom-up optimization model might have \(v = \infty\) (and \(i = 0\)), equivalent to a step function where the cheapest technology on a financial cost basis captures 100% of the market—a completely homogeneous market.

3.2. Parameter estimation for a hybrid model

A hybrid model like CIMS starts from the same basis as a bottom-up model—an explicit representation of technologies in the energy system (e.g., vehicles, commercial buildings, residential water heaters, industrial pumps, and conveyors), including their capital costs, operating costs, fuel consumption, lifespans, and emissions. However, unlike a conventional bottom-up model, it uses empirical research on the way consumers have or might make technology choices in real-world situations. The goal with this approach is to estimate the parameters \(v\), \(i\), and \(r\) in Eq. (1) from observed market behaviour or surveys asking prospective consumers what they would choose in certain circumstances.

To estimate values for these variables that reflect the real world, we have for several years surveyed the literature on empirical research into historical market choices. Studies of this nature provide information on the revealed preferences of consumers. The challenge with this approach is that new and emerging technologies can provide substantially different choices from the past. Also, historical situations may not have the variation in energy prices and other values that provide an approximate correspondence to the policy mix that policy-makers may wish to explore.

These constraints to revealed preference information push the estimation of the model’s parameters in many cases towards stated preference research—research in
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.

With responses to this type of question from many respondents, it is possible to assess, using discrete choice regression, the importance of each attribute to the purchase of a vehicle. This information is then used to provide empirical estimates of the \(v\), \(i\), and \(r\) parameters used in CIMS so that the hypothetical choices of consumers from the surveys are reflected in the hybrid model.

We have used surveys like the one presented in Fig. 2 to understand the technology choices made by consumers for a wide range of technologies:

- Consumers’ choice of commuting modes and response to changes in travel time, weekly commuting cost, number of public transit transfers, frequency of public transit service, amount of walking required for public transit, and presence or absence of dedicated cycling lanes.
- Consumers’ choice of residential building renovation and response to changes in capital cost, fuel cost, air quality, and the presence of a subsidy to encourage energy efficient home retrofits.
- Consumers’ choice of home heating system and response to changes in capital cost, operating cost, heating response time, and presence or absence of a subsidy to encourage energy efficient heating systems.
- Industrial firms’ choice of steam generation system and response to changes in capital cost, operating cost, fuel cost, and electricity value through the use of a combined heat and power system.

For application of CIMS to Canada, surveys were provided to 800–1200 final respondents for each of the household (transportation, residential) surveys and about 300 final respondents for the industrial survey. Surveys were conducted using a combined telephone–mail method, and achieved response rates ranging from 17% for the industrial survey to 84% for one of the transportation surveys. Analysis of survey results was conducted using a multinomial logit method, and

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\[ v, i, r \]

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\[ 1\text{We did not observe significant biases in any of the surveys except the industrial survey, where large firms were slightly over-represented, as were firms in the chemicals, petroleum refining, and pulp and paper sectors. These biases were not found to influence results significantly.} \]
resulted in highly statistically significant models with all estimated parameters taking on the expected signs.

Table 1 shows the implicit discount rate ($r$ 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 $\text{CRF} = r/(1-(1+r)^{-n}) = B_{CC}/B_{AC}$, where $\text{CRF}$ is the capital recovery factor, $r$ is the discount rate, $n$ is the lifespan of the technology, $B_{AC}$ and $B_{CC}$ are parameters empirically estimated from the data that reflect the importance of the annual costs and capital cost, respectively, to the choice outcome. For further discussion, refer to Train (1985) or Rivers and Jaccard (2005).
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 cogener-
ation. 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
modelling framework that allows integrated energy–ec-
onomy analysis and that captures the effects of feed-
backs throughout the economy. This is particularly
important for the analysis of overarching policies like
climate change mitigation policies, which have cascading
effects throughout the economy. For example, a tax
on GHG emissions would change the decisions made in
the electricity generation sector, which would change the
retail price of electricity, which would therefore change
the nature of the choice of heating technologies in the
residential sector. Stand-alone technology adoption
models would not capture the effect of these feedbacks,
and could provide misleading information to policy-
makers. In addition, a hybrid model allows for the kind
of aggregated analysis that interests policy-makers. For
example, using the CIMS model, we are able to measure
the economy-wide effect of broad policies like a GHG
tax, alongside sector-specific policies like a renewable
portfolio standard for electricity generators. Because of
the technological detail in the model, we are able to
estimate the detailed technological response in specific
end-use sectors, such as the likely penetration of hybrid
vehicles under a GHG tax.

The empirical studies reported in this paper cover
some of the key technology choices affecting energy
demand and energy-related emissions, but there are
many other, less significant choices for which we have
not yet conducted research. We therefore also use
research from other analysts to capture technology
preferences wherever possible. Where this research does
not exist, we have attempted to extrapolate the research
presented in this paper, and to select parameters that
calibrate the model to technology adoption witnessed in
the real world.

In any case, it is important to remember that there is
no crystal ball for predicting with high confidence future
technology choices. Discrete choice modelling of new
technologies is subject to the usual uncertainties from
problems like hypothetical bias in survey responses—
perhaps because of the difficulty of portraying all real-
world choices within the confines of a discrete choice
survey or adequately explaining the critical attributes of
a completely new technology like hydrogen fuel cell
vehicles. It may, however, represent the best approach
we have for somewhat reducing this uncertainty for
policy-makers.

3.3. Endogenous technological change in a hybrid model

A significant thrust in the energy–economy literature
over the past decade has been the inclusion of
endogenous technological change in policy models.
Significant evidence exists to suggest that appropriate
policies can induce technological change that lowers the
long-run cost of meeting environmental goals. Policy-
makers require models that assess the potential of
alternative policies to induce this technological change.

In hybrid models like CIMS, as in bottom-up models,
diffusion of technologies is endogenous to the model.
Technologies are replaced according to their physical
life or economic conditions. They are replaced with new
technologies, which compete based on their prices and,
in CIMS, the preferences of businesses and consumers.
CIMS also has a learning-by-doing formulation in
which the financial costs of technologies fall as firms
gain experience with producing them. The representa-
tion of learning-by-doing in CIMS uses parameters
drawn from empirical research conducted internation-
ally, as summarized in McDonald and Schrattenholzer

We have also conducted our own empirical research
to estimate how the preferences for technologies might
be affected by policies to induce technological change.
Norton et al. (1998) note how policy-makers need
help in understanding how economic actors might
change their preferences in response to the environment
that surrounds them, including changes to the social,
political, and economic environment. These changes
in behaviour, which are not captured by simple
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 (Hautch 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. Sample policy simulations using the CIMS hybrid model

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 policies and technology-specific policies. As an example of a broad fiscal policy simulation, Fig. 3 shows the GHG reductions resulting from the application of a tax on GHG emissions throughout the Canadian economy. Significant reductions are available at a relatively low tax, but increased tax levels result in decreasing marginal levels of emissions reductions. In addition, Fig. 3 shows that with a longer policy lead-time, more GHG reductions are available from the same policy signal. This reflects the long turnover time of most energy-using capital stocks. The dashed lines represent the GHG tax required to achieve a 150 Mt reduction in Canada’s GHG emissions over a 10-year timeframe.

As an example of a technology-specific policy simulation, Fig. 4 shows the change in the Canadian vehicle fleet in response to a vehicle emission standard that requires that vehicle manufacturers sell minimum quantities of low- and zero-GHG vehicles.

Fig. 5 shows the change in costs of alternative types of vehicles induced as a result of learning-by-doing spurred by the vehicle emissions standard. Costs for all low-GHG vehicles fall faster under the policy scenario than under the business-as-usual scenario.

In most of our studies, we have attempted to estimate the costs of policies, which requires defining what is meant by a cost. In some studies, we have estimated the strict financial cost of a policy—the difference between a business-as-usual and a policy scenario in terms of capital cost and discounted operating and energy costs. Defining costs in this manner is similar to the way costs are defined
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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