Statistical Simulation to Estimate Uncertain Behavioral Parameters of Hybrid Energy-Economy Models

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major feedbacks in the economy's inputs and outputs, they are referred to as computable general equilibrium models.

The last decade or so has seen the development of hybrid models that attempt to combine desirable attributes of top-down and bottom-up [12]. These models include some technological detail and macroeconomic feedbacks while also portraying the likely response of firms and households to changing prices and technological options.

But the inclusion of technological detail poses major challenges for hybrid models in terms of behavioral realism. At issue is the ability of such models to empirically estimate key assumptions about the technological choices firms and households are likely to make when faced with new options and changing prices. One approach to this challenge is to conduct discrete choice surveys in which large samples of firms and households are faced with choice sets involving conventional technologies and emerging technologies under different price conditions for energy and emissions [13, 19]. This approach has strengths and weaknesses. On one hand, discrete choice surveys elicit stated preferences under conditions that may be rather hypothetical for firms and households. This leads to a concern that survey responses may not accurately portray how they will respond when facing real-world conditions [17]. On the other hand, discrete choice surveys at least provide firms and households with an opportunity to choose among technologies that are not yet common in the market, which is important given that future choices are likely to be quite different from current choices.

One approach to this conundrum is to combine stated and revealed preference analysis in the estimation of the behavioral parameters of hybrid models. Recent efforts in this direction have produced potentially more satisfying parameter estimates for hybrid models [15]. However, even with this approach, empirical analysis shows a great deal of uncertainty about key behavioral parameters.

Exploring uncertainty is important for improving and applying energy-economy models. Bosetti and Tavoni [4], for example, find that explicitly including uncertainty in innovation and technological change affects the innovation investment conclusions emerging from the integrated assessment WITCH model. The implications and imporminimizing, bottom-up models. A key challenge, however, in improving CIMS forecasts is uncertainty regarding consumer behavior and determining appropriate values for these behavioral parameters.

2.1 The CIMS Model

Three main behavioral parameters are used in the CIMS algorithm to allocate technology shares for new plants, buildings, and equipment. These parameters are, degree of market heterogeneity; time preference of decision maker; and , intangible cost factors [13]. The and parameters reflect the fact that actual choices cannot be described only through traditional discounted life cycle financial cost minimization.

Market heterogeneity, can be regarded as a measure of firms' and households' sensitivity to cost when choosing technologies: at high values of most choose the option with the lowest apparent costs. At low values of large variation in technology choice suggests that decision makers are less sensitive to the cost of a technology and make their choices based on other criteria. Figure 1 illustrates the calculated market share splits between two technologies, A and B. As illustrated in the figure, when =1, even if one technology has a life cycle cost (LCC) twice that of a competing technology, a purchaser choosing the expensive technology has a probability of almost 40%. At the other end of the spectrum, when =15, the model trends toward a 100% probability of the less expensive alternative being purchased.

Intangible costs, , represent non-financial costs associated with a given technology. They include factors such as the risk of failure of a new technology, option value in delaying the adoption of new technologies, or qualitative differences in technology performance. Each competing technology is thus potentially associated with an intangible cost that represents these non-financial cost factors. In practice, is set equal to zero unless evidence suggests that intangible costs are significant for a given technology.

The CIMS market share function uses the life cycle costs of different competing technologies to calculate new market shares, MS, for each technology option, at each time interval, , as shown in Eq. 1.

$$\mathrm{MS}_{,} = \frac{CC}{\qquad}$$

of consumer behavior is based on real-world evidence.

3.2 Parameter Estimation Using Metropolis-Hastings

complete CIMS model—consisting of thousands of technologies—is clearly impractical. Rather, we focused on a few key technology competitions (nodes). Specifically, we calibrated CIMS nodes for refrigerators, furnaces, and gasoline vehicles. While it would have been useful to estimate parameters for a node in the industrial or commercial sector to compare the preferences of firms with those of individual consumers or households, obtaining sufficiently disaggregated market share from these sectors proved very difficult. These three nodes were modeled separately using a code that replicates the CIMS algorithm. These individual CIMS nodes allow for greater flexibility in slightly adjusting the configuration of the full CIMS model to better match available data and make running MCMC statistical calibration simulations (requiring thousands of model run iterations) possible. In this paper, however, we focus on the residential furnaces node as a representative example.

Dowlatabadi and Oravetz's [8] backcasting study provides specific suggestions for establishing consistency between the model framework and historical data. First, the start year of the model is reset to the beginning of the historical period, 1990, establishing a common initial condition between model and history. Second, all known observable parameters, such as capital and operating costs, are set to their historical values. Historical energy prices replace exogenous projections used in CIMS forecasts, and the macroeconomic equilibrium component of CIMS is not included; no price adjustment is required for equilibrium as historical energy prices are available. Though any relevant policies implemented over the historical period should also be represented in the backcast, initially, we include no

>95% to match the archetype characteristics. Second, due to limitations in available data, a single aggregate heat pump archetype was used in lieu of CIMS current dis-aggregation of ground source and air source heat pumps.

The node was calibrated using data for Ontario, as generated by Natural Resources Canada [5]. For calibration, total stock data were compared with forecasted stocks, and thus we implemented the CIMS stock turnover model to backcast historical stocks.

4 Results

Below, we show the results of our estimation of behavioral parameters for the residential furnace node in the CIMS model. We show only the results of this node for which the methodology had the best performance.

4.1 Estimated Parameter Distribution

The Hastings–Metropolis calibration algorithm successfully

1990 and 2005, market share shifted very quickly toward more efficient refrigerators. Yet, over this period, the price of electricity did not change dramatically, and the model could therefore not account for these dynamics. A few

(1) randomly sampling values for the behavioral parameter inputs from the joint posterior probability distributions estimated in calibration; (2) running the model for each sample; and (3) aggregating the iterations by calculating a weighted average, or expected value, as the model output. Calibration outputs are ideally suited to Monte Carlo simulation. To sample from the estimated joint posterior distributions over all calibrated parameters, the sample points can be taken directly from the posterior sample output by the Metropolis–Hastings calibration routine. Because the calibration generates a joint posterior over all the parameters calibrated, this distribution includes correlation between parameter values. Including correlation in this way is a better representation of the interactions between the behavioral parameters than running a Monte Carlo simulation using only marginal uncertainty distributions for each parameter individually, which ignores the fact that some parameter combinations are highly unlikely.

Still, Monte Carlo sampling in the full CIMS model is

carbon tax as fossil fuel-based electricity generation is phased out, than oil or natural gas). Under a carbon tax regime, the life cycle cost of heat pumps becomes very favorable relative to the other technology archetypes.

5.2 Impacts of Explicit Uncertainty Analysis

While the second panel in Fig. 7 runs the forecasting model using a single set of parameters (the mode of the calibrated replicate similar results with different behavioral parameters. This finding suggests that focusing on uncertainty from behavioral parameters alone underrepresents the uncertainty in the forecast.

Overall, while the calibration analysis can improve confidence in CIMS forecasts, its value may be more as a complement to stated preference empirical analysis than as a substitute. Challenges in extrapolating from the past,