An Ounce of Prevention or a Pound of Cure?

The Value of Health Risk Information

Alex Hoagland, Boston University

November 29, 2021

Social networks in health: the apple doesn't fall far

- Family & social networks provide important **health information**
  - Expectations of own health risks
  - Relative value of medical care and how to get it

Social networks in health: the apple doesn't fall far

- Family & social networks provide important **health information**
  - Expectations of own health risks
  - Relative value of medical care and how to get it
- How **individual experiences** $\Longrightarrow$ **family behaviors** is vital to policies:
  - Incentivizing take-up of **high-value** services
  - Curbing use of **low-value** services

Social networks in health: the apple doesn't fall far

- Family & social networks provide important **health information**
  - Expectations of own health risks
  - Relative value of medical care and how to get it
- How **individual experiences** $\Longrightarrow$ **family behaviors** is vital to policies:
  - Incentivizing take-up of **high-value** services
  - Curbing use of **low-value** services

I show family health events cause spillovers but **do not** improve welfare

- Individuals **(over-) update beliefs** about risks
- Leads to increased utilization (high- & low-value)
- Welfare gains are dampened by **misinterpretation**

Example: COVID-19 Cases & Vaccinations

He put off getting vaccinated. Now, he's in the ICU pleading for others to avoid his mistake: 'I messed up'

Example: COVID-19 Cases & Vaccinations

He put off getting vaccinated. Now, he's in the ICU pleading for others to avoid his mistake: 'I messed up'

'Get the vaccine:' Oregon man pleads as 23-year-old wife fights for her life

Example: COVID-19 Cases & Vaccinations

He put off getting vaccinated. Now, he's in the ICU pleading for others to avoid his mistake: 'I messed up'

'Get the vaccine:' Oregon man pleads as 23-year-old wife fights for her life

COVID-19: Family of anti-vaxxer nightclub boss who died from coronavirus urges people to get the jab

Example: COVID-19 Cases & Vaccinations

He put off getting vaccinated. Now, he’s in the ICU pleading for others to avoid his mistake: ‘I messed up’

'Get the vaccine:' Oregon man pleads as 23-year-old wife fights for her life

COVID-19: Family of anti-vaxxer nightclub boss who died from coronavirus urges people to get the jab

Family of San Diego COVID-19 victim makes emotional vaccine plea

Spillover Effects in Demand for Health Care

Health events provide type information to a household

- New chronic diagnoses from 2006–2018 (ex: Type 1 Diabetes)
- Observed changes in utilization $\Longrightarrow$ measure/value spillovers

Health events provide type information to a household

- New chronic diagnoses from 2006–2018 (ex: Type 1 Diabetes)
- Observed changes in utilization $\implies$ measure/value spillovers

Households appear **highly responsive** to new health information

- New diagnoses prompt spending increases by 10%
- Effects are persistent but affect services of varying quality

Spillover Effects in Demand for Health Care

Health events provide type information to a household

- New chronic diagnoses from 2006–2018 (ex: Type 1 Diabetes)
- Observed changes in utilization $\Longrightarrow$ measure/value spillovers

Households appear **highly responsive** to new health information

- New diagnoses prompt spending increases by 10%
- Effects are persistent but affect services of varying quality

Highlight role of **information interpretation** relative to other channels

1. Induced demand (“moral hazard"): $\downarrow$ spot prices of care
2. Salience: $\uparrow$ marginal utility of seeking care
3. Health system literacy: $\downarrow$ indirect costs of care

Key Questions & Contributions

1. How does health information **change health choices**?
   - Highlights a new channel of informational spillovers
   - Results paint a picture of risk reassessment
   - Diagnoses increase use of high- and low-value services

Key Questions & Contributions

1. How does health information **change health choices**?
   - Highlights a new channel of informational spillovers
   - Results paint a picture of risk reassessment
   - Diagnoses increase use of high- and low-value services

2. What is the **value** of new health information?
   - Novel structural model of health choices/learning
   - Monetize value of new info.: welfare penalties of $\sim$**\$2,750/yr**
   - *Ex-post* belief **overweighting** limits welfare gains

Key Questions & Contributions

1. How does health information **change health choices**?
   - Highlights a new channel of informational spillovers
   - Results paint a picture of risk reassessment
   - Diagnoses increase use of high- and low-value services
2. What is the **value** of new health information?
   - Novel structural model of health choices/learning
   - Monetize value of new info.: welfare penalties of ~**$2,750/yr**
   - *Ex-post* belief **overweighting** limits welfare gains
3. Why does **over-responsiveness** to health information matter?
   - Limiting belief responsiveness $\Longrightarrow$ welfare gains ~$2,027 annually
   - Returns further improved by targeting information

OUTLINE

1. Data: Major health events taking place within a household
2. Reduced-Form Evidence: Informational spillovers and mechanisms
3. Structural Model: Quantifying value of health information
4. Counterfactual Scenarios: The role of over-reaction in welfare
5. Conclusion: Discussion & policy importance

DATA

The Value of Claims Data

Data: Truven Commercial Claims and Encounters Marketscan, 2006–2018

- Detailed claims for households in group ESI plans
- Typically, families with middle-aged parents + young children
- 8 firms with consistent plan identifiers (N = 353,403 families)

The Value of Claims Data

Data: Truven Commercial Claims and Encounters Marketscan, 2006–2018

- Detailed claims for households in group ESI plans
- Typically, families with middle-aged parents + young children
- 8 firms with consistent plan identifiers (N = 353,403 families)

Key Variables:

- Health events based on Hierarchical Condition Categories Example
  - Generic set of conditions that alter risk, spending, & utilization
  - Limited to common non-pregnancy conditions
- Main outcomes:
  - Health spending/utilization: billed and out-of-pocket (OOP)
  - Health insurance plan choice
  - Use of preventive and low-value care

A Few Summary Statistics

	Full Sample	Plan-Identified Sample
Family size	3.00	3.01
Employee age	45.01	44.36
Total medical spending	\$2,504.41 [\$679.75]	\$2,454.88 [\$624.16]
OOP medical spending	\$443.07 [\$109.66]	\$337.98 [\$80.33]
% with new chronic diagnosis	6.32	5.21
Chronic condition costs:		
OOP, diagnosis year	\$1,082.05 [\$464.69]	\$854.62 [\$329.90]
OOP, future years	\$983.03 [\$521.39]	\$683.60 [\$446.69]
Years	2006–2018	2006–2013
$N_{\text{individuals}}$	1,087,353	555,733

Notes: Medians in brackets. Spending in 2020 USD.

Plan Characteristics

I use **multiple firms** to leverage variation in plan characteristics

- Useful to separate risk *preferences* from risk *beliefs*

	Firm							
	A	B	C	D	E	F	G	H
# of plans offered	**3.50**	**2.50**	**3.00**	**2.00**	**2.00**	**2.57**	**2.75**	**3.00**
Cost/Enrollee	12.70	9.82	9.73	10.16	9.34	8.93	9.13	11.53
HH deductible	**0.36**	**0.39**	**2.13**	**0.97**	**0.95**	**0.71**	**0.89**	**0.48**
% 0-deductible	**64.29**	**46.67**	**0.00**	**0.00**	**0.00**	**22.22**	**31.82**	**38.89**
HH OOP max.	3.47	4.55	5.05	5.92	4.32	4.11	5.15	3.92
HHI of all plans	0.43	0.60	0.40	0.56	0.86	0.61	0.64	0.44

Notes: Averages are pooled across all plans and years in a given firm. Prices in $1,000s.

Methodology

REDUCED-FORM EVIDENCE

I estimate the effects of new chronic diagnoses using a **two-way fixed-effects (TWFE)** approach:

$$\sinh^{-1}(y_{ft}) = \alpha_f + \tau_t + \sum_{k=-T}^{T} \gamma_k \mathbb{1}\left\{t - E_{ft} = k\right\} + \epsilon_{ft}.$$

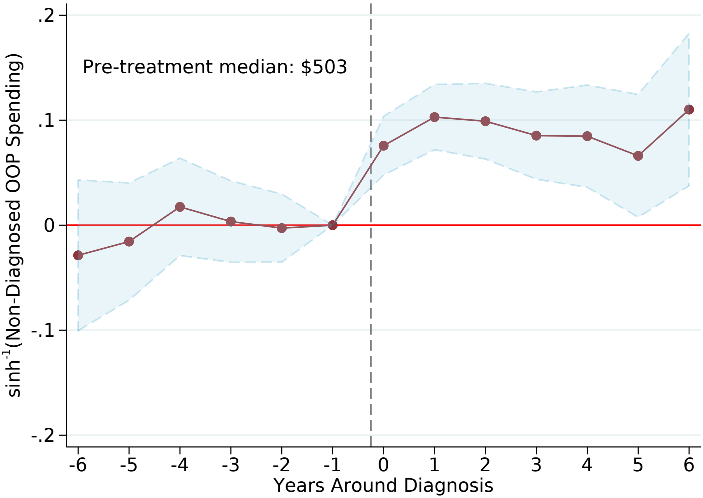
Mehtodology

I estimate the effects of new chronic diagnoses using a **two-way fixed-effects (TWFE)** approach:

$$\sinh^{-1}(y_{ft}) = \alpha_f + \tau_t + \sum_{k=-T}^{T} \gamma_k \mathbb{1}\left\{t - E_{ft} = k\right\} + \epsilon_{ft}.$$

- Relative to year prior to event
- Coefficients roughly interpretable as percentage changes
- Standard errors are clustered at household level
- Results are robust to standard TWFE concerns TWFE Robustness

Household Chronic Diagnoses ↑ (Non-Diagnosed) Spending



Evidence of Belief Updating: Preventive Care

Households also increase general takeup of **wellness visits** Details

- Generally considered high-value care (Tong et al., 2021)
- 1.5pp more likely to use wellness visit (from 92%)
- Increased (billed) spending on prevention of ∼10% ($50) annually

Evidence of Belief Updating: Preventive Care

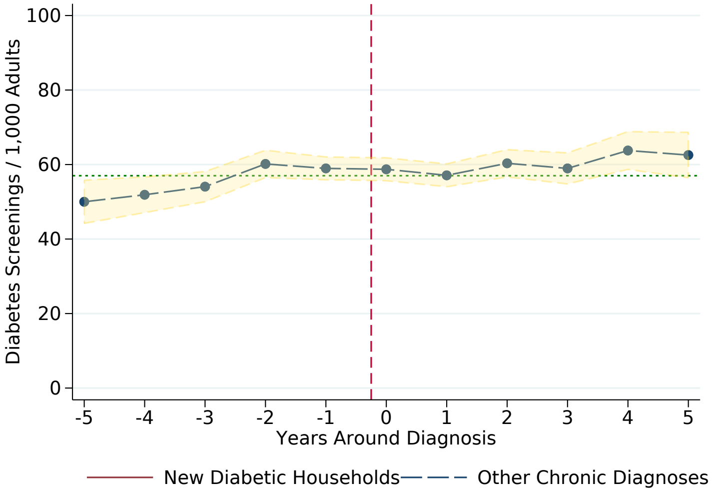
Households also increase general takeup of **wellness visits** Details

- Generally considered high-value care (Tong et al., 2021)
- 1.5pp more likely to use wellness visit (from 92%)
- Increased (billed) spending on prevention of ~10% ($50) annually

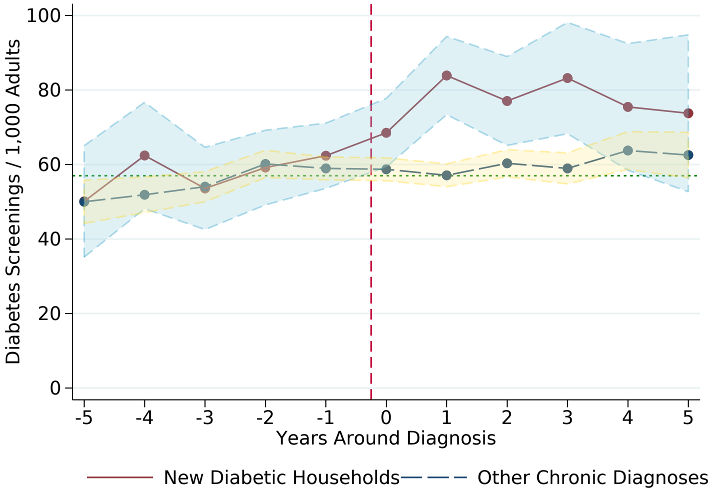
More interesting, households seek out **disease-specific prevention**:

- Diagnoses provide targeted risk signals (e.g., diabetes diagnoses)
- Preventive responses to risk *information* should be selective

Selective use of preventive services is visible even in *raw data*



Selective use of preventive services is visible even in *raw data*



For causal analysis, I estimate a **triple differences** approach:

$$
\begin{aligned}
Pr(\text{Screening})_{ftd} = {} & \beta_{\text{DD}}(\text{post}_t \times \text{chronic}_f) \\
& + \beta_{\text{DDD}}(\text{post}_t \times \text{chronic}_f \times \mathbb{1}\left\{\text{chronic}_f = d\right\}) \\
& + \alpha_f + \tau_t + \varepsilon_{ftd}
\end{aligned}
$$

For causal analysis, I estimate a **triple differences** approach:

$$
\begin{aligned}
Pr(\text{Screening})_{ftd} = {} & \beta_{\text{DD}}(\text{post}_t \times \text{chronic}_f) \\
& + \beta_{\text{DDD}}(\text{post}_t \times \text{chronic}_f \times \mathbb{1}\left\{\text{chronic}_f = d\right\}) \\
& + \alpha_f + \tau_t + \varepsilon_{ftd}
\end{aligned}
$$

Effect of *any* diagnosis

Effect of *specific* diagnosis

Effect of Chronic Events on Disease-Specific Screenings

For causal analysis, I estimate a **triple differences** approach:

$$\begin{aligned} Pr(\text{Screening})_{ftd} = {} & \beta_{\text{DD}}(\text{post}_t \times \text{chronic}_f) \\ & + \beta_{\text{DDD}}(\text{post}_t \times \text{chronic}_f \times \mathbb{1}\left\{\text{chronic}_f = d\right\}) \\ & + \alpha_f + \tau_t + \varepsilon_{ftd} \end{aligned}$$

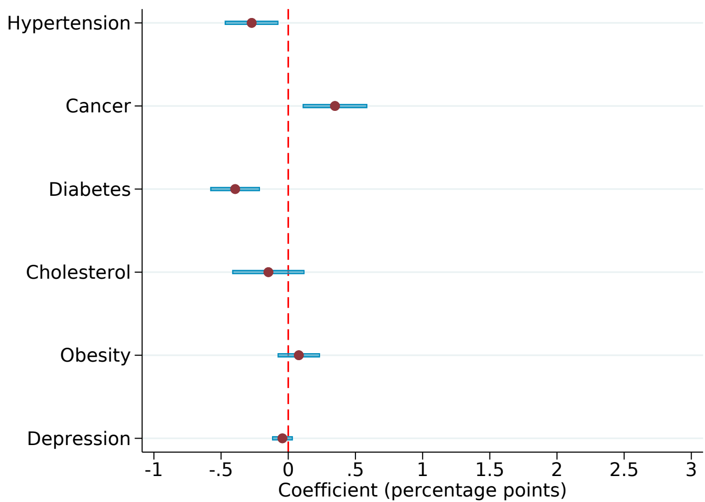
I use this approach for various **diagnoses** $\Longrightarrow$ **screenings**:

1. Any chronic diagnosis $\longrightarrow$ new hypertension diagnoses
2. Diabetes diagnoses $\longrightarrow$ diabetes screenings
3. Diabetes diagnoses $\longrightarrow$ cholesterol screenings
4. Cancer diagnoses $\longrightarrow$ cancer screenings

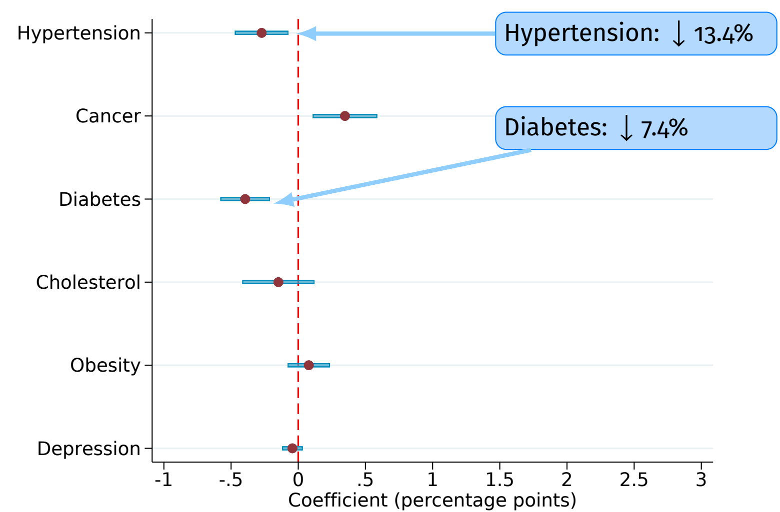
I also include placebo regressions to highlight role of *information*:

5. Diabetes diagnoses $\longrightarrow$ obesity diagnoses
6. Mental health diagnoses $\longrightarrow$ depression screenings

Screening decisions **respond little** to general health events:

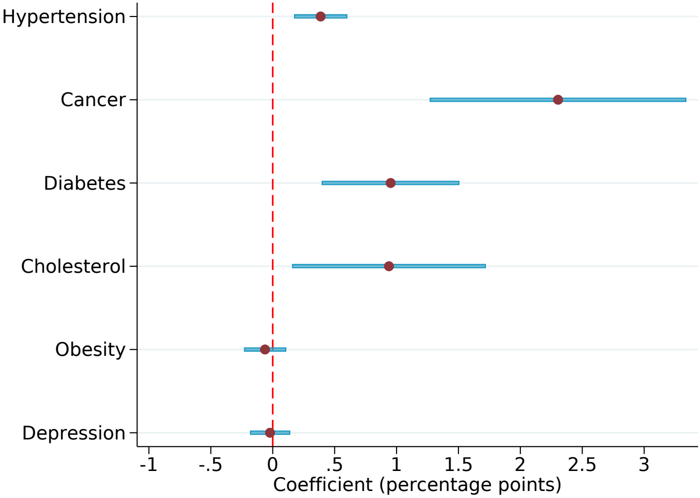


Screening decisions **respond little** to general health events:



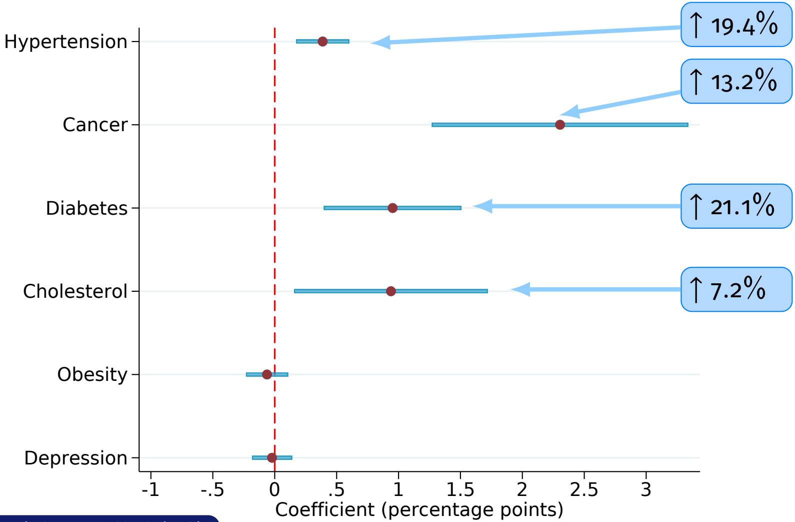
Triple Difference (β_{DDD}): Effect of Specific Diagnosis

Specific health events **trigger** specific screenings:



Triple Difference (β_{DDD}): Effect of Specific Diagnosis

Specific health events **trigger** specific screenings:



Heterogeneity by Household Relationship

Do *ex-post* choices look better?

Examine **spending** on low-value services:

- Health services identified as “low-return"
- Based on recommendations of Choosing Wisely initiative and other physician specialty organizations (Bhatia et al., 2015; Wolfson et al., 2014)

Do *ex-post* choices look better?

Examine **spending** on low-value services:

- Health services identified as "low-return"
- Based on recommendations of Choosing Wisely initiative and other physician specialty organizations (Bhatia et al., 2015; Wolfson et al., 2014)

Population	Pediatric	Adult			
Service Category	All	Drugs	Imaging	Screening	Surgery
$Post_t \times Diagnosis_f$	0.05*	-0.01	0.03***	0.10***	-0.10***
	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)
R^2	0.35	0.31	0.29	0.33	0.38

Notes: N=1,538,161. Standard errors clustered at the household level.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table. Estimated Effects of Chronic Illness on Low-Value Care Utilization

MECHANISMS

Major Health Events are ... Major

New diagnoses may do more than just **update risk beliefs**:

1. **Moral Hazard/Induced Demand Effects**:
   - Family member's maintenance costs associated with condition contribute to household deductible/OOP max
   - $\downarrow$ spot prices of care for rest of household

New diagnoses may do more than just **update risk beliefs**:

1. **Moral Hazard/Induced Demand Effects**:
   - Family member's maintenance costs associated with condition contribute to household deductible/OOP max
   - $\downarrow$ spot prices of care for rest of household
2. **Salience Effects**:
   - Health trauma may increase attention to one's overall health
   - $\uparrow$ marginal utility of seeking care

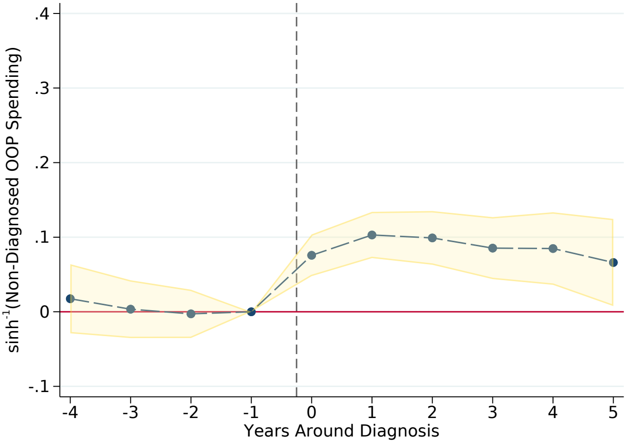
Major Health Events are ... Major

New diagnoses may do more than just **update risk beliefs**:

1. **Moral Hazard/Induced Demand Effects**:
   - Family member's maintenance costs associated with condition contribute to household deductible/OOP max
   - $\downarrow$ spot prices of care for rest of household
2. **Salience Effects**:
   - Health trauma may increase attention to one's overall health
   - $\uparrow$ marginal utility of seeking care
3. **Health System Literacy Effects**:
   - Diagnoses may improve knowledge of service availability/access
   - $\downarrow$ indirect costs of care

A natural question here is: “Isn’t this just a price response?"

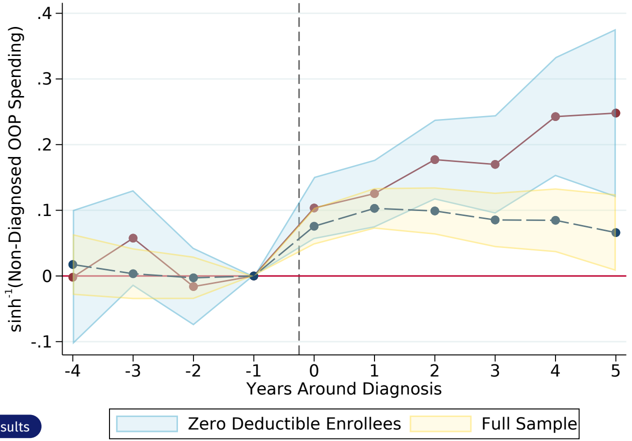
1. Responses are stable over time



Excluding Alternative Responses: Moral Hazard

A natural question here is: “Isn’t this just a price response?"

1. Responses are stable over time
2. Responses are mirrored for those with fewest financial incentives

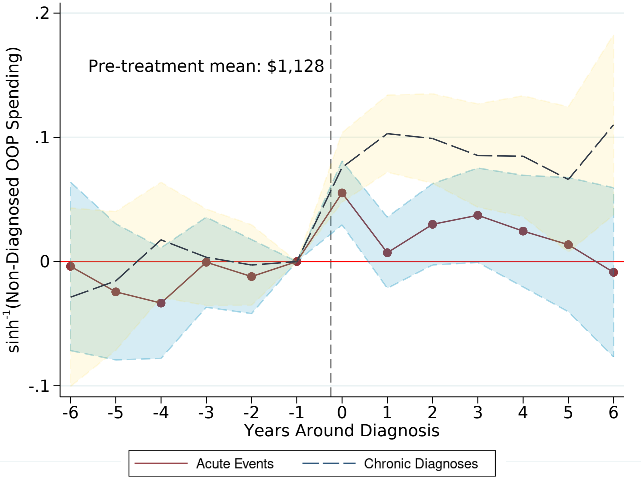


Additional Results

Excluding Alternative Responses: Salience Effects

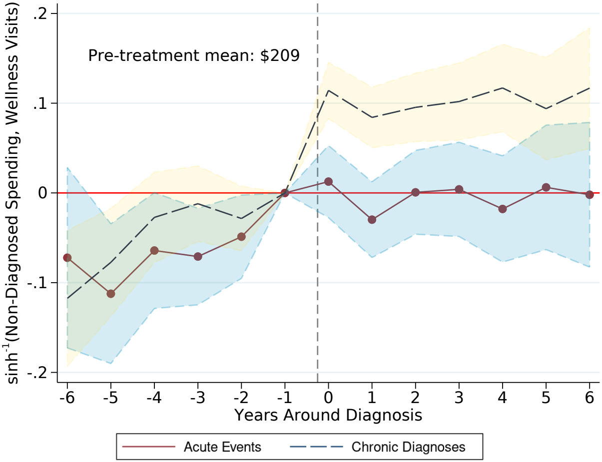
After *any* traumatic health event, families may reassess care value

1. Responses more pronounced for chronic events than acute ones



After *any* traumatic health event, families may reassess care value

1. Responses more pronounced for chronic events than acute ones
2. This is even more apparent when considering preventive utilization

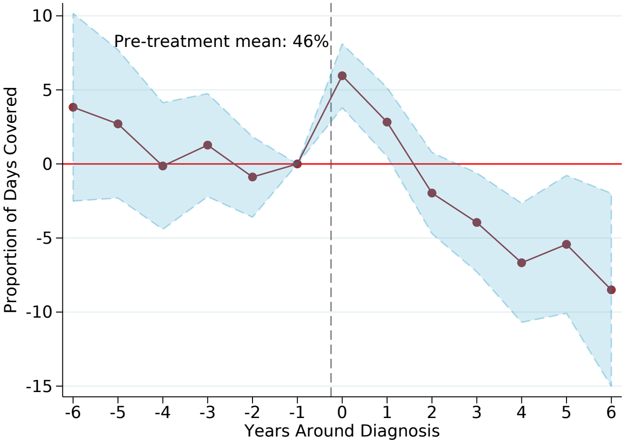


Might households be learning about health *systems* instead of risk?

- I examine impacts on adherence to prescribed preventive drugs

Might households be learning about health *systems* instead of risk?

- Health events spur (short-lived) re-adherence



Likelihood of Prescription Fills

STRUCTURAL MODEL

Model Setup & Timing

Main goal: quantify value of new health information

Two-stage choice model of consumer demand for health care

(Cardon & Hendel, 2001; Einav et al., 2013; Marone & Sabety, 2021)

1. Households choose health plans to maximize expected utility

Model Setup & Timing

Main goal: quantify value of new health information

Two-stage choice model of consumer demand for health care

(Cardon & Hendel, 2001; Einav et al., 2013; Marone & Sabety, 2021)

1. Households choose health plans to maximize expected utility
2. Individuals receive health shocks (acute and chronic)

Model Setup & Timing

Main goal: quantify value of new health information

Two-stage choice model of consumer demand for health care

(Cardon & Hendel, 2001; Einav et al., 2013; Marone & Sabety, 2021)

1. Households choose health plans to maximize expected utility
2. Individuals receive health shocks (acute and chronic)
3. Individuals choose health spending, trading off wealth and health

Model Setup & Timing

Main goal: quantify value of new health information

Two-stage choice model of consumer demand for health care

(Cardon & Hendel, 2001; Einav et al., 2013; Marone & Sabety, 2021)

1. Households choose health plans to maximize expected utility
2. Individuals receive health shocks (acute and chronic)
3. Individuals choose health spending, trading off wealth and health
4. Individuals update beliefs about probability of medical events

Model Setup & Timing

Main goal: quantify value of new health information

Two-stage choice model of consumer demand for health care

(Cardon & Hendel, 2001; Einav et al., 2013; Marone & Sabety, 2021)

1. Households choose health plans to maximize expected utility
2. Individuals receive health shocks (acute and chronic)
3. Individuals choose health spending, trading off wealth and health
4. Individuals update beliefs about probability of medical events

Important notes:

- Model is static: decisions today $\nrightarrow$ inputs tomorrow
- Type information evolves according to exogenous shocks
- Time is discrete (year)

Household Types & Heterogeneity

A household f is comprised of individuals $i \in \mathcal{I}_f$, characterized by:

1. Probabilities of diagnosis with a chronic illness, p_{ift}

Household Types & Heterogeneity

A household f is comprised of individuals $i \in \mathcal{I}_f$, characterized by:

1. Probabilities of diagnosis with a chronic illness, p_{ift}
2. Distributions of acute health shocks $\lambda_{ift} \sim F(\mu_\lambda, \sigma_\lambda, \kappa_\lambda)$
   - Shifted lognormal w/ mean μ_λ, variance σ_λ, and shift κ_λ

Household Types & Heterogeneity

A household f is comprised of individuals $i \in \mathcal{I}_f$, characterized by:

1. Probabilities of diagnosis with a chronic illness, p_{ift}
2. Distributions of acute health shocks $\lambda_{ift} \sim F(\mu_\lambda, \sigma_\lambda, \kappa_\lambda)$
    - Shifted lognormal w/ mean μ_λ, variance σ_λ, and shift κ_λ
3. Distribution of chronic care costs $m_{ft}^{\mathbf{CH}}$

Household Types & Heterogeneity

A household f is comprised of individuals $i \in \mathcal{I}_f$, characterized by:

1. Probabilities of diagnosis with a chronic illness, p_{ift}
2. Distributions of acute health shocks $\lambda_{ift} \sim F(\mu_\lambda, \sigma_\lambda, \kappa_\lambda)$
   - Shifted lognormal w/ mean μ_λ, variance σ_λ, and shift κ_λ
3. Distribution of chronic care costs $m_{ft}^{\mathbf{CH}}$
4. Risk aversion ψ_{ft} (hence, marginal utilities)

A household f is comprised of individuals $i \in \mathcal{I}_f$, characterized by:

1. Probabilities of diagnosis with a chronic illness, p_{ift}
2. Distributions of acute health shocks $\lambda_{ift} \sim F(\mu_\lambda, \sigma_\lambda, \kappa_\lambda)$
   - Shifted lognormal w/ mean μ_λ, variance σ_λ, and shift κ_λ
3. Distribution of chronic care costs $m_{ft}^{\mathbf{CH}}$
4. Risk aversion ψ_{ft} (hence, marginal utilities)

Health events affect:

- All individual beliefs $\{p_{ift}\}_{i \in \mathcal{I}_f}$
- Household risk aversion ψ_{ft}
- *de facto* care prices (moral hazard)

Model Stages: Medical Spending Choices

After choosing a plan $j \in \mathcal{J}$ and realizing health shocks $\{m_{ft}^{\text{CH}}, \lambda_{ift}\}_{\mathcal{I}_f}$, households choose **medical spending** that maximizes expected utility:

$$m_{ift}^{*} \equiv \text{argmax}_{m_{ift}} \text{EU}(m_{ift}; \lambda_{ift}, m_{ft}^{\text{CH}}, j) = p_{ift} u_{ift,\text{CH}} + (1 - p_{ift}) u_{ift,\text{H}}$$

Model Stages: Medical Spending Choices

After choosing a plan $j \in \mathcal{J}$ and realizing health shocks $\{m_{ft}^{\text{CH}}, \lambda_{ift}\}_{\mathcal{I}_f}$, households choose **medical spending** that maximizes expected utility:

$$m_{ift}^{*} \equiv \text{argmax}_{m_{ift}} \text{EU}(m_{ift}; \lambda_{ift}, m_{ft}^{\text{CH}}, j) = p_{ift} u_{ift,\text{CH}} + (1 - p_{ift}) u_{ift,\text{H}}$$

where

$$u_{ift,\text{H}} = \left[(m_{ift} - \lambda_{ift}) - \frac{1}{2\omega} (m_{ift} - \lambda_{ift})^2 \right] - c_j(m_{ift})$$

Model Stages: Medical Spending Choices

After choosing a plan $j \in \mathcal{J}$ and realizing health shocks $\{m_{ft}^{\text{CH}}, \lambda_{ift}\}_{\mathcal{I}_f}$, households choose **medical spending** that maximizes expected utility:

$$m_{ift}^{*} \equiv \text{argmax}_{m_{ift}} \text{EU}(m_{ift}; \lambda_{ift}, m_{ft}^{\text{CH}}, j) = p_{ift} u_{ift,\text{CH}} + (1 - p_{ift}) u_{ift,\text{H}}$$

where

$$u_{ift,\text{H}} = \left[(m_{ift} - \lambda_{ift}) - \frac{1}{2\omega} (m_{ift} - \lambda_{ift})^2 \right] - c_j(m_{ift})$$

and

$$u_{ift,\text{CH}} = \left[(\alpha_{1f} m_{ift} + \alpha_{2f} m_{ft}^{\text{CH}} - \lambda_{ift}) - \frac{1}{2\omega} (\alpha_{1f} m_{ift} + \alpha_{2f} m_{ft}^{\text{CH}} - \lambda_{ift})^2 \right] - c_j(m_{ift})$$

Solving the Utility Maximization Problem

Families **choose plans** with uncertain health states:

$$U_{fjt} = -\sum_{i \in \mathcal{I}_f} \left[\int \int \frac{1}{\psi_{ft}(x_{ft})} \exp\{-\psi_{ft}(x_{ft}) u^*_{ift}\} \, dF_{\lambda_i} dG_{m^{\text{CH}}} \right] - c_j(m^{\text{CH}}_{ft}) - \pi_{fj} - \eta \mathbb{1}_{fj,t-1}$$

Model Stages: Plan Choice

Families **choose plans** with uncertain health states:

$$U_{fjt} = -\sum_{i \in \mathcal{I}_f} \left[\int \int \frac{1}{\psi_{ft}(x_{ft})} \exp\{-\psi_{ft}(x_{ft}) u^*_{ift}\} \, dF_{\lambda_i} dG_{m^{CH}} \right]$$
$$-c_j(m^{CH}_{ft}) - \pi_{fj} - \eta \mathbb{1}_{fj,t-1}$$

- Households maximize sum of individual utilities
- Chronic care prices are attributed "first" (moral hazard)
- Changes to ψ_{ft} affect $\frac{\partial U_{fjt}}{\partial m^*_{ift}}$ (salience effects)

Parameter Responses to Health Events: Beliefs

Major health events provide households with **information** about risks p_{ift}

- Model as Bayesian learning
- **Prior beliefs** and **signals** assumed to be normally distributed
- **Posteriors** are thus given by:

$$\sigma^2_{pi,t+1} = \frac{\tilde{\sigma}^2_{ift}\sigma^2_{pio}}{\tilde{\sigma}^2_{ift} + s_{ift}\sigma^2_{pio}}$$

$$\mu_{pi,t+1} = \frac{\tilde{\sigma}^2_{ift}\mu_{pit} + \sigma^2_{pit}\tilde{\mu}_{ift}}{\tilde{\sigma}^2_{ift} + \sigma^2_{pit}}$$

Major health events provide households with **information** about risks p_{ift}

- Model as Bayesian learning
- **Prior beliefs** and **signals** assumed to be normally distributed
- **Posteriors** are thus given by:

$$\sigma^2_{pi,t+1} = \frac{\tilde{\sigma}^2_{ift}\sigma^2_{pio}}{\tilde{\sigma}^2_{ift} + s_{ift}\sigma^2_{pio}}$$

$$\mu_{pi,t+1} = \frac{\tilde{\sigma}^2_{ift}\mu_{pit} + \sigma^2_{pit}\tilde{\mu}_{ift}}{\tilde{\sigma}^2_{ift} + \sigma^2_{pit}}$$

- Updating is “triggered" by a **signal** parameterized by:

$$y_{ift} = \pi_1 \mathbb{1}\{\text{chronic}\}_{f,-i} + \pi_2 \mathbb{1}\{\text{acute}\}_{f,-i} + \pi_3 \mathbb{1}\{\text{acute}\}_{f,i} + \pi_4 x_{ift}$$

Major health events also change household **risk aversion**, ψ_{ft}

- Households update ψ_{ft} at the end of each period:

$$\psi_{ft} = \gamma_0 \psi_{f,t-1} + \gamma_1 \left\{ \text{Post}_t \times m_{f0}^{\text{CH}} \right\} + \gamma_2 \left\{ \text{Post}_t \times c_j(m_{f0}^{\text{CH}}) \right\} + \gamma_3 \left\{ \text{Post}_t \times \text{Hosp}_{f0} \right\}$$

- γ_0 measures **persistence** of risk aversion across years
- Impact of health event is allowed to vary by
  - Overall cost of event (billed spending)
  - OOP spending on event
  - Whether a hospitalization occurred

Data Variation & Identification

I identify **informational effects** separate from other channels using multiple sources of **variation**:

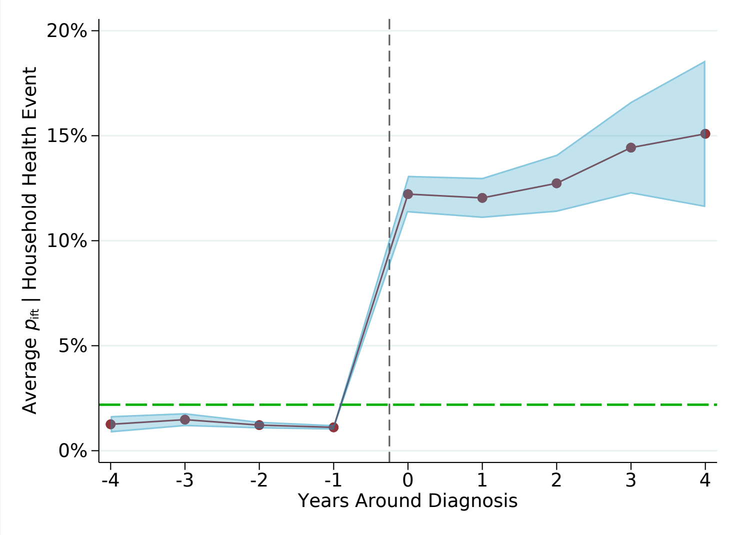
1. **Moral Hazard Effects** leverage cross-illness variation in:
   - Diagnostic cost
   - Maintenance cost
   - Plan characteristics
2. **Salience Effects** rely on plan choice set variation (Ericson et al., 2020)
   - Risk aversion drives plan choices in model, not spending
   - Repeated choices
   - Circumstances of major medical events

Estimation Overview

STRUCTURAL RESULTS

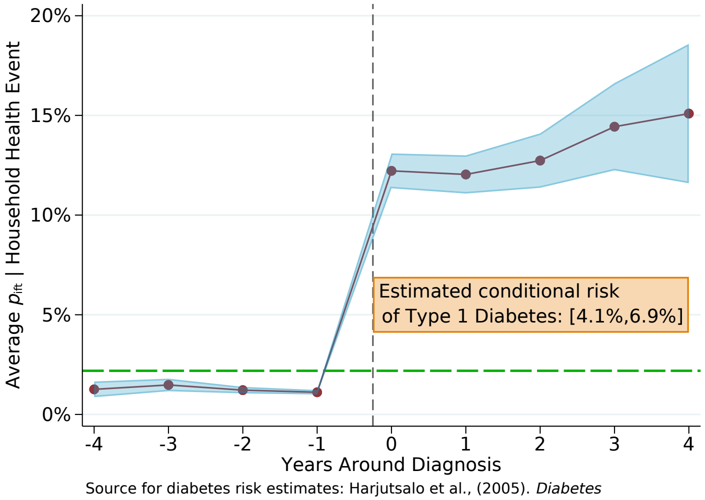
Finding 1: Large Belief Updating

Major health events are associated with **large increases** in risk beliefs:



Finding 1: Large Belief Updating

Major health events are associated with **large increases** in risk beliefs:



Parameter Estimates: Belief Changes

		Preferred Specification	
		Estimate	Std. Err.
Panel A: Dynamic Parameters			
Belief Evolution			
π_1	Family Chronic Event	0.33	(0.002)
π_2	Own Acute Event	0.05	(0.002)
π_3	Family Acute Event	0.06	(0.002)
π_4	Years since Event	0.01	(0.000)
σ_π	Error Variance	1.52	(0.018)

Notes: Average marginal effects on posterior means shown.

- **Chronic events** generate strong changes to risk beliefs
- Acute events generate weaker responses
- Effects are persistent

Finding 2: Residual Salience Effects

		Preferred Specification	
		Estimate	Std. Err.
Panel A: Dynamic Parameters			
Risk Aversion Evolution			
ψ_0	Persistence, Year $t-1$	0.95	(0.025)
ψ_1	Health Event (HE)	0.61	(0.015)
ψ_2	HE $\times$ Year 0 Cost	0.19	(0.020)
ψ_3	HE $\times$ Year 0 OOP	-0.88	(0.024)
ψ_4	HE $\times$ Hospitalization	1.51	(0.033)
σ_ψ	Error Variance	0.01	(0.016)

- Health events $\uparrow$ **risk aversion** by 34.9%
- Households respond to event **intensity**

Model Fit & Additional Parameters

Measure value of information as **marginal willingness to pay**

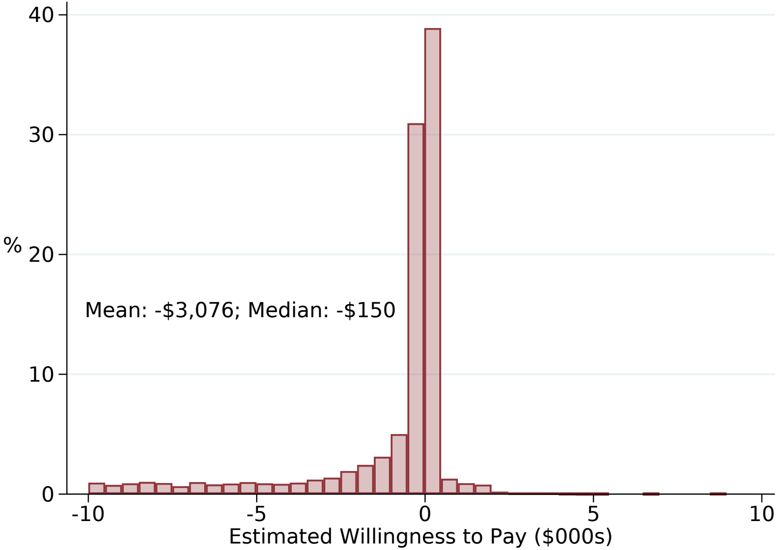
- Welfare metric: certainty equivalent

$$CE_{fjt} = -\psi_{ft}^{-1} \log(-U_{fjt})$$

- Report changes in CE_{fjt} relative to benchmark world:

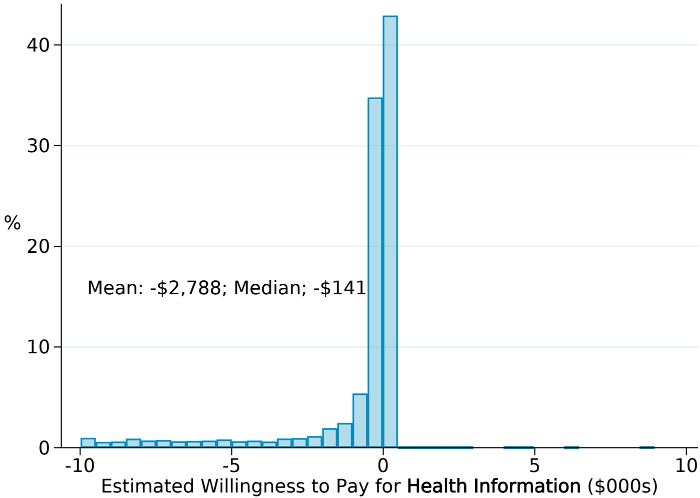
$$\Delta(CE) = CE_{fjt}(\text{event occurs}) - CE_{fjt}(\text{no event occurs})$$

Major Health Events Generate -$3,076 Loss



New Health Information Generates -$2,788 Loss

90% of welfare changes are attributable to **effect of new information**



Percentage Changes

Heterogeneity

COUNTERFACTUAL SCENARIOS

Scenario 1: What if Over-Responsiveness were Limited?

Welfare losses arise from **large changes** to risk beliefs

- Households overweight health risks by **6x**
- High risk beliefs $\Longrightarrow$ propagation of spending + low-value service use

Scenario 1: What if Over-Responsiveness were Limited?

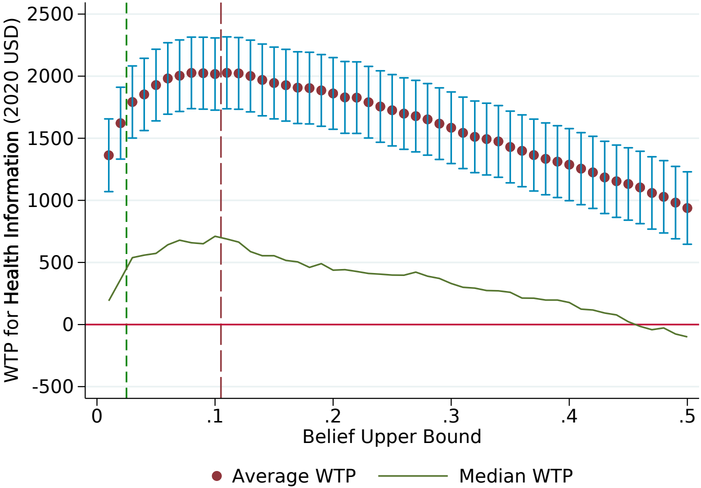
Welfare losses arise from **large changes** to risk beliefs

- Households overweight health risks by **6x**
- High risk beliefs $\Longrightarrow$ propagation of spending + low-value service use

What is the value of information when “correctly" interpreted?

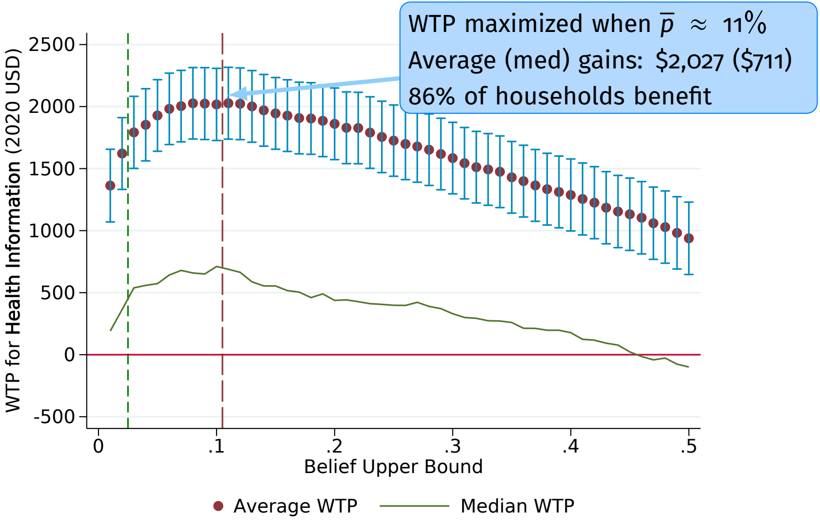
1. Place arbitrary **upper bounds** on $p_{if,t>0}$
2. Reevaluate **marginal WTP** with limits
3. Ignore moral hazard & salience effects

Bounding Belief Responsiveness Improves Welfare



Notes: Green dashed line indicates average in-sample rate of diagnosis.

Bounding Belief Responsiveness Improves Welfare



Notes: Green dashed line indicates average in-sample rate of diagnosis.

Scenario 2: Can Health Information be Targeted?

Policy revealing info. must balance heterogeneous returns:

Full revelation may not be optimal when:

1. Revelation is costly
2. Revelation disrupts insurance markets (Posey & Thistle, 2021)
3. Revelation is personally sub-optimal (Oster et al., 2013)

Scenario 2: Can Health Information be Targeted?

Policy revealing info. must balance heterogeneous returns:

Full revelation may not be optimal when:

1. Revelation is costly
2. Revelation disrupts insurance markets (Posey & Thistle, 2021)
3. Revelation is personally sub-optimal (Oster et al., 2013)

What is the value of **transmitting health risks**?

- For example: COVID-19 antibody screenings

Scenario 2: Can Health Information be Targeted?

Policy revealing info. must balance heterogeneous returns:
Full revelation may not be optimal when:

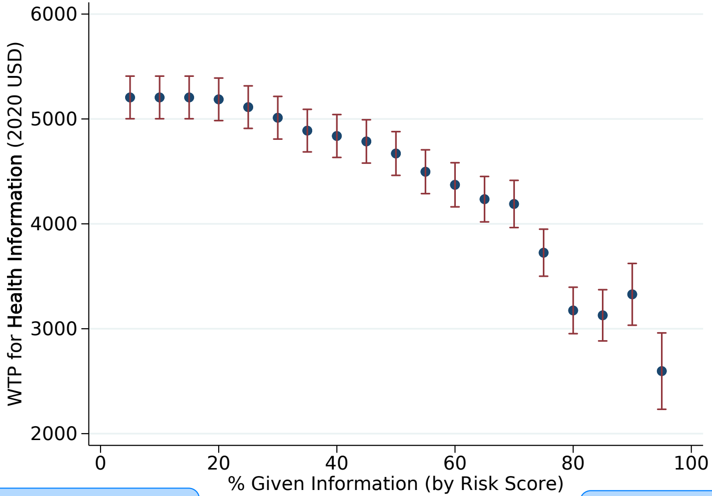
1. Revelation is costly
2. Revelation disrupts insurance markets (Posey & Thistle, 2021)
3. Revelation is personally sub-optimal (Oster et al., 2013)

What is the value of **transmitting health risks**?

- For example: COVID-19 antibody screenings

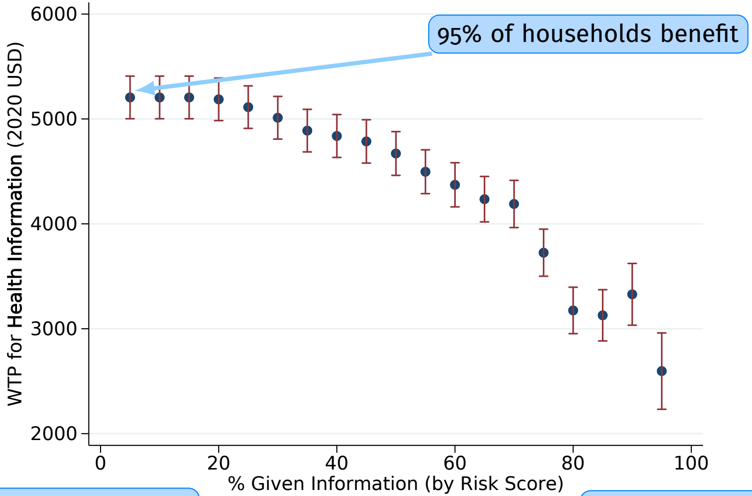
1. Simulate “revealing" health information to **control group**
2. At time t, individuals are given signal of predicted risk $\hat{p}_{if}$
3. Assume full responsiveness $(p_{if,t>0} = \hat{p}_{if})$

Targeting Information Revelation Improves Welfare



Only highest risk given information → Lower risk given information

Targeting Information Revelation Improves Welfare



Only highest risk given information → Lower risk given information

CONCLUSION

Conclusions & Future Work

Social networks provide **highly relevant** experiences for individuals

1. Observing **family health events** $\Longrightarrow$ to reassessment of risks
2. Volatile reassessments $\Longrightarrow$ **over-reactions** and welfare penalties
3. Limiting **responsiveness** can $\uparrow$ social value of health information

This analysis can be extended in several meaningful ways:

1. Endogenize chronic care health costs
2. Consider health production and liquidity constraints in modeling
3. Overlap between chronic conditions and job lock

AN OUNCE OF PREVENTION OR A POUND OF CURE?

THE VALUE OF HEALTH RISK INFORMATION

Alex Hoagland

Boston University

Additional Comments? alcobe@bu.edu

Website: alex-hoagland.github.io

APPENDIX

References (1/3)

- Abaluck & Compiani (2020). A Method to Estimate Discrete Choice Models that is Robust to Consumer Search. *NBER WP*
- Abaluck & Gruber (2011). Choice Inconsistencies among the Elderly: Evidence from Plan Choice in the Medicare Part D Program. *AER*.
- Abaluck & Gruber (2016). Evolving Choice Inconsistencies in Choice of Prescription Drug Insurance. *AER*.
- Alalouf et al. (2019). What Difference Does a Diagnosis Make? Evidence from Marginal Patients. *NBER WP*
- Baicker et al. (2015). Behavioral Hazard in Health Insurance. *QJE*.
- Barseghyan et al. (2018). Estimating Risk Preferences in the Field. *JEL*
- Bhatia et al. (2015). Measuring the effect of Choosing Wisely: an integrated framework to assess campaign impact on low-value care. *BMJ Quality & Safety*
- Cardon & Hendel (2001). Asymmetric Information in Health Insurance: Evidence from the National Medical Expenditure Survey. *RAND*
- Chernew et al. (2008). Learning and the value of information: Evidence from health plan report cards. *J Econometrics*
- Choudhry et al. (2009). Measuring Concurrent Adherence to Multiple Related Medications. *Am J Managed Care*.
- de Chaisemartin & D'Haultfoeuille (2019). Two-way fixed effects estimators with heterogeneous treatment effects. *NBER WP*.

References (2/3)

- Einav et al. (2013). Selection on Moral Hazard in Health Insurance. *AER*.
- Enthoven (1980). *Health Plan: The Only Practical Solution to the Soaring Cost of Medical Care.*
- Ericson et al. (2020). Inferring Risk Perceptions and Preferences Using Choice from Insurance Menus: Theory and Evidence. *The Economic J.*
- Fadlon & Nielsen (2019). Family Health Behaviors. *AER*.
- Fuchs (2004). More Variation In Use Of Care, More Flat-Of-The-Curve Medicine. *Health Affairs*
- Gruber et al. (2020). Managing Intelligence: Skilled Experts and AI in Markets for Complex Products. *NBER WP*.
- Grubb (2015). Overconfident Consumers in the Marketplace. *JEP*
- Handel (2013). Adverse Selection and Inertia in Health Insurance Markets: When Nudging Hurts. *AER*.
- Handel & Kolstad (2015). Health Insurance for "Humans": Information Frictions, Plan Choice, and Consumer Welfare. *AER*.
- Handel & Kolstad (2017). Wearable Technologies and Health Behaviors: New Data and New Methods to Understand Population Health. *AER*.
- Harjutsalo, Podar, & Tuomilehto. (2005). Cumulative incidence of type 1 diabetes in 10,168 siblings of Finnish young-onset type 1 diabetic patients. *Diabetes*.

References (3/3)

- Iizuka et al. (2021). Estimating the Marginal Value of Health Signals. *NBER WP*.
- Jones et al. (2019). What do Workplace Wellness Programs do? Evidence from the Illinois Workplace Wellness Study. *QJE*.
- Kenkel (1991). Health Behavior, Health Knowledge, and Schooling. *JPE*.
- Ketcham et al. (2012). Sinking or swimming in Medicare Part D. *AER*.
- Krummel (2019). The Rise of Wearable Technology in Health Care. *JNO*
- Marone & Sabety (in press). Should there be vertical choice in health insurance markets? *AER*.
- Oster et al. (2013). Optimal Expectations and Limited Medical Testing: Evidence from Huntington Disease. *AER*.
- Sloan et al. *The Smoking Puzzle: Information, Risk Perception, and Choice.*
- Shafer et al. (2021).Trends in pediatric wellness visits with out-of-pocket costs before and after the Affordable Care Act. *JNO.*
- Song & Baicker (2019). Effect of a Workplace Wellness Program on Employee Health and Economic Outcomes: A Randomized Clinical Trial. *JAMA*.
- Sorensen (2006). Social learning and health plan choice. *RAND*.
- Train (2009). *Discrete Choice Methods With Simulation.*
- Wolfson et al. (2014). Engaging Physicians and Consumers in Conversations About Treatment Overuse and Waste: A Short History of the Choosing Wisely Campaign. *Academic Medicine*

Example: **Asthma**

Codes

- J45 Asthma
  - J45.2 Mild intermittent asthma
    - J45.20 ...... uncomplicated
    - J45.21 ...... with (acute) exacerbation
    - J45.22 ...... with status asthmaticus
  - J45.3 Mild persistent asthma
    - J45.30 ...... uncomplicated
    - J45.31 ...... with (acute) exacerbation
    - J45.32 ...... with status asthmaticus
  - J45.4 Moderate persistent asthma
    - J45.40 ...... uncomplicated
    - J45.41 ...... with (acute) exacerbation
    - J45.42 ...... with status asthmaticus
  - J45.5 Severe persistent asthma
    - J45.50 ...... uncomplicated
    - J45.51 ...... with (acute) exacerbation
    - J45.52 ...... with status asthmaticus
  - J45.9 Other and unspecified asthma
    - J45.90 Unspecified asthma
      - J45.901 ...... with (acute) exacerbation
      - J45.902 ...... with status asthmaticus
      - J45.909 ...... uncomplicated
    - J45.99 Other asthma
      - J45.990 Exercise induced bronchospasm
      - J45.991 Cough variant asthma
      - J45.998 Other asthma

Additional restrictions:

- Require 1+ year of data **without** diagnosis
- Require 1+ year of **follow-up** data

Summarizing Major Medical Events

	Full Sample	Households with chronic conditions
Total spending	$2,504.41 [$679.75]	$3,378.17 [$957.52]
OOP spending	$443.07 [$109.66]	$531.93 [$151.18]
Incidence of chronic illness (per 1,000 individuals)		
Asthma	2.93	96.08
Breast/prostate cancer	0.35	11.58
Diabetes w/ complications	0.39	12.72
Diabetes w/o complications	1.18	38.57
Fibrosis of lung	0.46	15.10
MDD/biploar	1.62	52.76
Multiple sclerosis	1.10	36.17
Rheumatoid arthritis	0.17	5.70
Seizures	0.30	9.82
$N_{\text{individuals}}$	1,087,353	165,694

Back to Data

1. Individual and household deductibles (Zhang et al., 2018)
2. Household coinsurance rates and out-of-pocket maxima (Marone & Sabety, 2021)

Back to Data

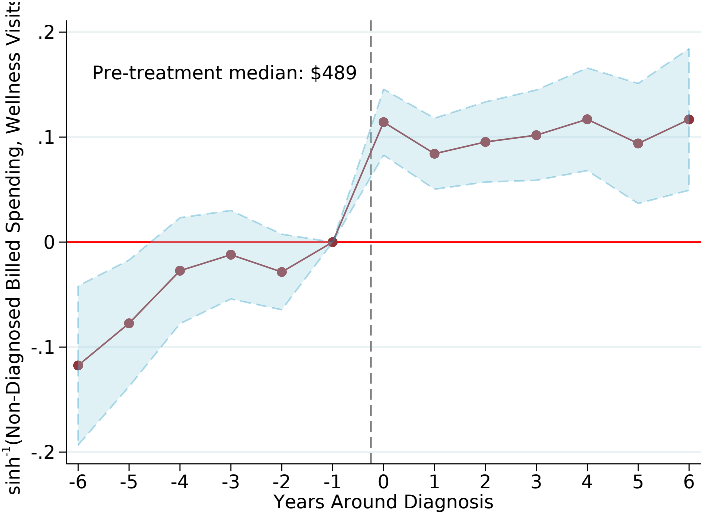
Robustness of Estimation Approach

I check my results against various **estimation approaches**:

1. Recentered Time Series: Results are visible in the raw data
2. Standard DD: Coefficients validate dynamic treatment effects
   - Results do not depend on measurement of dependent variable
3. Robust TWFE Estimation:
   - Use large control group to separately identify dynamic treatment effects and time trends (Sun & Abraham, 2020)
   - Verify lack of negative weighting in my approach (Goodman-Bacon et al., 2019)
   - Verify with robust estimators by Chaisemartin & D'Haultfoeuille, 2019 and Sant'Anna & Zhao, 2020

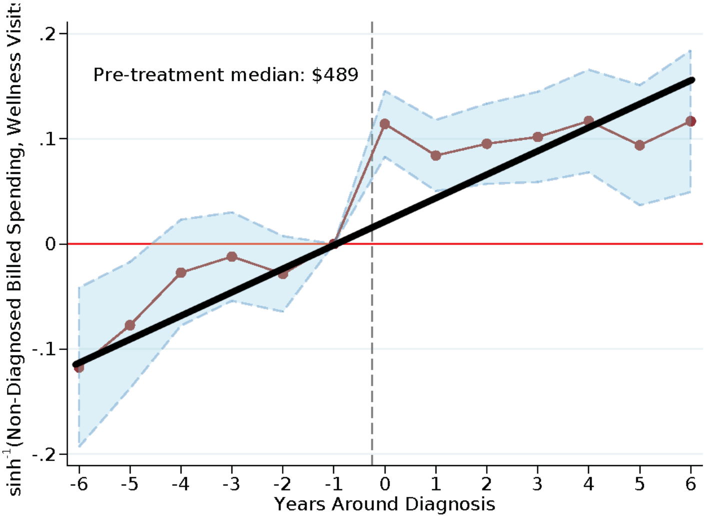
Back to Results

Observed Responses to Utilization of Preventive Care



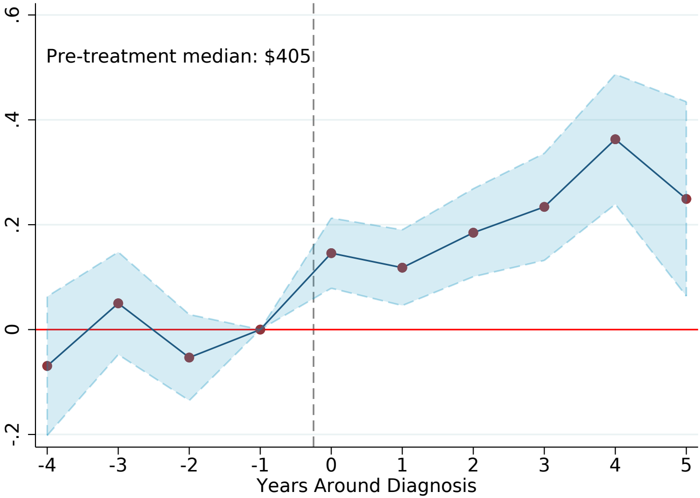
Back to Results

Time Trends in Utilization of Preventive Care

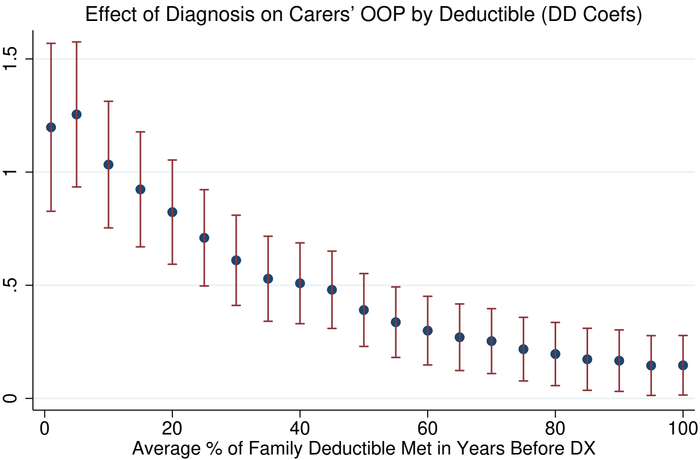


Back to Results

Takeup of Preventive Care Increases for those in 0-Ded Plans



Spending Responses are Largest for Low-Spending Families



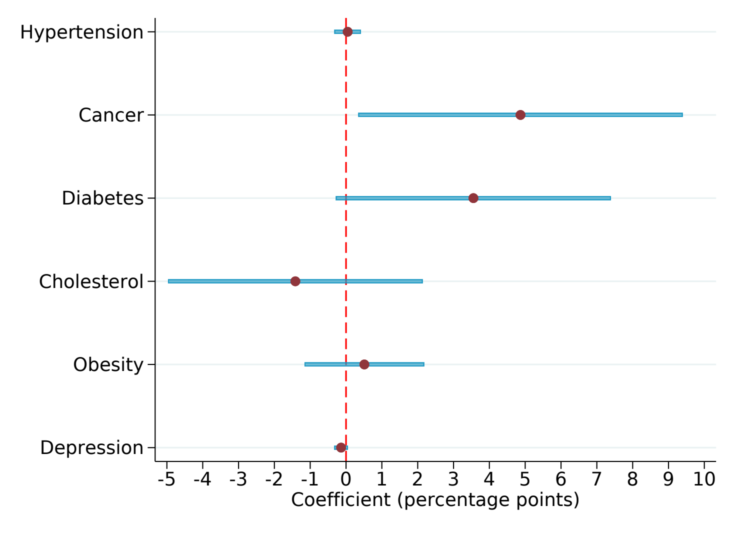
Note: Effect of chronic diagnoses for those spending q% of deductible or less prior to event.
Coefficient is for the inverse hyperbolic sine of OOP spending.

Extensive Margin Effects

	Year 0	Years 1–5 (average)
Any Billed Spending	1.54^{***}	0.60^{***}
	(0.08)	(0.13)
Any OOP Spending	2.62^{***}	1.41^{***}
	(0.11)	(0.18)
Any Outpatient Visits	2.20^{***}	0.65^{***}
	(0.09)	(0.15)
Any Preventive Care	3.23^{***}	0.90^{***}
	(0.15)	(0.22)
Any Prescription Fills	4.74^{***}	2.45^{***}
	(0.41)	(0.53)

Back to Results

Additional **placebo**: effect of a child's diagnosis on parent's screening



Heterogeneity in Disease-Specific Responses

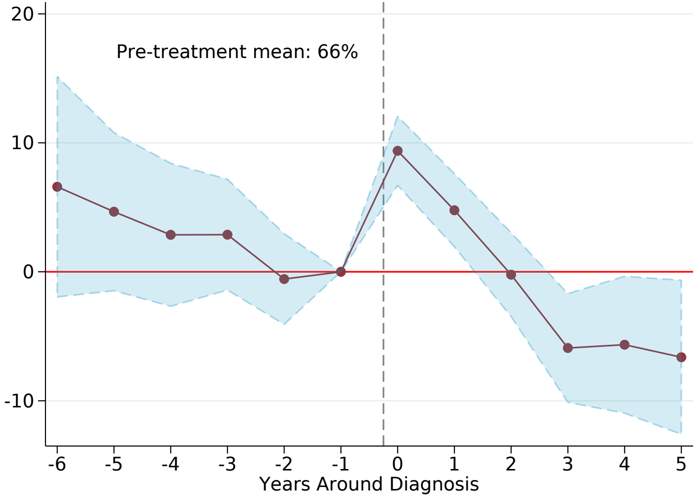
Screening *Diagnosis*	Hypertension *Any Chronic*	Cancer *Cancer*	Diabetes *Type 2 Diabetes*	Cholesterol
$Post_t \times Diagnosis_f \times Child_j$	**0.39***** (0.03)	**2.55***** (0.43)	**-0.85***** (0.21)	**-2.20***** (0.29)
$Post_t \times Diagnosis_f \times Parent_j$	-0.34** (0.11)	-1.90 (2.49)	3.49* (1.71)	3.73 (2.26)
$Post_t \times Diagnosis_f \times Spouse_j$	**-0.74***** (0.13)	**-3.33***** (0.81)	**2.54***** (0.45)	**5.15***** (0.60)
$Post_t \times Diagnosis_f \times Sibling_j$	**0.09** (0.04)	**1.56** (1.55)	0.76 (1.09)	2.89 (1.86)
Observations	4,039,602	3,671,064	3,680,725	3,680,725
Adjusted R^2	0.024	0.473	0.217	0.388

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Back to Results

Corresponding ↑ Likelihood in *Any* Prescription Refills



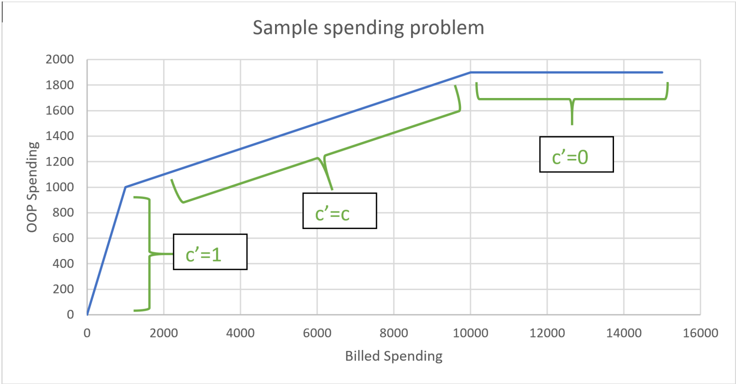
Back to Results

Solving the Model: Medical Spending

Optimal medical spending:

$$m^*_{ift} = \frac{1}{1 + p_{ift}(\alpha_1 - 1)} \left(\lambda_{ift} + \omega(1 + p_{ift}(\alpha_1 - 1) - c'_j(m_{ift})) - p_{ift}\alpha_2 m^{CH}_{ft} \right).$$

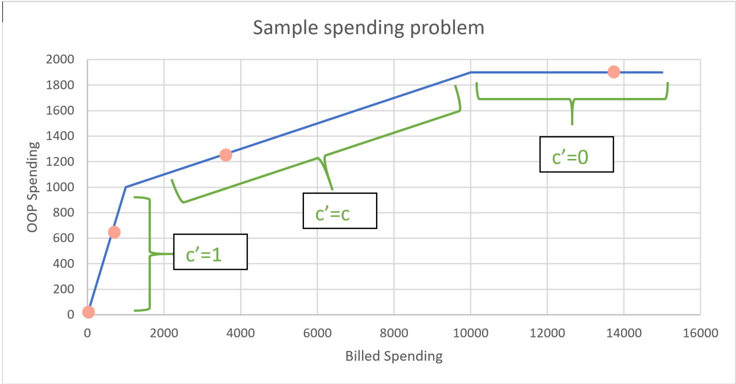
- Note that $c'_j(m_{ift})$ depends on overall spending



Optimal medical spending:

$$m^*_{ift} = \frac{1}{1 + p_{ift}(\alpha_1 - 1)} \left(\lambda_{ift} + \omega(1 + p_{ift}(\alpha_1 - 1) - c'_j(m_{ift})) - p_{ift}\alpha_2 m^{CH}_{ft} \right).$$

- Note that $c'_j(m_{ift})$ depends on overall spending



Back to Model

Estimation Overview

The model has the following parameters of interest **(θ)** to be estimated:

1. **Type shifters**: coefficients shifting starting means in $\{p_{ift}, \mu_{\lambda,i}, \psi_{f,t}\}$

$$\begin{bmatrix} p_{i,0} \\ \mu_{\lambda,i} \\ \log(\psi_{f,0}) \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \beta_p \mathbf{X}_k^p \\ \beta_\lambda \mathbf{X}_k^\lambda \\ \beta_\psi \mathbf{X}_k^\psi \end{bmatrix}, \begin{bmatrix} \sigma_p^2 & & \\ \sigma_{p,\lambda} & \sigma_\mu^2 & \\ \sigma_{p,\psi} & \sigma_{\lambda,\psi} & \sigma_\psi^2 \end{bmatrix}\right).$$

The model has the following parameters of interest **(θ)** to be estimated:

1. **Type shifters**: coefficients shifting starting means in $\{p_{ift}, \mu_{\lambda,i}, \psi_{f,t}\}$
2. **Type evolution**: coefficients that change p_{ift} and ψ_{ft} over time (including $\{\sigma_{\nu}^2, \sigma_{\psi}^2\}$)

The model has the following parameters of interest **(θ)** to be estimated:

1. **Type shifters**: coefficients shifting starting means in $\{p_{ift}, \mu_{\lambda,i}, \psi_{f,t}\}$
2. **Type evolution**: coefficients that change p_{ift} and ψ_{ft} over time (including $\{\sigma_{\nu}^2, \sigma_{\psi}^2\}$)
3. **Preference parameters**: $\alpha_{1f}, \alpha_{2f}, \omega, \eta$, and σ_{ε}^2

The model has the following parameters of interest **(θ)** to be estimated:

1. **Type shifters**: coefficients shifting starting means in $\{p_{ift}, \mu_{\lambda,i}, \psi_{f,t}\}$
2. **Type evolution**: coefficients that change p_{ift} and ψ_{ft} over time (including $\{\sigma_{\nu}^2, \sigma_{\psi}^2\}$)
3. **Preference parameters**: $\alpha_{1f}, \alpha_{2f}, \omega, \eta$, and σ_{ε}^2
4. Other **shape parameters** suppressed from notation

I estimate the model via **simulated maximum likelihood** (Train, 2009)

I estimate via the following steps:

1. Numerically integrate over dimensions of unobserved heterogeneity ($\{p_{i0}, \mu_{\lambda,i}, \psi_{f,\text{pre}}\}$)

I estimate via the following steps:

1. Numerically integrate over dimensions of unobserved heterogeneity ($\{p_{i0}, \mu_{\lambda,i}, \psi_{f,\text{pre}}\}$)
2. Simulate individual-level parameters across these support points

I estimate via the following steps:

1. Numerically integrate over dimensions of unobserved heterogeneity ($\{p_{i0}, \mu_{\lambda,i}, \psi_{f,\text{pre}}\}$)
2. Simulate individual-level parameters across these support points
3. Calculate implied λ_{ift} in each period given data/parameters

4 Construct conditional pdf of spending:

$$f_m(m_{ift}|\upsilon_{its}, \theta, \boldsymbol{X}) = \begin{cases} \Phi\left(\frac{-\kappa_i - \mu_{\lambda,i}}{\sigma_{\lambda,i}}\right) & m_{ift} = 0 \\ \Phi'\left(\frac{\lambda_{ift} - \kappa_i - \mu_{\lambda,i}}{\sigma_{\lambda,i}}\right) & m_{ift} > 0. \end{cases}$$

4 Construct conditional pdf of spending:

$$f_m(m_{ift} | \upsilon_{its}, \theta, \boldsymbol{X}) = \begin{cases} \Phi\left(\frac{-\kappa_i - \mu_{\lambda,i}}{\sigma_{\lambda,i}}\right) & m_{ift} = 0 \\ \Phi'\left(\frac{\lambda_{ift} - \kappa_i - \mu_{\lambda,i}}{\sigma_{\lambda,i}}\right) & m_{ift} > 0. \end{cases}$$

5 Construct choice probabilities:

$$L_{fits} = \frac{\exp(U_{fits}/\sigma_\epsilon)}{\sum_{i \in \mathcal{J}_{ft}} \exp(U_{fits}/\sigma_\epsilon)}$$

4 Construct conditional pdf of spending:

$$f_m(m_{ift}|\upsilon_{its},\theta,\boldsymbol{X}) = \begin{cases} \Phi\left(\frac{-\kappa_i-\mu_{\lambda,i}}{\sigma_{\lambda,i}}\right) & m_{ift}=0 \\ \Phi'\left(\frac{\lambda_{ift}-\kappa_i-\mu_{\lambda,i}}{\sigma_{\lambda,i}}\right) & m_{ift}>0. \end{cases}$$

5 Construct choice probabilities:

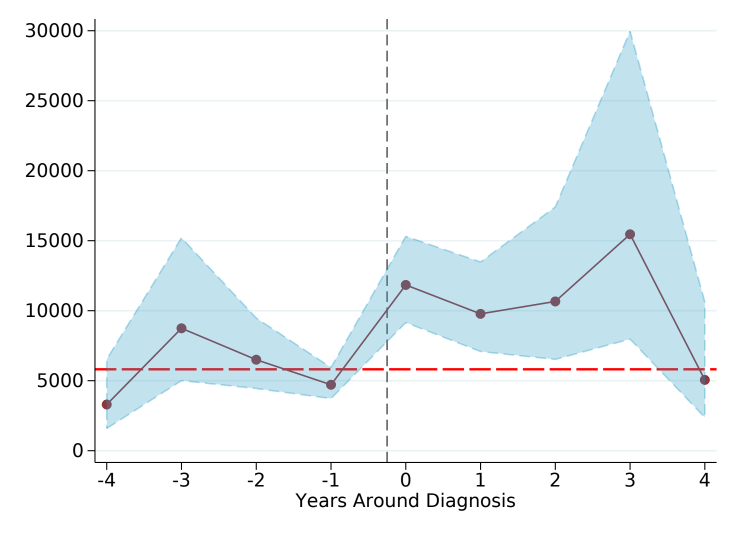
$$L_{fjts} = \frac{\exp(U_{fjts}/\sigma_\epsilon)}{\sum_{i\in\mathcal{J}_{ft}}\exp(U_{fits}/\sigma_\epsilon)}$$

6 Construct likelihood function and optimize:

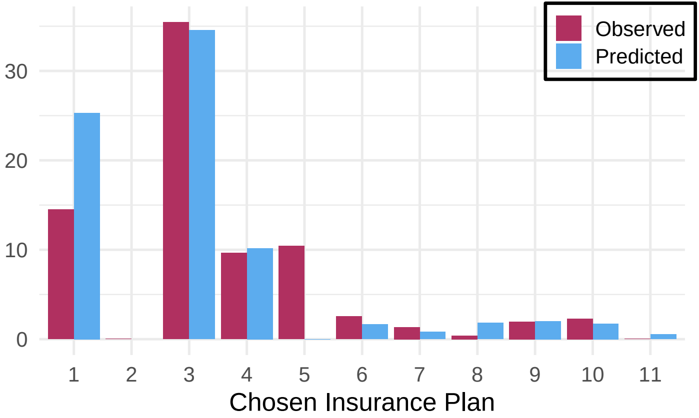
$$LL_f = \sum_{s=1}^{S} W_s \left(\prod_{t=1}^{T}\sum_{j=1}^{J} d_{fjt} f_m(m_{ft})\cdot L_{fjts}\right)$$

Back to Model Characterization

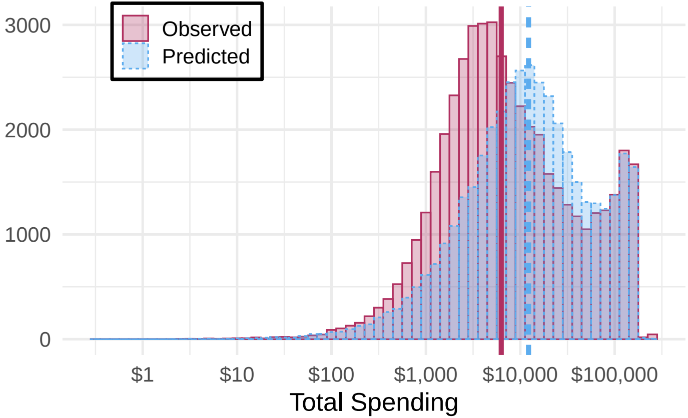
Model **captures** impacts of major health events on **predicted spending**



Model fit in the **plan choice** stage (match rate: **82.2%**)



Model fit in the **health spending** stage



Additional Parameters: Correlations

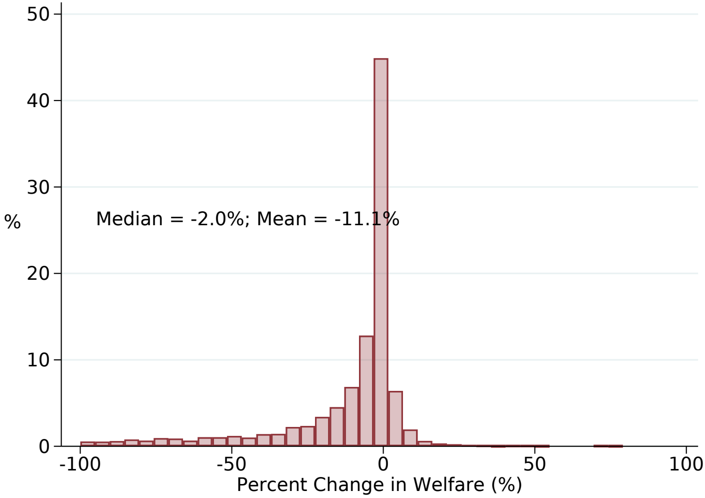
		Preferred Specification	
		Estimate	Std. Err.
Panel B: Heterogeneity in Types			
σ_ε^2	Idiosyncratic Shock	3.56	(0.085)
σ_p^2	Initial Beliefs	14.51	(0.001)
σ_ψ^2	Initial Risk Aversion	2.57	(0.005)
σ_λ^2	Acute Shocks	2.03	(0.001)
$\rho_{p,\psi}$		-0.54	(0.002)
$\rho_{p,\lambda}$		0.38	(0.002)
$\rho_{\psi,\lambda}$		0.09	(0.002)

Additional Parameters: Mean Shifters

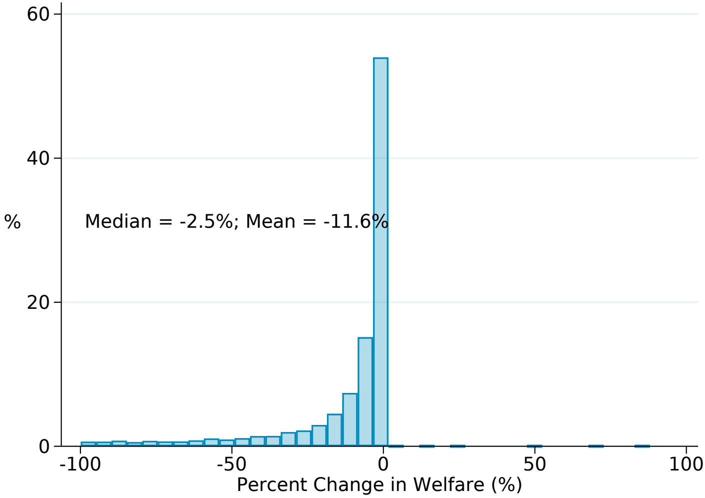
	p_0	λ	κ	ψ_0
Intercept	0.089	0.190	-0.105	0.112
Age	0.084	-0.088	-0.097	
Age^2	0.115	-0.006	-0.087	
Female	0.102	0.219	-0.117	
Individual risk score	0.100			
Any PE condition in family	0.107			
Type		0.152		
Family size				0.107
Average family age				0.052
Average family risk score				0.140

Back to Structural Results

Estimated Value of Information: Percentage Changes



Estimated Value of Information: Percentage Changes

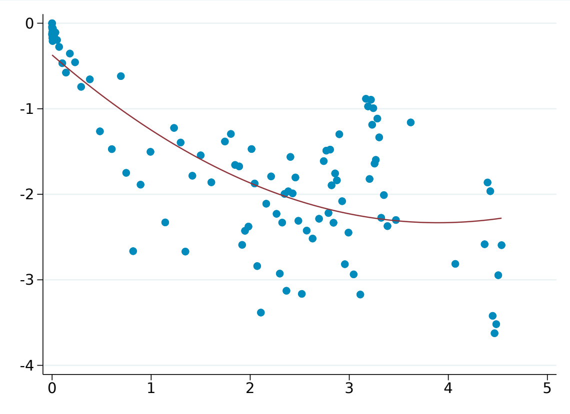


Back to Results

Heterogeneity in Welfare Effects of Information

Less averse households experience lower welfare penalties

- Higher risk aversion $\Rightarrow \uparrow$ “translation" of events into spending

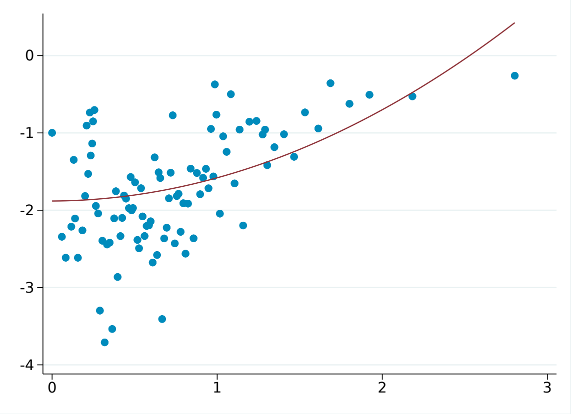


Initial Household Risk Aversion $\overline{\psi}$

Heterogeneity in Welfare Effects of Information

Households with ↑ expected risk experience lower welfare penalties

- Higher risk ⇒ smaller change in spending outcomes



Average Household Risk Scores

Back to Results