

A Unified Approach for Ex Ante Policy Evaluation

Supplemental Materials

John Graves, Vanderbilt University

1 Discrete Choice Model

This section describes the structure, assumptions and calibration of a discrete time and choice model of U.S. health insurance coverage.

To begin, 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 from selecting choice j at time t .

$$U_{itj} = V(\mathbf{x}_{itj}, \mathbf{z}_i) + \epsilon_{ij}$$

where \mathbf{x}_{itj} is a vector of time-varying attributes of the J choices and the health insurance unit (HIU), or the collection of related family members who could enroll under the same plan. Utility also depends on fixed attributes of the HIU (\mathbf{z}_i), and an unobservable component ϵ_{itj} .

For HIU i , the choice of insurance y_{it} is based on maximizing utility across the J alternatives at time t :

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

We next define a function $B(\cdot)$ mapping utility from choice j to $r_{ij} = P(y_{it} = j)$, the probability of individual i selecting choice j . If the error terms ϵ_{ij} are independent across units and are distributed Type I Extreme Value, we get a standard conditional logit for $B(\cdot)$. However, other link functions—such as based on a nested logit or multinomial logit model—could also be used.

2 From Utility to Probability: Linkages to Common Microsimulation Approaches

The specification of choice probabilities via a link function to an underlying utility maximization model is the theoretical chassis for most major microsimulation models of the U.S. health care system. This includes models used by the Congressional Budget Office (CB), the RAND Corporation, and the Urban Institute, among others.

For example, the CBO model utilizes a similar underlying utility equation:

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

where the parameter β rescales utility into dollar terms. In the CBO model, the systematic component of utility (i.e., V_{ij}) is modeled using microdata on individuals and simulated employer choices to offer insurance.

$$V_{ij} = y_i - C_{ij} - E[H_{ij}] - \frac{1}{2} \rho_j \text{Var}(H_{ij}) + \delta_{lj}(y_i, a_i)$$

The diagram illustrates the components of the utility equation V_{ij} . The equation is $V_{ij} = y_i - C_{ij} - E[H_{ij}] - \frac{1}{2} \rho_j \text{Var}(H_{ij}) + \delta_{lj}(y_i, a_i)$. Annotations include:

- An arrow from "Income" to y_i .
- An arrow from "Cost of plan choice (premium, mandate penalty, etc.)" to C_{ij} .
- An arrow from "Coef. abs risk aversion" to ρ_j .
- Arrows from "Income" and "Age" to y_i and a_i respectively, under the term $\delta_{lj}(y_i, a_i)$.
- A bracket labeled "Utility Adjuster" above $\delta_{lj}(y_i, a_i)$.
- Labels "OOP Costs" above the equation with arrows pointing to $E[H_{ij}]$ and $\frac{1}{2} \rho_j \text{Var}(H_{ij})$.

The CBO model similarly defines a link function $B(\cdot)$ converting utility to choice probabilities based on a nested logit in which individuals first select the *type* of insurance they will have (e.g., employer, non-group, public, or uninsured) and then conditional on that choice, select among plans within that type.

In addition to sharing a common “DNA” with major microsimulation models, another nice feature of the discrete choice model structure outlined above is that it also maps directly into a reduced form modeling structure. Under this structure, changes in choice probabilities are modeled using microdata on individuals by applying reduced form literature-based elasticity estimates to simulated changes in price. This “reduced-form” or “elasticity-based” approach to microsimulation of U.S. health reform was previously used by the CBO (prior to 2019) and in other major microsimulation models.

3 Insurance Choice as a Markov Process

As discussed in the introduction to this study, a major downside to common approaches to microsimulation is that they require considerable h

To address this shortcoming, we next take the utility maximization model developed above and map it into a “sufficient statistics” approach to modeling changes to U.S. health insurance policy. In so doing we can summarize policy changes in terms of a minimal set of parameters.

To do so we first recognize that the insurance choice process at two time periods can be summarized in terms of a Markov trace. First, define the *ex ante occupancy vector* $\tilde{\mathbf{p}}$ summarizing the count or fraction of the population at baseline.

- Also define a transition probability matrix $\mathbf{R}_i = [r_{irs}]$.
 - Cells in this $J \times J$ matrix defined by transition probabilities: $r_{irs} = P(y_{it} = s | y_{i,t-1} = r)$
 - At a population level (with size N) define $\mathbf{R} = [r_{rs}]$ where $r_{rs} = \sum_{i=1}^N r_{irs} / N$.
- \mathbf{p} , the distribution of coverage at time t , is given by $\tilde{\mathbf{p}}' \mathbf{R}$.

4 Development and Calibration of Policy Simulation Model

The basis for the simulation model is longitudinal data on insurance choice from the 2014 Survey of Income and Program Participation (SIPP) calibrated to American Community Survey (ACS) on insurance coverage from 2015 to 2018.

	Ex Ante Share		Transition Probability (Nonexpansion States)			
	Expansion	Nonexpansion	Employer - Own Policy	Private - Non-Employer	Public	Uninsured
Employer - Own Policy	0.579	0.554	0.9007	0.0278	0.0275	0.0441
NA			(p=0.92)	(p=0.18)	(p=0.96)	(p< 0.01)
Private - Non-Employer	0.047	0.051	0.2450	0.6216	0.0384	0.0951
NA			(p=0.24)	(p=0.75)	(p=0.88)	(p=0.01)
Public	0.156	0.134	0.0712	0.0062	0.8514	0.0712
NA			(p=0.22)	(p=0.94)	(p=0.64)	(p=0.39)
Uninsured	0.219	0.261	0.1567	0.0640	0.1173	0.6620
NA			(p=0.92)	(p=0.07)	(p=1.00)	(p< 0.01)

Graves, McWilliams and Hatfield (2019)

	Ex Ante Share		Change in Transition Probability			
	Expansion	Nonexpansion	Employer - Own Policy	Private - Non-Employer	Public	Uninsured
Employer - Own Policy	0.579	0.554	0.0081	-0.0037	0.0068	-0.0112
			(p= 0.17)	(p= 0.35)	(p= 0.11)	(p= 0.01)
Private - Non-Employer	0.047	0.051	-0.0169	0.0301	0.0318	-0.0449
			(p= 0.45)	(p= 0.47)	(p= 0.24)	(p= 0.02)
Public	0.156	0.134	-0.0072	0.0051	0.0071	-0.0050
			(p= 0.47)	(p= 0.14)	(p= 0.75)	(p= 0.78)
Uninsured	0.219	0.261	0.0210	-0.0221	0.1071	-0.1060
			(p= 0.16)	(p= 0.10)	(p< 0.01)	(p< 0.01)

Graves, McWilliams and Hatfield (2019)

```
## # A tibble: 8 x 6
## # Groups:   non_expansion_state [2]
##   non_expansion_state coverage_type `2015` `2016` `2017` `2018`
##           <int> <chr>           <dbl> <dbl> <dbl> <dbl>
## 1             0 01_esi_own      0.633 0.638 0.644 0.650
## 2             0 02_priv_oth    0.0854 0.0856 0.0809 0.0772
## 3             0 03_public     0.180 0.186 0.185 0.182
## 4             0 04_uninsured 0.102 0.0896 0.0895 0.0909
## 5             1 01_esi_own      0.608 0.615 0.620 0.623
## 6             1 02_priv_oth    0.102 0.103 0.0936 0.0894
## 7             1 03_public     0.110 0.112 0.111 0.110
## 8             1 04_uninsured 0.180 0.170 0.175 0.177

## Warning in min(rows_matched): no non-missing arguments to min; returning Inf
## Warning in max(rows_matched): no non-missing arguments to max; returning -Inf
```

	Employer-Sponsored		Non-Group		Public		Uninsured	
	Calibrated	Target	Calibrated	Target	Calibrated	Target	Calibrated	Target
Nonexpansion								
2015	0.638	0.633	0.084	0.085	0.183	0.180	0.096	0.102
2016	0.642	0.638	0.082	0.086	0.184	0.186	0.093	0.090
2017	0.644	0.644	0.081	0.081	0.184	0.185	0.091	0.089
2018	0.646	0.650	0.080	0.077	0.184	0.182	0.090	0.091
Expansion								
2015	0.613	0.608	0.099	0.102	0.111	0.110	0.177	0.180
2016	0.616	0.615	0.097	0.103	0.111	0.112	0.176	0.170
2017	0.619	0.620	0.095	0.094	0.111	0.111	0.175	0.175
2018	0.621	0.623	0.094	0.089	0.111	0.110	0.174	0.177

```
## Warning: `cols` is now required.
```

```
## Please use `cols = c(p)`
```

```
## Warning: `cols` is now required.
```

```
## Please use `cols = c(p)`
```

```
## Warning: `cols` is now required.
```

```
## Please use `cols = c(p)`
```

```
## Warning in min(rows_matched): no non-missing arguments to min; returning Inf
```

```
## Warning in max(rows_matched): no non-missing arguments to max; returning -Inf
```

Model Parameters							
Parameter	Short Name	Value	PSA Distribution	Mean	Standard Deviation	Maximum	Minimum
Price-Fixed Subsidy Parameters							
Moral hazard effect of insurance	phi	0.250	Normal	0.25	0.05		
Social welfare weight	eta	0.750	Uniform			1	0.5
Subsidized monthly premium	plan_premium	25.000					
Fraction of uninsured population eligible for subsidies	frac_uninsured_elig	0.700	Normal	0.7	0.05		
Medicaid Parameters							
Medicaid spending among control compliers	G_Cx	2.721	Normal	2721	20		
Average cost to the government per Medicaid recipient	G	3.600	Normal	3600	20		
OOP spending among control compliers	OOP_Cx	569.000	Normal	569	50		
OOP spending among treatment compliers	OOP_Tx	0.000	Normal	0	0		
Pure insurance value of Medicaid	I	760.000	Normal	760	200		
Shared Parameters							
Government incidence of uncompensated care	gov_incidence	0.500	Uniform			1	0
Welfare weight for targeted income group	v_i	0.650	Normal	0.65	0.02		
Welfare weight for high-income group	v_j	1.100	Normal	1.15	0.02		
FPL of recipients	pop_fpl	150.000					
Out-of-pocket share of expenditures among uninsured	uninsured_oop_share	0.209	Normal	0.2	0.1		

Model Parameters Shared Across Strategies							
Parameter	Short Name	Value	PSA Distribution	Mean	Standard Deviation	Maximum	Minimum
Government incidence of uncompensated care	gov_incidence	0.500	Uniform			1	0
Welfare weight for targeted income group	v_i	0.650	Normal	0.65	0.02		
Welfare weight for high-income group	v_j	1.100	Normal	1.15	0.02		
FPL of recipients	pop_fpl	150.000					
Out-of-pocket share of expenditures among uninsured	uninsured_oop_share	0.209	Normal	0.2	0.1		

Model Parameters: Medicaid Expansion							
Parameter	Short Name	Value	PSA Distribution	Mean	Standard Deviation	Maximum	Minimum
Medicaid spending among control compliers	G_Cx	2.721	Normal	2721	20		
Average cost to the government per Medicaid recipient	G	3.600	Normal	3600	20		
OOP spending among control compliers	OOP_Cx	569.000	Normal	569	50		
OOP spending among treatment compliers	OOP_Tx	0.000	Normal	0	0		
Pure insurance value of Medicaid	I	760.000	Normal	760	200		

```
## Warning in bind_rows(x, .id): binding character and factor vector, coercing
## into character vector
```

```
## Warning in bind_rows(x, .id): binding character and factor vector, coercing
## into character vector
```

```
## Warning in bind_rows(x, .id): binding character and factor vector, coercing
## into character vector
```

Model Parameters: Price-Linked Subsidy							
Parameter	Short Name	Value	PSA Distribution	Mean	Standard Deviation	Maximum	Minimum
Moral hazard effect of insurance	phi	0.25	Normal	0.25	0.05		
Social welfare weight	eta	0.75	Uniform			1	0.5
Subsidized monthly premium	plan_premium	25.00					
Fraction of uninsured population eligible for subsidies	frac_uninsured_elig	0.70	Normal	0.7	0.05		
Coverage Takeup: Regression-Discontinuity Estimates	beta		Multivariate Normal				

```
## Warning: Expected 4 pieces. Missing pieces filled with `NA` in 8 rows [3, 4, 7,
## 8, 11, 12, 13, 14].
```

```
## Warning in min(rows_matched): no non-missing arguments to min; returning Inf
```

```
## Warning in max(rows_matched): no non-missing arguments to max; returning -Inf
```

	Baseline	Expand In-Kind Benefits (Medicaid)	Price-Linked Subsidy
Coverage Effects			
Employer-Sponsored Insurance	0.641	0.006	0.0000000
Private Non-Group	0.087	-0.003	0.0481395
Public	0.133	0.027	0.0000000
Uninsured	0.139	-0.030	-0.0481395
Marginal Value of Public Funds		0.804	0.8927658