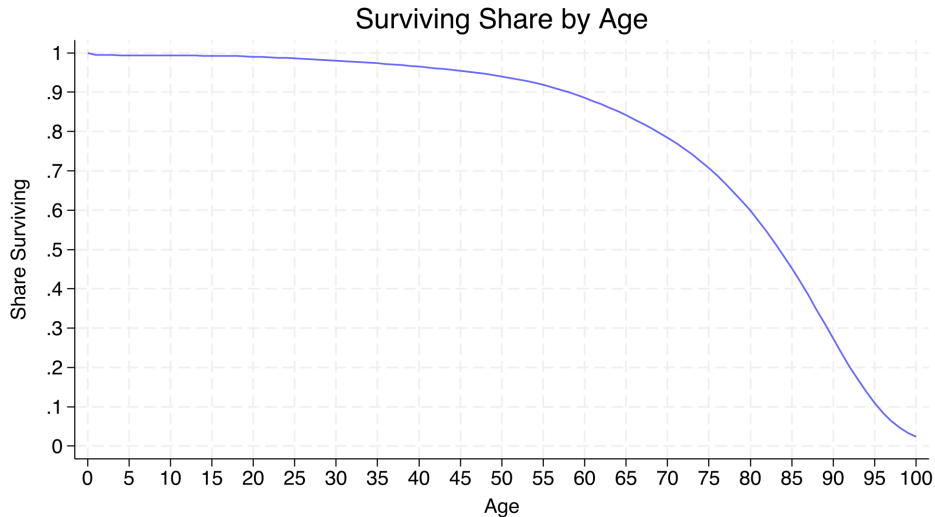


Endogenous Screening and Health Behaviors

Michael Darden Alex Hoagland

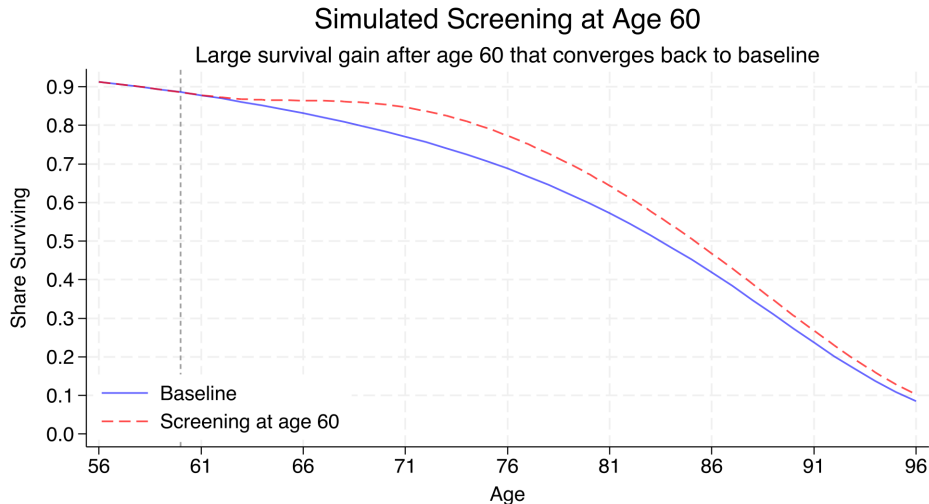
AHEW 2026

Johns Hopkins University & NBER · University of Toronto



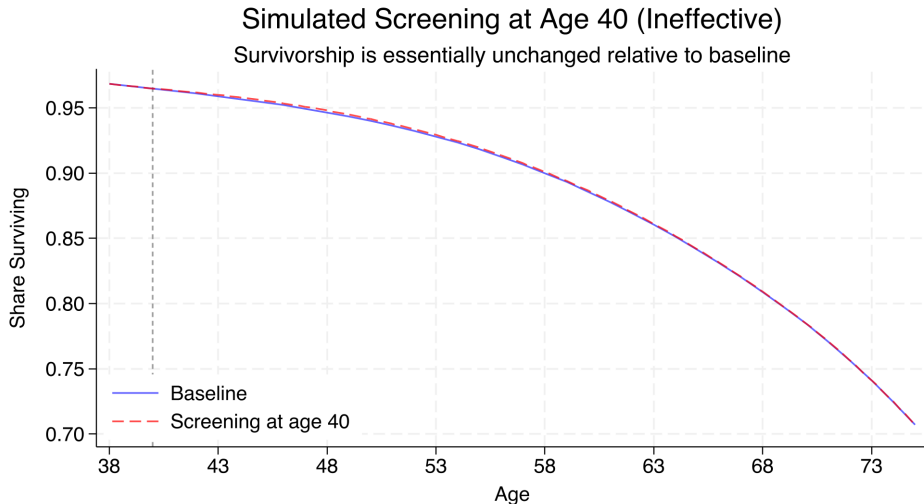
Source: United Nations, Department of Economic and Social Affairs, Population Division (2024). *World Population Prospects 2024, Online Edition*.

Screening at Age 60



Source: United Nations, Department of Economic and Social Affairs, Population Division (2024). World Population Prospects 2024, Online Edition.
Note: illustrative simulation of a large survival gain following screening at age 60.

Screening at Age 40



Source: United Nations, Department of Economic and Social Affairs, Population Division (2024). World Population Prospects 2024, Online Edition.
Note: illustrative simulation of an ineffective screen at age 40; the two curves nearly coincide.

Screening guidelines are frequently revised

NPR · 2024

Mammograms should start at age 40, new guidelines recommend

<https://www.npr.org/sections/health-shots/2024/04/30/1247941059/breast-cancer-screening-mammograms-women-health>

Fox News · 2021

Cancer group says colon screening should start at 45, not 50

<https://www.foxnews.com/health/cancer-group-says-colon-screening-should-start-at-45-not-50>

The New York Times · 2011

U.S. Panel Says No to Prostate Screening for Healthy Men

<https://www.nytimes.com/2011/10/07/health/07prostate.html>

STAT · 2023

American Cancer Society expands lung cancer screening guidelines for cigarette smokers

<https://www.statnews.com/2023/11/01/lung-cancer-screening-smokers-american-cancer-society/>

Healio · 2021

USPSTF makes “huge” change to prediabetes, diabetes screening recommendations for adults

<https://www.healio.com/news/primary-care/20210824/uspstf-makes-huge-change-to-prediabetes-diabetes-screening-recommendations-for-adults>

Health screening is **diagnostic**, its value depends on:

- Who is screened (Einav *et al.* (2020)) &
- What the test detects *and when*.

Health screening is **diagnostic**, its value depends on:

- Who is screened (Einav *et al.* (2020)) &
- What the test detects *and when*.

Health screening is also **information**; its value also depends on:

- How screening information **changes subsequent prevention**.

In this paper, we:

1. Develop a simple model of screening and prevention. Screening and prevention are connected by:
 - **Prevention Responsiveness:** Beliefs must impact the future value of prevention; otherwise, screening has no value
 - **Screening Informativeness:** Agents must (correctly or incorrectly) believe test has diagnostic value
 - **State-dispersion of Returns:** Captures the relative marginal value of prevention in survival across health states.
 - **Moral Hazard:** A negative screen “clears” me from needing prevention
 - **Value of Future Life:** A negative screen increases the utility from survival, incentivizing more prevention

In this paper, we:

1. Develop a simple model of screening and prevention. Screening and prevention are connected by:
2. Estimate a dynamic learning model in the context of lung cancer, lung cancer screening, and cigarette smoking.
 - Context implies a value-of-life hypothesis.
 - A one-time screen at age 45 lowers smoking by 11.9%, 7.5 additional years smoke-free, and lifetime lung cancer incidence by 2.2%.
 - Among those whose cancer incidence falls, 80.2% live longer, by an average of 7.9 years.

Our Contribution

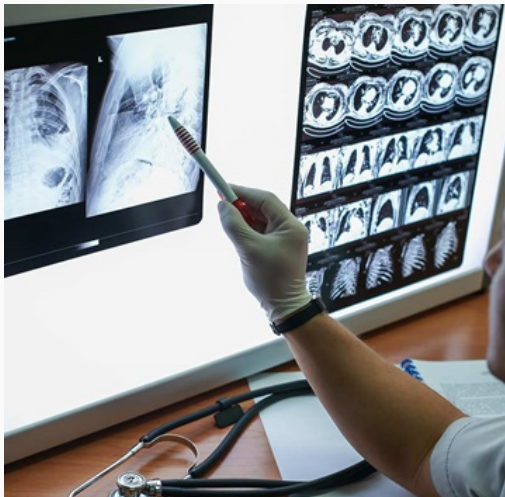
1. **Economics:** Preventive care presents an intertemporal tradeoff associated with a foundational form of human capital.
 - Grossman (1972); Becker and Ehrlich (1972); Gilleskie(1998); Miguel and Kremer (2004) Chandra *et al.* (2010); Baicker, Mullainathan & Schwartzstein (2015); Wang & Sloan (2018); Alsan, Garrick & Graziani (2019); Newhouse (2021).
 - “Mickey Mantle Effect” (Fang *et al.*, 2007)
 - Thornton (2008), Gong (2015), de Paula *et al.* (2014), Delavande & Kohler (2016)
2. **Medicine:** Preventive care is “underutilized”.
 - Pham *et al.* (2005); Maciosek *et al.* (2006); Maciosek *et al.* (2017); Choudhry *et al.* (2011); Levine *et al.* (2022); Taksler *et al.* (2021)
3. **Policy:** Recommendations and coverage decisions have evolved.

Table of contents

1. Introduction
2. Context
3. Structural Model
4. Data
 - Novel Experimental & Survey Data
 - Clinical & Observational Data
5. Estimation & Identification
6. Model Results & Counterfactuals
7. Conclusions

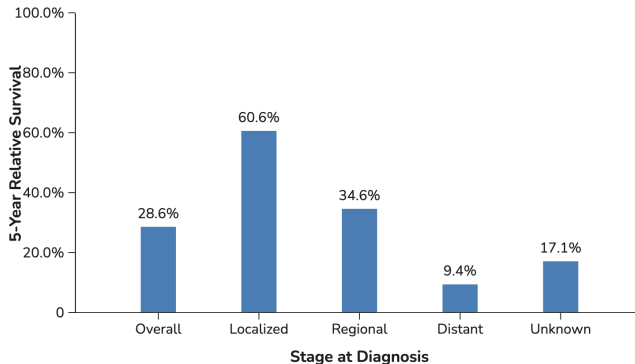
This Paper: Low-Dose Computed Tomography (LDCT) Lung Cancer Screening

We study these in the context of **lung cancer screening**, where LDCT scans provide information and may influence future smoking cessation (prevention)



Features of LDCT Lung Cancer Screening

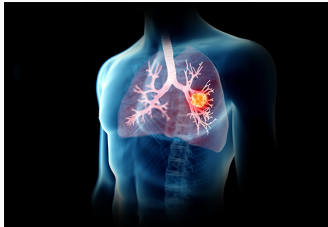
1. Early detection of LC has huge implications.
 - Lung cancer is the third most common cancer in the United States.
 - More people in the United States die from lung cancer than any other type of cancer.



*Based on cancers diagnosed from 2015 to 2021 and follow-up of patients through December 31, 2021.

Features of LDCT Lung Cancer Screening

1. Early detection of LC has huge implications.
2. 80% of lung cancers are caused by cigarette smoking.
 - Importantly, cessation before age 50 dramatically improves risk
 - Simultaneous decisions: smoking and screening
 - Addiction and risky behavior literature



Features of LDCT Lung Cancer Screening

1. Early detection of LC has huge implications.
2. Simultaneity: 80% of lung cancers are caused by cigarette smoking.
3. Significant shifts in policy
 - In 1996: United States Preventive Services Task Force (USPSTF) gives grade of D (due to limited evidence + concern over false positives)
 - **The National Lung Screening Trial (NLST)**: Randomized trial showed LDCT screening reduced mortality relative to chest radiography.
 - Cut to 2023: expanded screening eligibility based on **age** and **smoking history**

LDCT is a tractable, but generalizable, setting to study these questions

Table of contents

1. Introduction

2. Context

3. Structural Model

4. Data

Novel Experimental & Survey Data

Clinical & Observational Data

5. Estimation & Identification

6. Model Results & Counterfactuals

7. Conclusions

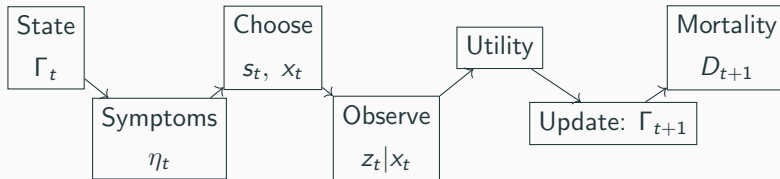
Structural Model Overview

- Dynamic model of smoking and screening behavior, estimated via GMM
- Model features include:
 - Addiction
 - Health Dynamics
 - Mortality
 - Learning
 - Competing Risk
- Rationalizes observed smoking/screening in observational data and provides empirical evidence on sufficient statistics above

Structural Model Overview

- Dynamic model of smoking and screening behavior, estimated via GMM
- Model features include:
 - Addiction
 - Health Dynamics
 - Mortality
 - Learning
 - Competing Risk
- Rationalizes observed smoking/screening in observational data and provides empirical evidence on sufficient statistics above

Representative Period:



Structural Model Overview

- Dynamic model of smoking and screening behavior, estimated via GMM
- Model features include:
 - Addiction
 - Health Dynamics
 - Mortality
 - Learning
 - Competing Risk
- Rationalizes observed smoking/screening in observational data and provides empirical evidence on sufficient statistics above

Utility Function:

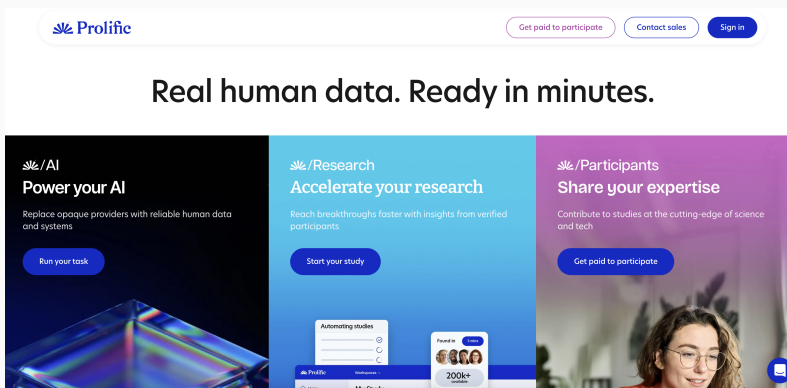
$$\begin{aligned} u(s_t, x_t; \Gamma_t) = & U_\theta + \frac{(W_t - p_s s_t - p_x x_t - p_y y_t)^{1-\gamma_0}}{1-\gamma_0} \quad \text{(CRRA Consumption)} \\ & + (\gamma_1 + \gamma_2 h_t + \gamma_3 h_t^2) \cdot s_t \quad \text{(Addiction)} \\ & - \sum_{v \in \nu} \gamma_{4,v} x_t \mathbb{1}\{\nu_i = v\} - \gamma_5 \tilde{p}_t - \gamma_6 \mathbb{1}\{\eta_t > 0\} \quad \text{(Screening/symptom disutility)} \end{aligned}$$

Table of contents

1. Introduction
2. Context
3. Structural Model
- 4. Data**
 - Novel Experimental & Survey Data
 - Clinical & Observational Data
5. Estimation & Identification
6. Model Results & Counterfactuals
7. Conclusions

To estimate the model, we combine data from:

1. **Experimental data**: a **pre-registered** survey, with a randomized information experiment among 4,000 current and former smokers
 - Identifies preferences, beliefs, and expectations of future cancer
 - Randomly varies information about prices, stigma, & test quality
 - Elicits how current smokers change smoking after negative screening
2. **Clinical data**: Truveta EHR Data, National Lung Screening Trial allow us to
 - Measure real-world diagnostic outcomes (false positives)
 - Recover (plausibly policy-invariant) transition probabilities for cancer onset, progression, & treatment
3. **Observational (social) data**: Behavioral Risk Factor Surveillance System – identifies smoking preferences & addiction patterns



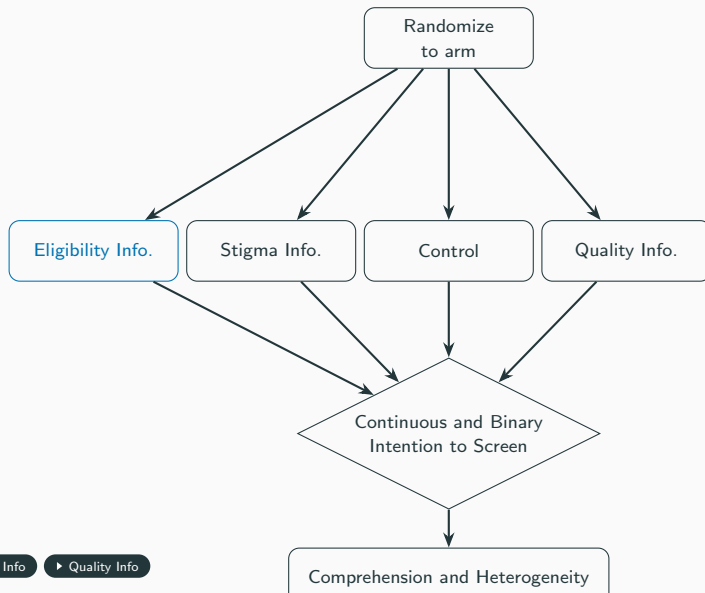
Survey Information:

- 4,000 respondents from November 20th, 2025 - February 15th, 2026.
- Sample of individuals with some smoking history, 40+ years of age.

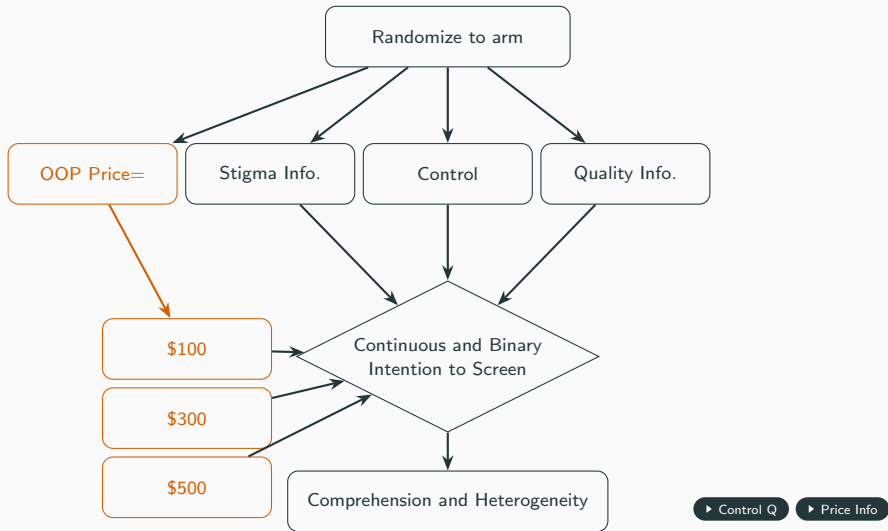
Baseline Information

- Risk Preferences (Kimball, Sahm, and Shapiro, 2008)
- Time Preferences (Falk *et al.* 2018)
- Health Insurance
- Income
- Zip Code
- Current Smoking Behavior and Smoking History.
- Beliefs and expectations regarding:
 - Cancer Risk
 - False Positives
- Screening Preferences

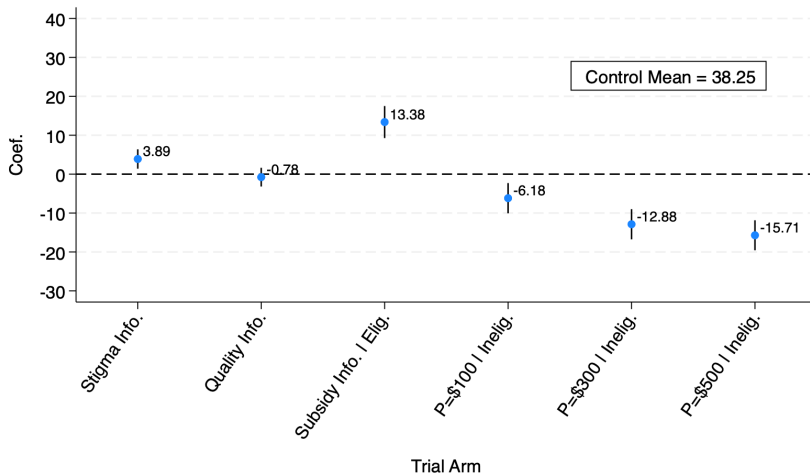
Experimental Design: USPSTF Eligible Branch



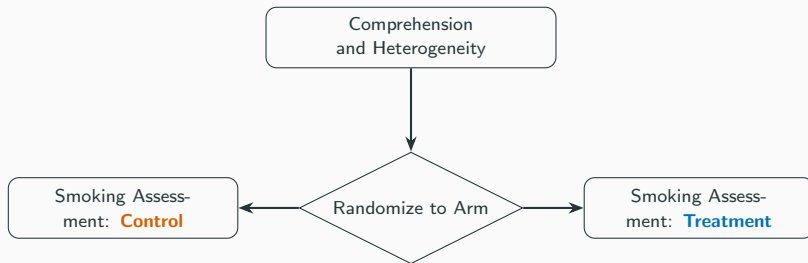
Experimental Design: USPSTF Ineligible Branch



Main Results: Intent to Screen



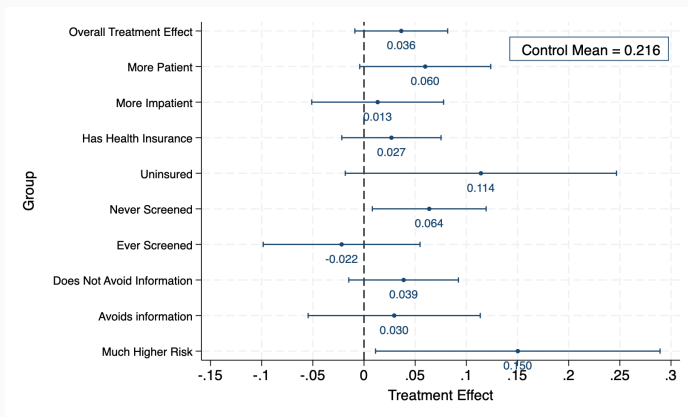
Smoking Experiment



Thinking about the next 12 months, please indicate which option best reflects your expectations regarding your smoking behavior.

Suppose a recent lung cancer screening revealed no evidence of cancer. Thinking about the next 12 months, please indicate which option best reflects your expectations regarding your smoking behavior.

Main Results: Smoking Experiment



- Treatment ↑ intention to quit by 16.7% ($N = 1,342$ current smokers)
- Effects largest for: self-assessed high risk (69.4%); uninsured (52.3%, imprecise); those without prior screening (29.6%); and more patient smokers (27.8%)

Table of contents

1. Introduction
2. Context
3. Structural Model
4. Data
 - Novel Experimental & Survey Data
 - Clinical & Observational Data
5. Estimation & Identification
6. Model Results & Counterfactuals
7. Conclusions

Estimation strategy: three tiers of parameters

1. Calibrated / elicited

- $\beta = 0.95$, CRRA $\gamma_0 = 2$ (survey)
- Prices p_s, p_x, p_y ; income W
- **Objective** test quality:
 $\rho = 0.703$, $\lambda = 0.121$ (Truveta EHR)
- **Subjective** test quality:
 $\hat{\rho} = 0.644$, $\hat{\lambda} = 0.179$ (survey)
- Symptom likelihoods $\Pr(\eta \mid \theta)$ (Literature)

2. Health Transitions, policy-invariant

- Cancer Onset (NLST logit, randomized arms)
- Cancer Progression (NLST discrete-time hazard, episode-split, right-censored)
- Chronic onset ψ (pooled risk tables)
- Mortality ω (SEER life tables, comorbidity evidence)

3. Simulated GMM

- Health-state utility
 $U_{\theta < 3}, U_{\theta = 3}$
- Smoking & addiction
 $\gamma_1, \gamma_2, \gamma_3$
- Screening disutility by type
 $\gamma_{4,0}, \dots, \gamma_{4,3}$
- OOP price disutility γ_5
- Symptom disutility γ_6
- Initial belief distribution b_0

Simulated GMM

For a candidate Θ :

1. Solve the finite-horizon model (ages 40–100) by **backward induction** over $\Gamma_t = (\theta_t, d_t, b_t, h_t, \phi_t, \nu)$; two binary choices (s_t, x_t) per period
2. Simulate **1,000,000 agents** with characteristics matched to BRFSS + survey
3. Stack person-period contributions $g_i(\Theta)$ and minimize

$$\hat{\Theta} = \arg \min_{\Theta} \bar{g}(\Theta)' W \bar{g}(\Theta), \quad \bar{g}(\Theta) = \frac{1}{N} \sum_i g_i(\Theta)$$

Moment block	Example target	Source
Smoking by age bin	$s_i - s_{k(a_i)}^*$	BRFSS
Smoking reinforcement	$100s_i - (17.126 + 1.105h_i - 0.009h_i^2)$	BRFSS
Screening by eligibility	$x_i - 0.254$ (inelig.), $x_i - 0.516$ (elig.)	Survey
Screening by age $\times$ pack-years	bin means, 4 profiles	BRFSS
Experimental effects	stigma 0.08, optimism 0.21, price -0.17	Survey RCT
Cancer incidence by age	$\mathbb{1}[\theta_i \geq 2] - \pi_{k(a_i)}^*$	SEER
Mean belief (cancer-free)	$b_i - 0.2217$	Survey

Identification I: addiction and the value of survival

Smoking preferences ($\gamma_1, \gamma_2, \gamma_3$)

- Level: age profile of smoking prevalence among those with smoking history by 40
- Shape: BRFSS smoking–pack-year relationship is **concave** (Table A3)
- $\gamma_2 > 0$ generates reinforcement; γ_3 and the quadratic target pin curvature

Health-state utility ($U_{\theta < 3}, U_{\theta = 3}$)

- Cardinalize the value of being alive in each state; death normalized to 0
- Disciplined by screening *and* cancer incidence: agents only pay to screen if resolving uncertainty raises expected continuation value

Magnitude check

At $h_t = 20$ pack-years, $U_{\theta < 3} \approx 5.7 \times$ the flow utility of smoking: addiction is strong but *not* strong enough to shut down prevention responsiveness.

Identification II: screening demand from the RCT

Randomization delivers **exogenous shifts in each channel**.

Parameter	Identifying variation	Target
γ_5 (OOP price)	Ineligible arm: randomized quotes \$100/\$300/\$500	Participation elasticity -0.17 at eligibility crossing
$\gamma_{4,1}$ (stigma)	Stigma-reduction arm; larger for high-baseline-stigma	Type 1 – 2, 3 – 4 contrasts: 0.08
$\gamma_{4,2}$ (pessimism)	Quality arm $\times$ baseline $\hat{\lambda}$ (good vs. bad news)	Type 3 – 1, 4 – 2 contrasts: 0.21
$\gamma_{4,3}$ (interaction)	Joint high stigma & pessimism	Residual across the four types
$\gamma_{4,0}, b_0$	Screening <i>levels</i> given beliefs	$0.254 / 0.516$; mean belief 0.2217
γ_6 (symptoms)	Symptom $\rightarrow$ belief $\rightarrow$ screening	Beliefs, cancer incidence

Separating price from information

Eligible respondents learn “covered at \$0” $\Rightarrow$ price *and* guideline signal (+40%). Ineligible respondents get a randomized price *and* a “not recommended” signal. Comparing across the three price levels *within* the ineligible arm nets out the guideline message, so γ_5 is identified off price alone.

Identification III: is complementarity assumed? No.

Where $\delta_B - \delta_G$ comes from

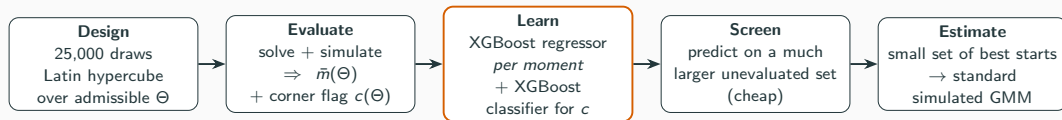
- Not a free parameter: implied by the structure of transitions
- Smoking raises onset (α_2), progression (ζ_4), chronic onset (ψ_1); mortality depends on smoking *only through* health states
- Once late-stage, cessation buys essentially nothing ($\delta_B \approx 0$).

Three checks that the sign is data-driven

1. **Untargeted validation.** The “clean scan” smoking experiment (+16.7% intent to quit) is *not* in $\bar{g}(\Theta)$; the estimated model reproduces the sign: stacked DiD on simulated data gives -8.4 pp (-25.5%)
2. **Falsifiability.** Perturbing smoking utility, symptom disutility, and the symptom $\rightarrow$ belief map (holding calibration fixed) produces a **moral-hazard** equilibrium where screening *raises* smoking (Appendix Fig. 8)
3. **Calibration sensitivity.** Re-solving at the bounds of every Table 3 parameter: effect stays negative in all specifications, mass near -20% to -30% (Appendix Fig. 10)

ML-assisted warm start for simulated GMM

Problem: each objective evaluation = full model solve + 1M-agent simulation; surface is non-convex, and large regions yield **corner solutions** (no one smokes / everyone screens) that are numerically admissible but uninformative.



Ranking criterion for candidate starts (mirrors the GMM objective)

$$\tilde{Q}(\Theta) = \hat{g}(\Theta)' \tilde{W} \hat{g}(\Theta) + \kappa \cdot \text{SD}_j[\hat{g}_j(\Theta)], \quad \text{drop if } \hat{\text{Pr}}(c = 1 \mid \Theta) \text{ high}$$

- $\tilde{W}$: optimal weighting matrix with **extreme eigenvalues trimmed** for stability
- Dispersion penalty removes starts that fit most moments but badly miss one

Warm start: design choices and relation to the literature

What ML does here

- Only chooses **where to start**; estimator, moments, and inference unchanged
- Per-moment models accommodate heterogeneous predictability across moments
- Corner flag used **only at initialization**; never a constraint or target in the final objective
- Multiple distinct starts $\Rightarrow$ built-in stability check
- Robustness: simulated annealing from the same starts, to rule out systematic local minima

Relative to existing work

- Catherine & Ebrahimian (2024); Duarte & Fonseca (2023): learn the parameter $\leftrightarrow$ moment map and *replace* the estimator
- Zila & Kukacka (2023): ML *selects* moments
- **Here:** theory selects moments; ML learns a good weighted objective surface for initialization

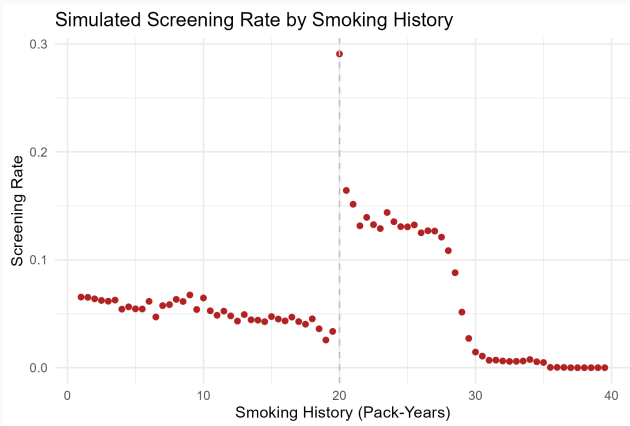
Portable

Useful whenever model solves are costly, objectives are irregular, and poor starts land in degenerate regions, e.g. life-cycle models à la Capatina & Keane (2026). The “undesirable region” classifier generalizes beyond corners.

Table of contents

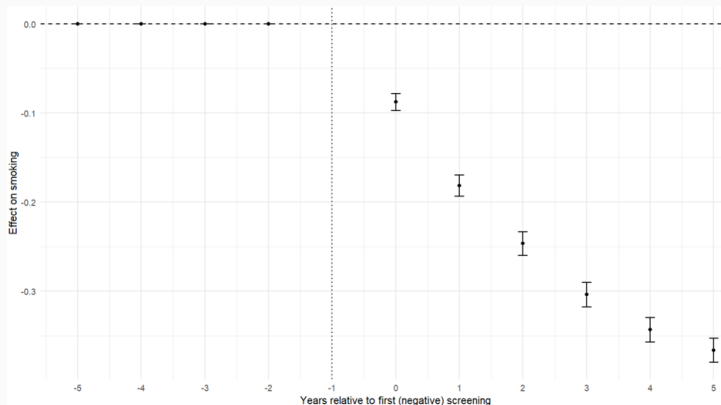
1. Introduction
2. Context
3. Structural Model
4. Data
 - Novel Experimental & Survey Data
 - Clinical & Observational Data
5. Estimation & Identification
6. Model Results & Counterfactuals
7. Conclusions

Model generates strong screening responses



1. **Strong price sensitivity:**
screening responds to USPSTF eligibility
2. However, 48.5% of LCS occurs outside eligibility; 28% occurs outside any eligibility threshold (consistent with BRFSS data).

Model suggests value-of-life channel dominates moral hazard channel

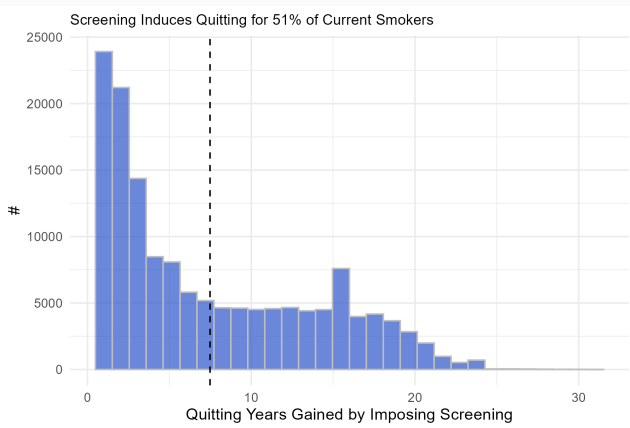


1. **Strong price sensitivity**
2. 48.5% occurs outside eligibility
3. **Quitting Effect:**
Screening reduces smoking by 25%

► Model Fit

Counterfactual Simulations I: Universal One-Time Screening

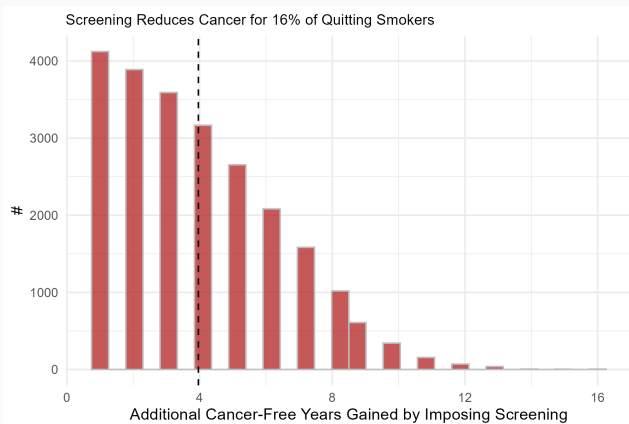
We assess how **negative LC screening** affects lifetime trajectories of smoking, cancer, and mortality. We assume a one-time, universal screening program for all smokers at age 45



1. Induced quitting for 51% of current smokers (only 1/3 of this lasts longer than 10 years)
2. Average quitter goes an additional 7.5 years without smoking

Counterfactual Simulations I: Universal One-Time Screening

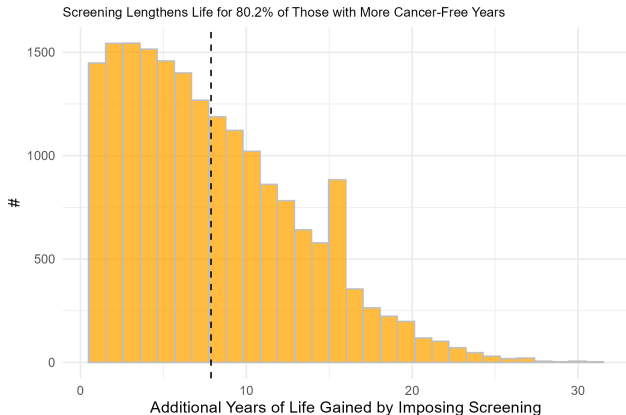
We assess how **negative LC screening** affects lifetime trajectories of smoking, cancer, and mortality. We assume a one-time, universal screening program for all smokers at age 45



1. Induced quitting for 51% of current smokers (only 1/3 of this lasts longer than 10 years)
2. Average quitter goes an additional 7.5 years without smoking
3. Increase in cancer-free years by 8 years (2.2% decline in incidence)

Counterfactual Simulations I: Universal One-Time Screening

We assess how **negative LC screening** affects lifetime trajectories of smoking, cancer, and mortality. We assume a one-time, universal screening program for all smokers at age 45



1. Induced quitting for 51% of current smokers (only 1/3 of this lasts longer than 10 years)
2. Average quitter goes an additional 7.5 years without smoking
3. Increase in cancer-free years by 8 years (2.2% decline in incidence)
4. 80% of those with less cancer have longer life (average gain = 7.9 years)

Counterfactuals: Information from screening complements prevention

We simulate the model under counterfactuals altering screening eligibility, quality, & stigma

Intervention 1: A one-time, universal screening at age 45 for those with smoking history shows a strong **value of life effect**:

- Reduces smoking by 11.9%, cancer by 2.2%, and improves longevity

Counterfactuals: Information from screening complements prevention

We simulate the model under counterfactuals altering screening eligibility, quality, & stigma

Intervention 1: A one-time, universal screening at age 45 for those with smoking history shows a strong **value of life effect**:

- Reduces smoking by 11.9%, cancer by 2.2%, and improves longevity

Intervention 2: Targeted policy adjustments – Modifying screening prices and expanding USPSTF eligibility along either age or smoking history margins produce similar results

- Unconditional welfare rises by 0.4%-0.6% of lifetime discounted utility at age 40
- Using standard value of life measurements (Murphy & Topel, 2006), this corresponds to \$60,000-\$70,000 per person over their lifetime
- Implies total gain of roughly \$73 to \$83 billion for an average 40-year-old cohort
- About 20% of this gain is attributable to **information** rather than **diagnostic** value of screening

Table of contents

1. Introduction
2. Context
3. Structural Model
4. Data
 - Novel Experimental & Survey Data
 - Clinical & Observational Data
5. Estimation & Identification
6. Model Results & Counterfactuals
7. Conclusions

Welfare, Decomposition, & Conclusions

We study the endogenous relationship between screening as **information** and **preventive behaviors** in the context of smoking

We find:

1. **Screening demand is endogenous and price-sensitive**
 - Strong response to USPSTF eligibility thresholds
 - Nearly half of screening occurs *outside* any eligibility criteria
2. **Screening information complements prevention**
 - A negative screen reduces smoking by **25%** from baseline
 - **Value-of-life channel** dominates **moral hazard channel**
3. **Screening access improves welfare**
 - Universal one-time screen reduces smoking, cancer, and lengthens life
 - Implied total welfare gain of **roughly \$73 to \$83 billion per cohort**
4. **Behavioral channel plays a significant role** About **20% of gains** are attributable to **information** rather than **diagnostic** value of screening

Endogenous Screening and Health Behaviors

Michael Darden Alex Hoagland

AHEW 2026

Johns Hopkins University & NBER · University of Toronto

Appendix

Control Framing

On a scale from 0 to 100, where 0 = definitely will not and 100 = definitely will, how likely are you to seek a lung cancer screening (low-dose CT) in the next 12 months?

◀ Eligible Branch

◀ Ineligible Branch

Price Target

Eligible Respondents

Because of your age and smoking history, the United States Preventive Services Task Force recommends annual lung cancer screening. For most people in your situation, insurance covers the test at no cost to you. On a scale from 0 to 100, where 0 = definitely will not and 100 = definitely will, how likely are you to seek a lung cancer screening (low-dose CT) in the next 12 months?

Ineligible Respondents

Because of your age and smoking history, you are not recommended for lung cancer screening under the United States Preventive Services Task Force guidelines. If you choose to receive a screening, most people in your situation pay an out-of-pocket price of about \$X. On a scale from 0 to 100, where 0 = definitely will not and 100 = definitely will, how likely are you to seek a lung cancer screening (low-dose CT) in the next 12 months?

Stigma Target

*Lung cancer screening is a clinical test like any other. Whether you smoke now or used to, staff are trained to treat every patient with dignity, and screening results are kept **private**. On a scale from 0 to 100, where 0 = definitely will not and 100 = definitely will, how likely are you to seek a lung cancer screening (low-dose CT) in the next 12 months?*

Quality Target

Out of every 100 people who get today's standard lung cancer screening (low-dose CT), about 12 will have a false alarm (a positive result when no cancer is present). Most of these are cleared with a repeat scan. On a scale from 0 to 100, where 0 = definitely will not and 100 = definitely will, how likely are you to seek a lung cancer screening (low-dose CT) in the next 12 months?

◀ Eligible Branch

Sample Construction

	# Individuals
Full sample: Respondents who completed the survey and whose submission was not rejected, returned, or timed-out	3,996
Observations with some smoking history	3,950
Qualtrics reCaptcha >0.5	3,925
Non-Missing Outcomes	3,912

Main Estimation Equation

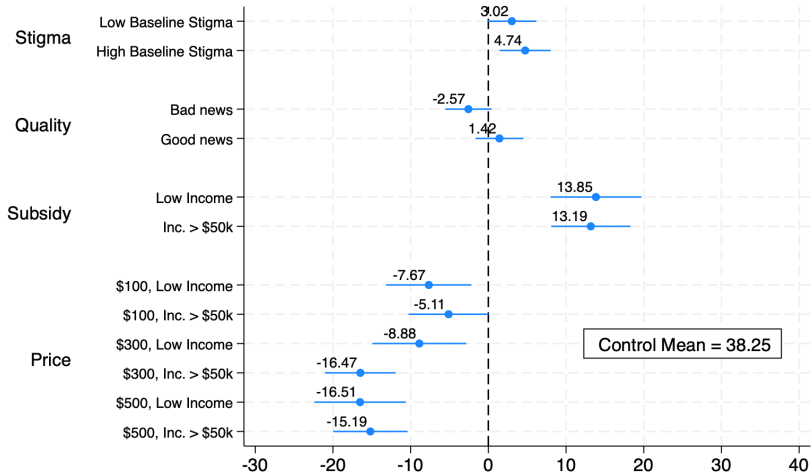
Final sample included **3,912 respondents** after some exclusions. We estimated intent to screen/quit effects as:

$$Y_i = \alpha + \beta_S 1\{\text{Subsidy}\} + \beta_Q 1\{\text{Quality}\} + \sum_j (\beta_P 1\{\text{Price}=j\} \cdot 1\{\text{Ineligible}\}) \\ + \beta_{PE} 1\{\text{Eligibility Information}\} \cdot 1\{\text{Eligible}\} + \mathbf{X}_i' \gamma + \varepsilon_i. \quad (1)$$

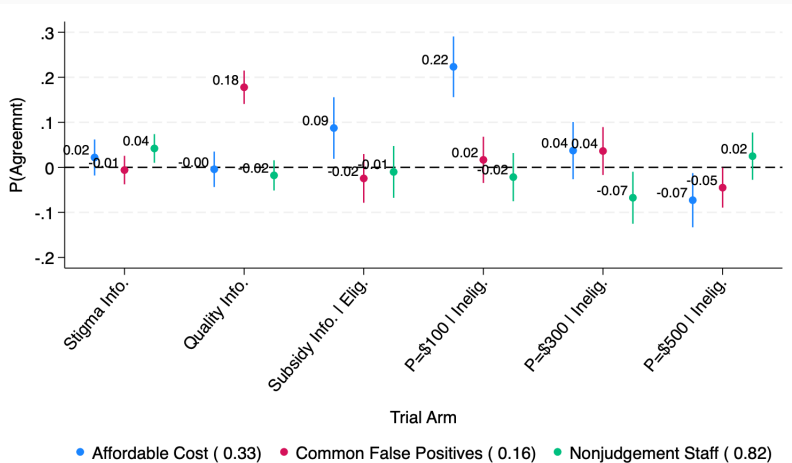
where $j \in \{\$100, \$300, \$500\}$

[◀ Main Results](#)

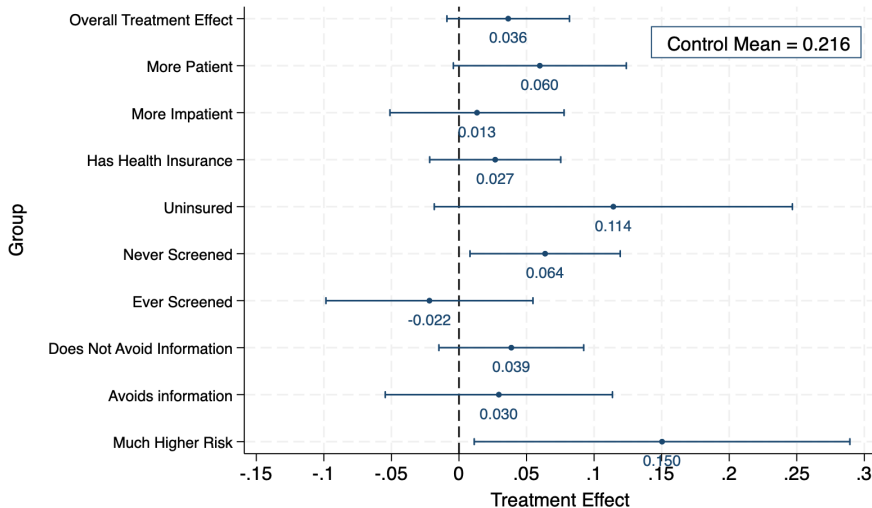
Heterogeneity



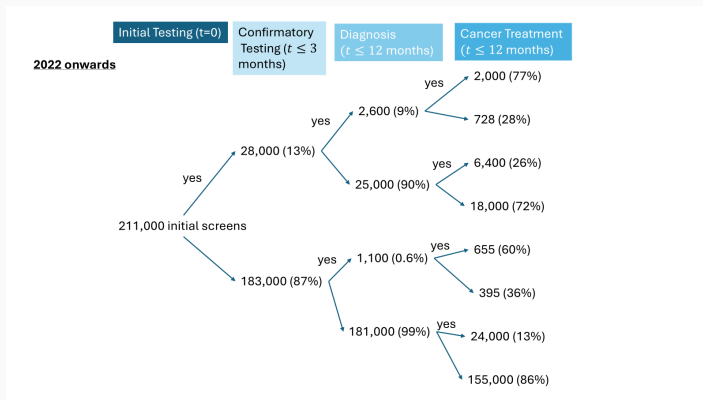
Comprehension Checks



Smoking Experiment Results: Intent to Quit



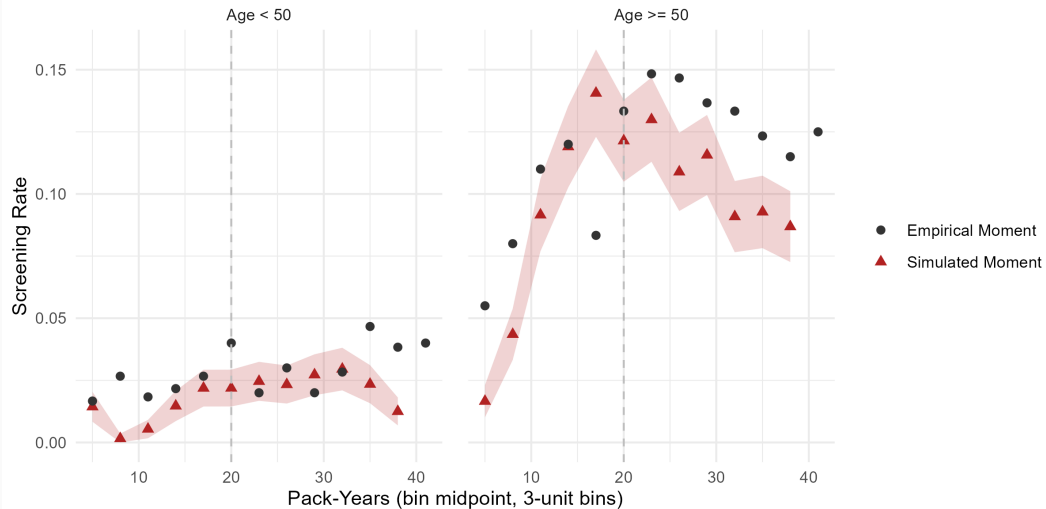
Truveta: False Positive Analysis



False Positive Rate:

$$P(\text{something other than a 'no cancer'} | \text{no cancer}) = 25000 / 206000 = 12.1\%$$

Model Fit



Stigma Effects

