Online Appendix

Estimating Equilibrium in Health Insurance Exchanges:
Price Competition and Subsidy Design under the ACA

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Contents

S1 Identifying Cost from Pricing Assumptions

In this appendix I provide conditions for nonparametric identification of the distribution of willingness to pay and of cost conditional on willingness to pay, assuming that observables consists of choices, prices, and products' characteristics.

For this I use a model that is not tailored to my specific application, omitting subsidies and other regulations. This allows me to focus on, and highlight, the novel aspect of the identification argument, which is to use equilibrium assumptions and variation in the preferences of marginal buyers to identify cross-buyer cost heterogeneity. I provide a positive result for the case of single-plan insurers (or plan-level pricing decisions), an important simplification that leaves open questions for future work. In fact, multi-product pricing decisions introduce several complications, with the need of additional conditions, a different constructive proof, or specific functional form assumptions.

S1.1 Model and observables

I start by adopting the model of demand used in Berry and Haile (2014) (BH), and then model supply allowing costs to vary with buyers' willingness to pay.

Demand (adapted from BH). Each consumer i in market r chooses a plan (or product) from a set $\mathcal{J} = \{0, 1, ..., J\}$. A market consists of a continuum of consumers in the same choice environment (e.g. geographic region). Formally a market r for the J products is a tuple $\chi_r = (x_r, p_r, \xi_r)$, collecting characteristics of the products or of the market itself. Observed exogenous characteristics are represented by $x_r = (x_{1r}, ..., x_{Jr})$, where each $x_{jr} \in \mathbb{R}^K$. The vector $\xi_r = (\xi_{1r}, ..., \xi_{Jr})$, with $\xi_{jr} \in \mathbb{R}$, represents unobservables at the level of the product-market. Finally, $p_r = (p_{1r}, ..., p_{Jr})$, with each $p_{jr} \in \mathbb{R}$, represents (endogenous) prices.

Consumer preferences are represented with a random utility model quasilinear in prices (Section 4.2 in BH). Consumer i in market r derives (indirect) utility $u^i_{jr} = v^i_{jr} - p_{jr}$ when purchasing j, with the usual normalization $v^i_{0r} = 0$, for all i, all r. Given prices, the choice of each buyer is then determined by the vector $v^i_r = (v^i_{1r}, ..., v^i_{Jr})$. For each buyer in market r, v^i_r is drawn i.i.d. from a continuous density $f_r(v)$. This satisfies the following:

D1. *BH Demand structure*: There is a partition of x_{jr} into $(x^{(1)}_{jr}, x^{(2)}_{jr})$, where $x^{(1)}_{jr} \in \mathbb{R}$, such that given indexes $\delta_r = (\delta_{1r}, ..., \delta_{Jr})$, with $\delta_{jr} = x^{(1)}_{jr} + \xi_{jr}$, $f_r(v) = f(v|\delta_r, x^{(2)}_r)$.

Therefore, assuming that $\arg\max_{j \in J} u^i_{jr}$ is unique with probability one in all markets, choice probabilities (market shares) are defined by

$$s_{jr} = \sigma_j(\chi_r) = \int_{\mathcal{D}_j(p_r)} f(v|\delta_r, x_r^{(2)})\,\mathrm{d}v, \;\; j = 0, 1, ..., J, \tag{S1}$$

$$\mathcal{D}_j(p_r) = \{v : v_j - v_k \geq p_j - p_k, \text{ for all } k \neq j\}. \tag{S2}$$

Observables. Let $z_r = (z_{1r}, ..., z_{Jr})$, $z_{jr} \in \mathbb{R}^L$, denote a vector of cost shifters excluded from the demand model. The econometrician observes $(p_{jr}, s_{jr}, x_{jr}, z_{jr})$ for all r and all $j = 1, 2, ..., J$.

Supply. Let $w_{jr} = (\xi_{jr}, x_{jr}, z_{jr}) \in \mathbb{R}^{K+L+1}$ collect characteristics (observable and unobservable) and cost shifters of product j in r. When purchasing j, a buyer i with valuations $v^i = v$ in market r increases the total expected cost for the insurer by $\psi_j(v, w_{jr})$, $\psi_j : \mathbb{R}^J \times \mathbb{R}^{K+L+1} \to \mathbb{R}$.

The function $\psi_j(\cdot, w_{jr})$ is continuous and bounded for all j, and describes how the expected cost of covering the buyer varies with her vector of valuations after conditioning on w_{jr}.

At the prices p_r the seller of j realizes profits in market r equal to

$$\Pi_{jr}(\chi_r) = p_{jr} \cdot \sigma_j(\chi_r) - \int_{\mathcal{D}_j(p_r)} \psi_j(v, w_{jr}) \cdot f(v|\delta_r, x_r^{(2)})\,\mathrm{d}v. \tag{S3}$$

I assume that in each market prices are set in a complete information Nash equilibrium in pure-strategies. To formalize this, the set of marginal buyers of product j can be described by

$$\partial\mathcal{D}_j(p_r) = \{v : v_j - v_k = p_{jr} - p_{kr} \text{ for some } k \neq j\} \tag{S4}$$

$$= \lim_{\varepsilon \downarrow 0} \left\{\mathcal{D}_j(p_r) \cap \left(\mathbb{R}^J \setminus \mathcal{D}_j(p_{jr} + \varepsilon, p_{-jr})\right)\right\}. \tag{S5}$$

Then, following Uryas'ev (1994); Weyl and Veiga (2014), quasilinearity of indirect utility with respect to price implies that, in equilibrium, in every market r:

S1. *Equilibrium*: For all $j = 1, ..., J$, $mr_{jr} = mc_{jr}$, where

$$mr_{jr} = \sigma_j(\chi_r) - p_{jr} \cdot \int_{\partial\mathcal{D}_j(p_r)} f(v|\delta_r, x_r^{(2)})\,\mathrm{d}v, \tag{S6}$$

$$mc_{jr} = -\int_{\partial\mathcal{D}_j(p_r)} \psi_j(v, w_{jr}) \cdot f(v|\delta_r, x_r^{(2)})\,\mathrm{d}v. \tag{S7}$$

From S1, marginal revenues are equal to marginal costs, which must be true in a Nash-in-prices equilibrium. The integrals in mr_{jr} and mc_{jr} are well defined because $f(\cdot|\delta_r, x_r^{(2)})$ and $\psi_j(\cdot, w_{jr})$ are both continuous and bounded functions of v.

S1.2 Conditions for identification

Identification is defined as in Roehrig (1988); Matzkin (2008): if the unobservables differ (almost surely), then the distribution of observables differ (almost surely), where probabilities and expectations are defined with respect to the distribution of (χ_r, s_r, z_r) across markets.

My result is obtained combining conditions for identification of demand provided in BH — yielding to identification of ξ_r and then of $f(v|\delta_r, x_r^{(2)})$ — with a constructive proof to identify ψ_j which I adapted from Somaini (2011, 2015).[1] To simplify notation without loss of generality, as in BH I condition on $x_r^{(2)}$ — which unlike $x_r^{(1)}$ can affect the distribution of preferences quite arbitrarily — and suppress it.

Beside the demand and supply assumptions D1 and S1, I will use the following conditions:

C1. *BH Exogeneity of cost shifters*: For all $j = 1, ..., J$, $E[\xi_{jr}|z_r, x_r] = E[\xi_{jr}] = 0$.

C2. *BH Completeness*: For all functions $B(s_r, p_r)$ with finite expectations, if $E[B(s_r, p_r)|z_r, x_r] = 0$ with probability one, then $B(s_r, p_r) = 0$ with probability one.

C3. *Large support*: For every j, supp $v_r|\delta_r, w_{jr} \subset$ supp $p_r|\delta_r, w_{jr} \subset P$, with P bounded.

Condition C1 is a standard exclusion restriction, requiring mean independence between demand instruments and the structural erros ξ_{jr}. Condition C2 is a completeness assumption, requiring instruments to move market shares and prices sufficiently to distinguish between different functions of these variables through the exogenous variation in these instruments. C3 is a large support assumption, requiring cost shifters excluded from ψ_j to move prices in a set that covers the support of (conditional) valuations. This is a stronger requirement than the large support assumption sufficient to identify the distributions $f(v|\delta_r)$, which would only require supp $v_r|\delta_r \subset$ supp $p_r|\delta_r$. The stronger condition in C3 allows to prove that cost functions ψ_j are also identified. One then has:

THEOREM 1 *Under D1, S1, C1, C2, C3, ξ_r, $f(v|\delta_r)$, and ψ_j are identified.*

[1] This highlights the parallelism between auctions with interdependent costs and selection markets. In the former case (expected) marginal costs depend on the competitors' signals, varying with differences of bids between competitors. In a selection market (expected) marginal costs depend on the preferences of buyers choosing the plan, varying with differences of prices between competitors.

Proof of Theorem 1. Condition C3 implies supp $v_r|\delta_r \subset$ supp $p_r|\delta_r$, and demand is identified:

LEMMA **1** (Berry and Haile, 2014) *Under D1, C1, C2, ξ_r is identified, and $f(v|\delta_r)$ is also identified if, additionally, supp $v_r|\delta_r \subset$ supp $p_r|\delta_r$.*

Proof. Follows from Theorem 1 and Section 4.2 in BH.□

Similarly to Somaini (2011, 2015), the rest of the proof amounts to approximating for every j, every w_{jr}, and every $\widehat{v} \in$ supp $v_r|\delta_r, w_{jr}$, the integral of cost conditional on $\mathcal{D}_j(\widehat{v})$:

$$\Psi_j(\widehat{v}; w_{jr}, \delta_r) = \int_{\mathcal{D}_j(\widehat{v})} \psi_j(v, w_{jr}) \cdot f(v|\delta_r)\,\mathrm{d}v. \tag{S8}$$

The mixed-partial J-1 derivative with respect to $\widehat{v}_{-j}$ yields then identification of the unknown cost function ψ_j, since

$$\frac{\mathrm{d}^{J-1}\Psi_j(\widehat{v}; w_{jr}, \delta_r)}{\mathrm{d}\widehat{v}_{-j}} = \psi_j(\widehat{v}, w_{jr}) \cdot f(\widehat{v}|\delta_r) \tag{S9}$$

and $f(\widehat{v}|\delta_r)$ is identified by Lemma 1. This exploits the fact that price enters linearly in buyers' indirect utility, hence the set $\mathcal{D}_j(\widehat{v})$ is described by a set of inequalities which defines a cone in $\mathbb{R}^J$ with vertex $\widehat{v}$. The boundary of this cone is the set $\partial\mathcal{D}_j(\widehat{v})$ defined in (S4); see also Figure 1 in BH.

To approximate $\Psi_j(\widehat{v}; w_{jr}, \delta_r)$, fix j, w_{jr}, and $\widehat{v} \in$ supp $v_r|\delta_r, w_{jr}$. Consider then a parametric curve $\eta : \mathbb{R}_+ \to \mathbb{R}$, with $\eta(\ell) = \widehat{v}_j + \ell$, and with this define the function $\widehat{\Psi}_j(\ell) = \Psi_j((\eta(\ell), \widehat{v}_{-j}); w_{jr}, \delta_r)$. Differentiating $\widehat{\Psi}_j(\ell)$ (and using again Uryas'ev, 1994; Weyl and Veiga, 2014) yields

$$\frac{\mathrm{d}\widehat{\Psi}_j(\ell)}{\mathrm{d}\ell} = -\int_{\partial\mathcal{D}_j((\eta(\ell),\widehat{v}_{-j}))} \psi_j(v, w_{jr}) \cdot f(v|\delta_r)\,\mathrm{d}v. \tag{S10}$$

The function $\phi_j(\ell) \equiv \frac{\mathrm{d}\widehat{\Psi}_j(\ell)}{\mathrm{d}\ell}$ is bounded and continuous, and hence Riemann integrable over $[0, T]$, where by C3 the upper bound T can be chosen to be such that $\widehat{\Psi}_j(T) = 0$. Therefore,

$$\Psi_j(\widehat{v}; w_{jr}, \delta_r) = \widehat{\Psi}_j(0) = -\int_0^T \phi_j(\ell)\,\mathrm{d}\ell. \tag{S11}$$

The integral in (S11) can be approximated with arbitrary precision. For this, one can choose a sequence $\{\ell^n\}_{n=0}^N$ for which $0 = \ell^1 < \ell^2, ..., < \ell^{N-1} < \ell^N = T$, and using C3 build a corresponding sequence $\{\chi_r^n\}_{n=0}^N \in$ supp $\chi_r|\delta_r, w_{jr}$, such that $p_r^n = (\eta(\ell^n), \widehat{v}_{-j})$. Then, as $\max_n\{\ell^n - \ell^{n-1}\}$ becomes arbitrarily small

$$\sum_{n=0}^{N-1} \phi_j(\ell^n)(\ell^{n+1} - \ell^n) \approx \int_0^T \phi_j(\ell)\, \mathrm{d}\ell, \tag{S12}$$

where all the elements in the Riemann sum are identified since by S1 each $\phi_j(\ell^n)$ can be replaced by

$$mr_{jr}^n = \sigma_j(\chi_r^n) - p_{jr}^n \cdot \int_{\partial\mathcal{D}_j(p_r^n)} f(v|\delta_r^n)\, \mathrm{d}v, \tag{S13}$$

which is identified by Lemma 1.■

S2 Estimation Steps

Estimation proceeds in steps. First, I obtain $\widehat{\xi}_{jmt}$ as the residual of the OLS regression:

$$b_{jmt} = \lambda^{35} \int \mathbf{1}\left[z^{\text{Age}} \leq 35\right] dG_{mt}(\mathbf{z}) + \lambda^{\text{Tier}} + \lambda^{\text{Year}} + \lambda^{\text{Insurer}} + \xi_{jmt}.$$

The results are shown in Table S1.

Taking $\widehat{\xi}_{jmt}$ as given, I estimate the demand parameters by simulated maximum likelihood on a subsample of 400,000 individuals. This is due to the very large sample size and the interest of keeping computation time within reason; the parameter estimates are robust to considering larger subsamples, at the cost of a (much) longer wait. For every year 2014-2017, and every age bin A^n, with $n = 1, ..., 7$, I draw 3,000 individuals and find the demand parameters that solve

$$\max_{\boldsymbol{\alpha}_t^n, \beta_t^n, \sigma_t^n, \boldsymbol{\mu}_t^n, \gamma_t^n} \sum_{i \in N_t^n} \ln\left(\frac{1}{1000}\sum_{s=1}^{1000} \frac{e^{-\alpha_t(\mathbf{z}_i)p_{ij(i)mt} + \delta_{j(i)mt}(\mathbf{z}_i, \theta_i^s)}}{1 + \sum_{k=1}^J e^{-\alpha_t(\mathbf{z}_i)p_{ikmt} + \delta_{kmt}(\mathbf{z}_i, \theta_i^s)}}\right),$$

where N_t^n is the set of sampled individuals in age bin A^n, year t, $j(i)$ is the choice of individual i, and θ_i^s is the s-th draw from $\mathcal{N}(0,1)$ specific to individual i. The estimates are reported in Table S2 and Table S3. Standard errors are calculated using the variance-covariance matrix obtained as the inverse of the negative Hessian of the simulated log-likelihood function at convergence. The Hessian is calculated using numerical differentiation, the gradient is analytical.

Separately from demand, I obtain $\widehat{\eta}^{\text{Age}}$ running a non-linear least squares regression of annual medical spending in the MEPS on age, geographic area, and year: this step finds the parameters that minimize

$$\frac{1}{N_{\text{MEPS}}} \sum_{\ell \in \text{MEPS}} \left\| Y_\ell - e^{\eta^{\text{Age}} \text{Age}_\ell + \text{Year}_\ell + \text{Region}_\ell} \right\|.$$

The results are shown in Table S5.

Lastly, with demand and $\widehat{\eta}^{\text{Age}}$ as given, I minimize the distance between observed and model-predicted expected average claims for each jmt combination as a function of demand estimates and remaining unknown cost parameters:

$$\min_{\eta^{WTP}, \boldsymbol{\phi}} \frac{1}{N_J} \sum_{jmt} \left\| \ln \left(\frac{AC_{jmt} \widehat{Q}_{jmt}}{AV_j^S} \right) - \phi_{jmt} - \ln \left(\sum_i \frac{1}{1000} \sum_{s=1}^{1000} e^{\eta(\mathbf{z}_i, \theta_i^s)} \widehat{q}_{jmt}(\mathbf{z}_i, \theta_i^s) \right) \right\|;$$

where N_J is the number of plans for which I observe average claims as reported in the RRF, θ_i^s is the s-th draw from $\mathcal{N}(0,1)$ specific to individual i, and $\widehat{Q}_{jmt}$, $\widehat{q}_{jmt}(\mathbf{z}_i, \theta_i^s)$ are calculated using the demand estimates. Nonlinear minimization is only required with respect to η^{WTP}: $\boldsymbol{\phi}$ enters the moment linearly, and can therefore be obtained through a simple orthogonal projection for any value of η^{WTP}. The estimates are reported in Table S6, standard errors are bootstrapped, repeating the minimization step using 100 independent draws of demand parameters.

S3 Risk Adjustment Formula

I apply the ACA risk adjustment formula described in Pope, Bachofer, Pearlman, Kautter, Hunter, Miller and Keenan (2014). Following Section 4, risk adjustment for each plan j is calculated as

$$RA_{jmt}(\mathbf{b}_{fmt}, \mathbf{b}_{-fmt}) = Q_{jmt} \underbrace{\frac{\sum_k R_{kmt}}{\sum_k Q_{kmt}}}_{\substack{\text{average premium} \\ \text{in region-year}}} \left(\text{Relative Risk}_{jmt} - \text{Relative Adjustment}_{jmt} \right);$$

where

$$\text{Relative Risk}_{jmt} \equiv \frac{IDF_j AV_j^S Q_{jmt}^{-1} \int L_{mt}(\mathbf{z},\theta) q_{jmt}(\mathbf{z},\theta) dG_{mt}(\mathbf{z},\theta)}{\left(\sum_\ell Q_{\ell mt}\right)^{-1} \sum_k IDF_k AV_k^S \int L_{mt}(\mathbf{z},\theta) q_{kmt}(\mathbf{z},\theta) dG_{mt}(\mathbf{z},\theta)}, \quad \text{and}$$

$$\text{Relative Adjustment}_{jmt} \equiv \frac{IDF_j AV_j^S Q_{jmt}^{-1} \int \text{Adj}(z^{\text{Age}}) q_{jmt}(\mathbf{z},\theta) dG_{mt}(\mathbf{z},\theta)}{\left(\sum_\ell Q_{\ell mt}\right)^{-1} \sum_k IDF_k AV_k^S \int \text{Adj}(z^{\text{Age}}) q_{kmt}(\mathbf{z},\theta) dG_{mt}(\mathbf{z},\theta)}.$$

The relative risk measure is the ratio of a product-specific average expected cost to the region-year average, where it is important to notice that $L_{mt}(\mathbf{z},\theta) \neq L_{jmt}(\mathbf{z},\theta)$. In particular, I set $L_{mt}(\mathbf{z},\theta) = L_{jmt}(\mathbf{z},\theta)e^{-\phi^3 \text{Insurer}_{jmt}}$: risk adjustment payments depend on differences in risk selection, and on differences across regions and years, but not on differences in insurer-specific cost functions. The induced demand factors IDF_j vary across metal tiers, as indicated in Pope et al. (2014): this is equal to 1 for Bronze, 1.03 for Silver, 1.08 for Gold, and 1.15 for Platinum. The relative adjustment measure is calculated in a similar way, but rather than average expected cost it considers average premium adjustments; $\text{Adj}(z^{\text{Age}}) = \text{Adjustment}(z^{\text{Age}})$.

The risk adjustment model is applied at the region-year level mt, rather than the entire state-year. This ensures the computational tractability of equilibrium simulations at the region-year level, in which each insurer faces a multi-product pricing problem. Linking risk adjustment payments across regions would require each insurer to consider more than seventy products at the same time, which would not be feasible. An alternative approach can be found in Saltzman (2021), who simplifies the model by considering fixed regional adjustments to premiums. For my analysis, it is important to consider separate pricing problems across regions, since regional composition and number of competing insurers are relevant determinants of equilibrium, and of the effect of different subsidy designs.

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S4 Additional Tables and Figures

Table S1: First Stage OLS Regression

	b_{jmt}	b_{jmt}	b_{jmt}	b_{jmt}
	(1)	(2)	(3)	(4)
$\int \mathbf{1}\left[z^{\text{Age}} \leq 35\right] dG_{mt}(\mathbf{z})$	-7896.8	-8176.2	-6830.3	-5207.9
	(1500.1)	(1075.8)	(1031.7)	(896.1)
Bronze		-	-	-
Silver		802.0	784.9	752.9
		(42.12)	(40.25)	(36.86)
Gold		1521.5	1504.4	1472.4
		(51.25)	(47.59)	(42.96)
Platinum		2203.2	2186.0	2154.0
		(63.45)	(58.47)	(52.12)
Anthem			-	-
Blue Shield			114.8	29.14
			(64.75)	(55.16)
CCHP			184.3	152.8
			(76.62)	(58.56)
Contra Costa			-408.9	-55.47
			(160.5)	(155.3)
Health Net			22.81	-14.88
			(80.96)	(74.54)
Kaiser			-343.7	-358.5
			(49.55)	(46.38)
L.A. Care			-1074.5	-1108.5
			(82.11)	(91.31)
Molina			-1118.6	-1195.7
			(64.72)	(74.43)
Oscar			-274.6	-629.9
			(186.7)	(161.7)
Sharp			-492.7	-516.3
			(84.69)	(85.38)
United			227.4	245.5
			(119.3)	(123.3)
Valley			-306.3	-309.0
			(56.44)	(89.62)
Western			-119.3	-95.83
			(79.35)	(77.05)
2014				-
2015				139.3
				(43.43)
2016				335.1
				(46.35)
2017				899.4
				(54.05)
Constant	6105.8	5032.3	4766.0	3972.4
	(448.1)	(319.2)	(307.1)	(269.6)
F-statistic:	27.71	57.76	43.83	33.78

Note: The Table shows the OLS estimates from Equation (8), also see Appendix S2. Robust standard error in parentheses. Each observation is a jmt combination (N=1382). The F-statistic corresponds to the rest of the null hypothesis in which the share of potential buyers younger than 35 has no effect on b_{jmt}.

Table S2: Simulated Maximum Likelihood Estimates of Demand Parameters 2014-2015; see Appendix S2

t:	2014 Coverage							2015 Coverage						
A^k:	26-31	32-37	38-43	44-49	50-55	56-61	62-64	26-31	32-37	38-43	44-49	50-55	56-61	62-64
$\alpha_t^{0,k}$	2.309	1.769	1.525	1.536	1.359	1.321	0.917	2.191	1.820	1.512	1.799	1.472	1.036	1.209
	(0.266)	(0.253)	(0.209)	(0.218)	(0.174)	(0.130)	(0.102)	(0.226)	(0.203)	(0.173)	(0.189)	(0.155)	(0.123)	(0.108)
$\alpha_t^{1,k}$	-0.00151	0.000881	-0.0000874	0.000886	0.000781	-0.000109	0.000142	-0.00265	-0.00133	-0.00111	-0.000939	-0.00000543	0.00102	-0.000408
	(0.00107)	(0.00101)	(0.000776)	(0.000909)	(0.000716)	(0.000490)	(0.000388)	(0.000788)	(0.000709)	(0.000606)	(0.000700)	(0.000607)	(0.000504)	(0.000397)
β_t^k	-3.414	-3.168	-3.335	-3.132	-2.852	-2.672	-2.773	-3.539	-3.444	-3.518	-3.167	-2.831	-2.647	-2.600
	(0.122)	(0.111)	(0.123)	(0.106)	(0.0862)	(0.0706)	(0.0771)	(0.125)	(0.122)	(0.129)	(0.0981)	(0.0765)	(0.0647)	(0.0645)
σ_t^k	0.832	0.731	0.701	0.783	0.653	0.574	0.590	0.812	0.760	0.681	0.766	0.658	0.608	0.600
	(0.0806)	(0.0671)	(0.0729)	(0.0696)	(0.0565)	(0.0444)	(0.0502)	(0.0770)	(0.0708)	(0.0730)	(0.0631)	(0.0519)	(0.0427)	(0.0409)
$\mu_t^{0,k}$	-3.850	-10.30	-8.371	-10.79	-16.87	-13.62	-3.961	-0.637	-6.711	-4.242	-14.27	-13.80	-12.17	-12.30
	(1.603)	(2.214)	(2.199)	(3.033)	(3.136)	(3.130)	(6.784)	(1.361)	(1.755)	(1.749)	(2.730)	(2.931)	(3.213)	(7.126)
$\mu_t^{1,k}$	0.0128	0.0164	0.0120	0.0107	0.00984	0.0102	0.00884	0.00967	0.00871	0.00686	0.00936	0.00974	0.00923	0.00748
	(0.00202)	(0.00207)	(0.00176)	(0.00182)	(0.00164)	(0.00136)	(0.00127)	(0.00176)	(0.00161)	(0.00144)	(0.00157)	(0.00149)	(0.00133)	(0.00126)
$\mu_t^{2,k}$	-0.145	0.0231	-0.00286	0.0409	0.139	0.0630	-0.0861	-0.220	-0.00751	-0.0563	0.134	0.0931	0.0480	0.0493
	(0.0559)	(0.0619)	(0.0527)	(0.0639)	(0.0589)	(0.0528)	(0.108)	(0.0489)	(0.0496)	(0.0426)	(0.0567)	(0.0547)	(0.0542)	(0.113)
$\mu_t^{3,k}$	-0.0840	-0.00760	-0.00841	-0.0979	-0.371	-0.592	0.0165	-0.322	-0.308	-0.340	-0.385	-0.424	-0.643	-0.602
	(0.167)	(0.168)	(0.164)	(0.159)	(0.155)	(0.140)	(0.130)	(0.165)	(0.164)	(0.158)	(0.159)	(0.147)	(0.139)	(0.138)
Anthem	–	–	–	–	–	–	–	–	–	–	–	–	–	
Blue Shield	0.414	0.176	0.172	0.183	0.184	0.132	0.156	0.333	0.123	0.0934	0.198	0.0289	0.0386	0.0497
	(0.117)	(0.123)	(0.122)	(0.117)	(0.106)	(0.0921)	(0.0924)	(0.114)	(0.115)	(0.112)	(0.109)	(0.101)	(0.0889)	(0.0871)
CCHP	-0.425	-0.995	0.133	-0.847	0.0372	0.109	-1.259	-0.355	-0.413	-0.787	-0.446	-1.395	-0.624	-0.559
	(0.404)	(0.449)	(0.367)	(0.428)	(0.359)	(0.365)	(0.409)	(0.382)	(0.404)	(0.501)	(0.411)	(0.502)	(0.371)	(0.375)
Contra Costa	-1.257	-20.65	-21.11	-18.97	-0.120	-0.848	-0.847	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
	(1.036)	(17122.6)	(17967.4)	(7690.9)	(0.765)	(1.035)	(0.617)							
Health Net	0.0304	0.224	0.274	0.306	0.190	0.257	0.142	0.267	0.210	0.308	0.179	0.375	0.339	0.198
	(0.142)	(0.138)	(0.136)	(0.129)	(0.126)	(0.111)	(0.110)	(0.150)	(0.150)	(0.145)	(0.146)	(0.130)	(0.124)	(0.126)
Kaiser	0.644	0.231	0.0829	0.381	0.724	0.933	0.523	0.805	0.475	0.482	0.457	0.525	0.628	0.721
	(0.216)	(0.226)	(0.222)	(0.222)	(0.213)	(0.196)	(0.176)	(0.176)	(0.179)	(0.176)	(0.178)	(0.168)	(0.162)	(0.159)
L.A. Care	-0.706	-1.011	-0.971	-1.119	-1.020	-0.477	-1.245	-1.939	-0.843	-0.825	-1.005	-0.877	-1.158	-1.148
	(0.291)	(0.305)	(0.308)	(0.316)	(0.315)	(0.269)	(0.283)	(0.495)	(0.342)	(0.352)	(0.348)	(0.335)	(0.367)	(0.357)
Molina	-2.368	-2.944	-2.293	-3.352	-2.823	-2.453	-2.674	-1.463	-1.535	-1.294	-1.031	-1.169	-1.660	-2.119
	(0.445)	(0.512)	(0.423)	(0.628)	(0.508)	(0.421)	(0.405)	(0.329)	(0.336)	(0.322)	(0.282)	(0.277)	(0.307)	(0.342)
Oscar	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Sharp	-0.576	-0.977	-0.657	-0.0926	-0.101	0.0273	-0.0885	0.431	0.164	0.650	-0.226	0.569	0.412	0.233
	(0.550)	(0.623)	(0.549)	(0.470)	(0.466)	(0.408)	(0.342)	(0.379)	(0.393)	(0.353)	(0.459)	(0.342)	(0.346)	(0.356)
United	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Valley	-2.039	-20.86	-1.202	-1.181	-0.308	-20.09	-1.611	-1.759	-0.995	-0.502	-19.27	-1.299	-19.78	-2.368
	(1.024)	(15872.5)	(0.745)	(0.744)	(0.554)	(9440.6)	(0.734)	(1.025)	(0.744)	(0.622)	(6730.6)	(0.740)	(7145.6)	(1.018)
Western	-1.899	-20.13	-1.423	-0.0808	-1.936	-1.881	-2.009	-0.731	-20.43	-0.498	-0.280	-1.487	-0.397	-1.206
	(1.025)	(9288.7)	(0.742)	(0.505)	(1.022)	(1.018)	(0.728)	(0.540)	(8841.4)	(0.492)	(0.461)	(0.607)	(0.398)	(0.479)
$\gamma_t^{1,k}$	0.131	0.158	0.160	0.358	0.319	0.418	0.411	0.285	0.453	0.655	0.432	0.513	0.683	0.415
	(0.208)	(0.230)	(0.215)	(0.229)	(0.214)	(0.199)	(0.184)	(0.173)	(0.178)	(0.171)	(0.190)	(0.182)	(0.178)	(0.177)
$\gamma_t^{2,k}$	0.159	-0.153	-0.0677	-0.0348	0.283	0.378	-0.222	-0.251	-0.197	-0.286	-0.255	-0.445	-0.396	-0.424
	(0.131)	(0.149)	(0.134)	(0.149)	(0.133)	(0.115)	(0.120)	(0.102)	(0.0948)	(0.110)	(0.0995)	(0.0930)	(0.0968)	(0.0895)
$\gamma_t^{3,k}$	-0.450	-0.549	-0.487	-0.660	-0.676	-0.859	-0.609	-0.201	-0.286	-0.262	-0.395	-0.321	-0.456	-0.259
	(0.107)	(0.123)	(0.111)	(0.119)	(0.106)	(0.0975)	(0.101)	(0.0623)	(0.0552)	(0.0692)	(0.0570)	(0.0526)	(0.0557)	(0.0495)

Table S3: Simulated Maximum Likelihood Estimates of Demand Parameters 2016-2017; see Appendix S2

t:	2016 Coverage							2017 Coverage						
A^k:	26-31	32-37	38-43	44-49	50-55	56-61	62-64	26-31	32-37	38-43	44-49	50-55	56-61	62-64
$\alpha_t^{0,k}$	1.725	1.357	1.526	1.560	1.310	1.169	0.895	1.361	1.238	1.029	1.256	1.236	1.106	0.807
	(0.176)	(0.155)	(0.175)	(0.148)	(0.120)	(0.105)	(0.0848)	(0.181)	(0.203)	(0.167)	(0.146)	(0.125)	(0.103)	(0.0830)
$\alpha_t^{1,k}$	-0.00213	-0.00134	-0.00121	-0.00154	-0.000918	-0.000450	-0.000212	0.000563	0.00138	0.000774	-0.00000953	-0.000400	0.0000457	0.000297
	(0.000600)	(0.000526)	(0.000611)	(0.000518)	(0.000432)	(0.000396)	(0.000307)	(0.000662)	(0.000735)	(0.000605)	(0.000492)	(0.000440)	(0.000361)	(0.000289)
β_t^k	-3.790	-3.794	-3.402	-3.215	-3.072	-2.774	-2.763	-3.507	-3.228	-3.238	-3.015	-2.938	-2.678	-2.660
	(0.151)	(0.155)	(0.119)	(0.0962)	(0.0846)	(0.0660)	(0.0660)	(0.141)	(0.114)	(0.117)	(0.0947)	(0.0842)	(0.0680)	(0.0687)
σ_t^k	0.729	0.737	0.690	0.660	0.613	0.599	0.564	0.661	0.640	0.539	0.542	0.559	0.585	0.536
	(0.0799)	(0.0843)	(0.0697)	(0.0598)	(0.0546)	(0.0441)	(0.0437)	(0.0824)	(0.0675)	(0.0677)	(0.0600)	(0.0562)	(0.0475)	(0.0459)
$\mu_t^{0,k}$	-2.804	-3.143	-4.238	-4.564	-9.627	-13.65	-7.353	-7.834	-9.412	-8.413	-11.07	-10.39	-8.778	-12.83
	(1.084)	(1.378)	(1.925)	(2.176)	(2.381)	(2.920)	(6.029)	(1.320)	(1.793)	(1.858)	(2.310)	(2.592)	(3.210)	(6.578)
$\mu_t^{1,k}$	0.00388	0.00304	0.00738	0.00371	0.00556	0.00358	0.00841	0.0160	0.0195	0.0103	0.00978	0.00689	0.00668	0.00981
	(0.00148)	(0.00135)	(0.00143)	(0.00131)	(0.00122)	(0.00117)	(0.00112)	(0.00197)	(0.00191)	(0.00159)	(0.00152)	(0.00127)	(0.00124)	(0.00120)
$\mu_t^{2,k}$	-0.0758	-0.0627	-0.0675	-0.0383	0.0448	0.0992	-0.0225	0.0132	0.00268	0.0188	0.0637	0.0487	0.00171	0.0554
	(0.0369)	(0.0393)	(0.0465)	(0.0462)	(0.0447)	(0.0492)	(0.0952)	(0.0429)	(0.0497)	(0.0442)	(0.0482)	(0.0486)	(0.0539)	(0.104)
$\mu_t^{3,k}$	-0.645	-0.799	-0.855	-0.748	-0.536	-0.637	-0.594	-1.459	-1.755	-1.714	-1.478	-1.418	-1.401	-1.437
	(0.177)	(0.178)	(0.174)	(0.155)	(0.149)	(0.145)	(0.138)	(0.181)	(0.189)	(0.189)	(0.170)	(0.166)	(0.154)	(0.146)
Anthem	–	–	–	–	–	–	–	–	–	–	–	–	–	
Blue Shield	0.296	0.453	0.187	0.229	0.329	0.448	0.277	0.527	0.719	0.520	0.786	0.625	0.755	0.556
	(0.109)	(0.109)	(0.110)	(0.101)	(0.0967)	(0.0933)	(0.0866)	(0.124)	(0.127)	(0.130)	(0.129)	(0.119)	(0.116)	(0.105)
CCHP	0.194	0.0979	-0.804	-0.879	-0.847	-0.364	-0.600	0.328	-0.320	0.151	0.427	0.364	1.231	0.363
	(0.375)	(0.403)	(0.484)	(0.475)	(0.429)	(0.372)	(0.376)	(0.494)	(0.662)	(0.577)	(0.473)	(0.457)	(0.377)	(0.413)
Contra Costa	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Health Net	-0.557	-0.0724	-0.0197	-0.0861	-0.0352	-0.00429	-0.291	0.401	0.823	0.499	1.329	1.047	1.087	0.873
	(0.187)	(0.177)	(0.173)	(0.151)	(0.145)	(0.140)	(0.136)	(0.211)	(0.216)	(0.211)	(0.185)	(0.175)	(0.161)	(0.155)
Kaiser	0.985	1.067	0.974	0.711	0.588	0.932	0.759	1.388	1.452	1.542	1.345	0.982	1.420	1.139
	(0.188)	(0.192)	(0.192)	(0.173)	(0.168)	(0.161)	(0.151)	(0.203)	(0.215)	(0.214)	(0.201)	(0.195)	(0.181)	(0.169)
L.A. Care	-0.972	-1.509	-1.483	-0.943	-1.244	-1.217	-1.590	-2.184	-0.904	-0.957	-0.481	-1.625	-1.453	-1.038
	(0.347)	(0.487)	(0.489)	(0.322)	(0.361)	(0.322)	(0.358)	(0.614)	(0.390)	(0.437)	(0.329)	(0.432)	(0.360)	(0.309)
Molina	-0.0980	0.0528	-0.158	-0.431	-0.380	-0.755	-1.192	0.357	0.229	0.476	0.326	0.302	-0.187	-0.461
	(0.224)	(0.229)	(0.235)	(0.214)	(0.203)	(0.210)	(0.212)	(0.230)	(0.249)	(0.243)	(0.232)	(0.220)	(0.227)	(0.217)
Oscar	-21.17	-3.004	-3.692	-21.88	-3.682	-3.835	-2.790	-2.947	-2.715	-21.02	-3.175	-3.262	-2.695	-3.224
	(5811.7)	(0.715)	(1.006)	(7835.3)	(1.006)	(1.006)	(0.587)	(0.591)	(0.519)	(5357.2)	(0.721)	(0.720)	(0.520)	(0.592)
Sharp	0.570	0.837	0.448	1.069	0.674	1.048	0.567	1.042	1.703	2.092	1.892	1.162	1.518	1.258
	(0.342)	(0.367)	(0.393)	(0.305)	(0.327)	(0.285)	(0.300)	(0.421)	(0.367)	(0.346)	(0.332)	(0.360)	(0.303)	(0.292)
United	-2.140	-21.16	-21.07	-20.96	-20.01	-19.42	-20.35	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
	(0.717)	(9738.3)	(8925.0)	(7630.6)	(5035.4)	(3614.9)	(4786.8)							
Valley	-0.105	-1.520	-1.013	-0.555	-2.211	-0.717	-1.443	-0.874	-1.295	-0.271	-19.64	-19.59	-1.510	-1.491
	(0.556)	(1.029)	(0.747)	(0.545)	(1.023)	(0.546)	(0.609)	(0.751)	(1.043)	(0.763)	(8026.2)	(6492.5)	(0.742)	(0.741)
Western	-1.212	-1.179	-0.632	-1.284	-1.070	-0.824	-0.758	0.0354	0.283	-1.444	0.570	-0.0203	-0.697	-0.536
	(0.612)	(0.741)	(0.549)	(0.612)	(0.451)	(0.420)	(0.335)	(0.468)	(0.480)	(1.030)	(0.425)	(0.399)	(0.455)	(0.425)
$\gamma_t^{1,k}$	0.221	0.718	0.881	0.668	0.760	0.571	0.567	0.110	0.836	0.237	0.0813	0.156	-0.283	-0.218
	(0.141)	(0.142)	(0.156)	(0.148)	(0.146)	(0.153)	(0.140)	(0.175)	(0.208)	(0.175)	(0.178)	(0.182)	(0.182)	(0.173)
$\gamma_t^{2,k}$	-0.00593	-0.111	-0.153	-0.182	-0.199	-0.136	-0.178	-0.289	-0.432	-0.184	-0.505	-0.572	-0.119	-0.297
	(0.112)	(0.0921)	(0.0928)	(0.0911)	(0.0943)	(0.0859)	(0.0824)	(0.165)	(0.173)	(0.162)	(0.180)	(0.205)	(0.119)	(0.158)
$\gamma_t^{3,k}$	-0.0445	-0.166	-0.176	-0.181	-0.195	-0.205	-0.174	0.0923	-0.178	0.119	0.167	0.183	-0.00212	0.108
	(0.0736)	(0.0464)	(0.0449)	(0.0477)	(0.0497)	(0.0437)	(0.0413)	(0.119)	(0.116)	(0.108)	(0.107)	(0.119)	(0.0745)	(0.0921)

Table S4: Impact of Control Function on Demand Estimates

	Coefficient on premium ($000/year) $\alpha_t(\mathbf{z}_i)$				WTP for 10% AV increase ($/year) $\beta_t(\mathbf{z}_i, \theta_i)/\alpha_t(\mathbf{z}_i)$			
Specification	Mean	P10	Median	P90	Mean	P10	Median	P90
Baseline, with Control Function	1.364	1.012	1.322	1.789	431.2	245.1	360.3	726.6
	(0.017)	(0.024)	(0.029)	(0.06)	(4.8)	(7.4)	(10.1)	(21.7)
No Control Function	1.317	0.974	1.255	1.731	418.1	250.1	335.4	718.9
	(0.017)	(0.03)	(0.02)	(0.055)	(5)	(7.3)	(8.7)	(17.5)

Note: The table shows the mean, median, and 10-th and 90-th percentiles of the estimated distribution of $\alpha_t(\mathbf{z}_i)$ and $\frac{\beta_t(\mathbf{z}_i,\theta_i)}{\alpha_t(\mathbf{z}_i)}$. The top panel shows the baseline results, which include the control function (third-degree polynomial in the residuals $\widehat{\xi}_{jmt}$ from column (4) in Table S1), and the estimates obtained omitting $\widehat{\xi}_{jmt}$. Standard errors in parentheses, obtained as the empirical standard deviation across 100 independent random draws of the demand parameters using the estimated variance-covariance matrix.

Table S5: MEPS Annual Expenditure: Non-linear Least Squares

	(1)	(2)	(3)
η^{Age}	0.0381	0.0379	0.0379
	(0.00214)	(0.00213)	(0.00213)
Constant	6.561	6.738	6.687
	(0.114)	(0.122)	(0.127)
Northeast		-	-
Midwest		-0.0973	-0.106
		(0.0624)	(0.0624)
South		-0.198	-0.202
		(0.0569)	(0.0567)
West		-0.293	-0.298
		(0.0656)	(0.0656)
2014			-
2015			0.0662
			(0.0578)
2016			0.0583
			(0.0584)
2017			0.0969
			(0.0580)

Note: Non-linear least squares parameter estimates from Equation (10). Standard errors in parentheses.

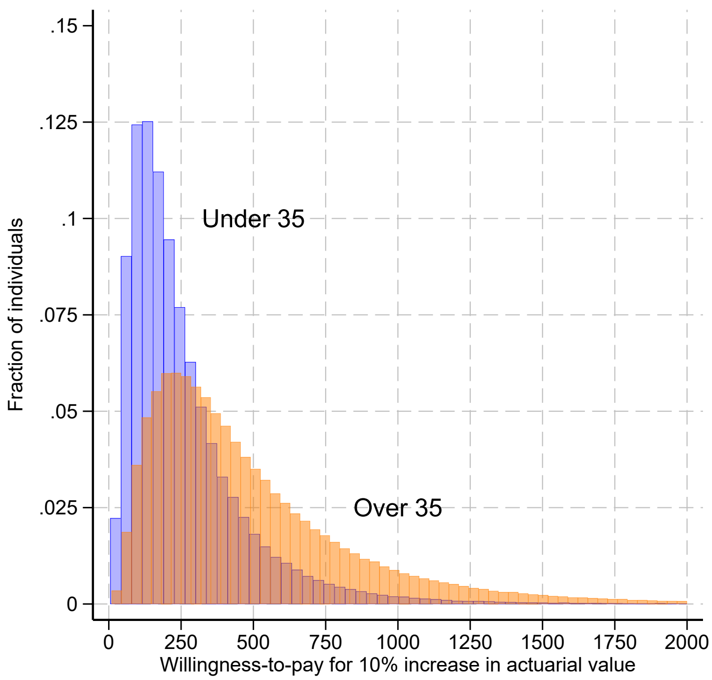
Table S6: Other Cost Parameters: Non-linear Least Squares

η^{WTP} ($100/year for +10% AV)	0.0803		
	(0.0104)		
Constant	5.376		
	(0.149)		
ϕ_m:		$\boldsymbol{\phi}^3$:	
Region 1 (see note)	-	Anthem	0.223
			(0.143)
Napa, Sonoma, Solano, Marin	0.187	Blue Shield	0.303
	(0.05)		(0.133)
Sacramento, Placer, El Dorado, Yolo	0.418	CCHP	−0.276
	(0.053)		(0.132)
San Francisco	0.34	Health Net	0.659
	(0.052)		(0.13)
Contra Costa	0.343	Kaiser	0.259
	(0.052)		(0.127)
Alameda	0.183	L.A. Care	−0.009
	(0.053)		(0.136)
Santa Clara	0.131	Molina	−0.154
	(0.063)		(0.124)
San Mateo	0.359	Western	0.226
	(0.054)		(0.153)
Santa Cruz, Monterey, San Benito	0.235	Other	-
	(0.235)		
San Joaquin, Stanislaus, Merced, Mariposa, Tulare	0.293		
	(0.046)		
Madera, Fresno, Kings	0.172	ϕ_t:	
	(0.055)		
San Luis Obispo, Santa Barbara, Ventura	−0.002	2014	-
	(0.051)		
Mono, Inyo, Imperial	−0.091	2015	0.288
	(0.072)		(0.072)
Kern	0.051	2016	0.211
	(0.045)		(0.082)
Los Angeles 1 (see note)	0.055	2017	0.378
	(0.047)		(0.08)
Los Angeles 2 (see note)	0.132		
	(0.049)		
San Bernardino, Riverside	−0.053		
	(0.054)		
Orange	−0.067		
	(0.047)		
San Diego	0.11		
	(0.052)		

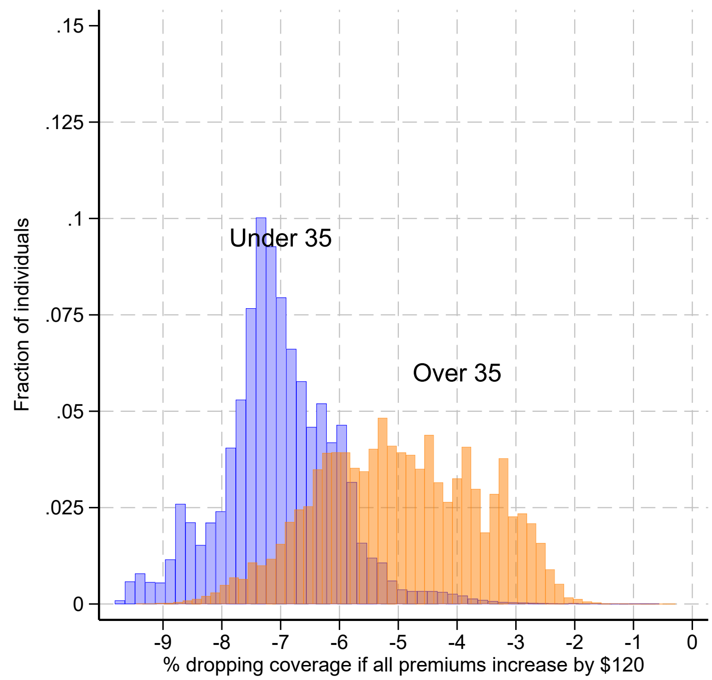
Note: Non-linear least squares cost parameters of Equation (5). See Appendix S2 for details.

Figure S1: Demand Heterogeneity

(a) WTP for 10% AV increase



(b) Extensive Margin Premium Responses



Note: Histograms of the estimated distribution of annual willingness-to-pay for a 10% increase in actuarial value, $\beta_t(\mathbf{z}_i, \theta_i)/\alpha_t(\mathbf{z}_i)$, and % change in probability of purchasing coverage if all annual premiums increase by $120. The figure pools across all individuals in 2014-2017 Covered California, divided between under- and over-35.