Supplemental Appendix: A Unified Approach for Ex Ante Policy Evaluation

Evaluating Mechanisms for Universal Health Coverage

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1 Modeling Coverage Changes

Recall from the main text that the impact of a modeled reform on coverage is summarized as

$$\boldsymbol{\theta} = \boldsymbol{p(1)} - \boldsymbol{p(0)} = \boldsymbol{\tilde{p}'R(1)} - \boldsymbol{\tilde{p}'R(0)} \tag{1}$$

where $\boldsymbol{\tilde{p}}$ is the *ex ante occupancy vector* summarizing the count or fraction of the population in each coverage category at time $t-1$ (i.e., at baseline). The transition probability matrix is defined as $\boldsymbol{R_i} = [r_{irs}]$. Cells in this $J \times J$ matrix are defined by transition probabilities among the J possible coverage categories based on conditional choice probabilities: $r_{irs} = P(y_{it} = s | y_{i,t-1} = r)$.

1.1 Estimating $\boldsymbol{\tilde{p}}$

The ex ante occupany vector simply summarizes the fraction or count of the target population in each coverage category at baseline. We can therefore appeal to survey samples to obtain estimates. In our results we estimate $\boldsymbol{\tilde{p}}$ based on the 2014 panel of the Survey of Income and Program Participation (SIPP). The SIPP provides us with a baseline distribution of coverage in 2015—one year after the Affordable Care Act's (ACA) major coverage reforms went into place.

1.2 Estimating and Calibrating $\boldsymbol{R}(0)$

We begin by first specifying a process for estimating and then calibrating the baseline transition probability matrix $\boldsymbol{R}(\mathbf{0})$ to match observed population totals on the evolution distribution of coverage over time.

- Basis is 2014 SIPP
- Use SIPPP to non-parameterically estimate transiton hazards among coverage types. Basis for this is a multi-state model as outlined in Graves and Nikpay (2017)

$$\boldsymbol{R}(0) = \begin{pmatrix} 0.881 & 0.005 & 0.05 & 0.065 \\ 0.151 & 0.665 & 0.126 & 0.058 \\ 0.145 & 0.059 & 0.503 & 0.293 \\ 0.294 & 0.163 & 0.295 & 0.249 \end{pmatrix}$$

1.3 Modeling $\boldsymbol{R}(1)$: Link to CBO and Other Microsimulation Models

Estimation or modeling of the transition probabilities can be accomplished several ways: by estimating or deriving them via literature-based reduced form evidence, or by modeling them directly using microsimulation. While our application relies on the reduced-form approach, we will first discuss briefly how this can be accomplished in a microsimulation model here.

A standard assumption is that an exogenous policy change does not affect the unobserved disturbance term ϵ_{itj} in the underlying discrete choice formulation:

$$U_{itj} = V(\mathbf{x_{itj}}, \mathbf{z_i}) + \epsilon_{itj} \tag{2}$$

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}. A function $B(\cdot)$ maps utility from choice j to $r_{ij} = P(y_{it} = j)$, the probability of individual i selecting choice j.

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.

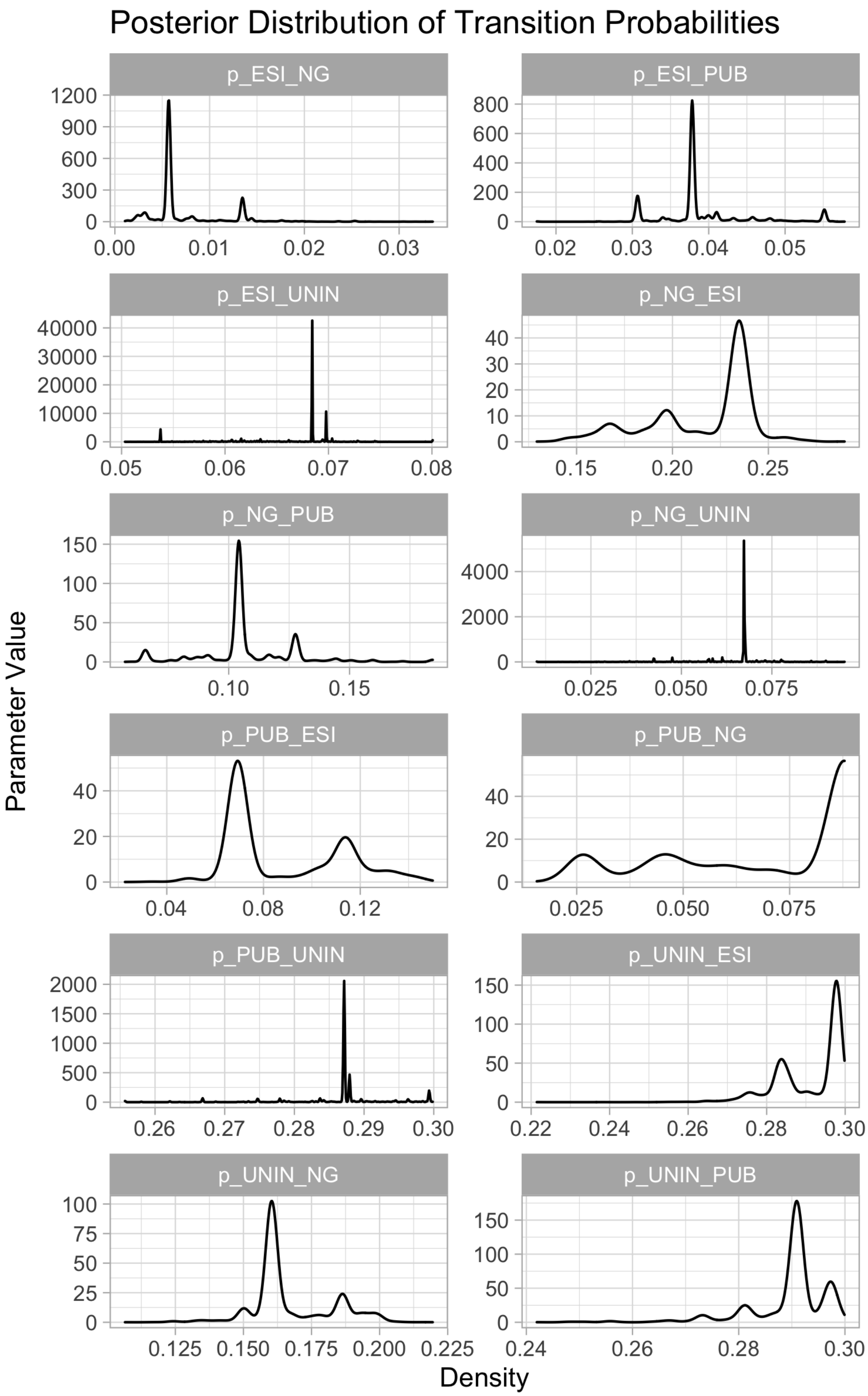

Figure 1: Posterior Distribution of Calibrated Transition Probabilities

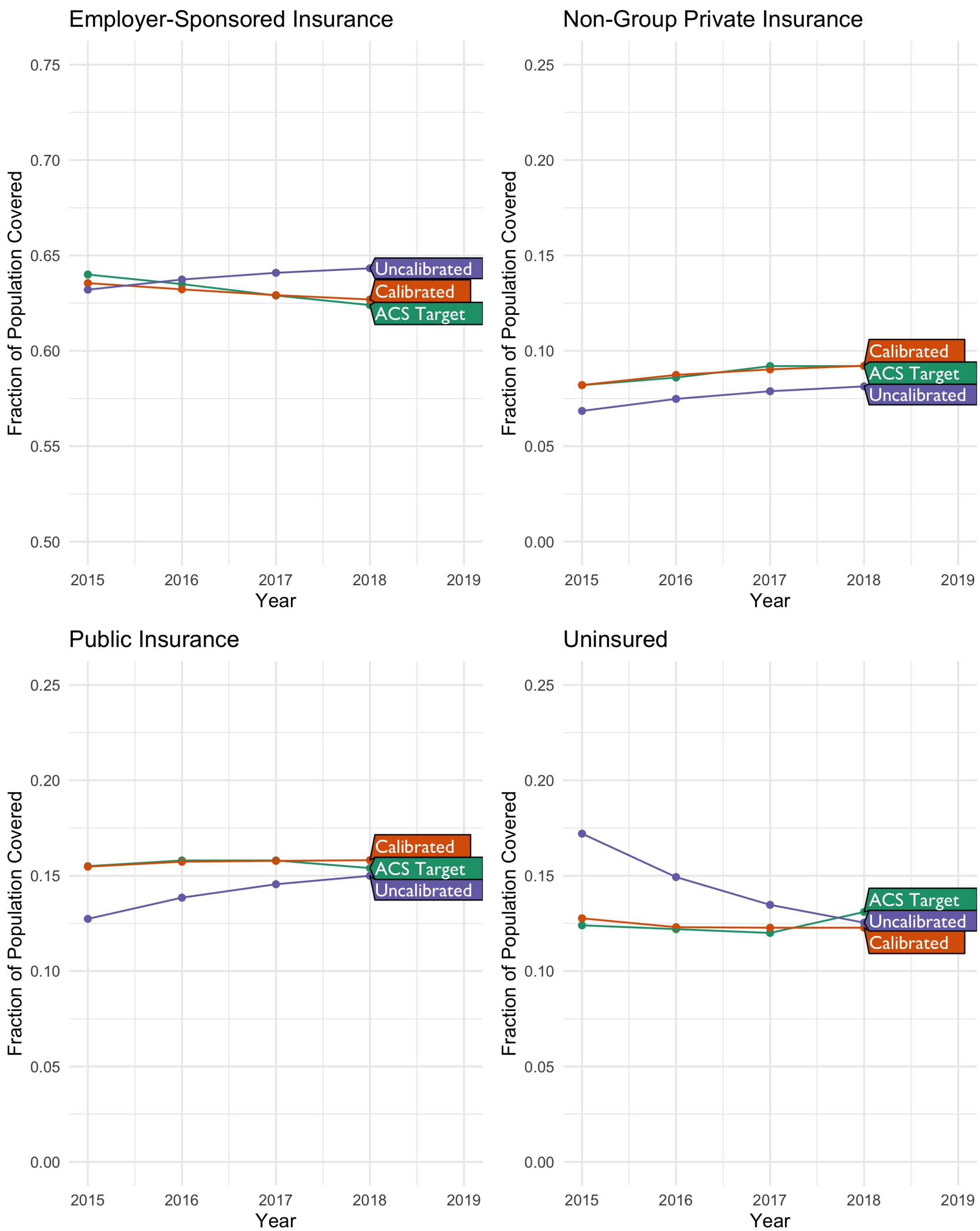

Figure 2: Calibration Plot for Distribution of Insurance Coverage by Year

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

$$U_{ij} = \beta_1 V_{ij} + \epsilon_{ij} \tag{3}$$

where the parameter β rescales utility into dollar terms.

The CBO health reform model similarly defines a link function $B(\cdot)$ converting utility to choice probabilities based a on 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. One difference, however, is that the CBO only models marginal changes in coverage, not transitions as we do here. In that sense the CBO model yields estimates analogous to repeated cross section data, versus longitudinal data.

With the underlying utility structure specified, policy changes are then modeled to affect utility/take-up through their impact on prices, quality, offers of employment-based insurance, etc. In a microsimulation model, this affects the systematic component of utility (i.e., V_{ij}), which is modeled directly using calibrated microdata on individuals and simulated employer choices to offer insurance. Attributes of plans and individuals in the microdata are adjusted to reflect the modeled reform scenario. Specific parameters in the systematic component of the CBO microsimulation model are summarized in the equation below.

$$V_{ij} = \underbrace{y_i}_{\text{Income}} - \underbrace{C_{ij}}_{\substack{\text{Cost of}\\ \text{plan choice}\\ \text{(premium,}\\ \text{mandate penalty,}\\ \text{etc.)}}} - \overbrace{E[H_{ij}] - \frac{1}{2}\underbrace{\rho_j}_{\substack{\text{Coef. abs}\\ \text{risk aversion}}}\mathtt{Var}(H_{ij})}^{\text{OOP Costs}} + \overbrace{\delta_{1j}(\underbrace{y_i}_{\text{Income}}, \underbrace{a_i}_{\text{Age}})}^{\text{Utility Adjuster}}$$

Similarly, in an elasticity-based microsimulation model—which the CBO used prior to 2018—price changes for each of the J insurance options are simulated for units in the microdata. Elasticities and further adjustments (e.g., income effects) are then applied to derive new choice probabilities. These aggregated choice probabilities, along with attributes of individuals (e.g., health status) and policy (e.g., subsidy schedules) are the building blocks for other modeled outcome changes (e.g., cost of subsidies, premiums, etc.). For example, the Gruber Microsimulation Model, which was used by the White House and Congress to model the ACA, used an underlying reduced-form take-up equation with the following form:

$$P(y_{it} = j) = (\texttt{Constant} + \texttt{Elasticity} \times \texttt{Percent Price Change} \times \texttt{Income Effect}) * \texttt{Income Adjustment}$$

1.4 Modeling $\boldsymbol{R}(1)$: A Reduced-Form Approach

A nice feature of the modeling structure developed here is that researchers can simply estimate or derive takeup probabilities from the applied literature rather than use a detailed microsimulation model. In this section we will detail how we derive estimates of $\boldsymbol{R_i}$ using differences-in-differences (for estimates of the impact of public program expansion) and regression discontinuity (for estimates of take-up of subsidized private plans).

Graves, John A., and Sayeh S. Nikpay. 2017. "The Changing Dynamics of US Health Insurance and Implications for the Future of the Affordable Care Act." *Health Affairs* 36 (2): 297–305. https://doi.org/10.1377/hlthaff.2016.1165.