Ex Ante Health Policy Evaluation: A Sufficient Statistics Approach

John A. Graves

Vanderbilt University

4/17/2019

Models projecting the impact of reforms to health insurance programs and markets play an important role in shaping U.S. health policy. In 2017, for example, Congressional attempts to repeal and replace the 2010 Affordable Care Act (ACA) were hampered by public outcry after the Congressional Budget Office (CBO) projected that upwards of 23 million people would become uninsured. The twists and turns of earlier debates over the ACA—and before it, the Clinton health plan—also were shaped by modelers' assessments of how reform would affect insurance coverage, premiums, health care spending, and government costs.

Microsimulation models used by the CBO and by others to produce these estimates draw on economic theory and on a large and growing literature evaluating past state and federal reform efforts. Yet while models derive inputs from this shared evidence base, the evidence is uncertain and not in uniform agreement. Models also differ in their structure, underlying data sources and assumptions. It should come as no surprise, then, that models often produce varying projections of the same reform proposal.

This current state of affairs has subjected microsimulation models to criticism over their "black box" like qualities and their tendency to produce estimates with a limited accompanying sense of sensitivity to alternative parameters and assumptions. Moreover, modelers have understandably but unfortunately shied away from producing comparative assessments of overall welfare impact. Existing models typically produce an array of intermediary point estimates on welfare-relevant outcomes (e.g., changes in coverage, premiums, spending and government costs) and leave it to policymakers to weigh those factors when comparing policy choices.

This approach to health policy modeling has a number of important shortcomings. First, despite modelers' attempts to caveat the high degree of uncertainty in their estimates, projections are often afforded a false sense of precision in policy debates. This results in key decisions being made without a full accounting of the uncertainty surrounding the budgetary and coverage impacts on millions of people. Second, despite recent efforts at greater transparency, the opacity of microsimulation models makes it difficult for researchers to know whether and how their work can inform modeling efforts. Finally, the development, execution, and maintenance costs of microsimulation models are considerable. Combined, these factors contribute to high barriers to conducting rigorous ex ante policy evaluation and a muddled sense of how the health economic research enterprise could be further refined to improve policy decision making.

This study outlines an approach to ex ante policy evaluation that addresses many of the above shortcomings. The first major contribution is a generalized discrete time and choice modeling framework for assessing the cost, coverage and welfare impact of health reform policies. This framework has roots in modeling methods commonly used for health technology assessment, and in the "sufficient statistics" approach to welfare evaluation developed in the public finance literature. I demonstrate that this modeling framework encompasses many existing approaches to health policy microsimulation, including elasticity-based and utility maximization-based models. Critically, however, the appraoch also facilitates simple yet powerful counterfactual policy assessments based on reduced form estimates. That is, the framework provides researchers with a tool to investigate the coverage and cost impacts of reform alternatives without the need for a detailed individual-level microsimulation model. As a proof of concept, I demonstrate how difference-in-differeces evidence on the impact of Medicaid expansion on coverage take-up, combined with estimates on take-up of subsidized private health insurance derived from regression-discontinuity estimates (Finkelstein, Hendren and Shepard 2019) can be harnessed to model the coverage and cost impact of further expansion of coverage via public programs versus via increased subsidies for private coverage.

Second, within this framework I tie together diverse approaches to assessing uncertainty and the welfare impacts of policy. Specifically, I draw linkages between the marginal value of public funds (MVPFs), a summary measure of the costs and benefits of public policies (Hendren 2017), and value of information (VOI) methods. Intuitively, VOI quantifies the opportunity cost of policy decision making under uncertainty. At a given policy efficiency or willingness-to-pay threshold (e.g., a MVPF value of 0.8, above which a policy might be desirable but below which it may not), uncertaninty may or may not affect optional policy choices (i.e., choices that maximize relative comparisons of benefits to costs). If decisions based on comparative assessments of MVPF are insensitive to varying assumptions or to variation stemming from estimation precision in the underlying model parameters, then the value of uncertain information is low—i.e., it is not worth additional effort to reduce uncertainty since the same decision would be made today as it would if we had better information. If optimal policy decisions are sensitive to this uncertainty, however, then VOI methods quantify the opportunity cost of making policy decisions based on *current* information versus if we had perfect information on uncertain parameters. Variation in modeled outputs can be further decomposed to identify the relative degree to which specific parameters contribute to the overall value of perfect information. These assessments, in turn, can provide guideposts for refining and prioritizing future research to focus on parameters and concepts where the value of information is high. I provide a concrete example of the application of VOI methods by assessing the relative contribution of estimation precision and assumptions on the incidence of uncompensated care in contributing to uncertainty in MVPF estimates for policies that subsidize the purchase of private insurance coverage.

The remainder of this paper proceeds as follows. In the next section, I outline a discrete time modeling framework that provides a set of sufficient statistics to estimate the coverage and cost impact of health reform policies. I then denomstrate how existing approaches to microsimulation, including utility maximization and elasticity-based approaches, tie to this generalized modeling framework. Thereafter, I show the ability of the framework to accomodate modeling using parameters derived reduced from reduced form estimates. To do so, I draw on novel analyses of coverage changes estimtated in the Survey of Income and Program Participation, and on estimates of subsidized coverage take-up estimated in Finkelstein, Hendren and Shepard (2019). The final section extends the generalized modeling framework to include comparative assessments of overall welfare impact based on the MVPF. By mapping each reform alternative to a MVPF, I show how VOI methods can be used to quantify and decompose modeling variation that derives from parameter uncertainty. The final section concludes with some thoughts on how the overall framework could be adopted to improve research in health economics.

Discrete Choice Model

Consider a model of insurance choice among J alternatives (including the choice not to insure). Define U_{itj} as the utility for choice unit i (e.g., individuals or families) from selecting choice j at time t. Suppose utility can be expressed in terms of a vector $(\mathbf{x_{itj}})$ of observable attributes of the choices and the choice units , fixed (over time) attributes of the choice unit $(\mathbf{z_i})$, and an unobservable component ϵ_{itj}, :

$$U_{itj} = V(\mathbf{x_{itj}}, \mathbf{z_i}) + \epsilon_{ij}$$

For any unit, the choice of insurance y_i is based on maximizing utility across the J alternatives at time t:

$$y_{it} = \arg\max_j [U_{itj}, j = 1, \ldots, J]$$

Following McFadden (1974) we further assume a linear utility specification:

$$U_{itj} = \alpha_j + \boldsymbol{\beta_j}'\mathbf{x_{itj}} + \gamma'\mathbf{z_i} + \epsilon_{itj}$$

We now define a function $B(\cdot)$ that maps the utility derived from choice j to the probability of selecting j. Assuming the error terms ϵ_{ij} are independent across units and are distributed Type I Extreme Value, the probability that unit i chooses insurance type k at time t is

$$\begin{aligned} C_{it}(k) &= P[U_{itk} > U_{itj} \forall k \neq j] \\ &= B(\mathbf{x_{itj}}, \mathbf{z_i}, \alpha_j \boldsymbol{\beta_j}, \gamma) \\ &= \frac{\exp(U(\mathbf{x_{itj}}, \mathbf{z_i}, \alpha_j \boldsymbol{\beta_j}, \gamma))}{\sum_{ij}[\exp(U(\mathbf{x_{itj}}, \mathbf{z_i}, \alpha_j \boldsymbol{\beta_j}, \gamma))]} \end{aligned}$$

This sets up a standard conditional logit model for insurance choice at time t.

Now need to model the transition probability from time t to $t+1$.

Now suppose we wish to model an exogenous change to the choice set. For example, in ex ante policy evaluation we typically model how a proposed reform alternative changes the characteristics, quality and price of insurance. These changes will affect utility and, in turn, can affect the ultimate choice of insurance covearge y_{it}.

A standard assumption in behavioral microsimulation is that the exogenous change does not affect the unobserved disturbance term ϵ_{itj}. Thus, differences in predicted utility can be used to derive transition probabilities among the J choices.

Health Reform Modeling as a Discrete Time Markov Process

This section outlines a simple discrete time markov model for health insurance coverage in the U.S. population. We begin by defining an ex ante occupancy vector $\mathbf{p_{exa}}$ that summarizes the fraction of the population in each major health insurance type (employer-sponsored insurance, other private insurance, public insurance, and uninsured) in the pre-reform period.

$$\mathbf{p_{exa}} = \begin{pmatrix} p_{exa,esi} \\ p_{exa,pri} \\ p_{exa,pub} \\ p_{exa,unin} \end{pmatrix}$$

where $p_{exa,k}$ is the fraction of the population in each insurance category k in the ex ante period.

Now define the transition probability matrix:

$$\mathbf{R} = [r_{k,j}] = \begin{pmatrix} r_{esi,esi} & r_{esi,pri} & r_{esi,pub} & r_{esi,unin} \\ r_{pri,esi} & r_{pri,pri} & r_{pri,pub} & r_{pri,unin} \\ r_{pub,esi} & r_{pub,pri} & r_{pub,pub} & r_{pub,unin} \\ r_{unin,esi} & r_{unin,pri} & r_{unin,pub} & r_{unin,unin} \end{pmatrix}$$

where $r_{k,j}$ is the probability of transitioning from ex ante category k to ex post category j.

Finally, we can define an ex post occupancy vector:

$$\mathbf{p_{exp}} = \begin{pmatrix} p_{exp,esi} \\ p_{exp,pri} \\ p_{exp,pub} \\ p_{exp,unin} \end{pmatrix}$$

Basic matrix algebra links the two occupancy vectors as follows:

$$\begin{pmatrix} p_{exa,esi} \\ p_{exa,pri} \\ p_{exa,pub} \\ p_{exa,unin} \end{pmatrix}' \cdot \begin{pmatrix} r_{esi,esi} & r_{esi,pri} & r_{esi,pub} & r_{esi,unin} \\ r_{pri,esi} & r_{pri,pri} & r_{pri,pub} & r_{pri,unin} \\ r_{pub,esi} & r_{pub,pri} & r_{pub,pub} & r_{pub,unin} \\ r_{unin,esi} & r_{unin,pri} & r_{unin,pub} & r_{unin,unin} \end{pmatrix} = \begin{pmatrix} p_{exp,esi} \\ p_{exp,pri} \\ p_{exp,pub} \\ p_{exp,unin} \end{pmatrix}'$$

In the equation above, the set of transition probabilities $r_{k,j}$ can be considered sufficient statistics for evaluating the impact of a policy change on health insurance coverage in the population. That is, once we know these probabilities and how they change under a given reform option, we can simulate the impact on the overall coverage distribution in the population. By attaching costs to population movements among insurance types, we can simulate the cost impact to the government. And finally, as we show below, social welfare weights can also be attached to population movements. These weights can then be aggregated and compared across reform alternatives to make comparative evaluations of policy options.

Link to Existing Microsimulation Approaches

Utility Maximization Models

CBO estimates the utility (U_{in}) for HIU i from coverage alternative n based on a systematic component (V_{in}) and an (unobservable) stochastic component ϵ_{in}:

$$U_{in} = \beta_1 V_{in} + \epsilon_{in}$$

In the equation above, the systematic component of utility (V_{in}) is adjusted upwards of downwards based on a scaling factor β_1 that translates the utility value HIUs place on a coverage alternative into dollars.

The systematic component of utility is further modeled using a utility specification. For a single individual this takes the following form:

$$V_{in} = y_i - C_{in} - E[H_{in}] - \frac{1}{2}\rho_n \texttt{Var}(H_{in}) + \delta_{1n}(y_i, a_i)$$

where y_i is the individual's income, a_i is the individual's age, C_{in} is the out-of-pocket cost to the individual of coverage alternative n (e.g., premium, any mandate penalty, etc.), $E[H_{in}]$ and $\texttt{Var}(H_{in})$ are the expectation and variance of the individual's out-of-pocket health expenditure on coverage alternaive n, ρ_n is the coefficient of absolute risk aversion, and δ_{1n} is a utility shifter specific to each coverage type n.

The utility shifter in the above equation is designed to either increase or decrease the value of each coverage type–possibly varying by age or income–based on various factors. These factors coudl include the individul's awareness of their eligibility for the program, their ability to enroll in the program (e.g., through a website, or through a more or less cumbersome enrollment process), their preferences for or against certain types of coverage, etc. In addition, the individual's out-of-pocket spending (H_{in}) varies by insurance type, and is capped (based on income) to reflect the availability of uncompensated care and bankruptcy as implicit sources of insurance.

Each indiviual in the model faces a set of insurance options in their choice set (e.g., based on whether an offer of emloyment-based coverage is available to them, whether they are eligible for public insurance, etc.). These utilities are then fed through a nested logit framework to derive coverage take-up probabilities.

Elasticity