Modeling Health Insurance Expansions: Effects of Alternate Approaches

Dahlia Remler, Columbia University
Joshua Graff Zivin, Columbia University
Sherry Glied, Columbia University

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Abstract

Estimates of the costs and consequences of many types of public policy proposals play an important role in the development and adoption of particular policy programs. Estimates of the same, or similar, policies that employ different modeling approaches can yield widely divergent results. Such divergence often undermines effective policymaking. These problems are particularly prominent for health insurance expansion programs. Concern focuses on predictions of the numbers of individuals who will be insured and the costs of the proposals. Several different simulation-modeling approaches are used to predict these effects, making the predictions difficult to compare. This paper categorizes and describes the different approaches used; explains the conceptual and theoretical relationships between the methods; demonstrates empirically an example of the (quite restrictive) conditions under which all approaches can yield quantitatively identical predictions; and empirically demonstrates conditions under which the approaches diverge and the quantitative extent of that divergence. All modeling approaches implicitly make assumptions about functional form that impose restrictions on unobservable heterogeneity. Those assumptions can dramatically affect the quantitative predictions made. © 2004 by the Association for Public Policy Analysis and Management.

INTRODUCTION

Estimates of the costs and consequences of public policy proposals play an important role when policymakers decide whether to proceed with a policy change. They also figure centrally in the deliberations that go into the development of policy options. Recently, Aaron (2000) and Penner (2002) have highlighted the policy problems of and some possible policy reactions to uncertainty in budget projections. Aaron and Penner focus primarily on general macroeconomic forecasting, but they also address the problems of predicting the effects of specific policy proposals. An important feature of the uncertainties in budget forecasting is that different estimates of the same, or similar, policies can yield widely divergent results, depending on which model is used to make the estimates. The health care reform proposals of the Clinton administration provide a striking example of both the power of and divergence among cost estimates (Bilheimer and Reischauer, 1995; Nichols, 1995; Sheils, 1995; Thorpe, 1995). Published estimates of the 5-year budgetary savings of
the Health Security Act ranged from the administration’s projection of $58.5 billion, to the Lewin–VHI projection of $24.6 billion, to the Congressional Budget Office (CBO) projection of $74 billion (Crippen, 2002).

The Medicare Catastrophic Coverage Act, which floundered on high CBO estimates of the premiums seniors would be required to pay to obtain drug coverage, provides another striking example of the tremendous political and policy consequences of divergent cost estimates (Glied and Brooks, 1997). HCFA initially estimated that the program would cost $6.4 billion. CBO, by contrast, initially projected a cost of $750 million.

Debates over cost estimates continue to bedevil current efforts to expand prescription drug coverage for Medicare beneficiaries. Costs to the government and to beneficiaries of such coverage are of considerable importance to the political future of these proposals. Yet estimates of these costs diverge substantially. CBO’s preliminary estimates for a catastrophic prescription drug coverage plan for Medicare beneficiaries were $26 billion per year (Crippen, 2002). In contrast, RAND has estimated costs of only $5 billion per year for a more generous plan design (Goldman, Joyce, and Malkin, 2002).

Cost estimates from different models diverge for many reasons. In its analysis of the divergent estimates of the Clinton Health Security Act, for example, the Office of Technology Assessment (OTA) enumerated a host of model differences, including differences in behavioral parameters, baseline data, and projected growth rates (OTA, 1994). Prior research has shown how differences in assumptions about parameters lead to discrepancies in estimates of the effects of health insurance expansions and discusses how many other factors potentially drive estimates’ divergence (Glied, Remler, and Graff Zivin, 2002). This paper examines the role of model design in generating discrepancies among estimates.

Models are used for projections of the effects of a wide variety of public programs, including welfare, food stamps, Social Security, Medicare, Medicaid, school expenditures, housing programs, and all areas of federal and most state government spending. For example, the Social Security Administration’s Model of Income in the Near Term (MINT) projects retirement behavior, the number of disabled, and a variety of other factors driving their budget (Toder et al., 2002). In each of these contexts, simulation modelers must design models that capture the behavioral effects of all features of a program that might affect costs. Models, however, forecast the future. Thus, modelers never have the information needed to model all these behavioral parameters. Instead, modelers must make simplifying assumptions to carry out the simulation. Foremost among these simplifying assumptions is the framework of the model itself.

One reason for the observed diversity in findings among models is that there are many different, accepted frameworks for simulation modeling. Differences in model design require modelers to incorporate behavioral assumptions in different formats that can be hard to compare, making models more opaque (Glied, Remler, and Graff Zivin, 2002). Moreover, differences in modeling approaches, alone, can generate variation in model outcomes, even when all modelers use the same parameters. In effect, the design of a model imposes constraints on how unobservable characteristics of the population and of their behavior affect outcomes. For this reason, variation in model design exacerbates the better-understood variations that are introduced by differences in parameter assumptions.

This paper focuses on health insurance expansion proposals. Not only are they an important and difficult policy area in their own right, but health insurance expansions represent an area where a variety of divergent and complex modeling approaches have been developed. Furthermore, they benefit from the availability of a rich set of data on
baseline parameters and behaviors. The modeling problems posed in estimating the effects of insurance expansions illustrate the kinds of issues that are central to efforts to estimate the effect of other policy changes, including situations where much less information is available. In our conclusions, we draw parallels to global warming, cigarette taxation, and school vouchers, illustrating the very general lessons learned.

The purposes of this paper are: to explain conceptually how the most widely used modeling approaches are related to one another; to show how the quantitative values of the parameters in the various methods can be directly compared; to illustrate empirically the (quite restrictive) conditions under which all approaches yield identical results; and to demonstrate empirically some common conditions under which the approaches diverge and the quantitative extent of that divergence. All empirical approaches by necessity can only make predictions based on observable characteristics. In reality, however, heterogeneity in unobservable characteristics causes observationally identical individuals to make different decisions. Assumptions about this unobserved heterogeneity, implicit in functional form, are the principal drivers of these divergent estimates when predicting out of sample.

HETEROGENEITY AND MEASURING INSURANCE UPTAKE

To predict health insurance acquisition decisions in the face of programmatic change, some measure of consumer responsiveness to “effective” price is necessary. Measures employed by simulation models can describe behavioral responses to small price changes (point elasticities) or large ones (discrete elasticities). Measures can be drawn from studies of price changes (elasticities) or from studies of changes in program eligibility (take-up). Lastly, two methods for representing elasticities prevail, the conventional price elasticity and the semi-elasticity. The former measures the percentage change in the number of insured for a given percentage change in price. The latter measures the percentage point change in the number of insured for a given percentage change in price. (The various measures are summarized in Table 1.) Before examining them in detail, we first describe the micro-behavior underlying the insurance acquisition decision, which provides the theoretical and conceptual basis to relate the various measures.

The underlying decision to enroll in any given insurance program is an individual-level discrete choice, in which one of several insurance options is selected. For ease of exposition, we abstract from issues of different forms of insurance (Employer Sponsored Insurance (ESI), Medicaid, individually purchased, etc.), different qualities of insurance, and issues of family structure. Only single individuals with a single insurance option and whether or not they have health insurance are considered, not the quantity of that health insurance.

This dichotomous approach differs from the continuous utility maximization approach typically used in public policy modeling. In the continuous approach, the effect of different types of health insurance expansions (proportional vs. flat tax credits, for example) is illustrated by comparing the effects of linear and kinked rotations of the budget constraint. Since participation is being modeled, this detail is generally irrelevant.1

Figure 1 shows the budget constraints for three health insurance regimes: no favorable treatment of health insurance, a tax credit, and a tax deduction—A, B,

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1 The analysis below assumes that the value of any tax credit is less than or equal to the cost of the minimum health insurance package.
Table 1. Different measures of health insurance responsiveness.

<table>
<thead>
<tr>
<th>Responsiveness Measure</th>
<th>Formula</th>
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<tbody>
<tr>
<td>Point Elasticity</td>
<td>$\varepsilon = \frac{p}{F(p)} \cdot \frac{dF(p)}{dp} = \frac{pf(p)}{F(p)}$</td>
</tr>
<tr>
<td>Point Semi-elasticity</td>
<td>$\varepsilon_s = p \frac{dF(p)}{dp} = pf(p)$</td>
</tr>
<tr>
<td>Discrete Elasticity</td>
<td>$\varepsilon = \frac{(F(p_1) - F(p_0))/F(p_0)}{(p_1 - p_0)/p_0}$</td>
</tr>
<tr>
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<td>$\varepsilon_s = \frac{F(p_1) - F(p_0)}{(p_1 - p_0)/p_0}$</td>
</tr>
<tr>
<td>Take-up Rate</td>
<td>$\tau = \frac{\varepsilon_s}{1 - F(p_0)} \left( \frac{p_1 - p_0}{p_0} \right) = \frac{\varepsilon}{1 - F(p_0)} \left( \frac{p_1 - p_0}{p_0} \right)$</td>
</tr>
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Figure 1. Budget constraints for (A) no favorable tax treatment of health insurance, (B) tax-credit for health insurance, and (C) tax-deduction for health insurance.
and C, respectively. Health insurance is plotted on the x-axis with all other goods on the y-axis. The purchase price for a minimum benefits health insurance policy, $H_{\text{min}}$, is shown as a dotted line. The accessible parts of the budget constraints are shown by the bold lines and the mass-point at $(0,Y_0)$, where all the uninsured cluster. The effect of an expansion program on participation is determined by how many people move from the mass-point of zero health insurance to any place beyond $H_{\text{min}}$. When examining how many people move from the mass-point of zero to the minimum purchasable amount of health insurance, the form of the subsidy does not matter: a tax deduction and a tax credit of equal size will have the same effect on the number who are insured. Rather than a budget constraint and indifference curve framework, discrete choice problems such as these are best represented through a reservation price framework.

Consider a population of observationally identical individuals. The population is homogeneous in all observable variables, such as income, and employment status, etc. It is assumed that everyone faces a single price for health insurance. The population is heterogeneous only in unobservable variables, such as unobservable aspects of health status, attitudes toward risk, opportunities for free care, non-health economic needs, and family support. Such heterogeneity causes observationally identical individuals to make different decisions when faced with the same health insurance purchase choice. Thus, some members of a population are insured at the market price while others are not.

The most intuitive way to represent such heterogeneity is through heterogeneity in the reservation price. The reservation price is the maximum amount that a given individual would be willing to pay for health insurance. The distribution of reservation prices in a population determines the number insured under any conceivable policy regime. This distribution is sufficient to fully characterize the market-level demand for health insurance in this population.

Clearly, the population distribution of reservation prices can take on many shapes. While the distribution function is illustrated graphically using the uniform distribution, all discussion and formulas are completely general, unless otherwise stated. Figure 2 depicts the cumulative distribution function, $F(r)$. If the market price is below $r_{\text{min}}$, everyone in the population is insured and the cumulative distribution function takes on the value one. If the market price is above the maximum reservation price in the population, $r_{\text{max}}$, no one is insured, corresponding to a cumulative distribution function value of zero. For any given market price, the cumulative distribution function reveals the share of the population that will purchase insurance. Coupled with the total number of people in the population, this determines the number of insured. Lowering the price from $p_0$ to $p_1$ raises the share of the population that is insured from $F(p_0)$ to $F(p_1)$. Thus, the cumulative distribution function is, in essence, the market demand function.

The distribution of reservation prices can be used to derive an elasticity measure. It is important to note, however; that while health insurance acquisition is an individual discrete choice, elasticity, as used in health insurance modeling, is a market-level concept. The demand elasticity represents a change in the number of individuals insured, not a change in the quantity of insurance purchased, as would be described by the elasticity of an individual demand curve. In this context, the elas-

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2 The demand function is conventionally plotted with price on the y-axis and quantity on the x-axis. In our case, the share insured is plotted on the y-axis to emphasize that it is the dependent variable.
ticity should be thought of as a participation elasticity, which is meaningful only when applied to a population.

A point elasticity, the percentage change in the number of insured per percentage change in price at a given price, can be expressed as:

$$
\varepsilon = \frac{p}{F(p)} \frac{dF(p)}{dp} = \frac{p f(p)}{F(p)}
$$

(Eq. 1)

A semi-elasticity does not use the percentage change in the population insured but rather the percentage point change in the number insured. Because the semi-elasticity is the “naturally estimated” parameter in a probit model with log price as the independent variable, it is sometimes used in the literature (e.g., Gruber and Poterba, 1994). The point semi-elasticity is:

$$
\varepsilon_s = p \frac{dF(p)}{dp} = pf(p)
$$

(Eq. 2)

In some empirical work, particularly when based on some actual discrete policy change, demand responsiveness is measured using a discrete price change. Since lowering price to $$p_1$$ increases the share of the entire population who takes-up insurance by $$F(p_1) - F(p_0)$$ percentage points,³

³ It would be possible and preferable in real empirical work, of course, to define arc elasticity versions of the discrete elasticities. Since that issue is not central to our points, we avoid the arc elasticities to keep the formulas simpler.
Discrete elasticity:

\[
\varepsilon = \frac{(F(p_1) - F(p_0))/F(p_0)}{(p_1 - p_0)/p_0}
\]  

(Eq. 3)

Discrete semi-elasticity:

\[
\varepsilon_s = \frac{F(p_1) - F(p_0)}{(p_1 - p_0)/p_0}
\]  

(Eq. 4)

The elasticity varies with price as we move through the reservation price distribution. The extent and form of this variation depends on the shape of the distribution function. Depending on that shape, discrete change elasticities can be strikingly different from the point elasticity at the starting price, as we will illustrate in the empirical section. In the case of a uniform distribution, the elasticity is 0 at prices below \( r_{\text{min}} \), and above \( r_{\text{max}} \), since either everyone or no one is insured and nothing further changes. Between those two prices, the uniform distribution elasticity is \( \frac{p}{r_{\text{max}} - p} \), as illustrated in Figure 3.\(^4\)

\[\text{Figure 3. Possible (point) elasticity as a function of price for a uniform distribution of reservation prices.}\]

\(^4\) Due to the unrealistic abrupt changes at the edges of the distribution, the elasticity actually goes to infinity at \( r_{\text{max}} \).
Furthermore, very different elasticities would be expected at the floor where almost no one is insured and at the ceiling where almost everyone is insured. When almost everyone who is observationally identical has taken up insurance, it seems highly likely that the remaining few uninsured are different along some important unobserved dimensions that influence the participation decision. Consequently, generalizing the elasticity from one part of the reservation price distribution to another part could be hazardous.

The elasticity is not the only measure of consumer responsiveness. Some simulation methods use take-up rates instead. The take-up rate is the share of the initially uninsured population who take up insurance in response to some policy or price change. Imagine that a homogeneous population was initially ineligible for a free program and faced a non-zero market price for insurance. For simplicity, consider the effect of making the population eligible for free health insurance, resulting in a 100 percent price reduction. In that case, the semi-elasticity, denoted $\varepsilon_s$, is $F(0) - F(p_0)$, or the fraction of the entire population who take up insurance. The take-up rate is the fraction of the uninsured population newly insured, $(F(0) - F(p_0)) / (1-F(p_0))$. In general, the take-up rate for an arbitrary price change is:

$$\tau = \frac{\varepsilon_s}{1-F(p_0)} \left( \frac{p_1 - p_0}{p_0} \right) = \frac{\varepsilon}{1-F(p_0)} \left( \frac{F(p_0)}{1-F(p_0)} \right)$$  
(Eq. 5)

If the initial group is all uninsured, the semi-elasticity and the take-up rate are identical. Applying an elasticity computed from a total population (including both the insured and uninsured) to an uninsured population, as if it were a take-up rate, creates a scaling error. To illustrate the importance of scaling the measured elasticity correctly when applying it to the uninsured population only, consider the following simple example.

Imagine a simple controlled experiment in which there are 10,000 people in the experimental group of whom 8000 are initially insured. Suppose the experiment reduces the price of health insurance faced by this group by 10 percent. In response, 1000 of those initially uninsured purchase coverage. In this case, the estimated semi-elasticity is equal to the change in probability of having insurance divided by the price change of 0.1, yielding a semi-elasticity of 0.1 / 0.1 = 1.0. (The corresponding elasticity is 1.25.)

Now consider what happens if this semi-elasticity is applied to the initially uninsured population only, as would be the case with a take-up rate. Applying the semi-elasticity to the 10 percent price change over a population of 2000 initially uninsured people yields an estimate that 200 people will gain new coverage. In the example, however, 1000 people gained coverage, five times as many as estimated.

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5 Non-financial costs of insurance are not included in the price and would need to be incorporated elsewhere.

6 Some researchers use the term take-up rate to refer to an average takeup rate, the share of all people who participate in a program. This rate is then applied only to the uninsured. The previously insured, albeit with a different form of insurance, have a different take-up rate (a crowd-out rate) applied to them. If not everyone in the initial population had been uninsured, then a similar scaling error occurs. In our simple model with only one form of insurance, the concept of crowd-out is not relevant. As such, we define the take-up rate as the share of the uninsured who take-up insurance, since that is how it will be applied.
Using a semi-elasticity as if it were a take-up rate will lead to inconsistencies. To be applied to a population that is entirely uninsured, the semi-elasticity must be scaled by the inverse of the share of the population that was initially uninsured, in this case one-fifth.

On theoretical grounds, there is no reason to prefer elasticities over take-up rates or vice versa. However, if predictions across studies are to be compared, transparent and consistent descriptions of how parameters are employed is critical. More generally, in order to compare simulation results, we need to understand the origins of differences and the circumstances under which different modeling approaches would yield identical results.

**Modeling Approaches in Practice**

Methods of modeling the effects of health insurance reform fall roughly into four broad categories. Note that all implementations are not always pure forms of these categories and that hybrids exist (Blumberg and Nichols, 2000). The first approach, the elasticity approach (EA), applies price elasticities to data on current prices and current insurance patterns. This approach is the most familiar and widely used. In some cases (e.g., Baumgardner, 1998; Gruber, 2000), price elasticities are obtained from data sources other than the one used for the microsimulation, while in other cases (e.g., RWJF, 2000), the elasticities are estimated from the same data used for the microsimulation. The EA uses individual-level data in determining prices, incomes, and other parameters and is thus considered a microsimulation approach. However, while the prices and incomes are individual-specific in the EA, the elasticity is not.

The second approach, the matrix approach (MA), applies take-up rates to groups of individuals defined by particular characteristics, such as income, family size, and so on. This approach has primarily been used for Medicaid take-up calculations (e.g., Holahan et al., 2000; Feder, Uccello, and O’Brien, 1999).

In the third approach, the discrete choice approach (DCA), a discrete choice model is estimated and used to predict the effects of policy changes (e.g., Blumberg and Nichols, 2000; Pauly and Herring, 2001, 2002). While only Pauly and Herring interpret such models as reservation prices, all discrete choice models implicitly define a cumulative distribution function of reservation prices. Thus, these estimated discrete choice models are conceptually akin to the insurance demand model we described in the previous section.

The final approach is the most recent. It compares health insurance options using reservation prices estimated through a utility-based structural model (Pauly and Herring, 2001, 2002; Zabinski et al., 1999). This fourth approach is idiosyncratic in the particular structural model employed and difficult to compare with the other three; therefore it is not discussed further.

The first three approaches, while appearing very different and, in existing practice, yielding quite different estimates, are actually closely related. To compare them, we need a formulation with at least two observationally distinct groups. Consider a case with two groups: group E is already eligible, while group N is initially ineligible. Each group initially contains both insured and uninsured individ-

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7 Blumberg and Nichols’ simulation method also incorporates a novel and rather sophisticated set of general equilibrium conditions, which are beyond the scope of our discussion here.
The take-up rate among the uninsured is distinct for each sub-group.\(^8\) The market price for insurance is initially \(p_0\) and is \(p_1\) in the subsidized program.

Elasticities vary across individuals and depend on the range of price changes. Each approach, therefore, will be applied to identical people and an identical price change. In this case, the price elasticity of demand for insurance is specific to the relevant population group, \(N\), and calculated based on the discrete price change that corresponds to the policy proposal. Thus, the semi-elasticity for the \(N\) group is:

\[
\varepsilon_N^s = \frac{F_N(p_1) - F_N(p_0)}{p_1 - p_0} p_0.
\]

Applying that semi-elasticity in an EA microsimulation to the entire \(N\) population would result in a change in the number of insured of:

\[
\Delta T(EA) = \sum_{i \in N} \varepsilon_i^s \left( \frac{p_1 - p_0}{p_0} \right) = N_N (F(p_1) - F(p_0))
\]  
(Eq. 6)

where \(N_N\) is the number of people in the \(N\) group.

The matrix approach uses take-up rates, rather than elasticities. A take-up rate is the fraction of the uninsured that participates in the new program. Calculating the take-up rate for the relevant population group, \(N\), based on the same discrete price change of the policy proposal, results in

\[
\tau_N = \frac{F(p_1) - F(p_0)}{1 - F(p_0)}.
\]

Using the matrix approach, the take-up rate would be applied to the uninsured members of the newly eligible group, resulting in:

\[
\Delta T(MA) = \sum_{i \in U_{i_n}N} \tau_N = N_N (F(p_1) - F(p_0))
\]  
(Eq. 7)

The discrete choice approach starts by estimating a discrete choice model, generally a logit or probit. To predict enrollment, the fitted model is applied to each individual to predict his probability of participating at the new price. This is equivalent to estimating the cumulative distribution function for each individual and adding them up.

\[
\Delta T(DCA) = \sum_{i \in U_{i_n}N} F(p_1) - F(p_0) = N_N (F(p_1) - F(p_0))
\]  
(Eq. 8)

Clearly, if all parameters are estimated from the affected population facing the proposal to be simulated, then all approaches yield the same predictions. This begs the question of why empirical estimates derived using different methods generally produce inconsistent results. One reason estimates differ is that they use parameters drawn from different sources. Occasionally, parameters are estimated from the same population to which a proposal will be applied. Sometimes, parameters are estimated from a larger sample that includes the small affected population (e.g., a discrete choice model that uses the full population to estimate parameters more precisely and then applies these to an expansion targeted at those less than 250 per-

\(^8\) For the matrix approach, there is also generally a different take-up rate for programs such as Medicaid among the already insured. Since we have only two states, insured and uninsured, that is not relevant here. Our already insured simply stay insured.
cent FPL). Alternatively, parameters may be drawn from an entirely different population (e.g., an elasticity computed from an independent natural experiment) to avoid problems of selection bias and endogeneity. Since the decision to acquire insurance is based on unobservable characteristics that may be correlated with price, any estimate of price responsiveness may falsely attribute all causality to the price change. Using estimates of consumer responsiveness obtained from a different population, however, may lead to errors because the elasticity can vary substantially across the population. The employment of these external sources must balance these bias and relevance concerns. Variations in predictions may also stem from differences in the choice of functional form and, implicitly, the treatment of unobservable heterogeneity.

An Empirical Illustration

This section demonstrates both the potential equivalence and the potential divergence of the three approaches and shows the stringent conditions needed for equivalence and how the kinds of extrapolations modelers must inevitably make will lead to divergences. By deriving the empirically predicted variation in responsiveness among observationally identical individuals using the DCA, the effect of unobservable heterogeneity is also illustrated. The empirical models, far simpler than real-world simulation models today, are meant to isolate the effect of model approach from other simulation features.

To demonstrate the equivalence of modeling approaches, a discrete choice model for having insurance is fitted using log price and other covariates. To implement the DCA, that model was used to predict the effect of a single health insurance expansion, a reduction in price for a certain sub-group. Next, the results of those predictions were used as if they were real-world data from a policy change, much as one would use simulated data in a Monte Carlo, taking advantage of the fact that we know the truth, having created it. Those data are used to calculate the implied discrete-price-change elasticity and take-up rate. The EA predictions are made by applying that elasticity to each of the income categories used in the estimation. The MA predictions are made by applying the derived take-up rate to each income category.

How the methods diverge in their predictions is illustrated in three different ways. First, when implementing the EA, the point elasticity estimated from the discrete choice model is used rather than using the discrete-price-change elasticity, as described above. This extrapolation is analogous to what is done in many simulations, including RWJF (2000), which apply point elasticities to larger price changes. Second, the discrete choice model was re-estimated on a moderately high-income sub-group and the implied discrete choice elasticity used to predict the impacts of the policy change on a low-income sub-group. This extrapolation is analogous to applying an elasticity calculated from the higher-income self-employed (Gruber and Poterba, 1994) to the lower-income CHIP eligibles. Third, the MA is more closely mimicked as practiced, by using take-up rates estimated for different price-income cells and applying them to those newly eligible for lower prices. This extrapolation is analogous to what Holahan et al. (2000) do when they apply take-up rates from Medicaid to CHIP expansions. It should be

9 Note that we are only examining predictions of the total number of insured, not the distribution of who is insured. Clearly, policymakers and individuals are also concerned about how insurance is distributed among income groups and other categories.

10 Our simple model, with its limited use of covariates, prevents us from implementing the matrix approach in a manner entirely consistent with the literature.
stressed that these examples are not intended to imply that real-world modelers are making “errors.” They are taking reasonable approaches to a difficult problem, but different reasonable approaches have different consequences.

**Empirical Methods**

Defining homogeneous sub-groups in a theoretical context is simple: one simply defines subscripts. In empirical practice, this is considerably more difficult. In effect, the individual characteristics, used as either regression model controls or a means of stratification, determine the populations treated as homogeneous.

For all calculations the March 2000 Current Population Survey was used; only the non-elderly (under 65) and those without Medicaid are included. All forms of insurance, ESI, individually purchased insurance, and so on, are treated as equivalent. For all models, a reduction of price by 50 percent was considered for a certain sub-group, specifically those below 200 percent of the federal poverty line (FPL). A weighted logistic regression model was estimated,

\[
Pr(Ins_i = 1) = f_i(p_i) = \frac{\exp(\beta \log p_i + \gamma X_i)}{1 + \exp(\beta \log p_i + \gamma X_i)}
\]  

(Eq. 9)

where the subscript \(i\) denotes the \(i\)th individual, \(\log p_i\) is the log out-of-pocket price of insurance, \(X_i\) is a vector of income categories—less than 50 percent FPL, 50–99 percent FPL, 100–149 percent FPL, and 150–199 percent FPL—and the weights are the survey sample weights. The estimated coefficients can be used to predict the probability of having insurance for each person in the sample. The predicted number of insured for the population, \(\Psi\), is calculated by multiplying the predicted probability of each person in the sample by the person’s sample weight \(w_i\): \(\Psi = \sum w_i f_i(p_i)\).\(^{13}\)

In the empirical exercise, these predictions were treated as if they were “real” data from an actual policy change. These were used to calculate the implied discrete semi-elasticity,

\[
\varepsilon_s = \frac{\Delta \Psi / N}{\Delta p / p}
\]  

(Eq. 10)

and implied take-up rate,

\[
\tau = \frac{\Delta \Psi / U}{\Delta p / p}
\]  

(Eq. 11)

---

\(^{11}\) The prices used here are the out-of-pocket prices. Chernew, Frick, and McLaughlin (1997) and Blumberg, Nichols, and Bantin (2001) find that employee payments, rather than total premiums, are statistically significant in worker take-up equations. While there remains some controversy about whether the employer share should also be included for ESI, it does not matter for the points we wish to illustrate.

\(^{12}\) Prices are assigned to individuals in the CPS by matching them to actuarial data using covariates. Non-group prices are assigned based on age, sex, Census region, and health status. Group prices are assigned based on firm size and Census region.

\(^{13}\) The logistic model fitting procedure ensures that predictions of the number of insured for the entire sample will return the correct number. The same, however, will not be true for any sub-group. This discrepancy can be and often is overcome through model calibration. We repeated the analysis using a calibrated model and there were no qualitative differences in our results.
where \( N \) is the number of people affected by the policy change and \( U \) is the initial number of uninsured affected by the policy change.

To implement the EA, the final number of insured was calculated within an income cell as:

\[
\Psi_{\text{cell}}^f = \Psi_{\text{cell}}^0 + \epsilon \left( \frac{\partial \theta}{\partial p} \right) N_{\text{cell}}
\]

where the subscript \( \text{cell} \) denotes the income cell, the superscript \( f \) denotes the final (post-intervention) state, \( \theta \) denotes the initial (pre-intervention) state, and \( N_{\text{cell}} \) denotes the total number of people in the cell affected by the policy. First the EA approach was implemented using the discrete price change semi-elasticity implied by the discrete choice model’s predictions for the policy change. Later the EA was implemented in a manner more like that used in actual EA simulations, by using the point semi-elasticity implied by the discrete choice model. The point semi-elasticity is calculated by taking the derivative of the probability with respect to log price for each individual in the sample and then taking the weighted average of those derivatives:

\[
\frac{1}{N_{\text{tot}}} \sum_{i} w_{i} [f_{i}(p_{i})]^2 \beta \exp\{-\beta \log p_{i} - \gamma' X_i\}
\]

To implement the MA, the final number of insured within an income cell was calculated as:

\[
\Psi_{\text{cell}}^f = \Psi_{\text{cell}}^0 + \tau (N_{\text{cell}} - \Psi_{\text{cell}}^0)
\]

applying the take-up rate \( \tau \) to the uninsured group, as if they were eligible for a new program. First used was the take-up rate implied by the predictions of the discrete choice model for the policy change. Later the MA was implemented in a manner more like that used in actual MA simulations, dividing the sample into cells defined by the usual income categories and the price categories: $0, $1–$499, $500–$999, $1000–$1499, $1500–$1999, $2000–$2499, $2500–$2999, $3000–$3499, and more than $3500. For example, one cell includes people with income 150–199 percent FPL who currently face prices of $500–$999 monthly. A cell-specific take-up rate was calculated by calculating the share of the cell that has insurance.14 Then the program was implemented by reducing everyone’s price by 50 percent so that they move into new price-income cells. For example, to the people in the cell in the example above the take-up rate was now applied of those with income 150–199 percent FPL who face prices of $1–$499 per month. The appropriate take-up rate was applied to all the uninsured newly eligible for the price. Those who are initially insured keep their prior insurance status. Those who do not move cells also keep their prior insurance status.

Equivalence of Approaches

The change in the number of insured resulting from the 50 percent price reduction, as predicted by the discrete choice model, is 12.2 million (Table 2). The implied discrete-price-change semi-elasticity was calculated as described by equation (10):

\[14\] This may seem like a contradiction with our definition of a take-up rate as the share of the uninsured who take-up a particular program. However, if one understands the existing data as being those otherwise uninsured people who respond to this price level by taking up insurance, the methods are consistent. In effect, this treats everyone in the cell facing a particular price as those eligible for a particular program (price level). The program we evaluate is then a new one, which changes the prices available to different individuals.

An alternative approach, closer to that taken by Holahan et al. (2000), would be to construct the take-up rates to ensure that final participation in each price-cell matches baseline rates. We did not take this approach, as it yields consistently unrealistic results when applied to our simple model, which is limited to one form of insurance and contains few covariates. Further technical details are available upon request from the authors.
change in the number of insured divided by the population subject to the price change, all divided by the proportional price change. To implement the EA, this semi-elasticity was applied to the populations in each income group below 200 percent FPL and the number of newly insured in each income group predicted.

The implied take-up rate is calculated as described by equation (11): the change in the number of insured divided by the initial number of uninsured affected by the policy. To implement the MA, the take-up rate was then applied to the number of uninsured in each income group in order to predict the number of newly insured in each of the income categories below 200 percent of FPL.

The EA and MA were then completely consistent with the DCA and yielded essentially identical predictions (Table 2), as predicted. Of course, this precise agreement requires the same data set and the same policy change. Moreover, the discrete-change-price elasticity is calculated from the very numbers of insured that resulted from the policy change. In this exercise, such numbers were created through the DCA, which serves as a benchmark for methodological comparisons. In effect, the results are the same because the calculation is essentially the implementation of an identity.

### Discrete versus Point Semi-Elasticity

If instead, predictions are made using the EA but with the estimated point semi-elasticity, rather than the implied discrete semi-elasticity, the results are different. Note that this approach is more like that commonly employed by EA simulation. As shown in Table 2, the predicted change in the number of insured is now 8.9 million. Both approaches use a semi-elasticity calculated from the same model applied to the same data and apply it identically. The only difference between these methods is the size of the price change used to measure the semi-elasticity—the discrete vs. point semi-elasticity. Despite the tremendous similarities across methods, the results now differ by 27 percent.

The very different predictions that result from the point semi-elasticity vs. the discrete-price-change semi-elasticity belie a more general phenomenon. The elasticity varies throughout the population, as individuals vary in both observable and unobservable dimensions. The treatment of unobservable heterogeneity is embodied by functional form assumptions, which impose restrictions on the distribution of reservation prices, and, in turn, on the point elasticity variation with price.

The effects of different functional form assumptions were illustrated using the logistic model. The empirical identification strategy is based on the heterogeneity in prices faced by individuals. First, the empirical estimation was paralleled with

### Table 2. Equivalence of approaches and point EA.

<table>
<thead>
<tr>
<th>Method</th>
<th>Predicted change in number insured</th>
<th>Implied discrete change price semi-elasticity</th>
<th>Implied discrete price take-up rate</th>
<th>Implied elasticity ea: predicted change in number insured</th>
<th>Implied take-up rate ma: predicted change in number insured</th>
</tr>
</thead>
<tbody>
<tr>
<td>DCA</td>
<td>12,222,288</td>
<td>0.353</td>
<td>0.440</td>
<td>12,222,288</td>
<td>12,222,288</td>
</tr>
<tr>
<td>Implied elasticity ea</td>
<td>12,222,288</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Point semi-elasticity</td>
<td>0.256</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Point elasticity EA</td>
<td>8,886,978</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Newly eligible population (those < 200 percent FPL without Medicaid): 69,183,929
Initial number insured in that population: 41,413,953
the calculation of a single point-estimate of the population semi-elasticity. To do this, the effect of a marginal increase in price was calculated for each person in the sample, starting from that individual's current price. The weighted average of each of those effects is calculated to give a unique point semi-elasticity based on current prices: 

\[ \frac{1}{N_{tot}} \sum_{i} w_i [f_i(p_i)]^2 \beta \exp\{-\beta \log p_i - \gamma' X_i\} \]

When applied empirically, this single parameter is assumed to apply to everyone at any price. This is shown in Figure 4 in the dotted line.

Since we want to hypothesize about everyone's behavior at different prices, we took a second approach to calculate a continuum of point semi-elasticities at all possible prices. We fixed everyone at the same single price and then saw how the semi-elasticity varied as that single price was varied, in order to trace out variability throughout the price distribution. Specifically, the effect of a marginal increase in price was calculated for each person in the sample, where each of those individuals faced the same given price but otherwise maintained their original covariates. Then the weighted average of the marginal effects over all individuals at that price was taken,

\[ \frac{1}{N_{tot}} \sum_{i} w_i [f_i(p)]^2 \beta \exp\{-\beta \log p - \gamma' X_i\} \]

This calculation was repeated throughout the distribution of prices, shown in the solid line in Figure 4.

Thus, Figure 4 presents graphically the results from these two calculations. It is the empirical counterpart to the earlier theoretical illustration in Figure 3. This illustrates the potentially enormous effect of unobservable heterogeneity. The constant semi-elasticity represents the simple assumption that the semi-elasticity is invariant to starting prices. The variable semi-elasticity reflects the assumption that

![Figure 4](image_url)

**Figure 4.** Variation of semi-elasticity with price. Dotted line is the constant semi-elasticity of the EA. Solid line is the semi-elasticity implicit in the DCA.
the coefficients of a logistic regression, including the coefficient of log price, are invariant to starting prices. Both approaches combine data with particular functional form assumptions, characterizing the unobservable heterogeneity. The correct characterization of unobservable heterogeneity is unknowable, but clearly different characterizations of that heterogeneity, through different functional form assumptions, will greatly influence predictions.

Out-of-Sample Predictions

Table 3 shows the results from fitting the discrete choice model on the population more than 250 percent FPL and using that model to predict the effects on those less than 200 percent FPL for both the DCA and the EA. For the DCA the coefficients of the logistic model fitted on the high-income group were assumed to apply to the low-income group. For the EA, the high-income logistic model was used to predict the effects of a 50 percent price reduction on the high-income group, and those predictions were used to calculate an implied discrete semi-elasticity. It is the predicted number of newly insured (from the DCA) divided by the total eligible population with income greater than 250 percent FPL, divided by the percentage change in price. That implied semi-elasticity was then applied to the low-income group for the EA predictions in the same manner as above. The only difference is the specific value of the semi-elasticity.

Clearly in this case the models do not yield identical results. The DCA predicts a change of 7.06 million while the EA predicts a change of 3.65 million. This difference arises despite the fact that the two methods differ only in the functional form with which parameters estimated are applied to predict changes for the lower-income group.

It is interesting to note that the size of the predicted effect is dramatically smaller than that predicted when the model was fitted on the entire sample. This is not surprising because in our estimation high-income individuals are less responsive to price than are low-income individuals.

Income-Price Cell Matrix Approach

The MA relies on tabulations of insured individuals disaggregated by a variety of covariates. An example of such a tabulation is shown in Table 4. The initial number of insured and the initial total population define a participation rate for each income-price cell. This participation rate is precisely the take-up rate that will be applied to new individuals as they enter that cell as a result of a policy change. The pattern of variation by price is quite strange, reflecting the institutional realities of employer-sponsored health insurance, rather than any real behavior determined by price itself. A real-world matrix approach, of course, would make use of

| Table 3. Predictions in lower-income group sample from higher-income group parameters. |
|---------------------------------|--------|
| DCA: Predicted change in number insured | 7,060,728 |
| Implied discrete change price semi-elasticity | .106 |
| Implied elasticity EA: Predicted change in number insured | 3,653,989 |
| Newly eligible population (those < 200 percent FPL without Medicaid): | 69,183,929 |
| Initial number insured in that population: | 41,413,953 |
| Population > 250 percent FPL: | 133,686,470 |
a variety of important other covariates and therefore would not imply such unrealistically behavior.

The MA for the proposed policy change was implemented by reducing by 50 percent the price of insurance for each person below 200 percent FPL. The proportion of the currently uninsured newly entering each cell that acquire insurance is simply equal to the old proportion of those in the cell who took-up insurance (the take-up rate marked). Table 5 shows the results of the MA with 16,806,756 million people predicted to be newly insured.

The price-cell MA assumes that if anyone is given a particular price, his insurance take-up behavior will be the same as those who currently face that particular price. In contrast, the DCA predicts insurance take-up behavior using a model estimated

---

### Table 4. Initial conditions.

<table>
<thead>
<tr>
<th>Price</th>
<th>Take-up rate</th>
<th>Income Relative to FPL</th>
<th>Number insured</th>
<th>Pop'n total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0–50</td>
<td>50–100</td>
<td>100–150</td>
<td>150–200</td>
</tr>
<tr>
<td>$0</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td></td>
<td>8,004,877</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$0–$499</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td></td>
<td>12,194,061</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$500–$999</td>
<td>0.6302</td>
<td>0.6554</td>
<td>0.8027</td>
<td>0.8431</td>
</tr>
<tr>
<td></td>
<td>0.7532</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1,000–$1,499</td>
<td>0.5253</td>
<td>0.6599</td>
<td>0.7595</td>
<td>0.8125</td>
</tr>
<tr>
<td></td>
<td>0.7078</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1,500–$1,999</td>
<td>0.4132</td>
<td>0.4069</td>
<td>0.3837</td>
<td>0.4512</td>
</tr>
<tr>
<td></td>
<td>0.4127</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2,000–$2,499</td>
<td>0.5588</td>
<td>0.3552</td>
<td>0.3390</td>
<td>0.4066</td>
</tr>
<tr>
<td></td>
<td>0.4523</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$2,500–$2,999</td>
<td>0.1657</td>
<td>0.2074</td>
<td>0.2030</td>
<td>0.1765</td>
</tr>
<tr>
<td></td>
<td>0.1863</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$3,000–$3,499</td>
<td>0.2354</td>
<td>0.2172</td>
<td>0.2412</td>
<td>0.2586</td>
</tr>
<tr>
<td></td>
<td>0.2374</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$3,500+</td>
<td>0.1341</td>
<td>0.1479</td>
<td>0.1630</td>
<td>0.1974</td>
</tr>
<tr>
<td></td>
<td>0.1530</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td>0.4795</td>
<td>0.5272</td>
<td>0.6338</td>
<td>0.7353</td>
</tr>
<tr>
<td></td>
<td>0.5986</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number insured</td>
<td>9,194,153</td>
<td>6,844,734</td>
<td>11,570,120</td>
<td>13,804,946</td>
</tr>
<tr>
<td>Pop'n total</td>
<td>19,172,909</td>
<td>12,983,045</td>
<td>18,253,829</td>
<td>18,774,146</td>
</tr>
</tbody>
</table>
from cross-sectional correlations in price and insurance status. Figure 5 illustrates the take-up rate as a function of price implied by both methods.\footnote{The DCA curve is calculated as follows. To trace out the curve, we give each person in the sample the same new insurance price, starting with $1 and repeating over the entire range of prices. The take-up rate is the share of the initially (predicted) uninsured that is predicted to become insured at the new price. However, if the new price is higher than the original price, we assume that they stay with the original price and that individual does not take-up at all. 

Formally, $\tau_{DCA} = \sum_i w_i (f_i(\min(p, p_i)) - f_i(p_i)) / \sum_i w_i (1 - f_i(p_i))$.}

This section has shown the empirical conditions under which the different approaches produce identical predictions. In addition, some commonly used practices have been shown to yield different predictions across the approaches—using the point instead of the discrete-price-change semi-elasticity, applying parameters estimated for one sub-group to another, and calculating take-up rates as existing average take-up rates. Furthermore, the section demonstrates the potential of unobservable heterogeneity to render out-of-sample predictions enormously inaccurate.

**CONCLUSIONS**

Given the variety of people engaged in estimating the responses to policies to expand health insurance as well as the great variety of policy changes examined, there is a great onus on researchers to precisely and exhaustively explain all modeling assumptions (Glied, Remler, and Graff Zivin, 2002). To allow a conversion of one simulation’s parameters into the terms of another simulation, it is critical to spell out exactly how an elasticity or take-up measure is actually employed.

Since all predictions inevitably involve out-of-sample predictions, it is important to assess how well parameters estimated in one situation generalize to the situation in which they will be employed. Obviously, there are limited sources for parameter estimation, particularly sources that do not suffer from selection bias, such as natural experiments. Therefore, there is an unavoidable tension between “clean” parameters and “relevant” parameters. While researchers may differ in how they handle this tension, they do policymakers a great service by clearly delineating the limitations of their choice.

**Table 5.** Comparison of MA methods.

<table>
<thead>
<tr>
<th>Method</th>
<th>Predicted Change in Number Insured</th>
</tr>
</thead>
<tbody>
<tr>
<td>DCA: predicted change in number insured</td>
<td>12,222,288</td>
</tr>
<tr>
<td>Implied take-up rate MA: predicted change in number insured</td>
<td>12,222,288</td>
</tr>
<tr>
<td>Price cell based MA: predicted change in number insured</td>
<td>16,806,756</td>
</tr>
</tbody>
</table>

Newly eligible population (those < 200 percent FPL without Medicaid): 69,183,929

Initial number insured in that population: 41,413,953
People are different. It is not sensible to assume that individuals who heretofore have resisted acquiring insurance will respond to a subsidy in the same way as those who eagerly scooped up less generous subsidies. Hence, unobservable heterogeneity will always be important. All modeling approaches implicitly make assumptions about functional form that impose restrictions on unobservable heterogeneity. Such functional form restrictions can have a profound impact on the quantitative predictions of policy simulations. Researchers should explore the sensitivity of their predictions to specific functional form assumptions in order to disentangle the data-driven and model-driven elements of their predictions.

While our focus has been on simulations to model health insurance expansions, many of the same concerns arise in simulations of other types of policy proposals. Global warming’s impact on agriculture, school vouchers, cigarette taxes, congestion road pricing (The Economist, 2003), and welfare to work are all areas of active policy debate where the need to predict out of sample is paramount. A look at several examples reveals how lessons from modeling of health insurance program participation can be extended to other policy areas, with varying degrees of directness.

Global warming is an important problem predicted to have major consequences on the world’s agricultural economies.¹⁶ As for health insurance, there is the need to predict out of sample—far out of sample. Predictions, in general, have two conceptual parts: the predicted effect of warming on climate and the predicted impact

¹⁶ Of course, global warming will have many other impacts besides those on agriculture, e.g., spread of disease and coastal flooding. Due to the availability of data and the considerable understanding of underlying scientific relationships, much of the research predicting impacts has focused on agriculture.
of climate change on the agricultural economy. Modeling approaches fall into two basic classes. The production function approach assumes that technology is static and does not allow behavioral changes, such as crop change (Cline, 1992; USEPA, 1989). This approach is conceptually akin to the MA for health insurance take-up. Both are notably accurate in their description of the world as it currently exists, but face similar challenges when trying to describe a different world order. The “Ricardian approach,” in contrast, does incorporate behavioral changes through the use of “optimization” rules that allocate land use to its highest value activity (Mendelsohn and Neumann, 1999; Mendelsohn, Nordhaus, and Shaw, 1994). Such optimization rules are based on cross-sectional regression analysis of the relationship between land value and climate, controlling for numerous other land characteristics. As with the DCA and EA, the Ricardian approach will be very sensitive to the functional form with which behavioral responses have been modeled. Economic principles could be used to relate the two methods, as the various health insurance modeling approaches were related. The ability to translate from one method to another would help disentangle agronomic responses from behavioral ones and facilitate comparisons of calculations based on different methods.

Cigarette taxation is another area where policy predictions are important, with a particular emphasis on modeling the smoking behavior of pregnant women (Colman, Grossman, and Joyce, 2002; Evans and Ringel, 1999; Ringel and Evans, 2001). As with health insurance participation, treatment of unobserved heterogeneity is of critical importance. Individuals vary in their taste for smoking and those who have not yet quit are clearly more resistant than those who have, potentially biasing predictions of the effect of future tax increases. Indeed, Colman, Grossman, and Joyce (2002) explicitly note that “a larger proportion of women who smoke just prior to pregnancy in high tax states are likely to have a stronger preference for smoking than their counterparts in low-tax states” (pp. 11–12). In this context, careful modeling of heterogeneous preferences is needed to accurately predict changes in smoking decisions resulting from cigarette tax increases.

School voucher programs are an area of intense policy debate. Most empirical evidence documenting the effects of such programs is based on evaluations of past experimental programs (Ladd, 2002; Levin, 1998; Neal, 2002), producing numbers not dissimilar to take-up rates in the health insurance context. The same caveats about generalizability apply. A notable exception is the work of Nechbya (e.g., 2000), who has developed sophisticated, iterative, multi-sector general equilibrium models, rather like the Blumberg and Nichols’ (2000) HIRSIM model for health insurance. While these models take differences in behavioral responses across settings quite seriously, they are still subject to concerns about functional form choice. As for health insurance modeling, sensitivity to price is likely to vary significantly among otherwise observationally identical individuals. The use of models estimated at one set of “prices” (including non-financial costs of using vouchers) is unlikely to apply at another set of “prices” (i.e., in other implementations or to a different population).

Health insurance is an area where the supply of data and research is relatively large. Consequently, there may be less uncertainty about parameter values than in other policy areas, making the role of unobservable heterogeneity comparatively important. Thus, in some sense, the problem could be even harder in some other policy areas.

The fate of many policy proposals hinges on the actual numbers predicted for them: How many will participate and at what cost? Often evaluators, using different methods, generate widely different numbers for the same proposal. Policymakers predisposed to reject the proposal then choose the less favorable numbers while
those predisposed to support the proposal choose the more favorable numbers. Without the ability to discuss the particular assumptions embedded in each estimate, there is little potential for constructive debate.

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DAHLIA K. REMLER is an Assistant Professor, Department of Health Policy and Management, Mailman School of Public Health, Columbia University.

JOSHUA GRAFF ZIVIN is an Assistant Professor, Department of Health Policy and Management, Mailman School of Public Health, Columbia University.

SHERRY A. GLIED is Professor and Chair, Department of Health Policy and Management, Mailman School of Public Health, Columbia University.

REFERENCES


