What Prevents Health Insurance Take-up? Quantifying Frictions and Policy Responses

Soheil Ghili, Igal Hendel, Michael Sullivan, Michael Whinston

February 10, 2026

Limited insurance take-up under Affordable Care Act

- In 2010, 50 million Americans lacked health insurance
- Affordable Care Act (ACA, 2010) created regulated marketplaces ("exchanges") serving Medicaid-ineligible consumers ages 25-64 lacking access to employer/union group plans

Limited insurance take-up under Affordable Care Act

- In 2010, 50 million Americans lacked health insurance
- Affordable Care Act (ACA, 2010) created regulated marketplaces ("exchanges") serving Medicaid-ineligible consumers ages 25-64 lacking access to employer/union group plans
- Exchanges have had mixed success in boosting insurance take-up despite (initial) penalties for non-participation and (continuing) subsidies for participation
  - Middling participation ($\approx$ 30% of eligible pop. by 2018)
  - More than 10 years after the ACA, $\approx$25 million remain uninsured, even with enhanced subsidies enacted in response to Covid

Limited insurance take-up under Affordable Care Act

- In 2010, 50 million Americans lacked health insurance
- Affordable Care Act (ACA, 2010) created regulated marketplaces ("exchanges") serving Medicaid-ineligible consumers ages 25-64 lacking access to employer/union group plans
- Exchanges have had mixed success in boosting insurance take-up despite (initial) penalties for non-participation and (continuing) subsidies for participation
  - Middling participation ($\approx$ 30% of eligible pop. by 2018)
  - More than 10 years after the ACA, $\approx$25 million remain uninsured, even with enhanced subsidies enacted in response to Covid
- Our research questions:
  1. What explains limited participation in ACA exchanges?
  2. Given these frictions, how can we improve insurance coverage and welfare?

Frictions limiting insurance take-up

- Literature has documented a number of frictions limiting insurance take-up:
  - Adverse selection (e.g., Handel et al. 2015)
  - Informational frictions: misperceptions of insurance benefits (Abaluck and Gruber 2011, Goldin et al. 2019, Domurat et al. 2021)
  - Hassle/transaction costs, non-pecuniary distastes for insurance, switching costs/inattention (Shepard and Wagner 2022, McIntyre et al. 2021, Handel 2013)
  - Uncompensated care: uninsured pay fraction of their medical bills (Mahoney 2015, Finkelstein et al. 2019)

Frictions limiting insurance take-up

- Literature has documented a number of frictions limiting insurance take-up:
  - Adverse selection (e.g., Handel et al. 2015)
  - Informational frictions: misperceptions of insurance benefits (Abaluck and Gruber 2011, Goldin et al. 2019, Domurat et al. 2021)
  - Hassle/transaction costs, non-pecuniary distastes for insurance, switching costs/inattention (Shepard and Wagner 2022, McIntyre et al. 2021, Handel 2013)
  - Uncompensated care: uninsured pay fraction of their medical bills (Mahoney 2015, Finkelstein et al. 2019)
- Additional literature on effects of ACA policies that encourage take-up (Saltzman 2019, Frean et al. 2017, Tebaldi et al. 2023)

What we do

1. Provide direct evidence on extent of uncompensated care

2. Estimate a binary choice model of insurance to provide evidence on choice frictions
   - Given measured uncompensated care and observed diagnoses indicating health status, use observed choices to recover taste frictions

3. Combine these estimates with an equilibrium model of exchanges incorporating adverse selection to assess:
   - the relative importance of the various frictions (run a "horse race")
   - the effects of the ACA's penalties/subsidies/pricing rules

Table of Contents

1. Data and setting
2. Uncompensated care
3. Model
4. Estimation
5. Counterfactual analysis

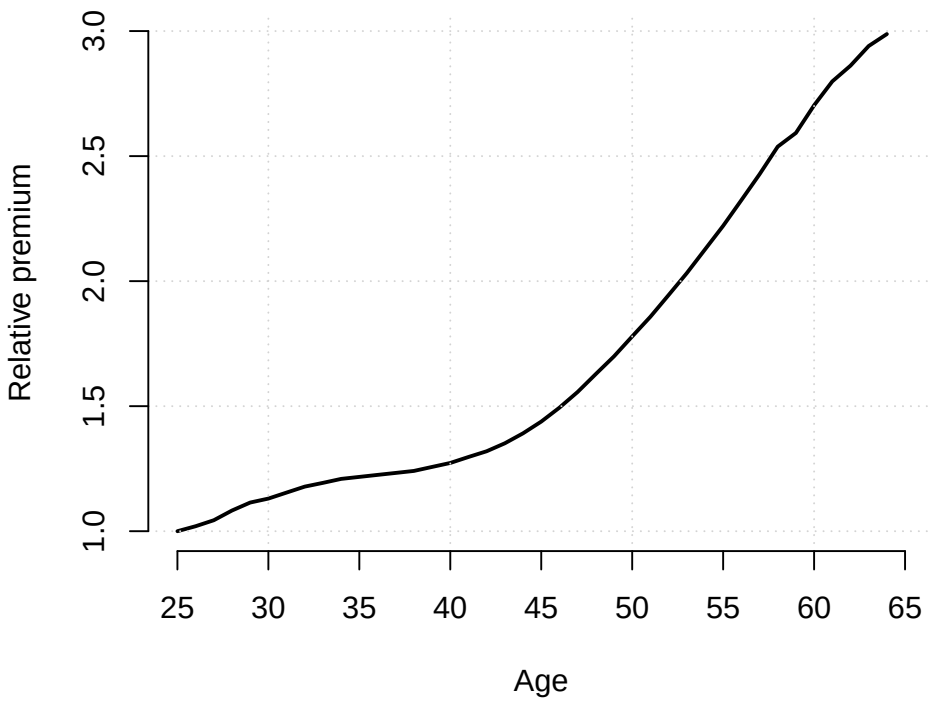
Data

- Medical Expenditure Panel Survey (MEPS), 2014–2019
  - Representative sample of panelists who are tracked over two years
  - Records of demographics, insurance status (*and type*), medical conditions, medical events, and medical expenses (*by payer*)
  - Medical conditions: granular ICD diagnostic codes
  - Restricted-access geographical data accessed through Agency for Healthcare Research and Quality (AHRQ) data center
  - Restrict sample to exchange-eligible panelists (income above 100% of Federal Poverty Level, age between 25 and 64); yields 4161 panelists
- Premiums for Silver plans from Kaiser Foundation

ACA policies: partial community rating

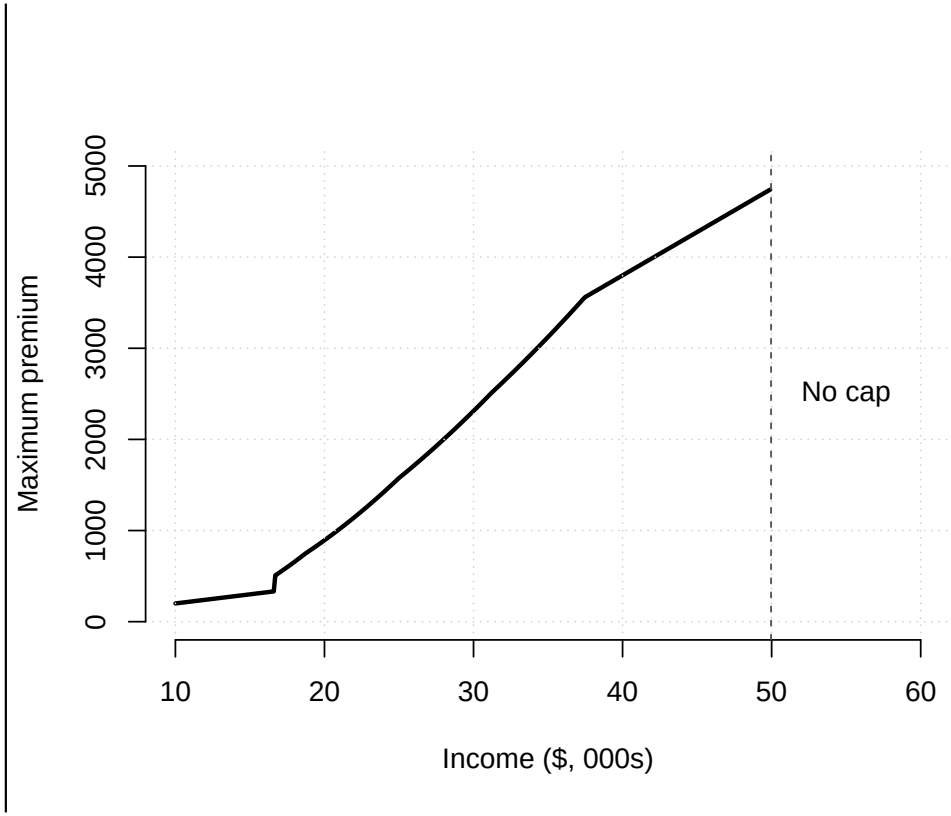
- ACA banned pricing based on pre-existing conditions, eliminating reclassification risk but creating adverse selection (HHW, 2015)
- ACA did allow pricing based on age according to a regulated schedule

ACA schedule of relative premiums by age



ACA policies: premium subsidies

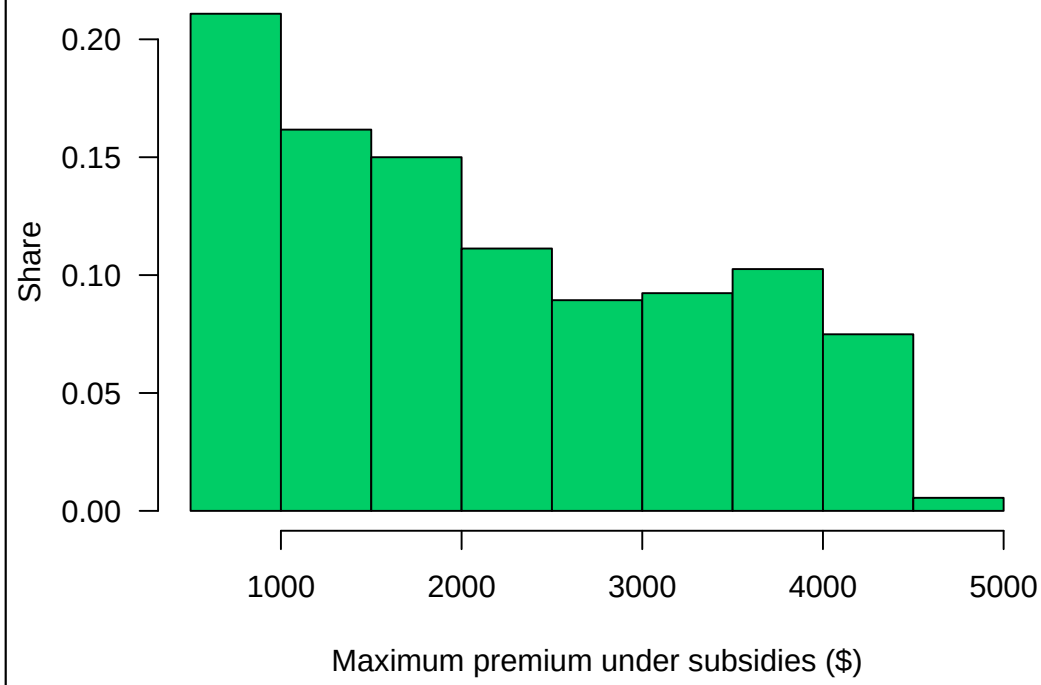
- ACA subsidies cap premiums as % of income
- Consumers under 400% of Federal Poverty Level (FPL) qualified
  - 65% of exchange-eligible consumers qualified in 2019 (FPL = 12,490)
- Mean premium (2019) $\approx$ \$5800



Many individuals received highly subsidized insurance

- Since mean premium in US (2019) $\approx$ \$5800, a large share received very large subsidies, including free/almost free coverage
- By itself, these subsidies greatly reduce the possible extent of reclassification risk many consumers would face if pricing is risk-based

Max. premium after subsidies among subsidy-eligible pop.



Cost-sharing levels under ACA Silver plans

	(I)	(II)	(III)	(IV)
Income (% FPL)	Under 150%	150–200%	200–250%	Over 250%
Actuarial value	94%	87%	73%	70%
Deductible	$0	$250	$1,750	$2,000
Maximum OOP	$1,000	$2,000	$4,000	$5,500

- Initially, government reimbursed insurers, but stopped starting in 2017 (led to "silver loading")

ACA policies: individual mandate

- ACA included a monetary penalty for failure to purchase insurance
- In 2018, 2.5% of income above tax filing threshold and subject to regulated min/max
- Penalty set to $0 starting in 2019

Individual mandate penalty by income (2018)

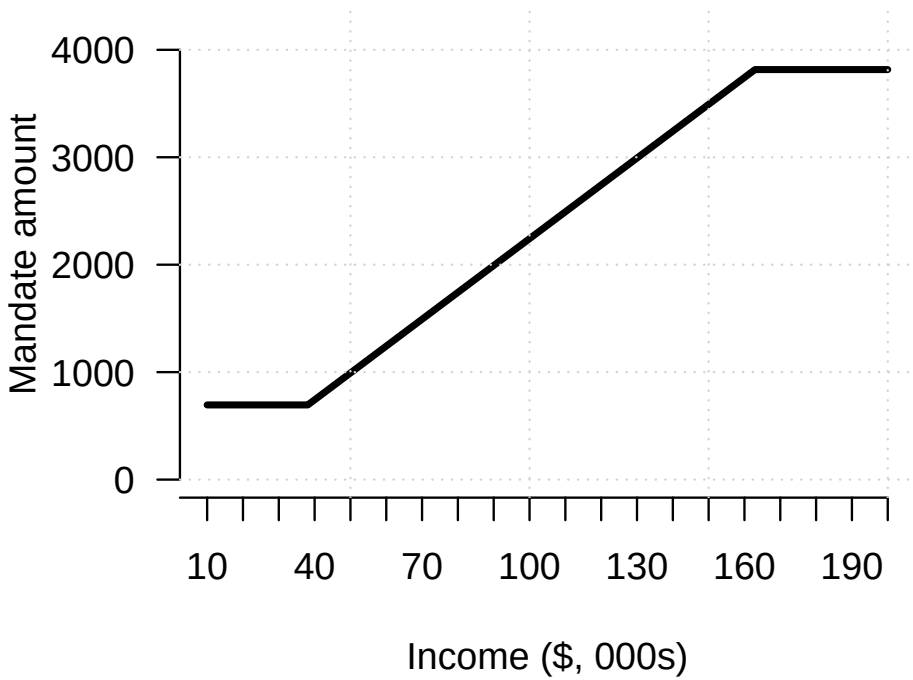


Table of Contents

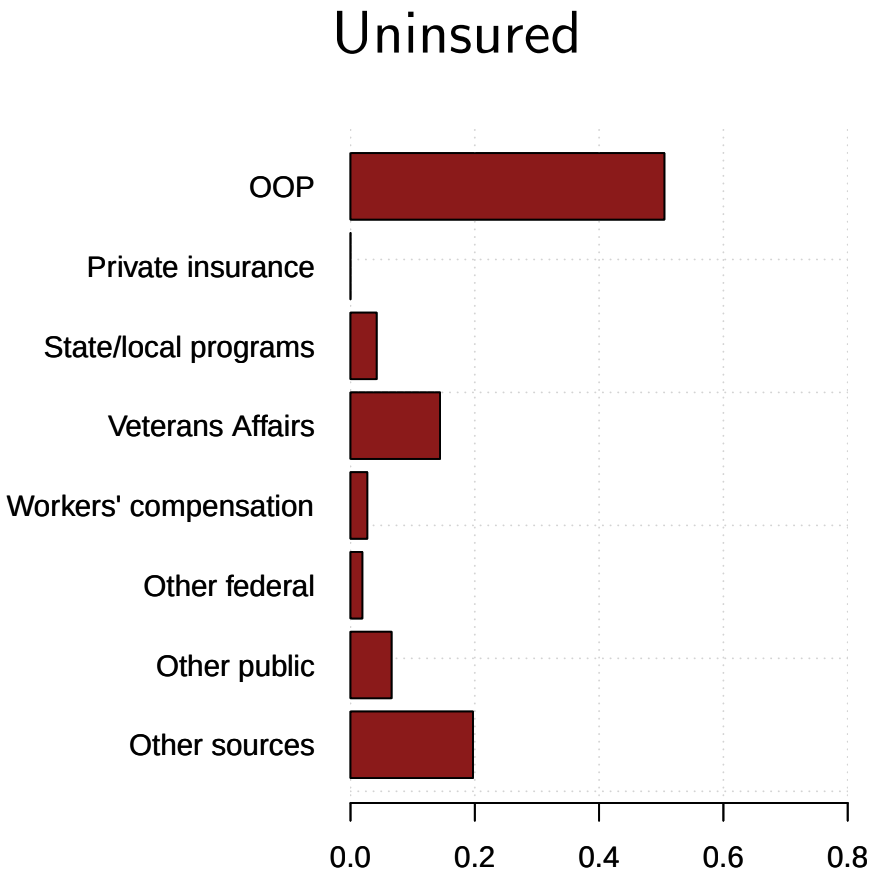
1. Data and setting
2. Uncompensated care
3. Model
4. Estimation
5. Counterfactual analysis

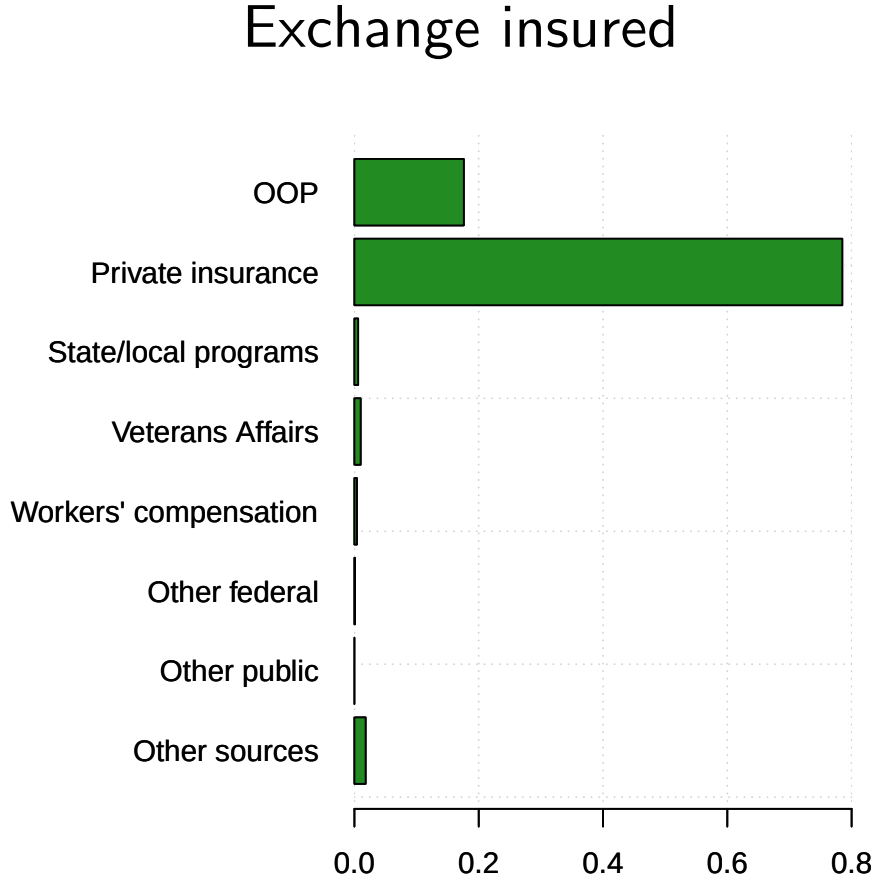
Uncompensated care

- Uninsured do not pay for entirety of medical bills
  - Government/charity assistance
  - Bad debt/bankruptcy (Mahoney, 2015)
- Two types of what literature has called "uncompensated" care:
  - **Charitable care:** payments for medical services by parties other than consumer or insurance company (reported by MEPS)
  - **True uncompensated care by providers:** all else equal, providers receive more from insured patients than uninsured patients (can be inferred from MEPS)
- We measure both to identify impact of uncompensated care on participation and to enable identification of impact of other frictions

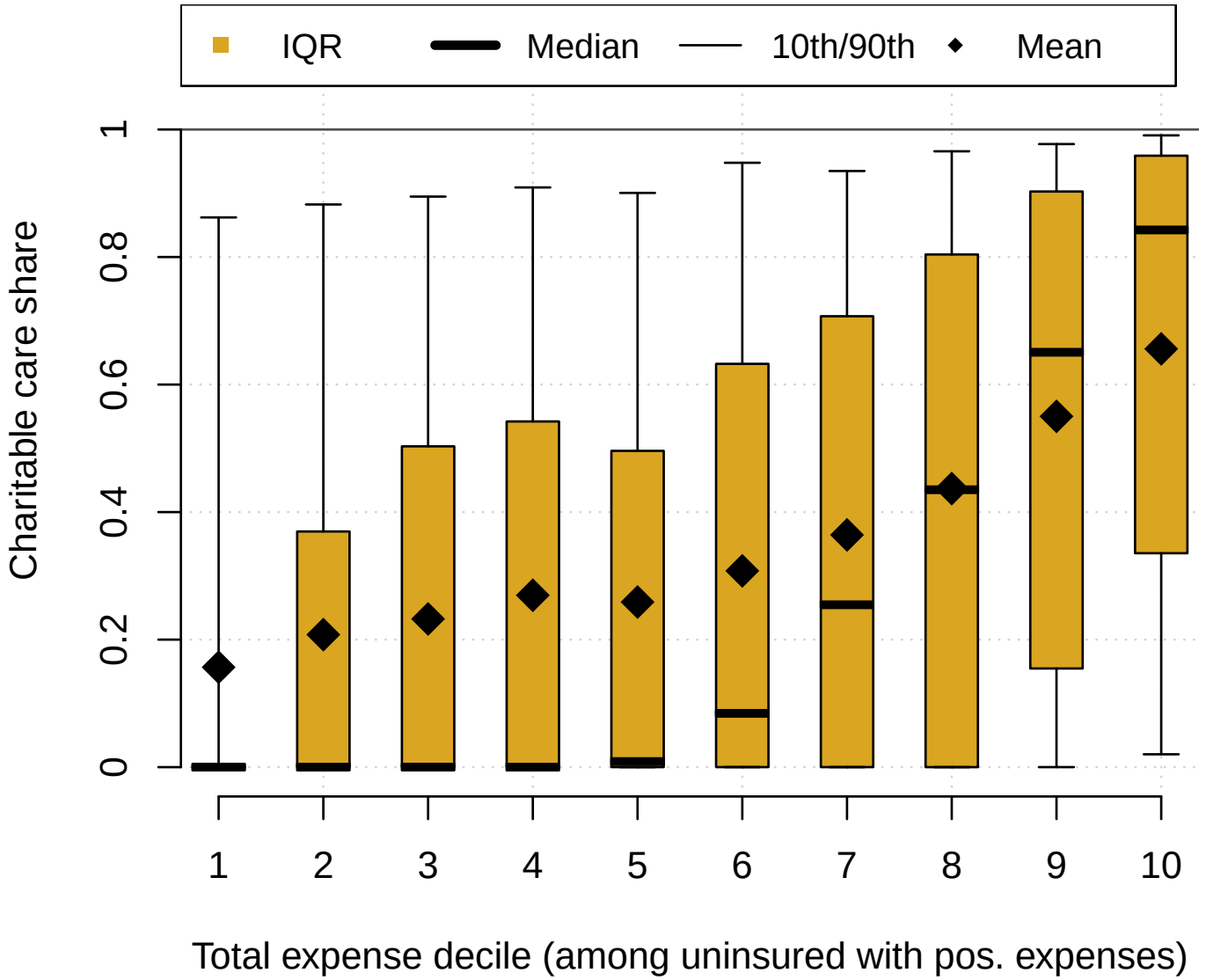
Charitable uncompensated care

Sources of payments for medical service in MEPS (2014–2019) among...





Charitable care share of total payments among uninsured



True uncompensated care

- Step 1: Use MEPS data on payments by the *insured* to map observed annual medical events into predicted payments to providers for an insured consumer – our *utilization measure*
- Step 2: Examine the share of predicted utilization $ that providers actually receive from the uninsured (again, by total expense decile)

Utilization measure

- Estimate by NLLS on sample of insured consumres:

$$\text{TOT}_{jt} = e^{\psi_t + \phi_{\text{region(j)}}}\left(x_{jt}'\beta + u_{jt}\right),$$

where

- j indicates a panelist; t indicates a year
- TOT_{jt} are total medical expenses (excluding dental expenses)
- region(j) is panelist j's census region
- Procedures x_{jt} include
  - # medical events by category (inpatient, outpatient, ER, office, etc.)
  - # of each category's events with certain procedures (anesthesia, MRI, CT, surgery, deliveries)
  - # inpatient nights

Utilization measure

- Estimate by NLLS on sample of insured consumres:

$$\text{TOT}_{jt} = e^{\psi_t + \phi_{\text{region(j)}}} \left(x_{jt}' \beta + u_{jt} \right),$$

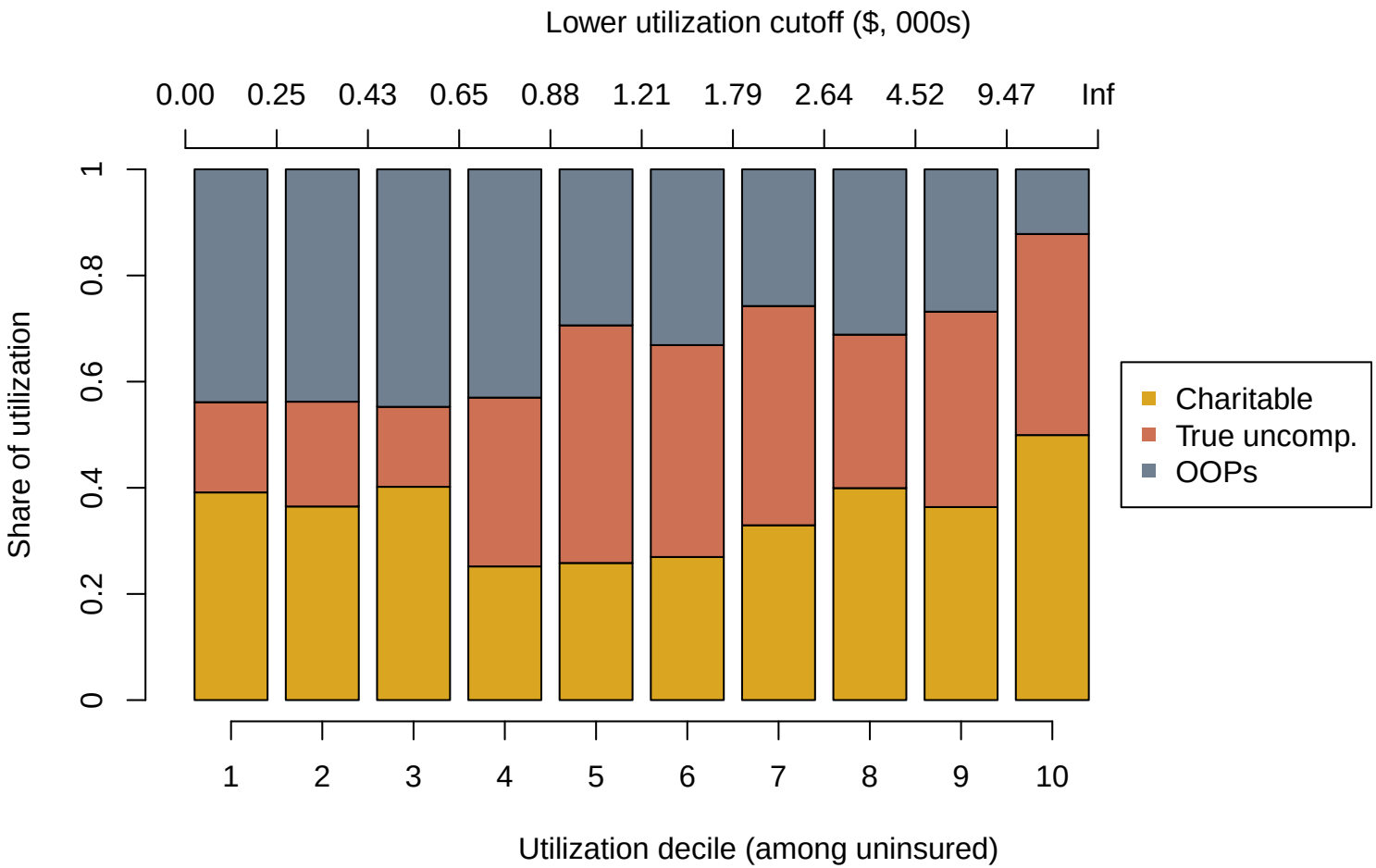
where

  - j indicates a panelist; t indicates a year
  - TOT_{jt} are total medical expenses (excluding dental expenses)
  - region(j) is panelist j's census region
  - Procedures x_{jt} include
    - # medical events by category (inpatient, outpatient, ER, office, etc.)
    - # of each category's events with certain procedures (anesthesia, MRI, CT, surgery, deliveries)
    - # inpatient nights

- Utilization is predicted expenses given events:

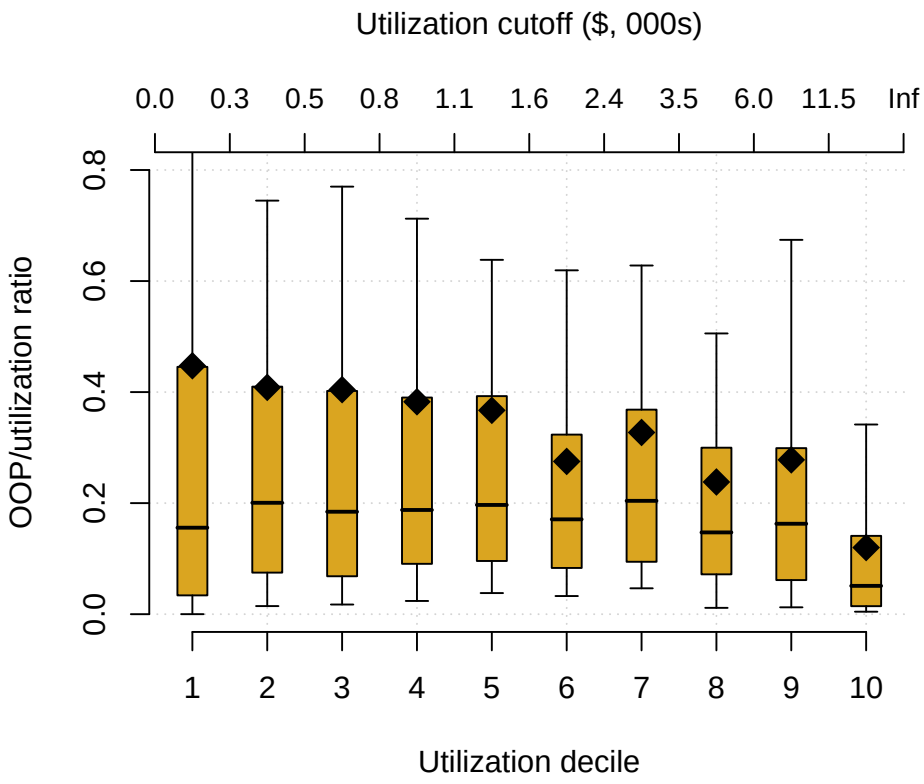
$$m_{jt} := e^{\hat{\psi}_t + \hat{\phi}_{\text{region(j)}}} \times x_{jt}' \hat{\beta}$$

True uncompensated care and charitable care — share of utilization among uninsured



OOPs for the insured and the uninsured

Uninsured



Exchange insured

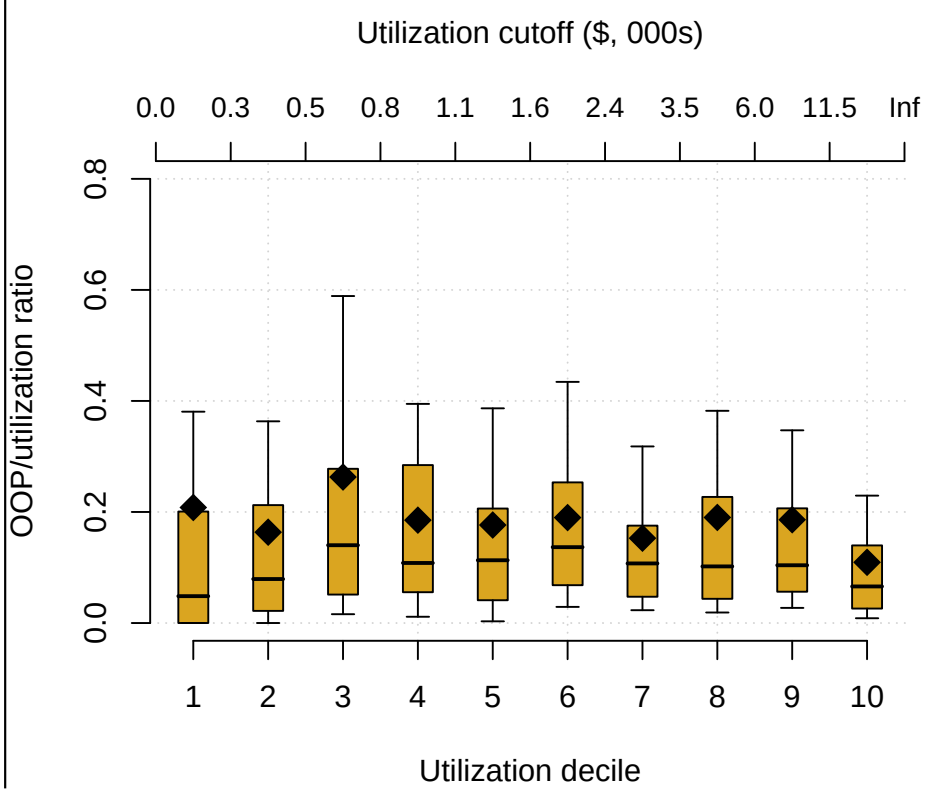


Table of Contents

1. Data and setting
2. Uncompensated care
3. Model
4. Estimation
5. Counterfactual analysis

Consumer participation decision

- Consumer j in year t has CARA preferences:

$$U_{jt}(c_{jt}) = -e^{-\gamma_{jt} \times c_{jt}},$$

  where γ_{jt} is the risk aversion coefficient

- Consumption c_{jt} is determined by

$$c_{jt}(I_{jt}) = \begin{cases} y_{jt} - p^c_{jt} - OOP^c_{jt}(I_{jt}) + z_{jt}, & I_{jt} = 1 \quad \text{(Insured)} \\ y_{jt} - OOP^c_{jt}(I_{jt}) - \ell_{jt}, & I_{jt} = 0 \quad \text{(Uninsured)} \end{cases}$$

  where
  - p^c_{jt} = after-subsidy premium
  - $OOP^c_{jt}(I_{jt})$ = *perceived* out-of-pocket payment
  - z_{jt} = taste for insurance unrelated to financial characteristics
  - ℓ_{jt} = penalty for being uninsured

Myopia

- Consumers may not equally weight a dollar in premiums and a dollar in OOPs (Abaluck and Gruber 2011)
  - Present-bias
  - Over-optimism about future health
  - Lack of cash to afford upfront premiums
- Consumers' *perceived* OOPs are

$$\mu_{jt} OOP_{jt}$$

- We specify myopia as a function of income and age

$$\mu_{jt} = \frac{e^{\mu_0 + \mu_{\text{age}} \log\left(\text{age}_{jt}\right) + \mu_y \log(y_{jt})}}{1 + e^{\mu_0 + \mu_{\text{age}} \log\left(\text{age}_{jt}\right) + \mu_y \log(y_{jt})}}$$

where y_{jt} is income relative to the FPL

Determinants of OOPs

We model the determinants of OOPs in two parts:

1. Utilization given a consumer's health state (as well as year and census region)
2. OOPs given utilization, insurance status, and income

1a. Health and utilization

- Utilization m_{jt} is determined by

$$m_{jt} = \begin{cases} 0, & \text{with probability } 1 - \rho_{jt} \\ g(h_{jt}), & \text{with probability } \rho_{jt}, \end{cases}$$

where

- $h_{jt} = \lambda_j(d_{j,t-1}) + \varepsilon_j$ – consumer's *health state*
- $d_{j,t-1}$ = observed diagnostics from previous year; age
- $\lambda_j(d_{j,t-1}) = e^{\psi_t + \phi_{\text{region}(j)}} d'_{j,t-1}\beta$ – consumer's *risk score* based on diagnostics (including age), year/region FEs
- $\varepsilon_j \sim N(0, \sigma_j^2)$; heteroskedastic with $\log(\sigma_j) = \sigma_{\text{cons}} + \sigma_\lambda \lambda_j$

and

$$\rho_{jt} = \frac{e^{(\alpha + h_{jt})/\omega}}{1 + e^{(\alpha + h_{jt})/\omega}}$$

$$g(h_{jt}) = \log(1 + \exp(h_{jt})) + a \times [\log(1 + \exp(h_{jt}))]^q$$

1b. Health and utilization: Selection

- Decompose unobservable $\varepsilon_j \sim N(0, \sigma_j^2)$ in health state h_{jt}:

$$\varepsilon_j = \varepsilon_{j0} + \varepsilon_{j1}$$

  where
  - ε_{j0} = private information known to consumer at time of choice
  - ε_{j1} = aspects of health state unknown to consumer at the time of choice

- ε_{j0}, unlike ε_{j1}, generates selection on unobservables into insurance

1b. Health and utilization: Selection

- Decompose unobservable $\varepsilon_j \sim N(0, \sigma_j^2)$ in health state h_{jt}:

$$\varepsilon_j = \varepsilon_{j0} + \varepsilon_{j1}$$

where

  - ε_{j0} = private information known to consumer at time of choice
  - ε_{j1} = aspects of health state unknown to consumer at the time of choice

- ε_{j0}, unlike ε_{j1}, generates selection on unobservables into insurance
- Specify as independent random variables

$$\varepsilon_{j0} \sim N(0, \sigma_{j0}^2) \qquad \varepsilon_{j1} \sim N(0, \sigma_{j1}^2)$$

with

$$\sigma_{j0}^2 = \lambda \times \sigma_j^2$$
$$\sigma_{j1}^2 = (1 - \lambda) \times \sigma_j^2,$$

where the parameter $\lambda \in [0, 1]$ governs the extent of selection

2. OOPs given utilization and insurance status

- Our model of OOPs is

$$\text{OOP}_{jt} = \begin{cases} 0, & m_{jt} = 0 \\ m_{jt} \times \frac{\exp(\kappa_0 + \kappa_m \log(m_{jt}) + \kappa_y \log(y_{jt}) + \xi_{jt})}{1 + \exp(\kappa_0 + \kappa_m \log(m_{jt}) + \kappa_y \log(y_{jt}) + \xi_{jt})}, & m_{jt} > 0, \end{cases}$$

  where
  - Distinct parameters for insured and uninsured (suppressed in notation)
  - $\xi_{jt} \sim N(0, \sigma_\xi^2)$ is a shock to OOPs conditional on utilization
  - y_{jt} is income relative to the FPL

Equilibrium: Insurer costs and equilibrium condition

- Realized cost to insurer (in 2019) is utilization minus OOPs

$$c_{jt} = m_{jt} - OOP_{jt}(1),$$

- Equilibrium condition

$$(1-\tau)\underbrace{\mathbb{E}[p_{jt}(p_{25}) \mid WTP_{jt} \geq p^c_{jt}(p_{25})]}_{\text{Premium revenue}} = \underbrace{\mathbb{E}[c_{jt} \mid WTP_{jt} \geq p^c_{jt}(p_{25})]}_{\text{Average cost}}$$

  where
  - WTP_{jt} = willingness to pay for insurance (depends on income, risk score λ_{jt}, private information ε_{j0}, risk aversion γ_{jt}, etc.)
  - $p_{jt}(p_{25})$ = pre-subsidy premium facing consumer j when age-25 premium is p_{25} (age schedule)
  - $p^c_{jt}(p_{25})$ = after-subsidy premium facing consumer j when age-25 premium is p_{25}
  - $1-\tau$ = MLR of 80% ($\tau = 0.20$)

Table of Contents

1. Data and setting
2. Uncompensated care
3. Model
4. Estimation
5. Counterfactual analysis

Step 1: Create utilization measure

Discussed earlier

Step 2: Health risk estimation (utilization given diagnostics, year, region)

- Estimate on full sample using GMM with following moments
  1. Covariances of diagnostic variables $d_{j,t-1}$ with utilization m_{jt}
  2. Mean utilization by year/region
  3. Mean utilization by decile of risk score λ_{jt}
  4. Variance of utilization by decile of risk score λ_{jt}
  5. Share of consumers with positive utilization by decile of risk score λ_{jt}
- Weight each moment $m_j(\theta) = g_j(\theta) - \hat{g}_j$ by $1/\hat{g}_j^2$
- Choose diagnostics $d_{j,t-1}$ to include in risk score using 10-fold cross-validated Lasso (kept 25 out of 748 variables)

Step 2: Health risk model estimates

Selected estimates

Coefficient	Estimate
α	-3.085
ω	0.147
σ_{cons}	1.213
σ_λ	-0.028
a	1.599
q	4.032

Model summary

$$m_{jt} = \begin{cases} 0, & \text{w.p. } 1-\rho_{jt} \\ g(h_{jt}), & \text{w.p. } \rho_{jt}, \end{cases}$$

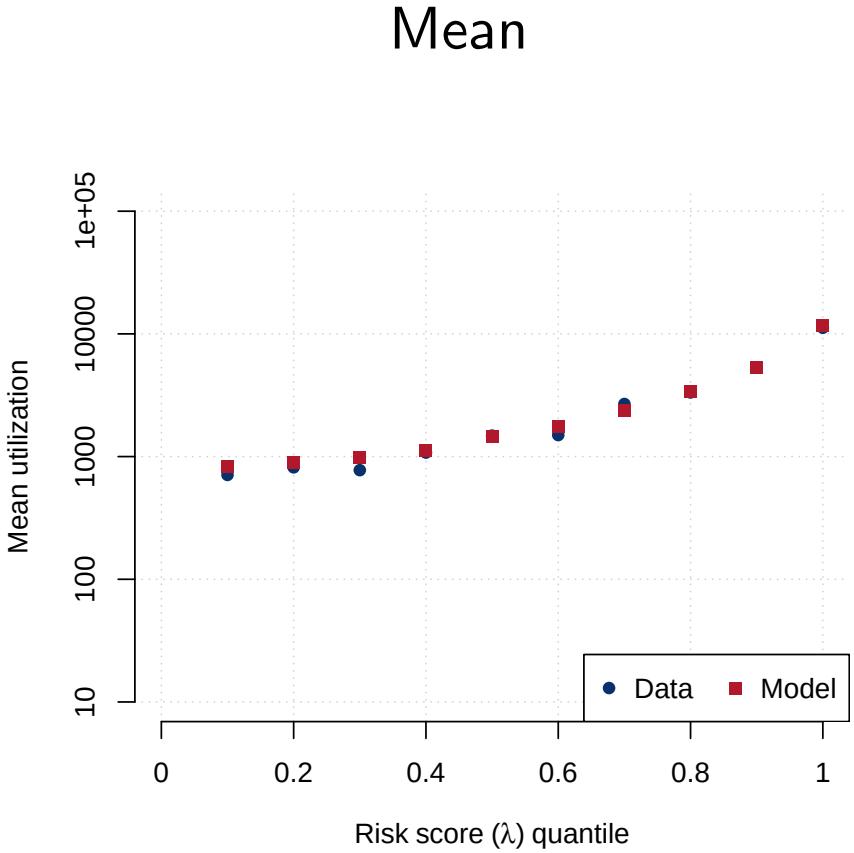
$$g(h_{jt}) = \log\left(1+e^{h_{jt}}\right) + a\left[\log\left(1+e^{h_{jt}}\right)\right]^q$$

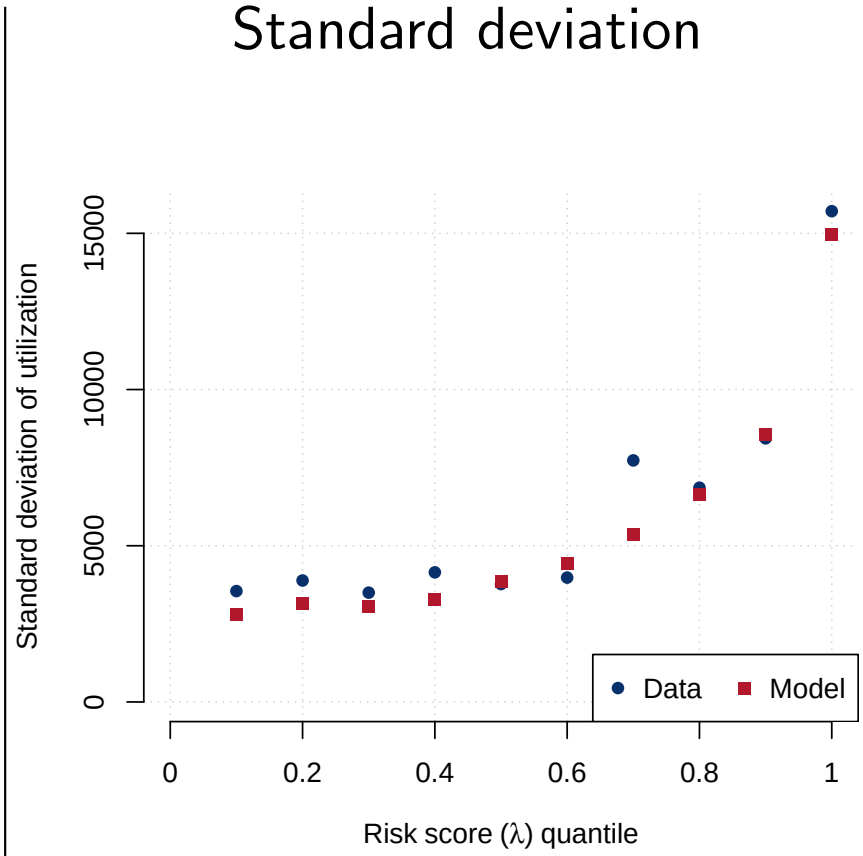
$$h_{jt} = \lambda_j(d_{j,t-1}) + \varepsilon_j$$

$$\log(\sigma_j) = \sigma_{\text{cons}} + \sigma_\lambda \lambda_j$$

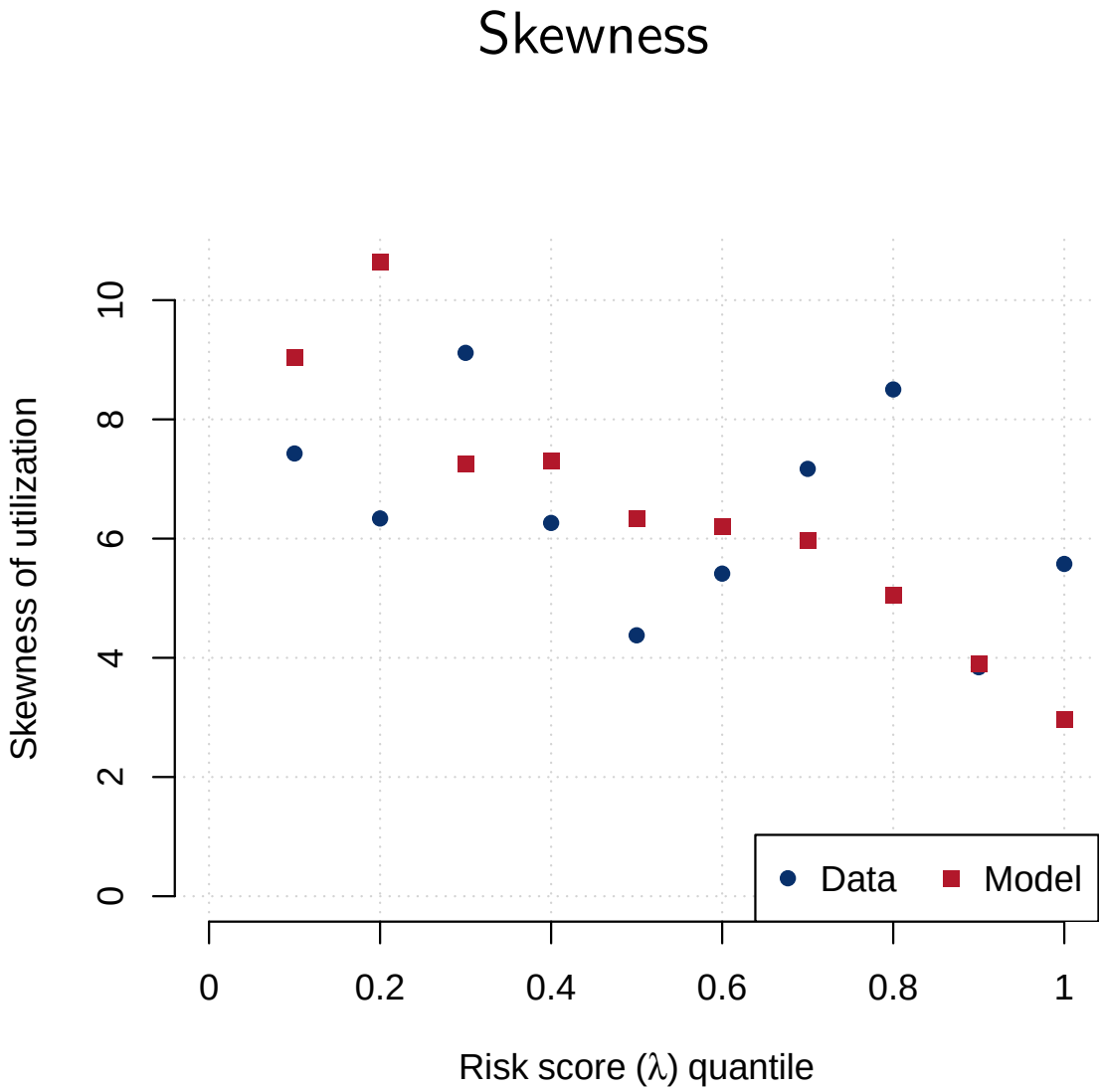
$$\rho_{jt} = \frac{e^{(\alpha+h_{jt})/\omega}}{1+e^{(\alpha+h_{jt})/\omega}}$$

Step 2: Health risk and utilization fit





Step 2: Health risk and utilization fit



Step 3: OOP model estimation (OOPs given utilization)

- Estimate via weighted OLS on subsample with positive utilization m_{jt}, separately for insured and uninsured, after transforming model into the linear equation

$$\Lambda^{-1}\left(\frac{OOP_{jt}}{m_{jt}}\right) = \kappa_0 + \kappa_m \log(m_{jt}) + \kappa_y \log(y_{jt}) + \xi_{jt},$$

  where y_{jt} = income relative to FPL and
  $\Lambda^{-1}(x) = \log(x) - \log(1-x)$ is the inverse logit function

- Estimate $\sigma_\xi = \text{SD}(\xi_{jt})$ as SD of regression residuals

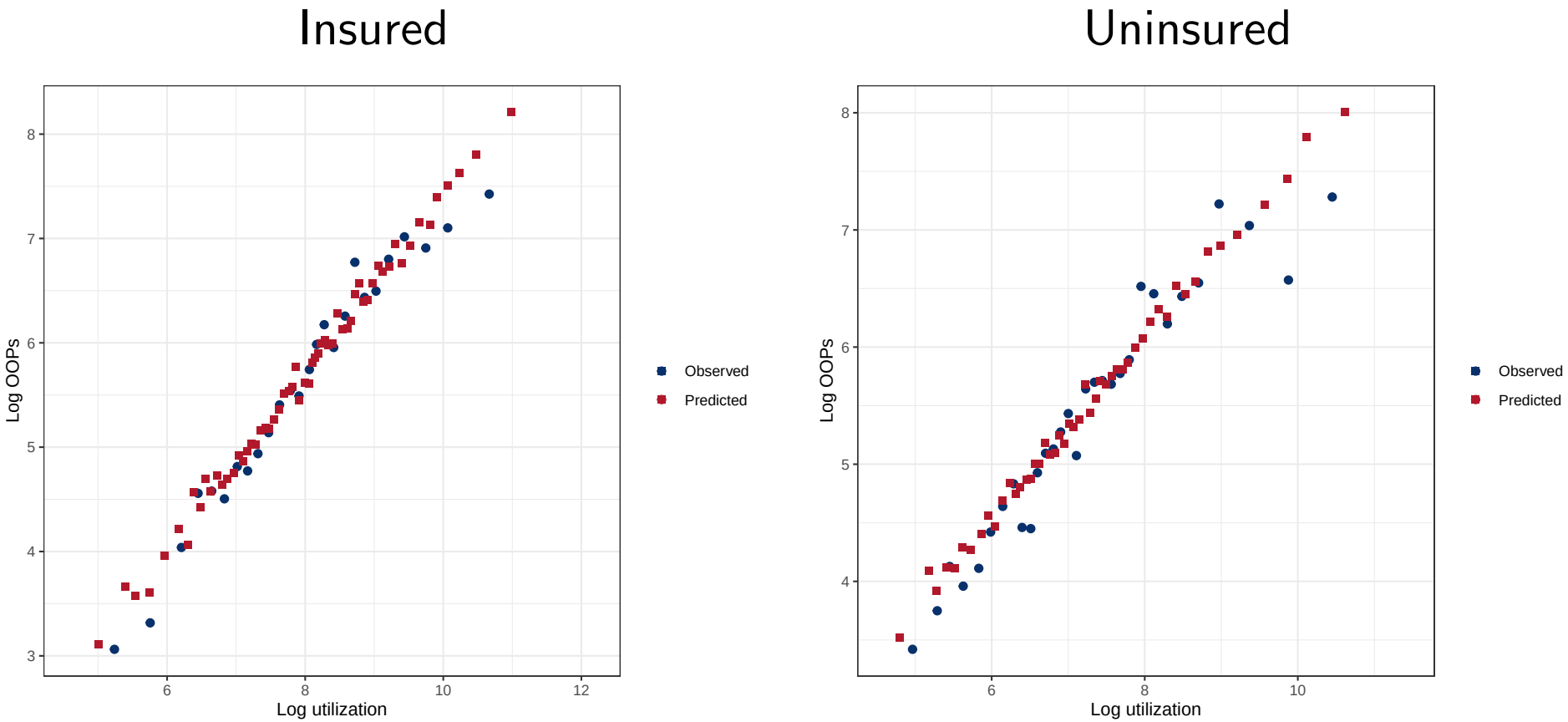
Insured

Coefficient	Estimate	SE
κ_0	-1.44	(0.20)
κ_m	-0.16	(0.02)
κ_y	0.42	(0.05)
σ_ξ	1.28	(0.19)

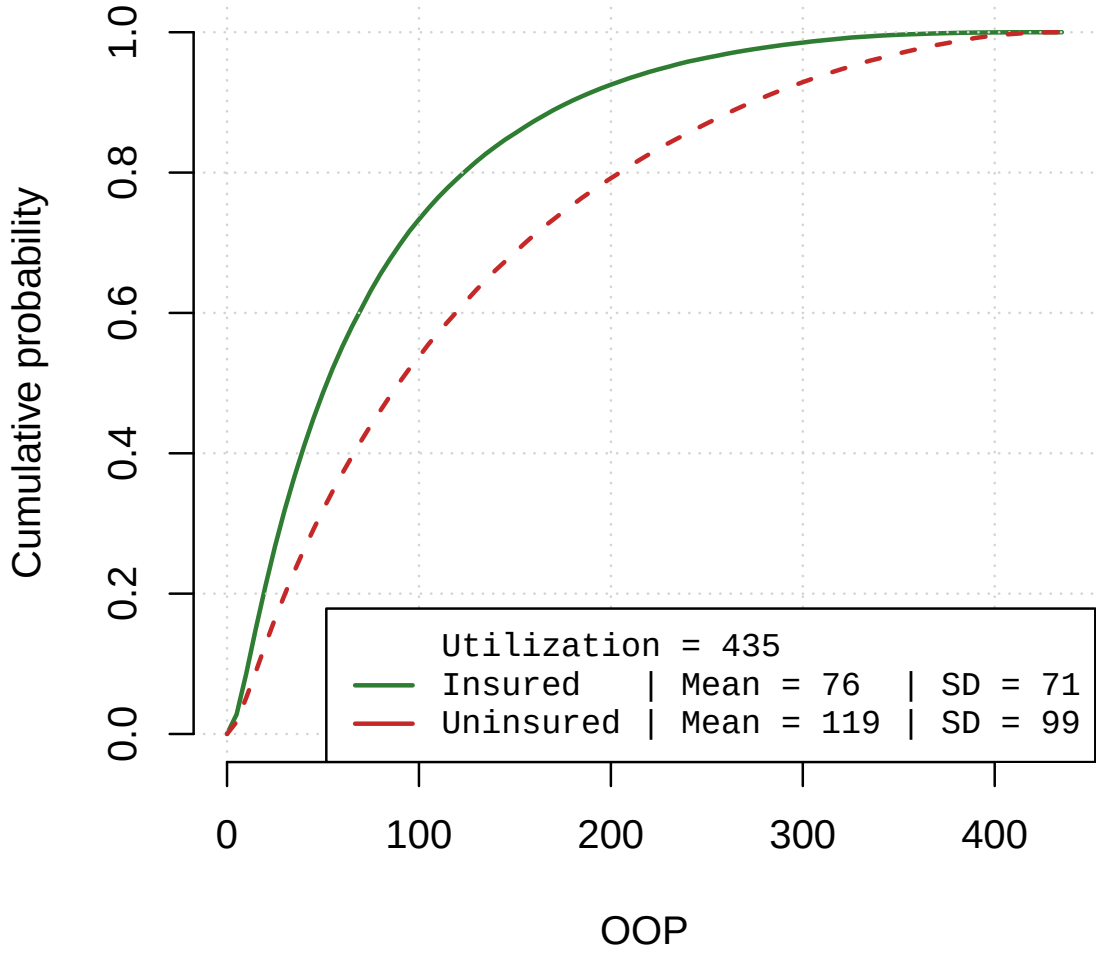
Uninsured

Coefficient	Estimate	SE
κ_0	-0.12	(0.14)
κ_m	-0.26	(0.02)
κ_y	0.35	(0.04)
σ_ξ	1.46	(0.05)

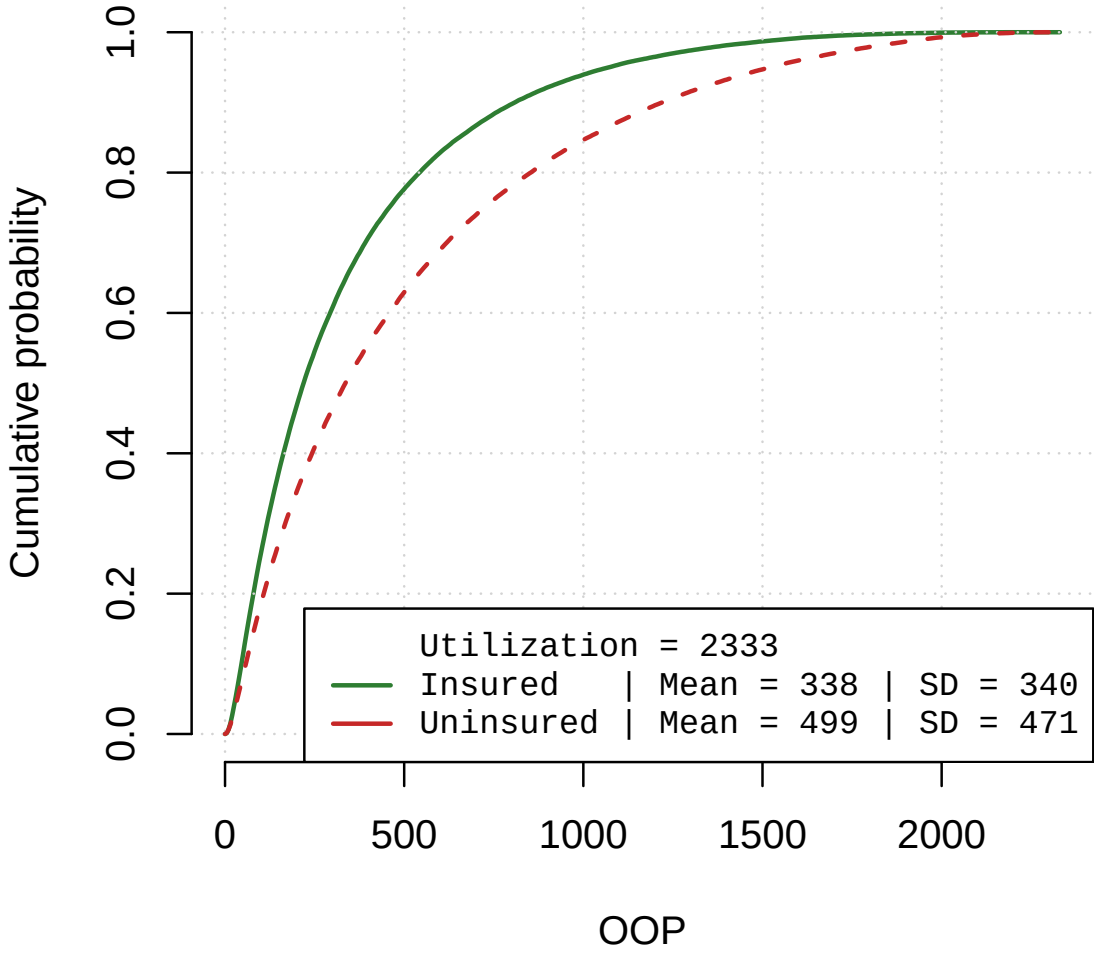
Step 3: Fit of mean OOPs by utilization level



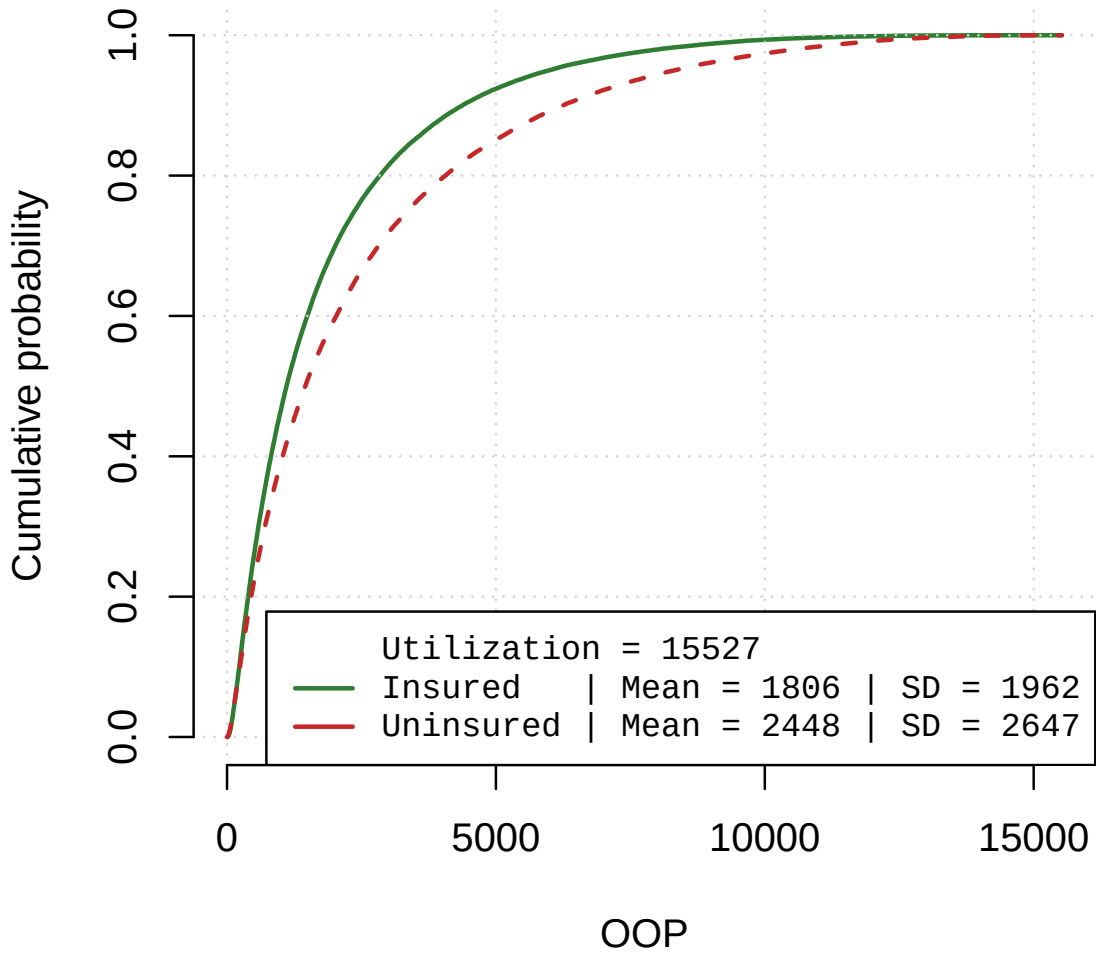
Step 3: Insured vs. uninsured OOPs at 50th percentile utilization, 50th percentile income



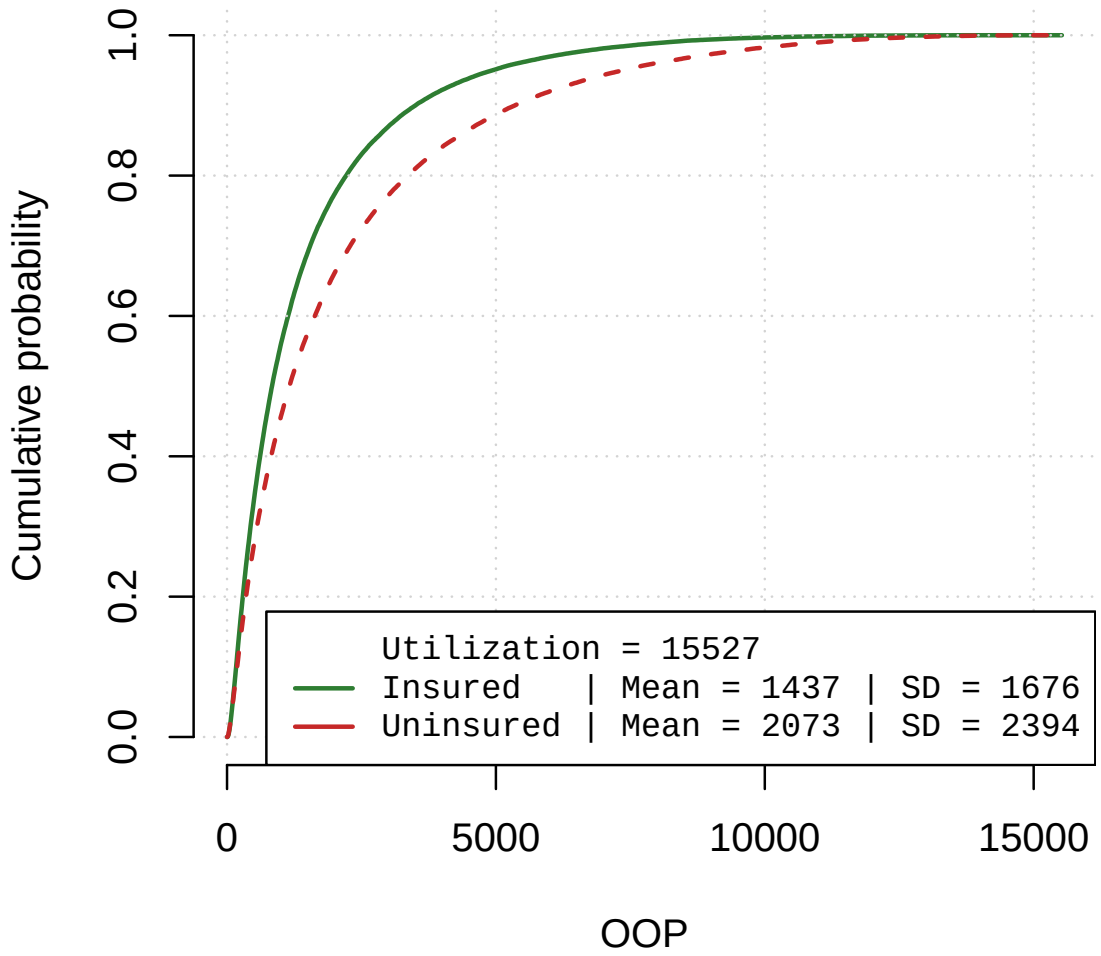
Step 3: Insured vs. uninsured OOPs at 75th percentile utilization, 50th percentile income



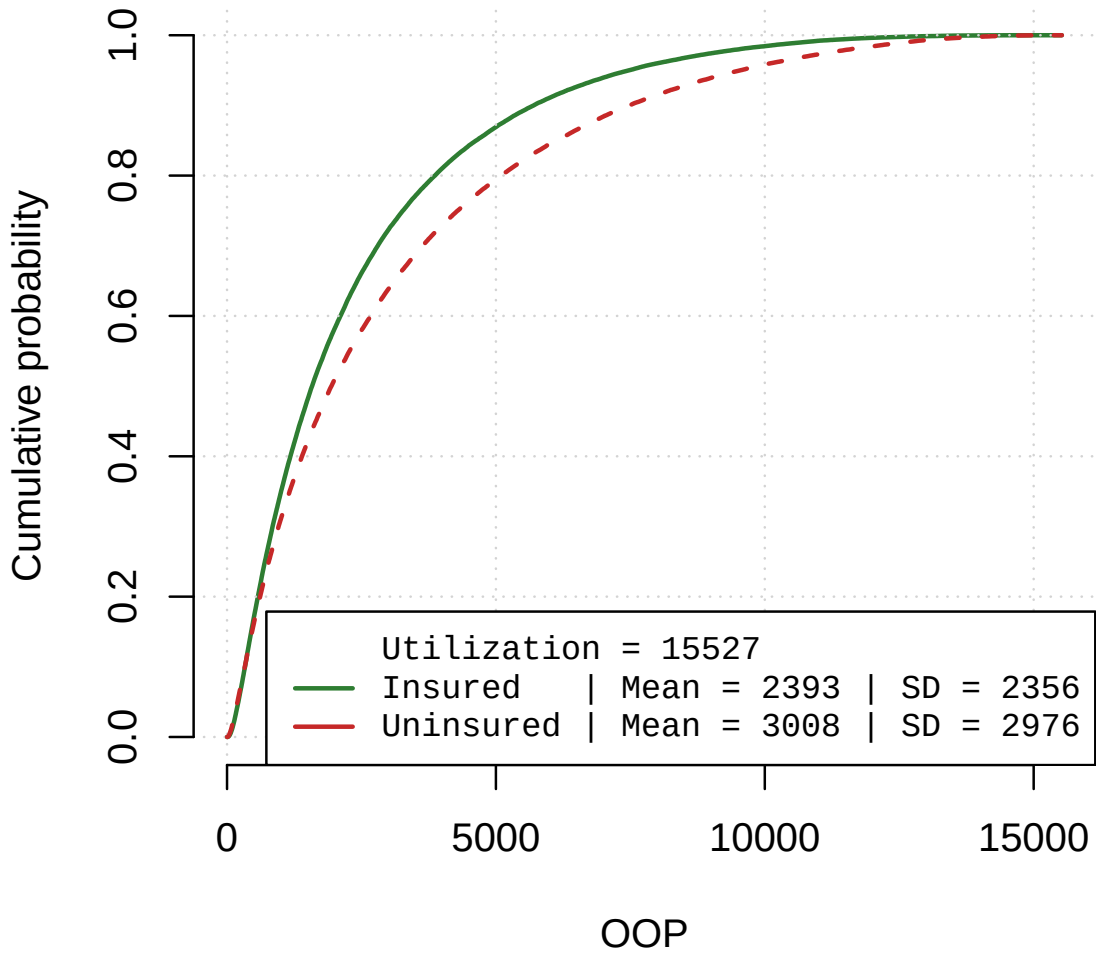
Step 3: Insured vs. uninsured OOPs at 95th percentile utilization, 50th percentile income



Step 3: Insured vs. uninsured OOPs at 95th percentile utilization, 10th percentile income



Step 3: Insured vs. uninsured OOPs at 95th percentile utilization, 90th percentile income



Step 4: Choice model estimation

- Recall $\varepsilon_j = \varepsilon_{j0} + \varepsilon_{j1}$ with ε_{j0} being a health shock **observed by the consumer prior to choice**
- Consumer j buys insurance based on expected utility comparison:

$$-\mathbb{E}[\exp\{-\gamma_j(y_j - p_j^c - \mu_j OOP_{jt}(1) + z_j)\} \mid \lambda_j, \varepsilon_{j0},\ y_j] \geq$$

$$-\mathbb{E}[\exp\{-\gamma_j(y_j - \mu_j OOP_{jt}(0) - \ell_j)\} \mid \lambda_j, \varepsilon_{j0}, y_j]$$

  - Variables:
    - p_j^c = post-subsidy premiums
    - Myopia: $\mu_j = \mu(\text{age}_j, y_j)$
    - Taste coefficients: $z_j = x_j'\psi$; x_j includes income group, region, and year fixed effects
    - ℓ_j = individual mandate penalties
  - Simulate participation with 10 draws per panelist of ε_0 and risk aversion γ_j (from Handel 2013)

Step 4: Choice model estimation

- Estimate year-2 insurance decisions (given year-1 diagnostics)
- The estimator matches the following model predictions to the data (with an identity weight matrix)
  - Coefficient b on insurance status in regression

$$\log(\max(m_{jt}, 1)) = a + b \times \text{insured}_{jt} + x'_{jt}\beta + u_{jt}$$

    with controls x_{jt} including risk score λ_{jt}, year, region; identifies degree of selection based on ε_{j0} (Chiappori and Salanie 2000)
  - Overall participation rate; targets intercept in z_j
  - Participation rates by income group, census region, and year; targets income/region/year-based tastes in z_j
  - Participation by risk score λ_j decile, separately for high- and low-income (above or below 250% of FPL) and for older and younger (above or below 45); targets myopia μ parameters

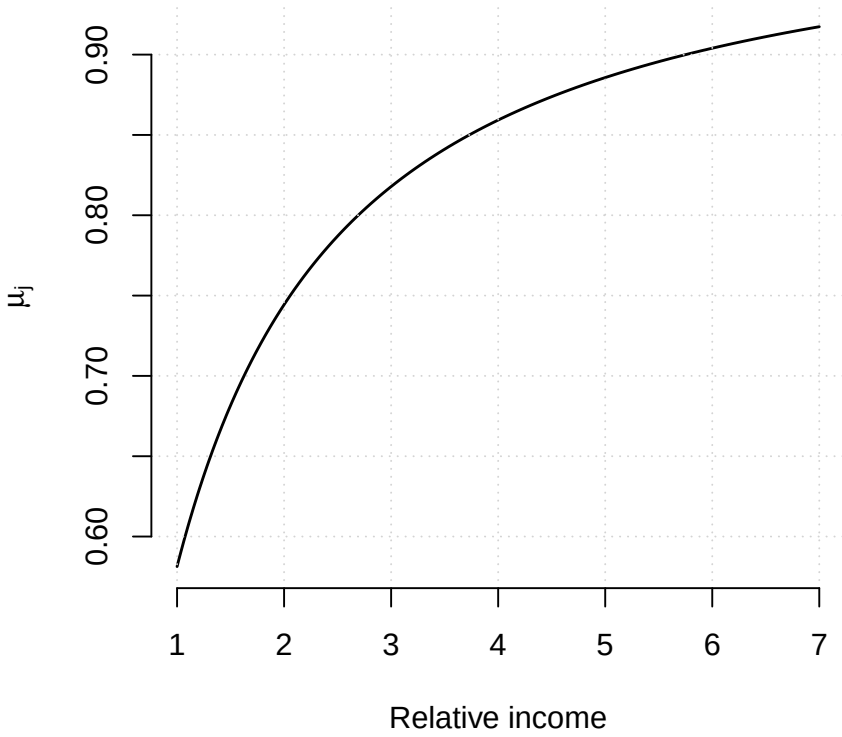
Step 4: Choice model estimates

- $\mathfrak{z} = 35\%$ of health state shock is known to consumers at time of insurance decision is known to consumer at time of choice
- Tastes for insurance increasing in income
- Exchange insurance grows more popular in later years

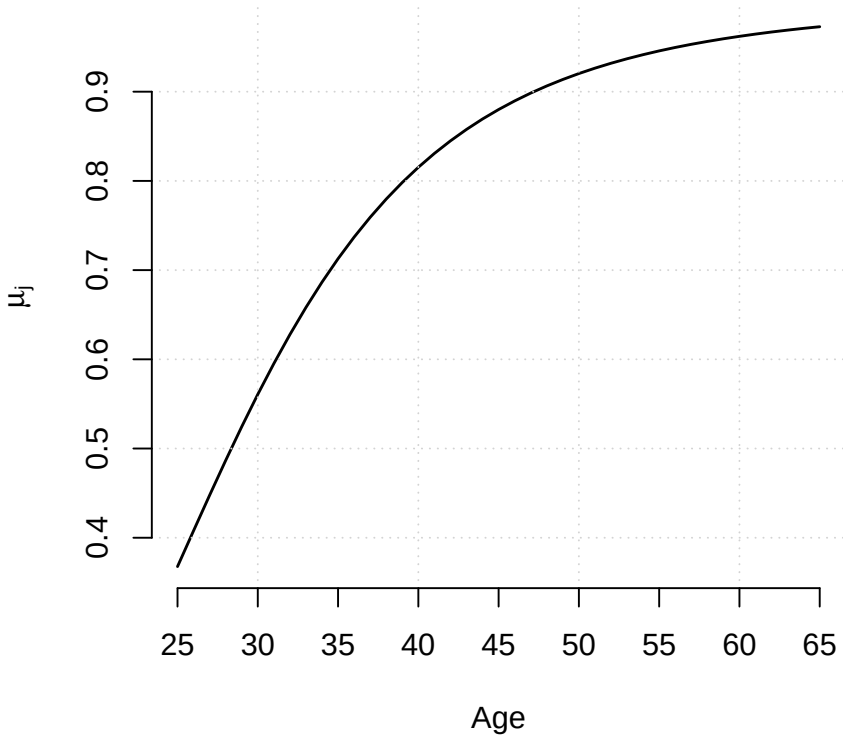
Parameter	Estimate
$\mathfrak{z}$	0.35
$\mu_{\text{intercept}}$	-15.58
μ_{income}	1.07
μ_{age}	4.31
$\psi_{\text{intercept}}$	-2.84
$\psi^{\text{inc}}_{1.50\text{–}2.00}$	-0.07
$\psi^{\text{inc}}_{2.00\text{–}2.50}$	0.99
$\psi^{\text{inc}}_{2.50\text{–}3.00}$	1.85
$\psi^{\text{inc}}_{3.00\text{–}3.50}$	2.26
$\psi^{\text{inc}}_{3.50\text{–}4.00}$	2.02
$\psi^{\text{inc}}_{4.00\text{–}5.00}$	2.82
$\psi^{\text{inc}}_{5.00+}$	2.56
$\psi^{\text{year}}_{2016}$	-0.24
$\psi^{\text{year}}_{2017}$	0.28
$\psi^{\text{year}}_{2018}$	0.48
$\psi^{\text{year}}_{2019}$	2.34
$\psi^{\text{region}}_{\text{Midwest}}$	1.71
$\psi^{\text{region}}_{\text{South}}$	1.17
$\psi^{\text{region}}_{\text{West}}$	1.78

Myopia estimates

μ_j by income (40 year old)

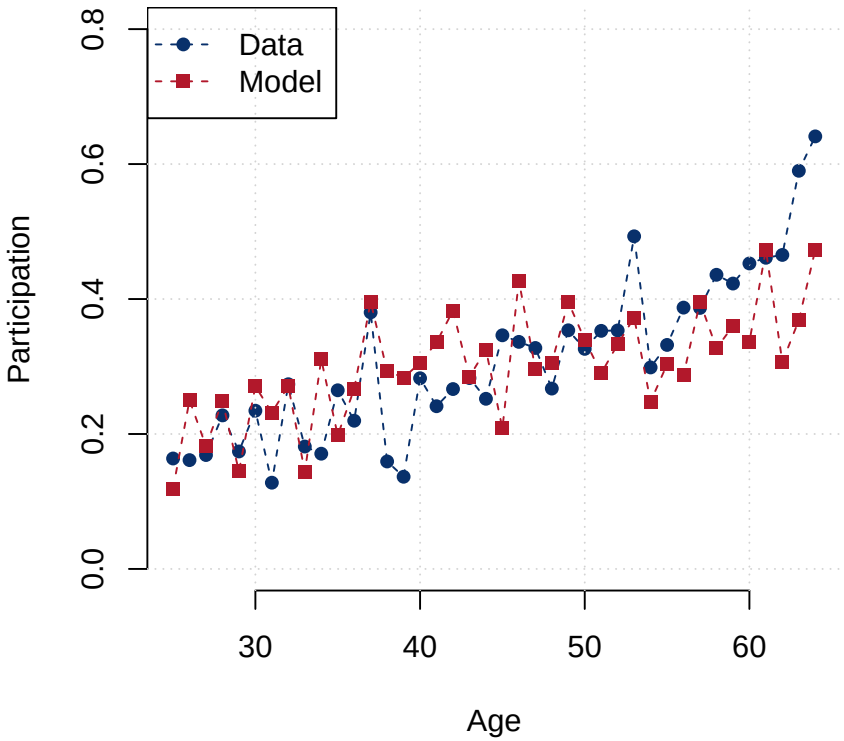


μ_j by age (median income)

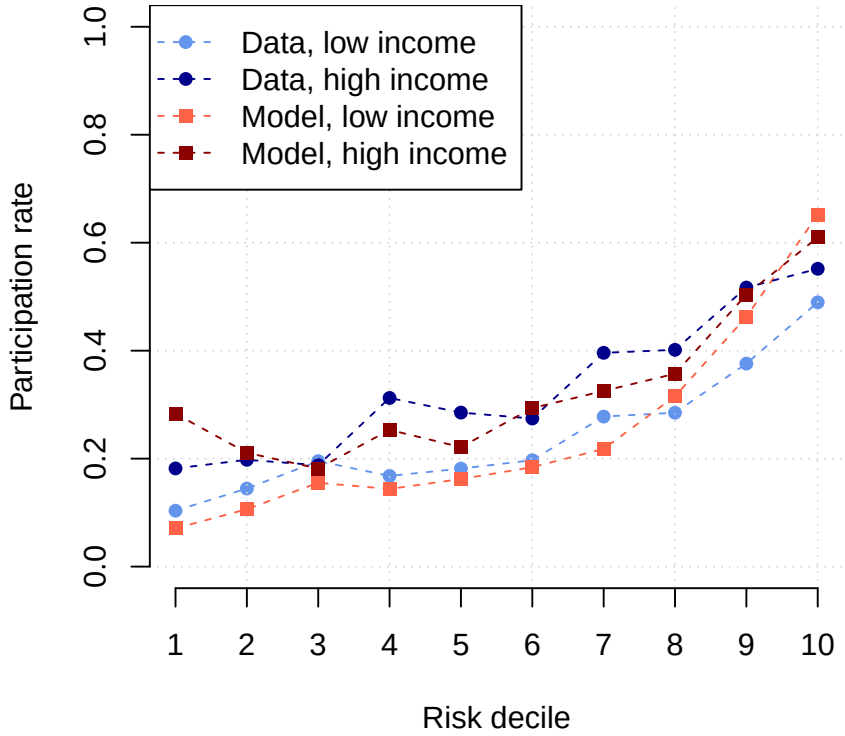


Choice model fit: age and health score gradients

Participation by age



Participation by risk score λ_j



Out-of-sample check: Enhanced Subsidies

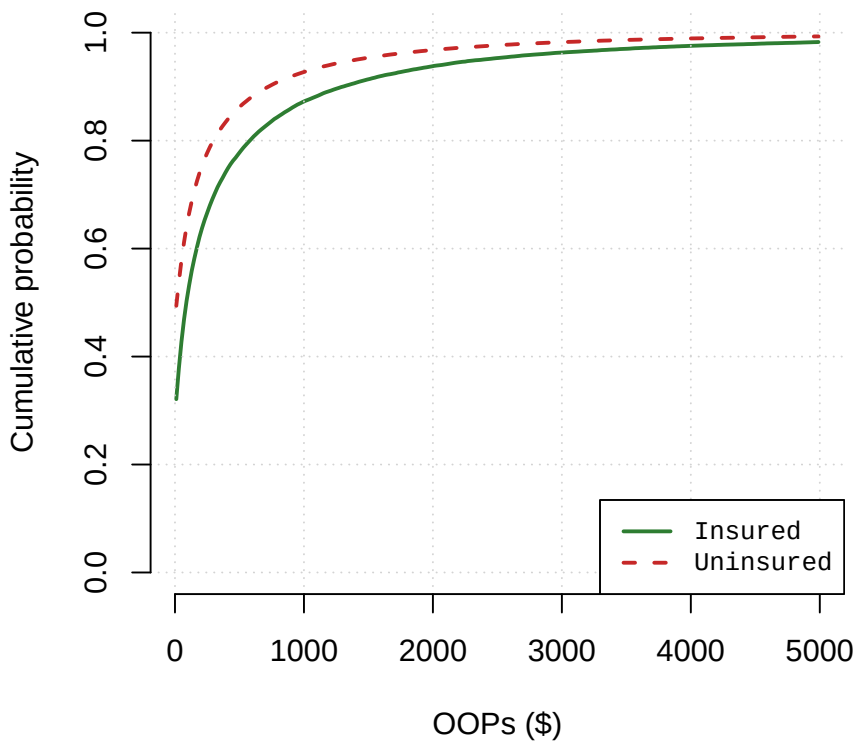
- In 2021, enhanced subsidies were passed into law in response to the Covid pandemic that greatly expanded the income range for which consumers received subsidies
- Participation in the exchanges approximately doubled by 2025 (KFF)
- Our model predicts that participation would go up 2.5x

Subsidized premiums as % of income

Income (% of FPL)	Baseline	Enhanced
Under 150%	2–4%	0%
150–200%	4–6.3%	0–2%
200–250%	6–8.05%	2–4%
250–300%	8–9.5%	4-6%
300–400%	9.5%	6–8.5%
Over 400%	No cap	8.5%

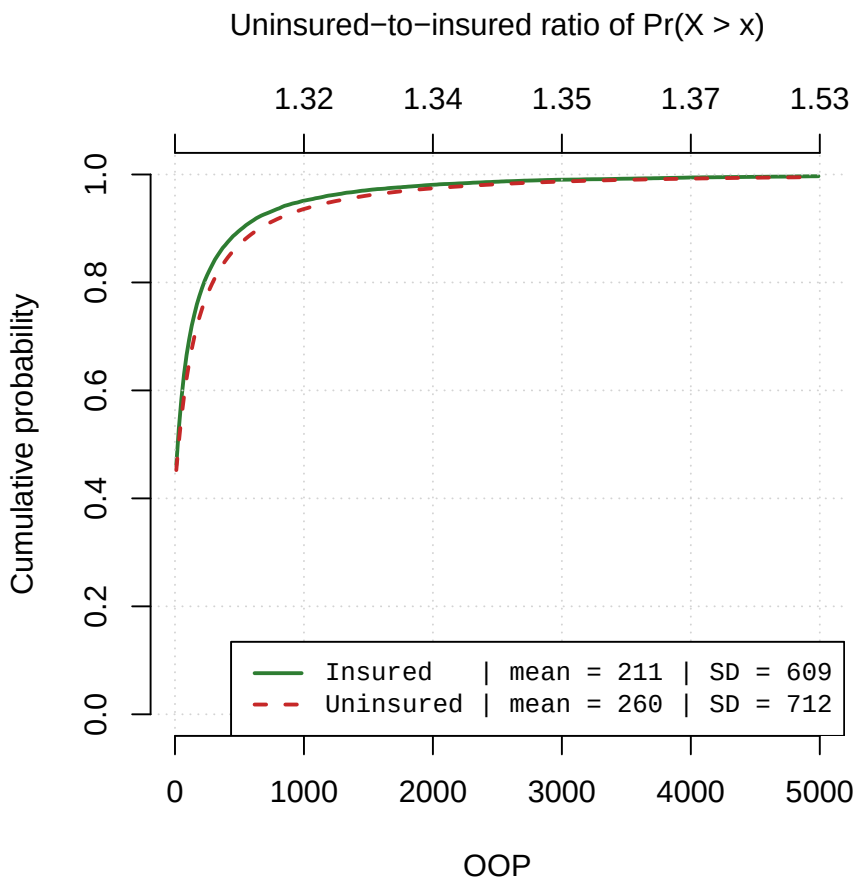
Effects of hidden selection

- OOP distributions conditional on only observed health risk score λ and income y show *reversed* CDFs (here, for 50th-percentile risk score and income):



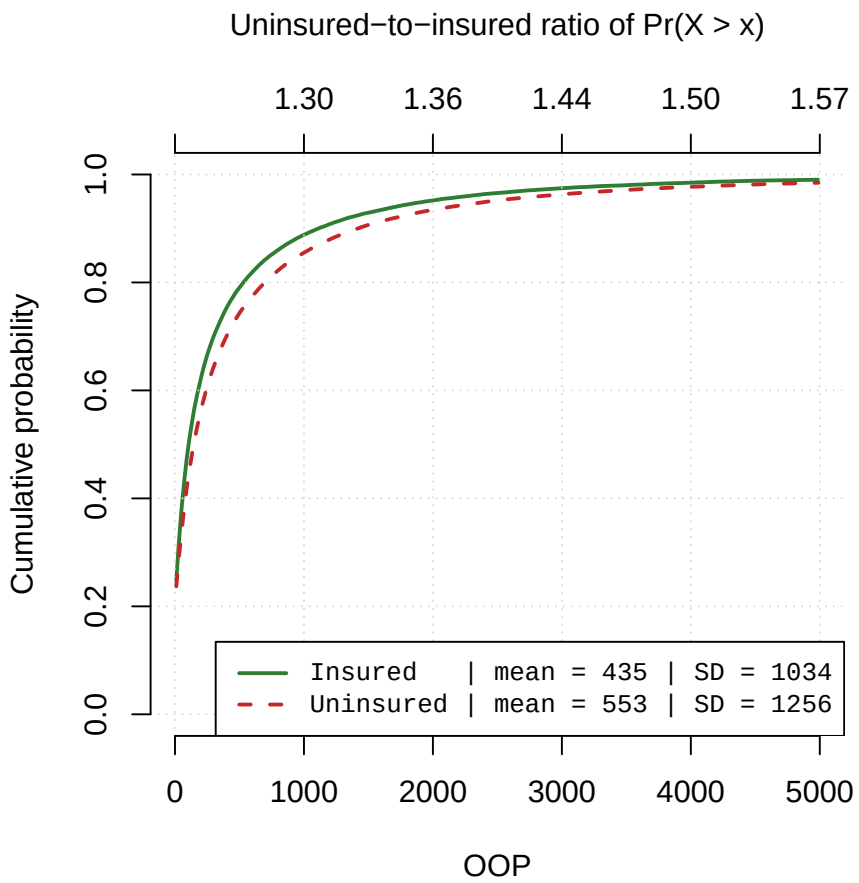
OOP distributions correcting for hidden selection

- Conditioning as well on ε_0 (here $\varepsilon_0 = 0$ and 50th-percentile risk score and income) corrects that:



OOP distributions correcting for hidden selection

- Conditioning as well on ε_0 (here $\varepsilon_0 = 0$ and 75th-percentile risk score and income) corrects that:



OOP distributions correcting for hidden selection

- Conditioning as well on ε_0 (here $\varepsilon_0 = 0$ and 95th-percentile risk score and income) corrects that:

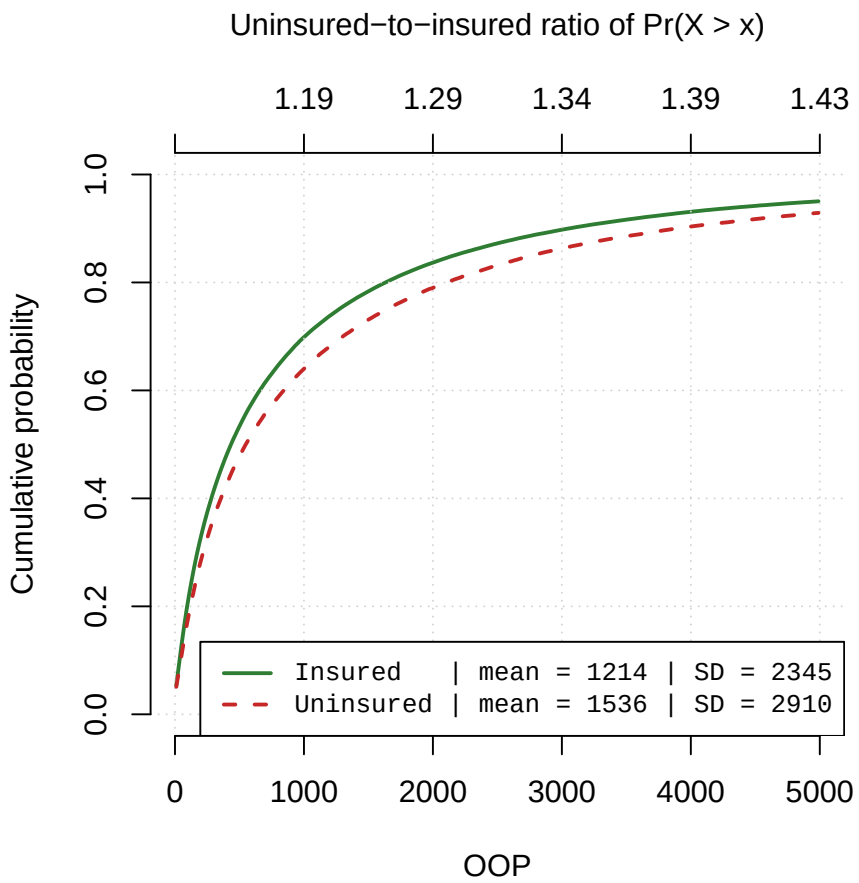


Table of Contents

1. Data and setting
2. Uncompensated care
3. Model
4. Estimation
5. Counterfactual analysis

Simulated population for counterfactual simulations

- We use MEPS to construct a simulated "pseudo"-population on which to compute exchange equilibria
- We focus on the Midwest in 2019
- For each MEPS panelist (who has an observed risk score λ, an observed income y, and age) we draw a values of ε_0 and risk aversion (γ) 10 times to create a sample of "pseudo"-consumers
- For each pseudo-consumer and possible age-25 price p_{25}, we can determine participation given their post-subsidy premium and OOP distributions with and without insurance, taking expectations over ε_1 and ξ.
- We can then find the price p_{25} that satisfies the equilibrium condition and the associated participation level

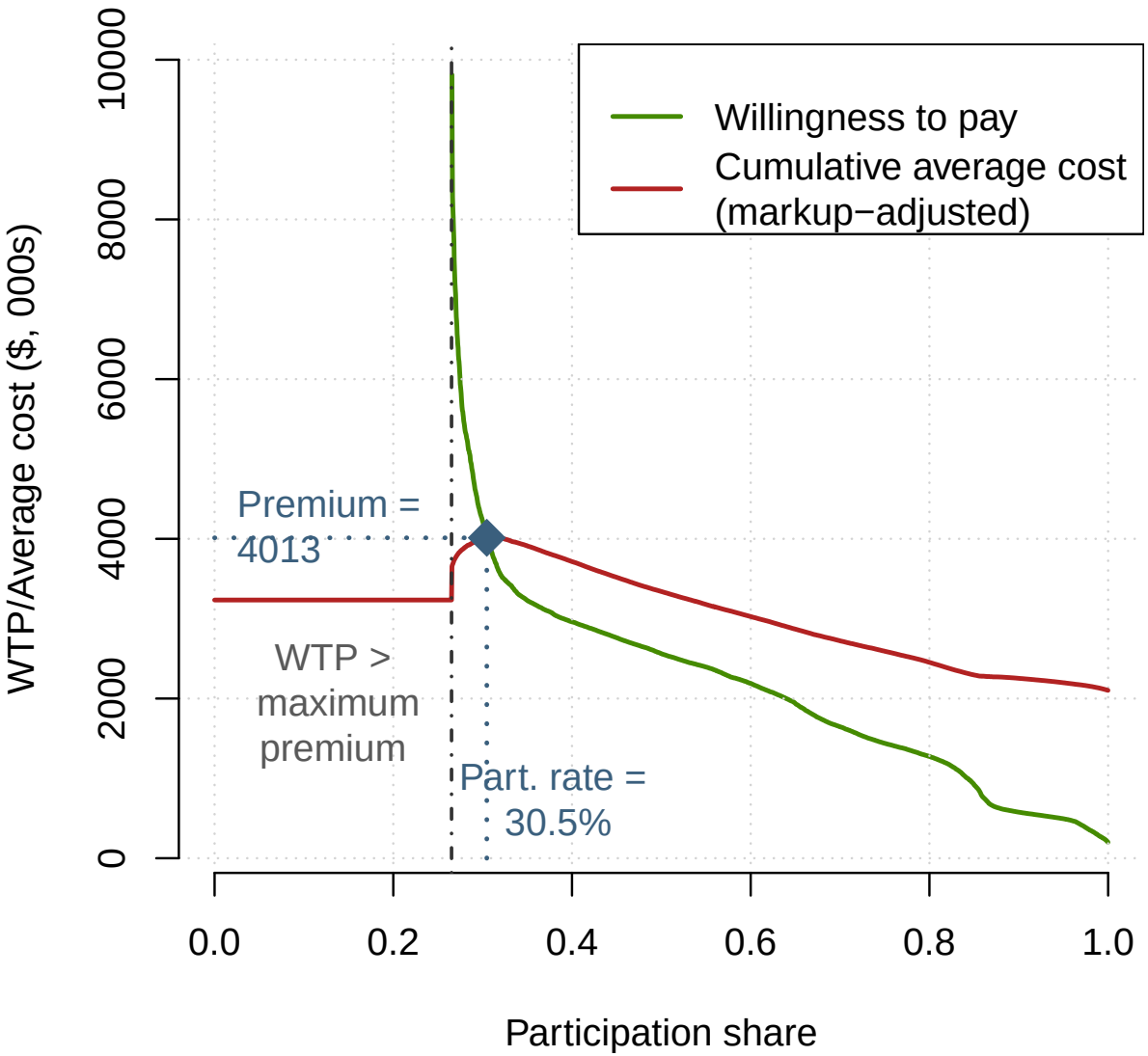
Decomposing frictions' effects on participation

- Examine impacts of myopia, uncompensated care, and adverse selection by computing equilibrium premiums and participation without them

Participation rates (%) under friction elimination

Regime	Current regime (no penalty)	Risk-based pricing
Baseline	30.5	66.0
No myopia	37.6	70.0
No uncompensated care	87.1	93.6
Neither	90.9	96.2

Willingness to pay and costs with subsidies



Decomposing frictions' effects on participation

- Examine impacts of myopia, uncompensated care, and adverse selection by computing equilibrium premiums and participation without them

Participation rates (%) under friction elimination

Regime	Current regime (no penalty)	Risk-based pricing
Baseline	30.5	66.0
No myopia	37.6	70.0
No uncompensated care	87.1	93.6
Neither	90.9	96.2

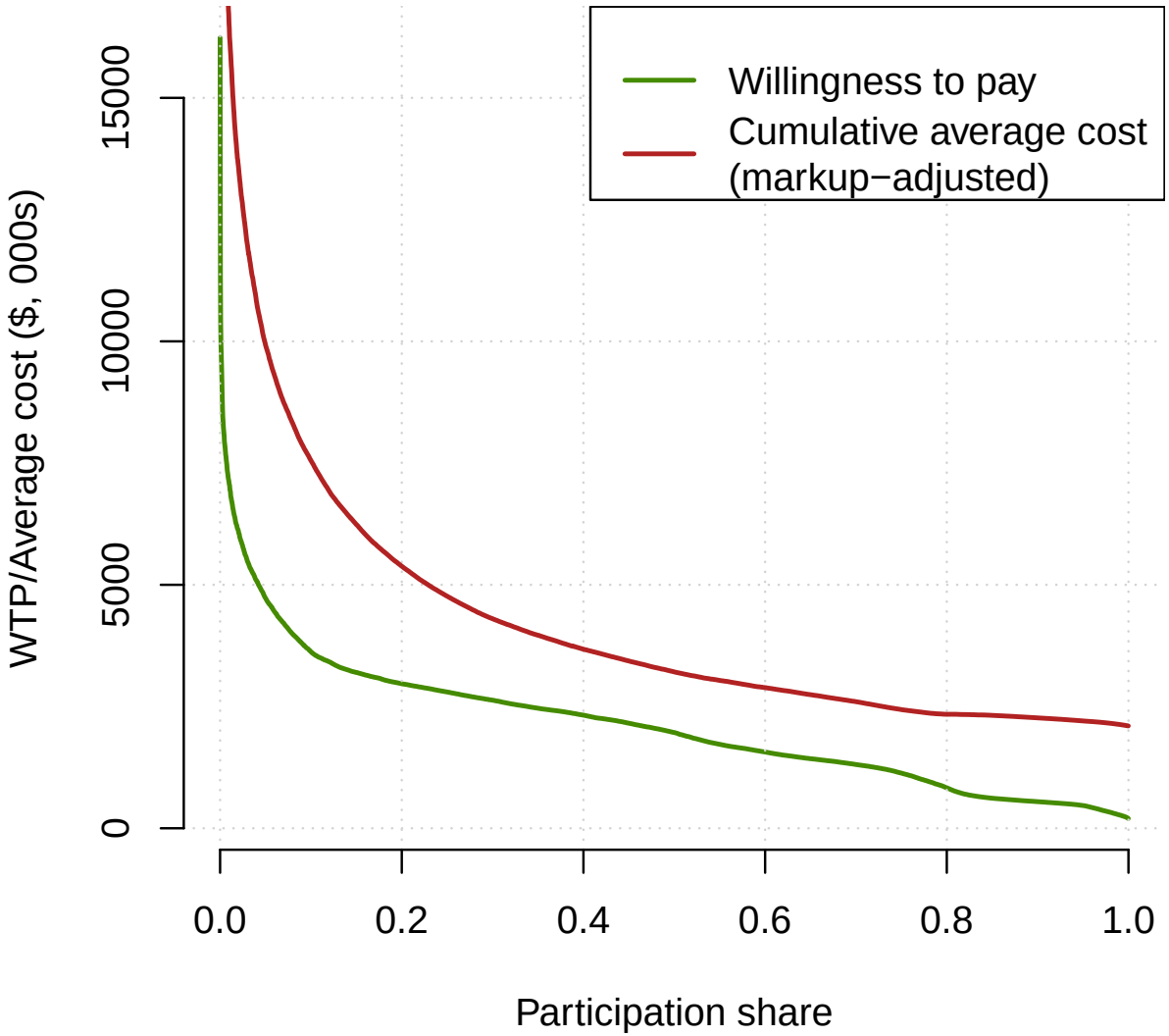
- Uncompensated care has a very large effect on participation
- Modest participation gains from eliminating myopia
- Reducing adverse selection by pricing based on risk score λ has smaller impact than eliminating uncompensated care

Effectiveness of ACA policies for ensuring participation

Policy regime	Baseline	No uncomp. care	Risk-based pricing
Mandate and subsidies	72.5	94.6	80.9
Subsidies but no mandate	30.5	87.1	66.0
Mandate but no subsidies	0.0	71.1	51.7
Neither	0.0	57.2	43.8

- Exchanges with community rating and uncompensated care completely unravel without subsidies

Willingness to pay and costs absent subsidies



Effectiveness of ACA policies for ensuring participation

Policy regime	Baseline	No uncomp. care	Risk-based pricing
Mandate and subsidies	72.5	94.6	80.9
Subsidies but no mandate	30.5	87.1	66.0
Mandate but no subsidies	0.0	71.1	51.7
Neither	0.0	57.2	43.8

- Exchanges with community rating and uncompensated care completely unravel without subsidies
- Current subsidies don't offset effect of uncompensated care on participation: getting rid of uncompensated care *and* subsidies raises participation from 30.5% to 57.2%
- Risk-based pricing without subsidies and mandate (but in presence of uncompensated care and selection on ε_0) would only get participation to 43.8%

Summary of participation results

- Uncompensated care explains most of limited take-up
  - Even more so than adverse selection caused by community rating, historical focus of take-up policies
- Myopia plays a more modest role in suppressing participation
- Subsidies required to prevent unravelling due to uncompensated care
- Subsidies much more powerful than mandate
- Subsidies and mandate together don't offset the impact of uncompensated care on participation

Is uncompensated care a bad thing?

- Literature has typically discussed it largely through the lens of something that undermines "good" formal insurance
- What if we call it "social insurance"?

Is uncompensated care a bad thing?

- Literature has typically discussed it largely through the lens of something that undermines "good" formal insurance
- What if we call it "social insurance"?
- Optimal level of uncompensated care depends on its efficiency, which may be lower than formal insurance for at least two reasons:
  - Uncompensated care may require more effort to gain "coverage"
  - Is riskier

Is uncompensated care a bad thing?

- Literature has typically discussed it largely through the lens of something that undermines "good" formal insurance
- What if we call it "social insurance"?
- Optimal level of uncompensated care depends on its efficiency, which may be lower than formal insurance for at least two reasons:
  - Uncompensated care may require more effort to gain "coverage"
  - Is riskier
- What happens if we make it formal – give the same level of coverage more efficiently?
  - Improvements will undermine current ACA policy participation to some degree. How much?

Is uncompensated care a bad thing?: Effects of more efficient catastrophic insurance

- We make uncompensated care into "formal insurance" by (i) making it's OOP shock variance σ_ξ^2 the same as for ACA insurance, and (ii) setting all z's $= 0$.

Regime	Participation rate (%)
Baseline	30.5
No z_j	9.9
Equalize σ_ξ	21.5
Both	3.5

Still to come...

- **Standard errors**
- **For analysis of participation:** Estimate risk aversion? Incorporate moral hazard?
- **Welfare analysis of alternative exchange policies** – some issues:
  - paternalistic vs. myopia-respecting welfare measure?
  - ex ante vs. interim welfare?
  - Need to allow for uninsurance occurring due to mistakes other than myopia?

Appendix

Consumer welfare measure

- Consider two regimes, R_0 and R_1
- Let $c_{jt}(R)$ be consumer j's consumption in year t under R
  - This is a random variable that captures insurance choice, income, premiums, penalties, and OOPs
- Welfare $w_{jt}(R_0, R_1)$ of R_1 (rel. to R_0) is amount that, when received annually from t onward under regime R_0, equates present discounted utility across regimes:

$$\sum_{\tau \geq t} \beta^{\tau - t} \mathbb{E}\left[e^{-r_{j\tau}[c_{jt}(R_0) + w_{jt}(R_0, R_1)]}\right] = \sum_{\tau \geq t} \beta^{\tau - t} \mathbb{E}\left[e^{-r_{j\tau} c_{jt}(R_1)}\right].$$

- Two ways to compute c_{jt}
  - Myopic approach: use $\mu_{jt} OOP_{jt}$ as OOPs
  - Paternalistic approach: use OOP_{jt} as OOPs in computing welfare under choices made according to $\mu_{jt} < 1$

Social welfare

- Aggregate social welfare $W^{s,N}$ is sum of consumer and monetary surpluses:

$$\underbrace{W^{s,N}}_{\text{Social welfare}} = \underbrace{W^{N}}_{\text{Consumer welfare}} + \underbrace{S^{i}}_{\text{Insurer profits}} + \underbrace{S^{g}}_{\text{Gov. surplus}} - \underbrace{S^{u}}_{\text{Uncomp. care}}$$

- S^g includes subsidies and revenues from fines

Back

References I

Abaluck, Jason and Jonathan Gruber (2011) "Choice inconsistencies among the elderly: evidence from plan choice in the Medicare Part D program," *American Economic Review*, 101 (4), 1180–1210.

Chiappori, Pierre-André and Bernard Salanie (2000) "Testing for asymmetric information in insurance markets," *Journal of political Economy*, 108 (1), 56–78.

Domurat, Richard, Isaac Menashe, and Wesley Yin (2021) "The Role of Behavioral Frictions in Health Insurance Marketplace Enrollment and Risk: Evidence from a Field Experiment," *American Economic Review*, 111 (5), 1549–74, 10.1257/aer.20190823.

Finkelstein, Amy, Nathaniel Hendren, and Mark Shepard (2019) "Subsidizing health insurance for low-income adults: Evidence from Massachusetts," *American Economic Review*, 109 (4), 1530–67.

References II

Frean, Molly, Jonathan Gruber, and Benjamin D. Sommers (2017) "Premium subsidies, the mandate, and Medicaid expansion: Coverage effects of the Affordable Care Act," *Journal of Health Economics*, 53, 72–86, https://doi.org/10.1016/j.jhealeco.2017.02.004.

Goldin, Jacob, Ithai Z Lurie, and Janet McCubbin (2019) "Health Insurance and Mortality: Experimental Evidence from Taxpayer Outreach," Working Paper 26533, National Bureau of Economic Research, 10.3386/w26533.

Handel, Ben, Igal Hendel, and Michael D Whinston (2015) "Equilibria in health exchanges: Adverse selection versus reclassification risk," *Econometrica*, 83 (4), 1261–1313.

Mahoney, Neale (2015) "Bankruptcy as Implicit Health Insurance," *American Economic Review*, 105 (2), 710–46, 10.1257/aer.20131408.

References III

McIntyre, Adrianna, Mark Shepard, and Myles Wagner (2021) "Can Automatic Retention Improve Health Insurance Market Outcomes?" *AEA Papers and Proceedings*, 111, 560–66, 10.1257/pandp.20211083.

Saltzman, Evan (2019) "Demand for health insurance: Evidence from the California and Washington ACA exchanges," *Journal of Health Economics*, 63, 197–222, https://doi.org/10.1016/j.jhealeco.2018.11.004.

Shepard, Mark and Myles Wagner (2022) "Do Ordeals Work for Selection Markets? Evidence from Health Insurance Auto-Enrollment," Working Paper 30781, National Bureau of Economic Research, 10.3386/w30781.

Tebaldi, Pietro, Alexander Torgovitsky, and Hanbin Yang (2023) "Nonparametric estimates of demand in the california health insurance exchange," *Econometrica*, 91 (1), 107–146.