D Additional Structural Results

D.1 Estimation Algorithm

I estimate the model described in Section 4 of the text using a maximum likelihood approach similar to Train (2009) and Revelt and Train (1998), with the appropriate extension to a discrete/continuous multi-stage choice model as discussed in Dubin and McFadden (1984). My estimation approach is similar to other models like mine, including Marone and Sabety (2021). I estimate the parameter values θ that maximize the probability density of households' observed total healthcare spending conditional on their plan choices. The estimation is done in R version 4.0.3, following the best practices laid out in Conlon and Gortmaker (2020).

My model allows for individuals to have three type-specific dimensions of unobservable heterogeneity, in addition to the typical Type 1 Extreme Value idiosyncratic shock (which can be integrated out analytically): individual health states, individual beliefs about health risks, and household risk aversion. I therefore must numerically integrate over the three dimensions $\beta_{ft} = (p_{it}, \mu_{\lambda,i}, \psi_{ft}) \in \theta$. Given a guess of θ, I use Gaussian quadrature with 27 support points (three in each dimension) to simulate underlying consumer types, yielding simulated points $\{\beta_{fts}(\theta)\}_s$ and weights W_s.

For each simulation draw s, I can then calculate the conditional density at individuals' observed total healthcare spending and the probability of households' observed plan choices.

D.1.1 Household Spending

Given data on realized choices m_{it}, I construct the distribution of healthcare spending for each individual-year implied by the model and guess of parameters θ. Based on underlying consumer types β_{fts}, I construct individual-level parameters for health states $(\mu_{\lambda,i}, \sigma_{\lambda,i}, \kappa_i)$ based on the parameters β_{fts} and the distributions outlined in Section 4.3.1 of the text.

The model predicts that given an acute-chronic health state $(\lambda_{it}, m_{ft}^{\text{CH}})$, households choose total healthcare spending m by trading off the benefit of healthcare utilization with its out-of-pocket cost, as discussed above. Given that m_{ft}^{CH} does not have individual parameters to be estimated (as these values are drawn from an empirical distribution), inverting the expression in equation 18 of the text yields the health state realization λ_{its} that would have given rise to observed spending m_{it} given m_{ft}^{CH}. Given that observed spending is truncated from below at 0, there are two possibilities for the conditional pdf:

$$f_m(m_{it}|c_{jt}, \beta_{fts}, \theta) = \begin{cases} \mathbf{\Phi}\left(\frac{\log(\kappa_i)-\mu_{\lambda,i}}{\sigma_{\lambda,i}}\right) & m_{it} = 0 \\ \mathbf{\Phi}'\left(\frac{\log(\lambda_{its})-\mu_{\lambda,i}}{\sigma_{\lambda,i}}\right) & m_{it} > 0, \end{cases} \tag{1}$$

where $\mathbf{\Phi}(\cdot)$ is the standard normal cumulative distribution function. In practice, there are iterations where the implied pdf is zero; hence, in order to rationalize the data for any parameter guess, I use a convolution of f_m with a uniform distribution over the range [-1e-75, 1e-75], as done by Marone and Sabety (2021).

D.1.2 Plan Choices

I next calculate choice probabilities for each available health insurance plan. Given θ and β_{fts}, I numerically integrate over the joint distribution of acute and chronic health care shocks using $D = 10$ support points in each dimension. The support points for the chronic health care shocks are chosen uniformly across the empirical distribution with the empirical pdf used in calculating the associated weights. For the acute health shocks, support points are calculated over the lognormal distribution as:

$$\lambda_{itsd} = \exp\left(\mu_{is} + \sigma_{is} Z_d\right) + \kappa_{is}, \tag{2}$$

where Z_d is the appropriate Gaussian quadrature vector of points (with corresponding weights W_d). The utility maximization framework discussed above (Equation 18 in the text) is then used to calculate the optimal spending levels given individual and household shocks and the underlying parameter p_{it}. Expected utility for each support point is calculated as in equation 9 of the text and summed (with weights) over all 100 points.[1] Choice probabilities for a plan j are then given by the standard logit formula

$$L_{ftjs} = \frac{\exp(U_{ftjs}/\sigma_\epsilon)}{\sum_{i \in \mathcal{J}_{ft}} \exp(U_{ftis}/\sigma_\epsilon)}. \tag{3}$$

D.1.3 Likelihood Function

Based on the choice probabilities and conditional density functions for observed spending, the likelihood function is approximated by

$$LL_f = \sum_{j=1}^{J} d_{fjt} \sum_{s=1}^{S} W_s \prod_{t=1}^{T} f_m(m_{it}|c_{jt}, \beta_{fts}, \theta) L_{ftjs}, \tag{4}$$

[1]In practice, to speed up estimation, I ignore points with associated weights smaller than 1e-5.

where d_{fjt} is an indicator variable equal to one if household f chose plan j at time t and zero otherwise. The log-likelihood function to be maximized is therefore the sum over households:

$$LL(\theta) = \sum_{f=1}^{F} \log(LL_f). \tag{5}$$

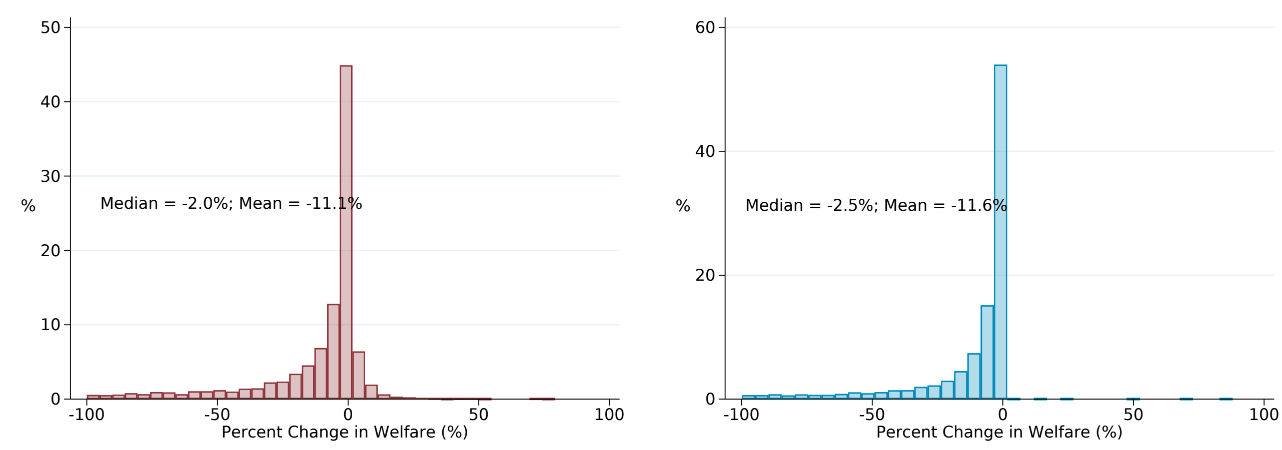
D.2 Additional Parameters

Table D.1 includes additional structural parameters not discussed in the text. These are reported only for the preferred specification of interest (column 3 in Table 5 of the text).

Figure D.1 illustrates the estimated percentage changes in welfare from new health information, the corresponding result to Figure 8 in the text.

Figure D.1. Percentage Changes in Household Welfare Following Health Information

(a) Full Welfare Effect (b) Health Information Effect Only



Notes: Figures show estimated percentage changes in household willingness to pay associated with major health events. The panel on the left shows differences in the case of a full response to a new diagnosis, including adjustments to risk aversion and moral hazard effects; the panel on the right shows only differences arising from adjustments to household risk assessments. Welfare effects are calculated in the year of the diagnosis relative to a benchmark in which no information is transmitted.

Figure D.2 illustrates heterogeneity in household characteristics and the value of new health information.

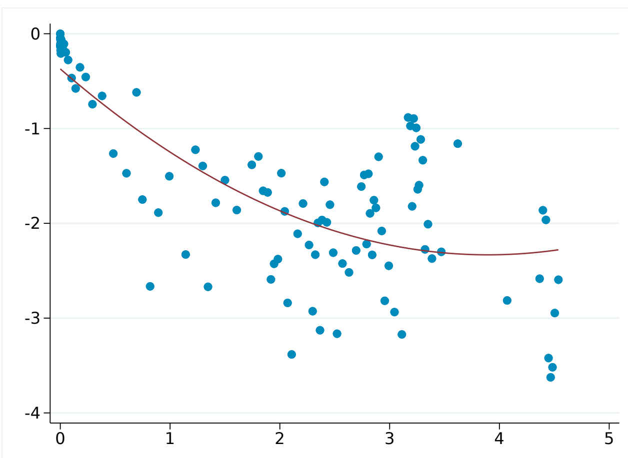
	(1)	(2)	(3)
Panel A: Mean-shifters			
Initial Probabilities			
Intercept	0.00	-9.91	-10.11
Age	-0.11	1.00	0.48
Age^2	0.32	0.34	0.33
Female	-6.94	5.00	0.50
Individual risk score	-5.12	-1.63	-0.88
Any PE in family	3.01	4.25	0.53
Acute Health Shocks			
Intercept	–	5.00	5.00
Age	–	0.09	0.11
Age^2	–	-0.14	-0.14
Female	–	0.49	0.77
Type	–	-0.59	0.30
Initial Risk Aversion			
Intercept	7.14	10.00	4.68
Family size	-0.10	-7.75	-0.10
Average family age	-0.75	9.27	1.93
Average family risk score	-1.51	-9.87	-4.93
Panel B: Other Parameters			
σ_κ^2 (acute health shifter, variance)	–	0.02	10.56
ω (moral hazard shifter)	249.36	146.60	250.00
η (switching costs)	40.13	34.34	23.13
Beliefs Evolve	Yes	Yes	Yes
Acute Shock Heterogeneity		Yes	Yes
Risk Aversion Evolves			Yes

Table D.1. Estimated Type Mean Shifting Parameters

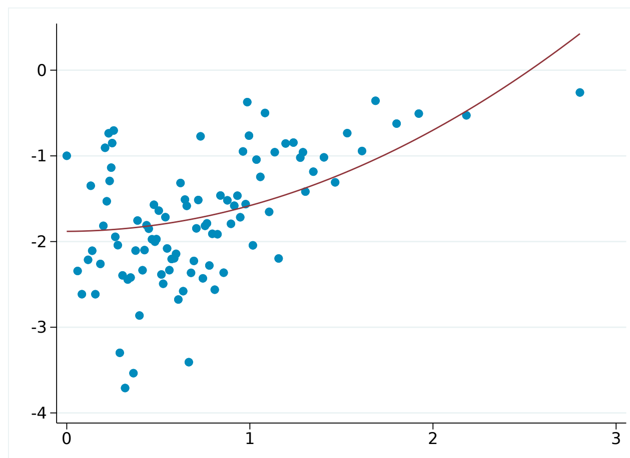
Notes: See Table 5 in the text for structural parameters of interest.

Figure D.2. Heterogeneity in Household Characteristics and WTP for Health Information

(a) Household Risk Aversion, $\overline{\psi}$



(b) Household Risk Scores



Notes: Figures show binscatters depicting the association between pre-diagnosis household health characteristics on the x-axis and the estimated welfare effects of receiving health risk information on the y-axis. Household characteristics include (a) average household risk aversion and (b) average household risk scores (calculated using the Johns Hopkins ACG System). Welfare effects are calculated in the year of the diagnosis relative to a benchmark in which no information is transmitted; see Figure 8 in the text for details. Binscatters are constructed using 100 bins and a quadratic fit line.