

Endogenous Screening and Health Behaviors*

Michael Darden and Alex Hoagland

June 2, 2026

Abstract

We develop a dynamic learning model in which health screening and other preventive behaviors jointly produce health. The value of health screening depends on endogenous responses to new information, and we study this relationship in the context of lung cancer and smoking. Combining experimental variation from a novel survey with electronic health records, National Lung Screening Trial data, and administrative survey information, we find evidence that screening information complements prevention: a negative screen reduces smoking by 8.3 percentage points. Counterfactuals show screening recommendations depend critically on selection and endogenous health behavior.

Keywords: Health screening; preventive behavior; smoking; dynamic choice; information and belief updating; structural estimation

JEL Classification: I12, I18, D83, D91, C61

*Darden: Johns Hopkins University and NBER. Hoagland: University of Toronto

1 Introduction

Health screening is both a diagnostic technology and an information technology. Its value depends not only on who is screened and what the test detects, but also on how screening information changes subsequent health investment. In the context of cancer screening, recent evidence shows average screening benefits may differ significantly from the benefits for those who select into screening on the margin (Einav et al., 2020). Furthermore, while health screening, and preventive care more generally, are widely considered to be underutilized, concerns have grown that both new and old forms of health screening may lead to over-diagnoses, especially for groups on the margin of official screening recommendations.¹

We develop and estimate a dynamic learning model in which an individual jointly selects whether to obtain cancer screening and whether to invest in other forms of prevention. In the model, screening affects health through two channels. First, it changes the timing of diagnosis. Second, it changes beliefs about future health and therefore the return to preventive behavior. This second channel implies that the marginal value of screening depends not only on disease risk and test accuracy, but also on whether marginal screeners are more or less responsive to health information. A negative screen lowers current perceived cancer risk, which could discourage preventive investments. At the same time, however, it also increases expected survival and therefore raises the value of investing in healthy future outcomes. The contribution of the model is to value screening not in isolation, but rather as jointly chosen alongside other relevant health behaviors.

We study these mechanisms in lung cancer screening, a setting in which screening recommendations are explicitly tied to a behavior that individuals can also change: cigarette smoking. Lung cancer is the third most common cancer diagnosis in the United States and the leading cause of cancer death. Early detection is especially valuable: five-year relative survival is 65.5 percent for localized lung cancer, compared with 10.5 percent for distant-stage disease. Smoking is the dominant risk factor, and cigarette smoking is linked to roughly 80 to 90 percent of lung cancer deaths in the United States.² United States Preventive Services Task Force (USPSTF) guidelines recommend annual low-dose computed tomography (LDCT) screening based on age and smoking history criteria, yet screening prevalence is only 24.5% in the recommended population (Burus et al., 2026).³ Furthermore, nearly half of all lung cancer screening occurs in people who do not meet USPSTF guidelines (Darden and Hoagland, 2025), suggesting considerable heterogeneity in who screens and why, as well as significant out-of-pocket financing of lung cancer screening.⁴

More broadly, lung cancer screening provides a tractable setting in which preventive care is explicitly linked to a

¹Underutilization is typically defined as less than 100% compliance with official guidelines. In this sense, screening for breast (80.0%), cervical (75.4%), and colorectal (67.4%) cancers are underutilized (Sabatino et al., 2025). At the same time, the dramatic increase in direct-to-consumer health screening tools has been met with concern regarding medically inappropriate screening that leads to unnecessary followup procedures and radiation exposure (Gram et al., 2024; Davenport and Reeder, 2026).

²SEER Statistics at a Glance, accessed on May 5th, 2026.

³Current USPSTF guidelines recommend screening for adults ages 50 to 80 with at least a 20 pack-year smoking history who currently smoke or quit within the past 15 years.

⁴Typically, Medicare follows USPSTF guidelines and covers services and procedures that receive a B grade or higher. Following USPSTF’s 2021 updated lung cancer screening guidelines, Medicare issued a [National Coverage Determination](#) covering LDCT lung cancer screening. Most private payers and state Medicaid offices also follow these guidelines. See Section 2 for more information.

modifiable behavior. While we focus on lung cancer screening and smoking, the same economic forces arise in other contexts. For example, preventive screenings for conditions such as diabetes, cardiovascular disease, and stroke are complementary to and most effective with lifestyle modification (e.g., exercise) and preventive medication use (e.g., statin therapy) to prevent or maintain the condition. Similarly, GLP-1 pharmaceuticals directly alter the marginal utility of consumption through the reduction in “cravings”, but these drugs are most effective when combined with a healthy diet and regular exercise (Mehrtash et al., 2025). Our model emphasizes that such complementary behaviors change the marginal value of screening, and they are endogenous with respect to health, longevity, and welfare.

To estimate our model, we combine novel experimental variation with rich clinical and population data. First, to identify preferences, beliefs, and expectations, we conduct a randomized information experiment among 4,000 current and former smokers. The experiment randomly varies information about screening prices, stigma-related barriers, and test quality, allowing us to identify key components of screening demand. It also directly elicits how current smokers expect to change smoking behavior after receiving favorable screening information, which allows us to distinguish a moral-hazard effect from a value-of-life response. In our model, we combine these experimental moments with three large data sources. First, we consider Truveta’s standardized electronic health records from more than 100 United States health systems to measure contemporary, real-world diagnostic outcomes, including false positives. Second, we use National Lung Screening Trial data to identify arguably policy-invariant clinical transition probabilities. Finally, we identify smoking preferences and addiction patterns from large-scale survey data in the Behavioral Risk Factor Surveillance System. We estimate the parameters of our structural model via simulated GMM, matching both experimental and observational moments to simulated model predictions. In the process, we offer a new method for identifying starting values that involves pairing a grid search over the parameter space with a machine learning algorithm.

The estimated model shows that screening demand is shaped by both standard price incentives and endogenous selection on risk. Results suggest that screening is highly price sensitive: the model-implied elasticity is close to the experimental elasticity of -0.17 , and screening rates rise discontinuously when individuals cross eligibility thresholds that lower the out-of-pocket price. At the same time, the model implies substantial screening outside formal USPSTF eligibility. Roughly 60% of screening occurs among individuals paying out of pocket, including 36% among individuals who meet neither the age nor smoking-history threshold. This selection is informative about the private value of screening, and rationalizes both under-use among eligible high-risk smokers and substantial use among ineligible smokers.

Simulations of the estimated model show that the welfare and health consequences of screening depend critically on the behavioral response to information. There is large value in negative screens that cause smoking cessation. We estimate that a one-time universal screening program at age 45 would induce meaningful smoking cessation and increase the fraction of life that is cancer free as well as overall life expectancy for two-thirds of current smokers. Our results are consistent with the smoking and longevity literature that has found survival curves to be roughly equivalent between never smokers and smokers who quit before age 50 (Darden et al., 2018; Doll et al., 2004). Importantly, these effects can be induced through existing policy levers, including directly modifying screening prices and expanding USPSTF eligibility along either the age or smoking-history margin. By contrast, interventions

that remove stigma or pessimism about screening quality generate much smaller health effects. Taken together, these results imply that screening information complements prevention rather than crowding it out, and that screening recommendations should account for both selection into screening and the endogenous smoking response to favorable health information.

Taking inspiration from both [Grossman \(1972\)](#) and [Ehrlich and Becker \(1972\)](#), a large economic literature has studied preventive healthcare as an investment in insuring better health.⁵ Our work contributes to this literature by emphasizing the joint determination of preventive care and other health behaviors in an intertemporal setting. In our framework, preventive care not only affects health directly, but also changes beliefs and therefore the returns to other health investments, particularly those characterized by addiction ([Becker and Murphy, 1988](#); [Gruber and Kőszegi, 2001](#); [Bernheim and Rangel, 2004](#); [Gul and Pesendorfer, 2007](#); [DeCicca et al., 2022](#)). While we study this interaction in the context of lung cancer screening and smoking, the underlying mechanism applies more broadly to settings in which individuals jointly choose screening, lifestyle changes, and preventive treatments. More generally, our results highlight the importance of modeling these interactions when evaluating the value of preventive care. We also emphasize competing risk, the idea that disease-specific investments may affect other forms of health.

This paper contributes to the economics of information by modeling health screening as a dynamic information technology that shapes what agents learn, when they learn it, and how they update beliefs prior to making health investments. In doing so, we connect to a large structural literature on learning and information acquisition. A first strand studies how agents update beliefs about product quality or health risk over time and how these beliefs shape behavior ([Crawford and Shum, 2005](#); [Hoagland, 2026](#)). A second strand embeds learning in dynamic choice environments, emphasizing how forward-looking behavior interacts with information accumulation ([Chan and Hamilton, 2006](#); [Ching et al., 2013](#); [Darden, 2017](#)). Relative to this work, we focus on screening as an endogenous information choice: agents decide not only how to act given beliefs, but also when and whether to acquire new information. In our model, this generates an equilibrium screening threshold, with individuals optimally selecting the timing and frequency of information acquisition as part of their broader health investment problem.

Finally, we make a methodological contribution to the estimation of structural models with complex, irregular objective functions. We introduce a machine-learning-assisted warm-start procedure for simulated GMM that uses flexible prediction algorithms to identify economically meaningful and computationally efficient starting values. The approach combines a large-scale, design-based exploration of the parameter space with supervised learning to approximate the mapping from parameters to model moments and to screen out regions associated with corner or degenerate solutions. In contrast to recent work that uses machine learning to approximate or replace the structural estimator itself ([Catherine and Ebrahimian, 2024](#); [Duarte and Fonseca, 2023](#)), we preserve the standard GMM framework and use machine learning only to guide initialization. Our approach is also complementary to recent efforts to use machine learning to select or weight moments in structural estimation ([Zila and Kukacka, 2023](#)). This strategy improves convergence and stability in settings where solving the model is costly and the objective surface is highly non-convex, and is broadly applicable to a wide class of dynamic structural models, including life-cycle

⁵Among many examples, see [Gilleskie \(1998\)](#); [Miguel and Kremer \(2004\)](#); [Chandra et al. \(2010\)](#); [Baicker et al. \(2015\)](#); [Alsan et al. \(2019\)](#); [Newhouse \(2021\)](#).

models like our own (Capatina and Keane, 2026).

2 Background

Lung Cancer Screening

In 1996, the United States Preventive Services Task Force gave LDCT lung cancer screening a “D” grade (U.S. Preventive Services Task Force, 2004). The report cited evidence that screening may detect lung cancer at an earlier stage, but it cited poor evidence on its effectiveness regarding lung cancer survival, and it highlighted a lack of randomized-controlled trial evidence. Following this determination, in 2002, the National Lung Screening Trial (NLST) began, enrolling over 53,000 participants between the ages of 55 and 74 who had at least 30 pack-years of smoking history.⁶ Participants at one of ten locations were randomized into LDCT screening or chest radiography, and they received three screenings over roughly three years. The participants were followed through 2010. In the LDCT arm, there were more lung cancer diagnoses in the LDCT group (645 vs. 572), but there were fewer lung cancer deaths (247 vs. 309) (The National Lung Screening Trial Research Team, 2011).

The NLST had a transformative effect on lung cancer screening policy in the United States. In 2013, USPSTF revised their recommendation for LDCT to a “B” grade for adults 55 to 80 with 30+ pack-years and who currently or recently (within 15 years) have smoked (U.S. Preventive Services Task Force, 2014). The recommendation concluded that screening should be stopped after a person has been a non-smoker for 15 years. Following the USPSTF update, Centers for Medicare and Medicaid Services (CMS) issued a National Coverage Determination for LDCT screening, ensuring Medicare coverage for LDCT lung cancer screening for the first time. The criteria for coverage included the age and smoking history requirements from the USPSTF recommendation, in addition to screening counseling and a shared decision-making visit to be furnished by a physician. Furthermore, the beneficiary needed to be free of cancer or other health condition that “substantially limits life expectancy or the ability or willingness to have curative lung surgery.” (Centers for Medicare & Medicaid Services, 2015)

The shared decision-making requirement was controversial, mainly because shared decision-making was not required for coverage of other cancers (Volk et al., 2020). Furthermore, comments to CMS indicated that this additional step required for a covered lung screening represented a barrier to access, and it was deemed to be an overly complex requirement (Volk et al., 2026). In defending this requirement, CMS cited important heterogeneity in costs and benefits across individuals. In particular, the associated National Coverage Analysis (Centers for Medicare & Medicaid Services, 2015) stated that, “Shared decision-making is important for the population for whom screening is recommended. The benefit of screening varies with risk because persons who are at higher risk because of smoking history or other risk factors are more likely to benefit.”

Following evidence of lower false positives and of greater survival benefits relative to the NLST, USPSTF expanded recommended LDCT screening to those between the ages of 50 and 80 with a 20-pack year smoking history (U.S. Preventive Services Task Force, 2021). CMS’ National Coverage Determination quickly followed in 2022,

⁶One pack-year of smoking history is equal to smoking one, 20-cigarette pack of cigarettes per day for an entire year.

broadening coverage of LDCT screening to the expanded population while preserving the shared-decision making requirement (Centers for Medicare & Medicaid Services, 2022). Both traditional Medicare and Medicare Advantage enrollees who meet the expanded criteria may receive LDCT screening with no cost-sharing. Furthermore, individuals who meet the expanded criteria and who qualify for Medicaid may receive screening with no cost-sharing. The Affordable Care Act requires non-grandfathered private plans to cover “A” or “B” graded preventive services (Internal Revenue Service et al., 2010), ensuring coverage in most large individual and group insurance plans. For those outside of the current USPSTF recommendations, there is less evidence of insurance coverage. The typical LDCT screening costs between \$100 and \$400.⁷ A timeline of these policy changes in lung cancer screening is provided in Appendix Section 1.

In the most recent 2021 USPSTF guidelines, screening is recommended to occur annually among those who meet the criteria, and screening is to be discontinued only after 15 years of smoking cessation. Of those recommended for screening according to the 2021 USPSTF guidelines, Bandi et al. (2024) find that only 18% have screened in previous year. Similarly, Henderson et al. (2024) find that compliance with the USPSTF guidelines is only 16.4% of the recommended population. More recent evidence suggests that prevalence has increased to 24.5% (Burus et al., 2026). Darden and Hoagland (2025) find that nearly half (45.2%) of 2022 past-year screenings came from people outside of USPSTF guidelines.

3 Model

The goal of the model is to rationalize the observed rate of lung cancer screening. To do so, we model screening and smoking decisions jointly in an environment with uncertainty about disease state and the quality of screening. We consider two forms of health: lung cancer and other chronic health. Unless lung cancer is advanced such that symptoms are apparent, the state is unobserved by both the individual and the econometrician. Early stage lung cancer, if diagnosed, can potentially be cured, but advanced lung cancer cannot. Other health is a binary variable for the presence of any other chronic health condition, which introduces the notion of competing risk. We present the model in the order of a representative period t .

State Variables

Agents enter the model at age 40 and make annual decisions about health behaviors (smoking) and preventive care investments (lung cancer screening). They are characterized by a vector of state variables, Γ_t :

$$\Gamma_t = (\theta_t, d_t, b_t, h_t, \phi_t, \nu_i, a_t).$$

First, agents have a lung cancer state corresponding to none, early-stage, and late-stage lung cancer, $\theta_t \in \{1, 2, 3\}$. Lung cancer is observed only when detected via screening (in the absence of a false negative screen). Hence,

⁷Estimate from the American Lung Association.

individuals also have a diagnosed state $d_t \in \{0, 1\}$, where it is possible for an agent to have cancer $\theta_t > 1$ without being diagnosed ($d_t = 0$).

In the absence of a diagnosis, agents have a subjective probability of any lung cancer, b_t .⁸ Agents also are characterized by their smoking history, h_t ; their other health state, $\phi_t \in \{1, 2\}$;⁹ and a type variable $\nu_i \in \{1, 2, 3, 4\}$. Individuals may have either high or low stigma associated with testing, and high or low optimism about test quality based on their subjective beliefs about screening quality. Finally, individuals have an exogenously determined age, a_t ; in the model, age and time are synonymous. We consider a time horizon from age 40 to age 100, at which point death occurs with probability 1.

Start of the Period: Symptoms

At the start of a period, an individual receives a draw of symptoms influencing both their beliefs about their lung cancer risk and their utility. In each period, let η_t represent this draw, where:

$$\eta_t \sim F(\eta|\theta_t, \phi_t).$$

For tractability, we assume that symptoms are normally distributed, with mean and variance determined by the true underlying stage of cancer (including no cancer) and the presence of other health conditions. Based on this draw of symptoms, an individual's period-specific beliefs about any cancer (where conditional beliefs about early- and late-stage cancer are approximately equally distributed) are given by a conjugate posterior. We calibrate these symptom draws to match prior literature, and allow for individuals to have endogenous, potentially idiosyncratic, beliefs about these two probabilities.¹⁰

Actions

Based on their state, an individual simultaneously chooses whether to smoke cigarettes, s_t , and whether to screen for lung cancer, denoted by x_t . The action space is therefore given by

$$A_t = (s_t, x_t).$$

⁸If $d_t = 1$, then $b_t = 1$. We abstract away from separate belief distributions of early- and late-stage lung cancer by using the fact that roughly 50% of new lung cancer diagnoses in the U.S. are late-stage.

⁹If $\phi_t = 2$, this indicates that an individual has chronic conditions that are highly co-morbid with lung cancer, including COPD and cardiovascular conditions.

¹⁰In practice, we calibrate these symptom draws to match prior literature, such that the probability of observing symptoms is 0.033 if $\theta = 1$, 0.064 if $\theta = 2$, and 0.246 if $\theta = 3$. Given a binary draw for symptoms, rational belief updating of beliefs using Bayes' rule can be expressed as:

$$\begin{aligned} \tilde{b}_t|\eta = 1 &: \frac{0.156 b_t}{(0.156 b_t + 0.033 (1 - b_t))} \\ \tilde{b}_t|\eta = 0 &: \frac{(1 - 0.156) b_t}{((1 - 0.156) b_t + (1 - 0.033) (1 - b_t))}, \end{aligned}$$

where the probability of symptoms given (any) cancer is 0.156 and the probability of symptoms given no cancer is 0.033.

Note that if $\theta_t = 3$ is known by the individual, no screening occurs ($\theta = 3$ is an absorbing state).

Screening Outcomes

At the time an agent makes smoking and screening decisions, there are two outcomes that are uncertain, both of which are observed if the agent chooses to screen. First, conditional on screening, they receive a signal of early stage lung cancer $z \in \{0, 1\}$. The quality of the test depends on its rates of false positives and false negatives. Define:

$$\Pr(z_t = 1 \mid \theta_t) = \begin{cases} \rho & \text{if } \theta_t = 2 \\ \lambda & \text{if } \theta_t = 1. \end{cases}$$

In this case, ρ is the accuracy of the test (i.e., sensitivity), the probability that the test reveals a true early-stage lung cancer. Thus, $1 - \rho$ is the probability of a false negative. Similarly, λ is the probability of a positive test result in the absence of early-stage lung cancer (i.e., the rate of false positive), and $1 - \lambda$ is the probability of a correctly negative test result. Both ρ and λ have objective average values that we intend to estimate from Truveta data. However, what matters for behavior are an individual's subjective beliefs about $\hat{\rho}$ and $\hat{\lambda}$. We intend to measure average subjective beliefs from the survey.

Treatment is the second outcome. In the event that an agent receives a positive signal, we assume that the agent undergoes additional testing. The subsequent testing, which we assume incurs the same cost as the initial testing, is able to precisely determine the value of $\theta \in \{1, 2, 3\}$. If $\theta_t \in \{2, 3\}$, we assume that the agent undergoes immediate treatment y , which affects the probability that early-stage θ will transition to late-stage cancer at the end of the period. If the screening signal is positive (i.e., if $z_t = 1$) and the agent is free of lung cancer (i.e., $\theta_t = 1$), then we assume that subsequent testing, which is still costly, rules out lung cancer.

Utility Function

Utility is a function of the current state, the actions selected, and the outcomes of screening, if screening is chosen. Specifically, we specify a CRRA function of income net of expenditures on screening, smoking, and cancer treatment, and additively separable terms for smoking, screening, and treatment. Utility from smoking depends on its price p_s and the history of smoking h_t , which captures reinforcement (Becker and Murphy, 1988). The financial cost of screening is given by p_x , and the disutility of screening (including stigma) is given by γ_4 .

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

Utility is health state specific in the sense that we normalize the utility of death to 0. To ensure positive utility

when alive, we also specify an additive parameter U_θ that we allow to vary by whether an individual has late-stage cancer ($\theta = 3$) or not ($\theta < 3$). To the extent that $U_{\theta < 3} > U_{\theta = 3}$, these utility shift terms create dynamic incentives for good health, and they are identified by individual's willingness to engage in preventive care. The second term represents CRRA utility over residual consumption, where wealth W_t is net of expenditures on smoking, screening, and treatment based on their respective prices; γ_0 is the typical CRRA risk aversion coefficient. Smoking may directly affect utility (γ_1), as well as through linear and quadratic reinforcement effects through smoking history (γ_2, γ_3). The summation term introduces type-specific heterogeneity in the marginal disutility of screening, with $\gamma_{4,\nu}$ indexing differential costs by individual type. $\gamma_5 \tilde{p}_t$ captures utility loss from realized OOP medical spending, where $\tilde{p}_t$ is the expected price of both the initial test (which may be free to patients who qualify for screening under the USPSTF guidelines) and any confirmatory testing. Finally, γ_6 captures disutility from symptoms in each period.

If $d_t = 1$, the individual is aware that they have cancer. If cancer is early-stage, we assume that screening is automatic in order to manage stage progression; if $\theta = 3$, we assume no screening is required. If, on the other hand, $d_t = 0$, the agent is unaware of the value of θ , and this generates uncertainty about the payoff from screening. Thus, the contribution of current utility to the value function depends on the diagnosis state and screening choice. If there is no screening, then the contribution of current utility is simply $u(\cdot)$; with screening, however, expected current utility is the expectation over the likelihood of θ and the (symptom-updated) beliefs about the quality of the screening test:

$$E(u(x_t, s_t; \Gamma_t)) = (1 - \tilde{b}_t) [(1 - \lambda) u(x_t, s_t; z_t = 0, \theta_t = 1) + \lambda u(x_t, s_t; z_t = 1, \theta_t = 1)] + \tilde{b}_t [(1 - \rho) u(x_t, s_t; z_t = 0, \theta_t \geq 2) + \rho u(x_t, s_t; z_t = 1, \theta_t \geq 2)].$$

This term is the weighted average of utility over the two possible cancer states (collapsing early- and late-stage cancers) and the signals from symptoms and screening, with weights determined by subjective probabilities both about underlying cancer incidence ($\tilde{b}_t$) and screening quality (ρ and λ).

The price of screening depends on the agent's state and on exogenous health insurance and location. Because the USPSTF guidelines dictate insurance coverage, we assume that the out-of-pocket price of screening is \$0 if an individual has health insurance and meets the 2021 criteria.

State Evolution

Age and Smoking History

There is no uncertainty about an individual's smoking history. Define the evolution of deterministic state variables smoking history and age:

$$h_{t+1} = h_t + s_t, \quad a_{t+1} = a_t + 1.$$

Cancer Transition

We make simplifying assumptions that the probability of late stage lung cancer conditional on no lung cancer is zero

($Pr(\theta_{t+1} = 3 | \theta_t = 1) = 0$). We also, given the structure of our utility function, ignore recovery from early-stage lung cancer to “no cancer” and focus only on cancer progression ($Pr(\theta_{t+1} = 1 | \theta_t = 2) = Pr(\theta_{t+1} = 2 | \theta_t = 3) = Pr(\theta_{t+1} = 1 | \theta_t = 3) = 0$). We calibrate parameters governing the following health transitions:

- From $\theta_t = 1$:

$$\pi_{12}(h_t, s_t, a_t) = Pr(\theta_{t+1} = 2 | \theta_t = 1, s_t, h_t, a_t) = \text{logit}^{-1}(\alpha_0 + \alpha_1 h_t + \alpha_2 s_t + \alpha_3 a_t) \quad (2)$$

- From $\theta_t = 2$:

$$\textit{Progression} : \pi_{23}(h_t, s_t, a_t) = \text{logit}^{-1}(\zeta_0 + \zeta_1 \tau_t + \zeta_2 y_t + \zeta_3 (\tau_t \times y_t)) \quad (3)$$

$$\textit{Stasis} : \pi_{22}(h_t, s_t, a_t) = 1 - \pi_{23}, \quad (4)$$

where τ_t represents the years since diagnosis ($\tau_t = t - T_i^{d=1}$).

Cancer Belief Updating

Beliefs at time t ($\tilde{b}_t$) reflect subjective beliefs about any lung cancer at time t (θ_t). The goal is to understand how beliefs evolve given possible screening and cancer outcomes. As cancer may progress even without being detected, beliefs about lung cancer are relevant until cancer is diagnosed ($d_t = 1$). That is, if $d_t = 1$, then beliefs are fixed at 1; otherwise, beliefs update differently given the screening decision and the results of screening. If the agent chooses not to screen, then the posterior belief of any lung cancer is given as:

$$b_{t+1} = \tilde{b}_t + (1 - \tilde{b}_t)\pi_{12},$$

where π_{12} represents the objective transition probability of cancer onset. This says that agents have rational expectations regarding the average evolution of cancer risk. In the case in which they choose to receive no private signal of information, agent's update beliefs based on this average.

If the person chooses to screen and observes a negative signal $z_t = 0$, then uncertainty about θ_{t+1} stems from both the possibility of a false negative test and the average likelihood of transiting to (or remaining in) early stage cancer. Taking these sources of uncertainty in steps, first, the agent updates beliefs from the negative screening test via Bayes' rule: In this case, beliefs are:

$$\tilde{\tilde{b}}_t = \frac{(1 - \rho)\tilde{b}_t}{(1 - \rho)\tilde{b}_t + (1 - \lambda)(1 - \tilde{b}_t)},$$

and now accounting for the fact that cancer may develop by $t + 1$:

$$b_{t+1} = \tilde{\tilde{b}}_t + (1 - \tilde{\tilde{b}}_t)\pi_{12}.$$

If the person chooses to screen and observes $z_t = 1$, then screening has the effect of resolving uncertainty about period t θ , because even a false positive signal generates confirmatory testing. Thus, updated beliefs about period

$t + 1$ θ are the rational expectations of early stage lung cancer in $t + 1$ conditional on the known value of θ_t

$$b_{t+1} = \begin{cases} \pi_{12} & \text{if } \theta_t = 1 \\ 1 & \text{if } \theta_t \geq 2. \end{cases}$$

Health Transitions

We also assume that the other health state $\phi = 2$ is an absorbing state such that:

$$\Pr(\phi_{t+1} = 2 \mid \phi_t = 2) = 1,$$

and

$$\Pr(\phi_{t+1} = 2 \mid \phi_t = 1, h_t, a_t, s_t) = \text{logit}^{-1}(\psi_0 + \psi_1 s_t + \psi_2 a_t + \psi_3(s_t \times a_t)) \quad (5)$$

Mortality

The model also incorporates mortality, the probability of which is increasing in lung cancer and other health states. Note that mortality is not a function of smoking or smoking history—these terms work through lung cancer and other health.

$$\Pr(D_{t+1} = 1 \mid \theta_{t+1}, \phi_{t+1}, a_t) = \text{logit}^{-1}(\omega_0 + \omega_1 \cdot 1[\theta = 2] + \omega_2 \cdot 1[\theta = 3] + \omega_3 \cdot \phi + \omega_4 \cdot a_t) \quad (6)$$

Bellman Equation

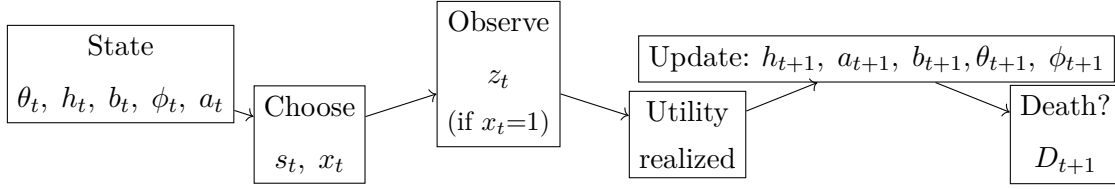
If $\theta_t = 3$, then θ is known to the agent. Conditional on $\theta_t \neq 3$, contemporaneous θ is uncertain, the value function is the maximum over action space A of the expected value over the perceived distribution of θ .

$$\begin{aligned} V(\Gamma_t \mid \theta_t < 3) = \max_{A_t} \bigg\{ & (1 - \tilde{b}_t) * (E(u(s_t, x_t; \Gamma_t, \theta_t = 1)) + \beta \mathbb{E}_{\theta, \phi} [(1 - P(D_{t+1} = 1 \mid \theta_t = 1)) V(\Gamma_{t+1} \mid \theta_t = 1)] \\ & + (\tilde{b}_t) * [u(s_t, x_t; \Gamma_t, \theta_t = 2) + \beta \mathbb{E}_{\theta, \phi} [(1 - P(D_{t+1} = 1 \mid \theta_t = 2)) V(\Gamma_{t+1} \mid \theta_t = 2)]] \bigg\} \quad (7) \end{aligned}$$

If $\theta_t = 3$, then θ is known to the agent, screening is irrelevant, and the only remaining decision is whether to smoke. The value function in this case is:

$$V(\Gamma_t \mid \theta_t = 3) = \max_{s_t \in \{0,1\}} \left\{ (E(u(s_t, x_t; \Gamma_t, \theta_t = 3)) + \beta \mathbb{E}_{\phi} [(1 - P(D_{t+1} = 1 \mid \theta_t = 3)) V(\Gamma_{t+1} \mid \theta_t = 3)]) \right\} \quad (8)$$

Model Summary



Model Implications

Screening Decision. The model's implications for screening can be best understood by considering the threshold of risk beliefs that trigger screenings. Screening is useful in the model as it may induce treatment, thereby increasing survival values, as well as for its value in resolving uncertainty about one's future cancer risks. Hence, if we fix other objects in the model, including prices, wealth, and individual type, then a screening decision for a given individual with a specific age, smoking history, and current smoking decision will screen if and only if:

$$x_t = 1 \iff Q^S(\tilde{b}_t) \geq Q^N(\tilde{b}_t),$$

where we let Q^S be the value from screening and Q^N be the value from not screening. Here, the relevant belief entering the decision is the symptom-updated belief, $\tilde{b}_t$.¹¹

Given this, we can define the screening gain as

$$\Delta(\tilde{b}_t) \equiv Q^S(\tilde{b}_t) - Q^N(\tilde{b}_t).$$

This implicitly defines a belief threshold, $\bar{b}$, as the solution to $\Delta(\bar{b}) = 0$. Any belief above this threshold will trigger screening.

A fully-derived, closed form solution for this threshold would be unwieldy. However, we can derive important comparative statics for this threshold (and hence, screening decisions) even by considering current payoff effects separate from future informational value.

To see this, let

$$u_t^S(\tilde{b}_t) = (1 - \tilde{b}_t) \left[(1 - \lambda)u_0^- + \lambda u_0^+ \right] + \tilde{b}_t \left[(1 - \rho)u_1^- + \rho u_1^+ \right],$$

where $u_t^S(\tilde{b}_t)$ is the current period utility with screening (let u_t^N be the current period utility with no screening). Then

$$\Delta(\tilde{b}_t) = \underbrace{(u_t^S(\tilde{b}_t) - u_t^N)}_{\text{current-period net benefit}} + \beta \times \underbrace{(C^S(\tilde{b}_t) - C^N(\tilde{b}_t))}_{\text{continuation information value}}.$$

Although closed-form solutions for the continuation values cannot easily be expressed analytically, the first term

¹¹ Appendix Section 3 provides definitions for Q^S and Q^N implied by the model.

is still affected by the cost of screening, type-specific screening disutility, any utility consequences of treatment after a positive result, and any immediate utility differences from learning one's status. To see this, suppose that the only benefit of screening is expected resolution or treatment benefit in the current period. Then, screening occurs when

$$(1 - \tilde{b}_t) \left[(1 - \lambda)u_0^- + \lambda u_0^+ \right] + \tilde{b}_t \left[(1 - \rho)u_1^- + \rho u_1^+ \right] \geq u_t^N.$$

This gives the static cutoff

$$\tilde{b}_t \geq \bar{b}^{static} \equiv \frac{u_t^N - (1 - \lambda)u_0^- + \lambda u_0^+}{\left[(1 - \rho)u_1^- + \rho u_1^+ \right] - \left[(1 - \lambda)u_0^- + \lambda u_0^+ \right]}.$$

This cutoff, although incomplete, still highlights several important ways in which screening decisions respond to a person's type or environment. First, higher screening costs raise u_t^N relative to screening utility, thereby increasing the implicit threshold. At the same time, increased stigma (which imposes a type-specific disutility from screening) will likewise raise the threshold necessary to induce screening, while optimism about a test's outcome will reduce it. Finally, a higher perceived cancer payoff from early detection lowers the threshold and may induce additional screening.

Smoking Decision. Screening also has ambiguous implications for subsequent smoking. A screen may generate moral hazard effects that might induce smoking, as a negative screen lowers the level of perceived cancer risk under either smoking choice. On the other hand, both positive and negative screens may improve expectations of future healthy utility, as a positive screen improves objective survival through early treatment while a negative screen gives the individual better posterior odds of being in a long-lived state. This can increase the continuation-value cost of smoking after a favorable screen, reducing the incentive to smoke or even generating cessation incentives. We term this channel the health-capital preservation channel. Both channels matter for smoking because agents are forward looking and smoking is addictive, so smoking impacts both current and future utility as well as worsening future cancer/health risks and therefore reducing the value of future life.

To see this, let

$$Q_j^s(\Gamma) = \max_{x \in \{0,1\}} E[u(j, x; \Gamma) + \beta(1 - P(D_{t+1} = 1))V(\Gamma_{t+1}) \mid \Gamma, s = j, x],$$

for $j \in \{0, 1\}$. The individual smokes when

$$Q_1^s(\Gamma) - Q_0^s(\Gamma) \geq 0.$$

A negative screen changes this comparison through the posterior belief state. In particular, after a negative signal,

$$\hat{b}_t^0 = \frac{(1 - \rho)\tilde{b}_t}{(1 - \rho)\tilde{b}_t + (1 - \lambda)(1 - \tilde{b}_t)},$$

which is below $\tilde{b}_t$ whenever the test is informative, $\rho > \lambda$. This lower posterior may increase smoking by reducing perceived cancer risk: under either smoking choice, the next-period belief

$$B(b, s) = b + (1 - b)\pi_{12}(h, s, a)$$

is lower when $b = \hat{b}_t^0$ than when $b = \tilde{b}_t$. This is the standard moral-hazard channel.

However, the model also generates an opposing force. The incremental effect of smoking on next-period cancer beliefs is

$$B(b, 1) - B(b, 0) = (1 - b) [\pi_{12}(h, 1, a) - \pi_{12}(h, 0, a)].$$

Thus, when smoking raises cancer onset risk, a favorable screen can increase the marginal future health cost of smoking by moving the individual into a state with a larger stock of expected healthy life at risk. At the same time, this favorable information also raises the continuation value of survival, further reducing incentives to smoke. Screening may therefore complement preventive health behaviors, and might even induce quitting if the value-of-life effect dominates the risk-compensation effect. The model does not sign this relationship *ex ante*; the direction of the smoking response is an empirical object disciplined by the smoking-intention experiment and the estimated dynamic policy functions.

4 Data

Survey

Following a burgeoning economic literature on survey methods (Elías et al., 2019; Ferrario and Stantcheva, 2022; Haaland et al., 2024, 2025), we present results from a novel survey of 4,000 current or former smokers. Our survey ran on the survey research platform Prolific from November 20th, 2025 - February 15th, 2026.¹² Survey respondents come to Prolific and are presented with a set of surveys for which they meet eligibility criteria. Because our interest is in the population at risk for lung cancer, we restrict our eligible survey population to those with some smoking history and who are 40+ years of age. Our final analysis sample consists of 3,912 respondents.¹³

We begin our survey by asking standard assessments of CRRA risk preferences (Barsky et al., 1997) and time-consistent time preferences (Falk et al., 2018). In both cases, we are able to bound these parameters by classifying respondents based on responses to risk and intertemporal tradeoff questions, respectively. For risk aversion, our survey identifies six categories of respondents ranging from CRRA risk aversion parameters (γ_0) exceeding 7.52 to those less than 0.31. Similarly, for time preferences, our survey identifies eight groups such that the time consistent discount factor β ranges from less than 0.476 to greater than 0.943. We then measure health insurance status, income, and residential location at the zip code level. Next, we measure whether the respondent meets the 2021

¹²Prolific has been used extensively in recent economic research (McGranaghan et al., 2024; Graeber et al., 2024; Augenblick et al., 2025; Exley et al., 2025; Bordalo et al., 2026; Andre et al., 2026).

¹³Appendix Table 1 presents more information on sample construction, and Appendix Table 2 demonstrates that our sample is similar to 2022 Behavioral Risk Factor Surveillance System data in key individual characteristics. The [full survey](#) is also available via Qualtrics.

USPSTF recommendations for LDCT lung cancer screening. Specifically, we ask about current smoking status and age, and we assess a respondent’s pack-year smoking history. Whether a respondent is eligible for subsidized screening determines the set of options presented in the randomized experiment that follows.

In the next section, we assess beliefs regarding early lung cancer for a generic person who matches the respondent’s age, smoking history, and overall health. We follow this question with an assessment of how different the respondent feels they are from the average matched on these characteristics. Next, we ask respondents about the respondent’s history with, and beliefs regarding, LDCT lung cancer screening. These beliefs include subjective assessments of false and true positive rates, as well as assessments of past lung cancer screening. We also ask two questions about perceived stigma, both regarding support from family and about the signal that screening sends about past smoking behavior. We end this section with an assessment of “information avoidance,” in which we ask, “If lung cancer screening might bring bad news, I prefer to delay it, even if it’s recommended.” These questions provide evidence on heterogeneity in beliefs and attitudes regarding screening. Together with basic demographic information provided by Prolific, our baseline information on respondents includes rich measures of smoking and screening history, beliefs regarding lung cancer and screening outcome probabilities, and perceptions of stigma related to screening. We control for variation in these preferences, beliefs, and characteristics in our analysis below.¹⁴

Table 1 presents summary statistics on the baseline sample, including the count of nonmissing observations, the mean, and three p-values, to be defined below.¹⁵ The mean age of our sample is 52.3; 62% are female; and the percentages of White, Black, and Other races are 82.5%, 7.3%, 10.3%, respectively. Our least risk averse category is defined as having a CRRA γ parameter less than 0.31, which characterizes 5.3% of our sample; the most risk averse group are those with a CRRA γ greater than 7.52, which captures 29% of our sample. Similarly, 37.7% of the sample are in our least patient group, with a discount factor less than 0.476, and 4.1% of the sample have a discount factor greater than 0.941. The sample percentage with no health insurance is 8%, and the income distribution that ranges from 16.1% with annual income less than \$25,000 and 4% with greater than \$200,000 annual income. USPSTF guidelines are based on age, smoking history, and current smoking behavior, and 24.2% of our sample meet all three criteria; 52.7% meet the age criteria, 53% meet the pack-year criteria; and 71.0% are either current or recent smokers.

To gauge beliefs and expectations regarding lung cancer risk, screening quality, and stigma, we ask respondents the likelihood of early-stage cancer for a person with their age, smoking history, and health characteristics. The mean is 22.17%, and the modal respondent felt that their own risk was similar to the average person’s risk. The mean subjective belief that an LDCT lung cancer screen would detect an actual cancer case is 64.37%; and the mean subjective belief of a false positive is 17.9%. We characterized 45.4% of our sample as having “high stigma” surrounding screening, which we defined as the belief that both screening sends a signal about past behavior and that friends and family would be judgmental about seeking a screen. Finally, we asked respondents about information avoidance. In our sample, 17.1% agreed or strongly agreed that they prefer to avoid screening information.

Following the baseline questions, the survey turns to a randomized information experiment, the goal of which is

¹⁴See Appendix Figures 1 and 2 for evidence that risk and time preferences are correlated with subjective beliefs and intention to seek screening.

¹⁵We keep observations with missing baseline information in Table 1, but we drop observations with missing experimental variables. See Appendix Table 1.

to understand how preferences, beliefs, perceptions regarding screening quality, stigma, and prices shape the demand for lung cancer screening.¹⁶ First, we classify respondents based on whether they meet USPSTF guidelines, and we randomize respondents into four treatment arms: control, stigma, quality, and price. The arms are differentiated by how the intention to screen question is framed. We ask both a 0 to 100 scale question and a binary question, but our focus is on the former. The neutral framing of the screening question, which serves as the control arm, is:

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?

The framing that attempts to alleviate screening stigma keeps the control wording, adding the following italicized language:

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?

Similarly, the screening quality framing informs respondents of the false positive rate, as identified in our analysis of Truveta EHR data below, for LDCT lung cancer screening:

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?

Finally, the price treatment arm depends on USPSTF eligibility. For those who meet the guidelines and who are randomized to the price treatment arm, they receive the following framing:

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?

For those outside of USPSTF guidelines and who are randomized to the price treatment arm, we frame the question as:

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?

¹⁶Appendix Section 2 provides a graphical depiction of the experimental design.

We randomly vary the value $X \in \{100, 300, 500\}$. Each question is followed by a binary yes/no question about lung cancer screening in the next year.

After asking the randomly framed screening intention questions, we ask a series of comprehension questions that target understanding about the quality of screening, the process of screening, and the cost. We hypothesize that those receiving the treatment that corresponds to each target should be more likely to agree with our comprehension questions. For example, we ask respondents whether they agree with the statement, “Clinic staff would be nonjudgmental if I asked about screening,” which we hypothesize will find more support in those who received the positively framed stigma question. Appendix Figure 3 provides evidence in support of these hypotheses.

Our survey ends with a randomized framing of a question regarding expecting smoking behavior over the following 12 months. The control arm receives the following neutral framing:

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

In contrast, to capture how smoking behavior may respond to the results of lung cancer screening, the treatment framing adds the following italicized language:

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.

Importantly, in our intent-to-smoke question, we do not ask respondents to imagine a state of cancer. Here, we are attempting to alleviate uncertainty by presenting a hypothetical clean test result. The goal is to evaluate how intended smoking behavior differs relative to the neutral control framing of the question.

Table 1 presents evidence of experimental balance on three dimensions. The first p-value (p_1) is of the F-test that there are no differences in means between the control arm and the three treatment arms: stigma, quality, and price. The second p-value (p_2) is on the F-test of no differences in means between the lowest price treatment (\$100) and the other two prices (\$300 and \$500), conditional on being randomized to the price arm and being ineligible for free screening. The final p-value (p_3) is on the t-test that there is no difference in means between the treatment and control arm of the smoking experiment. We find very little evidence, beyond what would be expected randomly, of statistically significant differences across treatment arms. Nevertheless, we control for baseline characteristics in Table 1 in our analysis of the treatment effects.¹⁷

Our main regression equation relates Y_i , the measure of intention to screen, to binary variables for our treatment arms and the baseline characteristics:

$$Y_i = \alpha + \beta_S 1\{\text{Stigma}\} + \beta_Q 1\{\text{Quality}\} + \sum_j (\beta_P 1\{\text{Price}=j\} \cdot 1\{\text{Ineligible}\}) + \beta_{PE} 1\{\text{Eligibility Information}\} \cdot 1\{\text{Eligible}\} + \mathbf{X}_i' \boldsymbol{\gamma} + \varepsilon_i, \quad (9)$$

¹⁷Rather than drop observations, we record the small number of missing values of our control variables and control for these recoded observations.

where $j \in \{\$100, \$300, \$500\}$. Here, coefficients β_S and β_Q reflect treatment effects of the stigma and quality treatment arms, relative to the control arm, and β_P and β_{PE} represent treatment effects of the price arm those who do and do not meet the USPSTF guidelines, respectively.

Figure 1 presents estimates of the treatment effects in Equation 9, along with robust, 95% confidence intervals. Relative to the control mean of 38.25, the intention to screen is 10.2% higher in the stigma arm, but it is not significantly different in the quality information arm. Conditional on USPSTF eligibility, information about screening coverage increases intention to screen by 35.0%. For those who do not meet the guidelines, intention to screen falls by 16.2%, 33.7%, and 41.1% for price quotes of \$100, \$300, \$500, respectively, relative to the control arm. A feature of our experiment is that comparing treatment effects within those randomized to the price arm separately identifies the effect of prices from the effects of learning about USPSTF guidelines. Indeed, focusing on ineligible respondents receiving a price quote, we calculate an average extensive margin participation elasticity of -0.17.

Next, we assess heterogeneity in treatments effects. Specifically, we hypothesize larger effects of the positive stigma framing among those who, at baseline, admit to feeling stigma. Relative to the control mean, the effect of the positive stigma information is 13.0% among those classified as having high stigma at baseline. For those with low baseline stigma, the effect smaller at 7.9%.

Our quality framing presents the true false positive rate of screening of 12%; for respondents whose baseline, subjective assessment of the false positive rate is higher, our treatment represents "good" quality news, and we expect that our quality treatment should encourage screening. Similarly, for respondents whose baseline, subjective assessment of the false positive rate is lower than 12%, our treatment reflect "bad" news. Allowing the quality information treatment effect to vary by baseline beliefs, we see that "bad" news respondents in this arm are less likely to screen, and "good" news respondents are more likely to screen, but neither effect is statistically significant. Finally, we assess heterogeneity in the price effects by income, allowing the price treatment effects to vary by whether the respondent reports more or less than \$50,000 in annual income. Here, we do not find significantly different treatment effects, even as we are controlling for other socioeconomic characteristics, including health insurance status.

Finally, we evaluate treatment effects from our smoking experiment by focusing on the subset of respondents who claim to be currently smoking at baseline, and we model how their intention to quit smoking varies by our "clean scan" treatment. Define $Q_i = 1$ if the respondent selected "I will completely quit smoking," and 0 otherwise. We estimate:

$$Q_i = \beta_0 + \beta_1 1\{\text{Treatment}\} + \mathbf{X}_i' \boldsymbol{\gamma} + \epsilon_i, \quad (10)$$

where β_1 is our coefficient of interest. Figure 3 presents estimates and robust confidence intervals of β_1 , both overall and across several subgroups of interest. The control mean of intention to quit among our 1,342 current smokers is 0.216. Overall, intention to quit smoking is 16.7% higher in the treatment group. Next, we allow for heterogeneity in the treatment effect by time preference. We define "more patient" and "more impatient" groups based on whether the time consistent discount factor is more or less than 0.5. The more patient group constitutes 38.57% of our sample. The "clean scan" treatment is larger for the more patient group (27.8%). We also find a much larger treatment effect (0.114 vs. 0.027) in those without insurance, although these results are imprecise. We find a large and statistically

significant increase in intention to quit (29.6%) for those who had never received a lung cancer screening. Finally, we find the largest treatment effect on those who assessed their own risk as “much higher than average.”

Truveta

Truveta compiles and standardizes daily electronic health record (EHR) data from over 130 million patients, representing 100 health systems across the United States. The Truveta data provide longitudinal, patient-level clinical information, including diagnoses, procedures, imaging utilization, and follow-up care. Indeed, for patients who seek care in different systems within Truveta coverage, we are able to link standardized records across providers and payers. We use Truveta to measure real-world screening outcomes and diagnostic pathways. These data are particularly well suited to our setting because they allow us to observe the full sequence of events surrounding lung cancer screening, including initial low-dose CT (LDCT) scans, subsequent diagnostic testing, and confirmed cancer diagnoses. Our primary use of the Truveta data is to identify objective screening test characteristics and diagnostic outcomes. In particular, we estimate rates of false positives and follow-up testing conditional on screening, as well as the distribution of diagnostic resolution after an initial positive screen.

Within the Truveta environment, we define a population of individuals who have ever either had an LDCT lung cancer screening or been diagnosed with lung cancer. Of this 4.8 million individual population, we take a 1.5% sample, representing 67,000 patients and 17 million medical encounters. Over 95% of our sample are above the age of 31; 71.8% are white, 48.1% are male; and the modal group, representing more than 43,000 patients, are observed in over 61 medical encounters over at least 15 years.

Within our sample, we observe 264,000 initial, LDCT lung cancer screens. Figure 4 presents a flow diagram of the outcomes. Following the initial screen, we define a category of any confirmatory testing within the subsequent three months. In our sample, 14% had confirmatory testing within three months. Next, we define a binary variable of any cancer diagnosis within 12 months of the initial screening. Of those with confirmatory testing, 88% had no cancer diagnosis within 12 months, and, of those with no confirmatory at three months, 99% had received no cancer diagnosis at 12 months. We base our definition of a “false positive” from the diagnosis indicator. Specifically, of the 264,000 initial screens, 259,000 had not resulted in a cancer diagnosis. However, the 12.5% (33,000) who received confirmatory testing likely received something other than a “no cancer” result from the initial screen. The ratio of these counts yields a false positive rate of 12.7%.

National Lung Screening Trial

We use data from the National Lung Screening Trial (NLST), a large-scale randomized controlled trial of LDCT screening, to identify policy-invariant health transition parameters. The NLST enrolled over 50,000 high-risk individuals with substantial smoking histories and randomly assigned them to LDCT screening or chest radiography, generating experimental variation in screening exposure and subsequent health outcomes. The trial provides detailed information on cancer incidence, stage at diagnosis, disease progression, and mortality over up to 7 years.

We use the NLST to estimate transition probabilities governing the onset and progression of lung cancer in the

absence of endogenous behavioral responses. Specifically, we calibrate the model’s transition functions using the trial data estimates, including for cancer incidence, progression across stages, and survival (including conditional on diagnosis and treatment). Because screening assignment in the NLST is randomized, these estimates are not confounded by selection into screening and therefore provide a natural benchmark for the biological evolution of disease. We treat these transition parameters as fixed inputs in estimation, allowing the structural model to separately identify how individuals respond to risk and information. This separation is important for isolating behavioral responses from underlying disease dynamics.

BRFSS

Finally, we use data from the Behavioral Risk Factor Surveillance System (BRFSS), a large, nationally representative survey of U.S. adults, to generate empirical moments on smoking behavior and screening prevalence among US adults with smoking history. The BRFSS provides detailed information on smoking status, smoking history (including pack-years), demographics, and self-reported health, as well as information on preventive care utilization including cancer screening. We restrict the sample to individuals with a history of smoking and construct age-specific profiles of smoking and screening behavior that are comparable to the population targeted in our model and experimental data.

The BRFSS plays three roles in our analysis. First, it provides externally valid moments on the distribution and dynamics of smoking behavior over the life cycle, which we use to discipline preference parameters governing addiction and habit formation. Second, it provides reduced-form evidence on screening utilization, including variation by age and smoking history, which we use to match screening rates inside and outside USPSTF eligibility thresholds (Darden and Hoagland, 2025). These moments identify how individuals value screening and endogenously select into screening, even when ineligible for fully cost-sharing exempt screening. Finally, because the BRFSS is nationally representative, we use it to anchor the model’s cross-sectional distribution of observables, ensuring that simulated moments map to population-level behavior.

Appendix Figure 4 provides evidence on moments that inform the addiction parameters of the model, namely $\gamma_1 - \gamma_3$. We also show how screening prevalence evolves around thresholds for age and pack-years.

Reduced-Form Evidence

Our randomized information experiment yields three findings. First, price effects dominate other behavioral mechanisms; informing USPSTF recommended respondents of their eligibility for free screening increases intention-to-screen by 40%, whereas informing respondents of the 12% rate of false positives identified in Truveta EHR data does not change behavior on average.¹⁸ Second, baseline heterogeneity in beliefs and stigma interact with treatment to drive behavior. For example, for those respondents exhibiting some stigma associate with screening at baseline, there was a significant effect of information targeting these beliefs on screening intention. Finally, we find no evidence

¹⁸Our data suggest the false positive rate is 12.7%, but there is considerable variance in the literature (Aberle et al., 2011; Pinsky et al., 2013; de Koning et al., 2020; Pinsky et al., 2015).

of moral hazard. Being informed of a clean screening result increases the intention to quit smoking among current smokers by 16.7%, an effect that is driven by time preferences, screening history, and self-assessed risk perceptions.

5 Empirical Implementation

Moments & Estimation

Some parameters, such as those governing health transitions, are fixed in our model based on prior literature and our own first stage estimates using claims data. These include the coefficient of risk aversion ($\gamma_0 = 2$), the discount factor ($\beta = 0.95$), and health transition parameters summarized in Table 2. These transition probabilities are identified using the NLST data.

We estimate the equilibrium model parameters using simulated GMM, matching observed moments from our experimental and clinical data to simulated moments in the model. As our model is based on a combination of multiple unique data sources, we estimate the model on a simulated dataset of 1 million smokers, whose characteristics are calibrated to be representative of the BRFSS and experimental data. In each step of solving the model, for a given guess of the parameters (Θ_0), we solve the full model by backward induction, allowing agents' health, beliefs, and utilities to evolve over time according to the optimal policy functions derived above. Solving the model in this way is feasible, as agents have a finite lifespan and make only two binary choices in each period (smoking and screening). Doing so yields estimates of the optimal smoking and screening decisions across the entire state space, meaning for all agents conditional on their demographics, smoking history, and health; it also allows us to compute the selected moments. We then iterate over this approach until the observed and simulated moments converge to identify Θ^* .

In estimation, we use moment conditions capturing (i) age-specific smoking prevalence, (ii) the relationship between smoking and cumulative smoking history, (iii) screening rates by eligibility status, and (iv) our experimentally identified responses of screening to price, stigma, and perceived test quality. First, we target age profiles of smoking by matching mean smoking rates across age bins observed in the BRFSS data for those with smoking history by age 40. Second, we match the relationship between smoking and cumulative smoking history (pack-years), including both levels and slopes, to capture persistence and reinforcement in smoking behavior over the life cycle (Becker and Murphy, 1988). Third, we match average screening rates separately for individuals above and below each USPSTF eligibility threshold, capturing those who opt into screening as they cross one threshold but not another (Darden and Hoagland, 2025). Finally, we use experimental variation to discipline how screening responds to prices, stigma-related barriers, and perceived test quality. All moments are constructed at the individual level and aggregated in estimation.

***** YET TO BE INCLUDED: Table listing all model parameters, whether they are estimated or calibrated, the moments used, robustness bounds.

Machine-Learning-Assisted Initialization for Structural GMM

Estimating structural models by GMM often requires solving a difficult, non-convex optimization problem. In such settings, convergence and equilibrium parameter vectors can be highly sensitive to the initial starting point. We therefore implement a machine-learning (ML)-assisted warm-start procedure designed to deliver starting values that are both computationally efficient and economically plausible. The procedure preserves the conventional structural GMM estimator while incorporating ML algorithms to guide the choice of initial conditions.

The algorithm proceeds in three steps. First, we perform a grid search, in which we draw 25,000 candidate parameter vectors using a Latin hypercube design over the admissible parameter space. For each candidate, we solve the structural model, simulate a cohort, and compute the vector of average model-implied moments. We also generate a binary indicator for whether the candidate vector implied a corner solution (e.g., no smoking or no screening). Second, using the simulated moments as training data, we estimate a separate XGBoost regression for each moment and a separate XGBoost classifier for whether the candidate vector resulted in a corner solution. The moment-specific regressions produce a flexible approximation to the mapping from structural parameters to model moments, while the classifier estimates the probability a candidate start lies in a region leading to a corner solution. Because the regressions are fit moment by moment, the procedure can accommodate heterogeneity in predictability across moments (e.g., an optimal weighting matrix from a previous iteration). Finally, we generate a much larger set of unevaluated candidate parameter vectors and use the trained models to predict their implied moments and corner-solution probabilities.¹⁹ This results in a small set of optimal starting vectors, which can be used for the actual structural estimation and to evaluate model stability relative to distinct starting values.²⁰

A novel part of the grid search is that for each candidate, we compute an indicator for whether the simulated behavior is effectively at a corner solution. That is, for a given starting vector, we simulate the model and assign a flag if the implied smoking or screening rates are near zero or one. This classification step is important because some regions of the parameter space generate behavior that is numerically admissible but economically uninformative for local optimization. Such regions can trap gradient-free or local-search routines in parts of the parameter space that are unlikely to yield an empirically credible interior fit. The corner indicator is used only in the warm-start stage; in the main structural estimation, we do not constrain the predicted smoking or screening behaviors in any way.

Our approach to using ML-assisted techniques to identify a warm start to standard GMM optimization is novel, but related to several important developments in structural estimation. Some work in this area has relied on ML to learn the relationship between moments and parameters directly, particularly for simulated estimation techniques (Catherine and Ebrahimian, 2024; Duarte and Fonseca, 2023). These papers use supervised learning to exploit the geometry of a model-implied moment surface, but they ultimately replace the structural estimation routine itself. We, on the other hand, leave in place the conventional GMM estimator and use ML approaches in a conservative way

¹⁹These predictions are generated using a criterion mirroring the objective used in estimation. Specifically, we use the optimal weighting matrix to combine individual moment predictions, but trim extreme eigenvalues to maintain numerical stability. We additionally include a dispersion penalty based on the cross-moment standard deviation of the predicted values to exclude starting values with extremely poor predictions in one or more moment dimensions.

²⁰As a robustness check, we also perform simulated annealing as an optimization method for our starting points, to verify that the optimizer is not routinely converging to local, rather than global, optima.

only to improve the starting parameter vector. Our approach also allows for ML selection of weights on moments, complementary to recent work using ML to automate moment selection (Zila and Kukacka, 2023). While this work empirically selects moments, we continue to prioritize theoretically-selected moments while learning from the data the best weighted objective function to apply across those moments. Our approach is especially useful in applications where solving the model is costly, the objective is irregular, and poor starts frequently lead to local minima or economically degenerate solutions.

Preliminary Model Fit & Key Results

The estimated model provides a good fit to a large number of statistics from our various data sources, including smoking and screening rates from the BRFSS data and our experimental results. In particular, we verify that the equilibrium model prediction validates the experimental evidence presented above: the model generates strong price effects as well as responses to changes in an individual’s optimism or stigma for screening. Here, we highlight three key implications validated by our model; additional results are presented in the Appendix.

First, the model implies that screening decisions are highly price sensitive, but that screening also happens frequently outside of the USPSTF eligibility thresholds (Darden and Hoagland, 2025). Figure 5 shows both empirically observed and predicted screening rates stratified by both age and smoking history. The figure highlights two facts: first, 60% of all LCS screening happens when individuals choose to pay out of pocket for a screening. A substantial portion of this screening (36% of all screening) occurs even for individuals who meet neither of the relevant thresholds. Second, screening rates discontinuously increase when the price drops (for example, when individuals in the high smoking-history group pass the age 50 cutoff in the first panel of Figure 5). The equilibrium estimated price elasticity of screening is -0.15, consistent with our experimentally obtained price elasticity of -0.17. The preliminary model matches the qualitative discontinuities around eligibility thresholds and the relative ranking of screening rates by age and smoking history, although it currently over-predicts screening levels among older high-pack-year individuals.

Individuals choosing to pay for screening are informative about the relative value of screening, as discussed above. Screening is triggered in the model when subjective beliefs about cancer risk rise, driven by signals from smoking, health transitions, or symptoms. Based on the estimated model parameters, when individuals face the full price of screening (roughly \$300), they choose to screen when their beliefs about cancer risk are 3.6%. After meeting USPSTF eligibility requirements, this threshold drops by roughly one third to 2.4%.

Second, the model fit also highlights intent to quit decisions. In the model, we estimate that screening is associated with a 8.3 percentage point reduction in smoking, roughly a 25% drop from the baseline smoking rate. This response is consistent with a value-of-life channel in which favorable health information increases the return to preserving future health and matches the experimental evidence presented above.

Third, we also find strong evidence that selection into screening and smoking is endogenously driven by one’s own lifetime survival risk. Figure 6 stratifies screening and smoking decisions by those who die before age 70 versus those who survive. Individuals who die earlier are both more likely to smoke (directly contributing to their lifetime mortality risk), but also more likely to take up screening. This could be driven either by correct beliefs about their

own risk, induced screening eligibility (e.g., based on smoking history), or the more frequent presence of symptoms triggering screening. Importantly, however, the differences in screening are most notable once price changes take place at age 50, and then diminish with time.

Finally, the equilibrium model parameters give a sense of the relative importance of each of the mechanisms we study. While the model fits the requisite moments well (e.g., identifying a price effect when an individual becomes eligible for free screening), the model moments are agnostic about the relative importance of each channel, making this an interesting equilibrium exercise. As a benchmark, one can compare estimated utility losses from screening under various states to the utility loss from symptoms. Without taking into account price, optimism, or stigma effects, the estimated utility losses from screening are roughly 8% of the utility losses from symptoms. However, we estimate that this constitutes only a small fraction of utility losses from screening. Stigma effects impose utility losses 1.2 times as large as symptoms, while pessimism about screening quality imposes utility losses 1.6 times as large.²¹ Importantly, the price effect dominates here: the equilibrium utility parameters imply that eliminating screening prices results in utility gains 4.5 times larger than eliminating all screening disutility for both types. However, we also estimate strong selection into screening based on beliefs about screening quality; this is particularly true once screening becomes free, as illustrated in Figure 7.

6 Counterfactual Simulations

Given the estimated model, we are now able to answer key questions related to the value of screening when screening and health behaviors are endogenously correlated. In this section, we present the results of two key counterfactuals. First, we examine the value of a negative screen even for low-risk individuals, by highlighting the effects of exogenous, universal screening at ages 45 and 50. Second, we explore counterfactual simulations that attempt to induce this screening by varying the price of screening, USPSTF eligibility, and targeting individuals with high stigma or pessimism about a test.

First, we assess how negative LC screening, even for individuals with relatively little *ex-ante* cancer risk, may affect lifetime trajectories of smoking, cancer incidence, and mortality. We do this by imposing a counterfactual policy meant to exogenously provide information on cancer risk, and then assess the extent to which this generates continuation value effects that outweigh any potential moral hazard effects. That is, we assume universal screening for all individuals with any smoking history at age 45 (age 50 in a robustness exercise) and examine how this induces individuals to quit smoking, as well as any downstream effects this has on cancer development and progression and mortality.

Figure 8 presents the results. We find that imposing a one-time universal screen for smokers at age 45 results in individuals quitting smoking 2.8% of the time; conditional on being a current smoker at age 44, this jumps to 10.7%. For this sample, the average quitter goes an additional 3.82 years without smoking compared to baseline. This extends the number of cancer-free years for 0.5% of individuals, a 2.7% decline in cancer incidence in this

²¹We also estimate an interesting interaction effect, where individuals facing high stigma and pessimism about screening quality incur additional utility losses roughly 1.3 times as large as utility losses from symptoms.

population. For these individuals, screening at age 45 leads to an average of 5.77 additional cancer-free years. This directly translates to improved longevity: of those with extended cancer-free years, two thirds experience longer life, with an average gain of 9.06 years.

Taken together, these results imply that even universal screening for an overall low-risk population can improve health behaviors and generate real returns on cancer development, progression, and mortality. With that in mind, a natural question is whether policy levers such as eligibility criteria or cost-sharing can meaningfully induce screening. We therefore present the results of a second set of simulations, where we vary these policy levers and measure whether screening was induced, and how much other outcomes changed as a result.

Table 3 presents the results. Offering screening at no cost to anyone with a history of smoking dramatically increases screening takeup and increases overall lifetime utility among this population by 5%; this meaningfully induces just over a fourth of the population to quit smoking sooner than they otherwise would have, and ultimately increases cancer free time for 0.5% of the population. However, these health effects can be obtained from more targeted policy interventions; Table 3 indicates that extending eligibility for USPSTF-covered screenings along either dimension generates similar results for smoking cessation, cancer detection and progression, and longevity (albeit with reduced utility gains). On the other hand, targeting individuals based on screening stigma or pessimism about screening outcomes (or both) are far less effective at inducing quitting and, ultimately, improving health.

This pattern is plausible, given that the value of a negative screen is likely maximized for individuals under the age of 50. It has generally been established that when an individual ceases to smoke before age 50, the subsequent risk of lung cancer is greatly reduced as lung tissue is most likely to recover (Yoshida et al., 2020). Hence, if negative screening induces smoking cessation due to the continuation-of-life effect, health effects will be maximized for screens that are incentivized for those under the age of 50. This is more effectively done by relaxing the USPSTF eligibility thresholds, rather than more sweeping reforms or relying on individual type changes.

7 Conclusion

This paper studies screening as an endogenous information technology whose value depends on the behavioral response it induces. This is common when healthcare services, such as screening, are more effective when combined with preventive health behaviors. We write a dynamic model in the context of lung cancer screening, where individuals choose whether to acquire information about latent cancer risk while also choosing whether to continue smoking, the primary behavior that generates that risk. We estimate the model by relying on a randomized information experiment with clinical records, trial evidence, and nationally representative survey data. In estimating and evaluating the model, we show that screening cannot be evaluated independently of other health investments. Screening demand is highly price sensitive, but selection into screening is not governed by price alone: subjective risk beliefs, stigma, and perceived test quality all shape who screens and when. The model rationalizes substantial screening outside USPSTF eligibility thresholds, even as many eligible individuals remain unscreened, and it implies that marginal screeners differ meaningfully from average screeners in both risk and responsiveness to information.

Our main finding is that screening information complements, rather than substitutes for, prevention. A favor-

able screening result lowers perceived current cancer risk, but it also raises the value of preserving future health. Empirically, this health-capital preservation channel dominates moral hazard effects, so that negative screens reduce smoking in both the experimental data and the estimated model. Counterfactual simulations show that screening policy has consequences beyond earlier diagnosis. Expanding access to screening can induce cessation, increase cancer-free years, and improve longevity, with particularly large returns when screening reaches smokers early enough for cessation to meaningfully alter subsequent disease risk. These results imply that the design of screening recommendations should account not only for clinical risk and test accuracy, but also for endogenous health behavior and selection into information acquisition. More generally, preventive care policies that reveal health information may have first-order effects on behavior, and those effects should be incorporated into both welfare analysis and the construction of clinical guidelines.

References

- Aberle, D. R., Adams, A. M., Berg, C. D., Black, W. C., Clapp, J. D., Fagerstrom, R. M., et al. (2011). Reduced lung-cancer mortality with low-dose computed tomographic screening. The New England Journal of Medicine, 365(5):395–409.
- Alsan, M., Garrick, O., and Graziani, G. (2019). Does diversity matter for health? experimental evidence from oakland. American Economic Review, 109(12):4071–4111.
- Andre, P., Haaland, I., Roth, C., Wiederholt, M., and Wohlfart, J. (2026). Narratives about the macroeconomy. The Review of Economic Studies, page rdag014. Advance article / corrected proof.
- Augenblick, N., Lazarus, E., and Thaler, M. (2025). Overinference from weak signals and underinference from strong signals. The Quarterly Journal of Economics, 140(1):335–401.
- Baicker, K., Mullainathan, S., and Schwartzstein, J. (2015). Behavioral hazard in health insurance. The Quarterly Journal of Economics, 130(4):1623–1667.
- Bandi, P., Star, J., Ashad-Bishop, K., Kratzer, T., Smith, R., and Jemal, A. (2024). Lung cancer screening in the us, 2022. JAMA Internal Medicine, 184(8):882–891.
- Barsky, R. B., Juster, F. T., Kimball, M. S., and Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. The Quarterly Journal of Economics, 112(2):537–579.
- Becker, G. S. and Murphy, K. M. (1988). A theory of rational addiction. Journal of political Economy, 96(4):675–700.
- Bernheim, B. D. and Rangel, A. (2004). Addiction and cue-triggered decision processes. American Economic Review, 94(5):1558–1590.
- Bordalo, P., Conlon, J., Gennaioli, N., Kwon, S., and Shleifer, A. (2026). How people use statistics. The Review of Economic Studies, 93(1):250–285.
- Burus, T., McAfee, C. R., Knight, J. R., Mullett, T. W., and Hull, P. C. (2026). Lung cancer screening prevalence and changes in 2024. JAMA Internal Medicine, 186(6). Published online April 27, 2026.
- Capatina, E. and Keane, M. P. (2026). Health shocks, health insurance, human capital, and the dynamics of earnings and health. Journal of Political Economy.
- Catherine, S. and Ebrahimian, M. (2024). Robustness checks in structural analysis. Working Paper 30443, National Bureau of Economic Research.
- Centers for Medicare & Medicaid Services (2015). Screening for lung cancer with low dose computed tomography (ldct) (cag-00439n): Decision memo. National Coverage Analysis; accessed 2026-05-11.

- Centers for Medicare & Medicaid Services (2022). National Coverage Determination (NCD): Lung Cancer Screening with Low Dose Computed Tomography (LDCT) (210.14). <https://www.cms.gov/medicare-coverage-database/view/ncd.aspx?NCDId=364>. Version 2; effective February 10, 2022. Accessed May 11, 2026.
- Chan, T. Y. and Hamilton, B. H. (2006). Learning, private information, and the economic evaluation of randomized experiments. *Journal of Political Economy*, 114(6):997–1040.
- Chandra, A., Gruber, J., and McKnight, R. (2010). Patient cost-sharing and hospitalization offsets in the elderly. *American Economic Review*, 100(1):193–213.
- Ching, A. T., Erdem, T., and Keane, M. P. (2013). Invited paper—learning models: An assessment of progress, challenges, and new developments. *Marketing Science*, 32(6):913–938.
- Crawford, G. S. and Shum, M. (2005). Uncertainty and learning in pharmaceutical demand. *Econometrica*, 73(4):1137–1173.
- Darden, M. (2017). Smoking, expectations, and health: A dynamic stochastic model of lifetime smoking behavior. *Journal of Political Economy*, 125(5):1465–1522.
- Darden, M., Gilleskie, D. B., and Strumpf, K. (2018). Smoking and mortality: New evidence from a long panel. *International economic review*, 59(3):1571–1619.
- Darden, M. E. and Hoagland, A. (2025). Lung cancer screening and uspstf recommendations. *JAMA Network Open*, 8(2):e2458916–e2458916.
- Davenport, M. S. and Reeder, S. B. (2026). Elective mri screening of the general public—buyer beware. *JAMA*. Published online May 6, 2026.
- de Koning, H. J., van der Aalst, C. M., de Jong, P. A., et al. (2020). Reduced lung-cancer mortality with volume CT screening in a randomized trial. *The New England Journal of Medicine*, 382(6):503–513.
- DeCicca, P., Kenkel, D., and Lovenheim, M. F. (2022). The economics of tobacco regulation: A comprehensive review. *Journal of Economic Literature*, 60(3):883–970.
- Doll, R., Peto, R., Boreham, J., Gray, R., and Sutherland, I. (2004). Mortality in Relation to Smoking: 50 Years’ Observations on Male British Doctors. *British Medical Journal*, 328:1519–1528.
- Duarte, G. and Fonseca, J. (2023). Global identification with gradient-based structural estimation. Working paper.
- Ehrlich, I. and Becker, G. S. (1972). Market insurance, self-insurance, and self-protection. *Journal of Political Economy*, 80(4):623–648.

- Einav, L., Finkelstein, A., Oostrom, T., Ostriker, A., and Williams, H. (2020). Screening and Selection: The Case of Mammograms. American Economic Review, 110(12):3836–3870.
- Elías, J. J., Lacetera, N., and Macis, M. (2019). Paying for kidneys? a randomized survey and choice experiment. American Economic Review, 109(8):2855–88.
- Exley, C. L., Hauser, O. P., Moore, M., and Pezzuto, J.-H. (2025). Believed gender differences in social preferences. The Quarterly Journal of Economics, 140(1):403–458.
- Falk, A., Becker, A., Dohmen, T., Enke, B., Huffman, D., and Sunde, U. (2018). Global evidence on economic preferences. The Quarterly Journal of Economics, 133(4):1645–1692.
- Ferrario, B. and Stantcheva, S. (2022). Eliciting people’s first-order concerns: Text analysis of open-ended survey questions. In AEA Papers and Proceedings, volume 112, pages 163–169. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.
- Gilleskie, D. B. (1998). A dynamic stochastic model of medical care use and work absence. Econometrica, 66(1):1–45.
- Graeber, T., Roth, C., and Zimmermann, F. (2024). Stories, statistics, and memory. The Quarterly Journal of Economics, 139(4):2181–2225.
- Gram, E. G., Copp, T., Ransohoff, D. F., Plüddemann, A., Kramer, B. S., Woloshin, S., and Shih, P. (2024). Direct-to-consumer tests: emerging trends are cause for concern. BMJ, 387:e080460.
- Grossman, M. (1972). On the Concept of Health Capital and the Demand for Health. Journal of Political Economy, 80(2):223–255.
- Gruber, J. and Köszegi, B. (2001). Is addiction “rational”? theory and evidence. The Quarterly Journal of Economics, 116(4):1261–1303.
- Gul, F. and Pesendorfer, W. (2007). Harmful addiction. The Review of Economic Studies, 74(1):147–172.
- Haaland, I., Roth, C., Stantcheva, S., and Wohlfart, J. (2025). Understanding economic behavior using open-ended survey data. Journal of Economic Literature, 63(4):1244–1280.
- Haaland, I. K., Roth, C., Stantcheva, S., and Wohlfart, J. (2024). Measuring what is top of mind. Working Paper 32421, National Bureau of Economic Research.
- Henderson, L. M., Su, I.-H., Rivera, M. P., Pak, J., Chen, X., Reuland, D. S., and Lund, J. L. (2024). Prevalence of lung cancer screening in the US, 2022. JAMA Network Open, 7(3):e243190–e243190.
- Hoagland, A. (2026). An ounce of prevention or a pound of cure? The value of health risk information. Review of Economics and Statistics.

- Internal Revenue Service, Employee Benefits Security Administration, Department of Labor, and Office of Consumer Information and Insurance Oversight, Department of Health and Human Services (2010). Interim Final Rules for Group Health Plans and Health Insurance Issuers Relating to Coverage of Preventive Services Under the Patient Protection and Affordable Care Act. *Federal Register*, 75(137), 41726–41760. Document No. 2010-17242; TD 9493; OCHIO-9992-IFC; interim final rules with request for comments; effective September 17, 2010.
- McGranaghan, C., Nielsen, K., O’Donoghue, T., Somerville, J., and Sprenger, C. D. (2024). Distinguishing common ratio preferences from common ratio effects using paired valuation tasks. *American Economic Review*, 114(2):307–347.
- Mehrtash, F., Dushay, J., and Manson, J. E. (2025). I am taking a glp-1 weight-loss medication—what should i know? *JAMA Internal Medicine*, 185(9):1180–1180.
- Miguel, E. and Kremer, M. (2004). Worms: Identifying impacts on education and health in the presence of treatment externalities. *Econometrica*, 72(1):159–217.
- Newhouse, J. P. (2021). An ounce of prevention. *Journal of Economic Perspectives*, 35(2):101–118.
- Pinsky, P. F., Church, T. R., Izmirlian, G., and Kramer, B. S. (2013). The National Lung Screening Trial: results stratified by demographics, smoking history, and lung cancer histology. *Cancer*, 119(22):3976–3983.
- Pinsky, P. F., Gierada, D. S., Black, W., Munden, R., Nath, H., Aberle, D., and Kazerooni, E. (2015). Performance of Lung-RADS in the National Lung Screening Trial: a retrospective assessment. *Annals of Internal Medicine*, 162(7):485–491.
- Sabatino, S. A., Thompson, T. D., Croswell, J. M., Villarroel, M. A., Rodriguez, J. L., Adam, E. E., and Richardson, L. C. (2025). Use of cancer screening tests, united states, 2023. *Preventing Chronic Disease*, 22:250139.
- The National Lung Screening Trial Research Team (2011). Reduced lung-cancer mortality with low-dose computed tomographic screening. *New England Journal of Medicine*, 365(5):395–409.
- U.S. Preventive Services Task Force (2004). Lung cancer screening: recommendation statement. *Annals of Internal Medicine*, 140(9):738–739.
- U.S. Preventive Services Task Force (2014). Screening for lung cancer: U.s. preventive services task force recommendation statement. *Annals of Internal Medicine*, 160(5):330–338. PMID: 24378917.
- U.S. Preventive Services Task Force (2021). Screening for lung cancer: Us preventive services task force recommendation statement. *JAMA*, 325(10):962–970.
- Volk, R. J., Lowenstein, L. M., Leal, V. B., Escoto, K. H., Cantor, S. B., Munden, R. F., Rabin, V. A., Bailey, L., Cinciripini, P. M., Lin, H., Houston, A. J., Luckett, P. G., Esparza, A., Godoy, M. C., and Bevers, T. B. (2020). Effect of a patient decision aid on lung cancer screening decision-making by persons who smoke: A randomized clinical trial. *JAMA Network Open*, 3(1):e1920362–e1920362.

- Volk, R. J., Maki, K. G., Rogova, A., Tu, A., Nguyen, C. V., Ma, H., and Hoffman, R. M. (2026). The counseling and shared decision-making visit for lung cancer screening: A thematic analysis of public comments to the centers for medicare & medicaid services during the 2021-2022 national coverage analysis process. CHEST, 169(5):1402–1414.
- Yoshida, K., Gowers, K. H., Lee-Six, H., Chandrasekharan, D. P., Coorens, T., Maughan, E. F., Beal, K., Menzies, A., Millar, F. R., Anderson, E., et al. (2020). Tobacco smoking and somatic mutations in human bronchial epithelium. Nature, 578(7794):266–272.
- Zila, J. and Kukacka, J. (2023). Moment set selection for the simulated method of moments using simple machine learning. Journal of Economic Behavior & Organization, 211:1–20.

8 Tables

Table 1: Baseline Covariate Balance

	N	Mean	p_1	p_2	p_3
Age in Years	3912	52.298	0.567	0.769	0.526
Female	3912	0.622	0.565	0.466	0.296
Race					
White	3912	0.825	0.681	0.955	0.336
Black	3912	0.073	0.401	0.705	0.475
Other	3912	0.103	0.924	0.596	0.553
Least Risk Averse, $\gamma \in [0, 0.3]$	3880	0.053	0.733	0.576	0.354
Most Risk Averse, $\gamma \geq 7.52$	3880	0.290	0.643	0.671	0.023
Least Patient, $\beta < 0.476$	3873	0.377	0.524	0.783	0.420
Most Patient, $\beta \in [0.943, 1]$	3873	0.041	0.914	0.402	0.770
Uninsured	3912	0.080	0.957	0.733	0.269
Income					
Less than \$25,000	3908	0.161	0.632	0.712	0.194
\$25,000-\$49,999	3908	0.241	0.557	0.549	0.176
\$50,000-\$99,999	3908	0.349	0.294	0.922	0.831
\$100,000-\$199,999	3908	0.209	0.895	0.827	0.555
More than \$200,000	3908	0.040	0.768	0.578	0.222
Currently Smoke Cigarettes.	3912	0.343	0.226	0.785	0.725
Pack-Years	3912	27.779	0.840	0.396	0.754
Eligibility for Free Screening	3912	0.242	0.714	.	0.593
Age Eligible	3912	0.527	0.339	0.844	0.173
Pack-Years Eligible	3912	0.530	0.822	0.070	0.601
Smoking Eligible	3912	0.710	0.382	0.946	0.451
Belief of Early-Stage Lung Cancer	3851	22.170	0.232	0.981	0.144
Lower Expected Risk	3912	0.234	0.733	0.216	0.966
About the Same.	3912	0.533	0.357	0.070	0.671
Higher Expected Risk	3912	0.233	0.040	0.591	0.647
Belief of True Positive	3851	64.370	0.755	0.466	0.866
Belief of False Positive	3827	17.901	0.850	0.990	0.859
High Stigma	3909	0.453	0.028	0.531	0.036
Avoids Information	3912	0.171	0.768	0.162	0.840

Notes: Table 1 presents the overall mean of key variables and three p-values. The first p-value is of the F-test that there are no differences in means between the control arm and the three treatment arms quality, stigma, and price. The second p-value is on the F-test of no differences in means between the lowest price treatment (\$100) and the other two prices (\$300 and \$500) conditional on being randomized to the price arm and being ineligible for free screening. The final p-value is on the t-test that there is no difference in means between the treatment and control arm of the smoking experiment.

Table 2: Calibrated Parameters Governing Health Transitions

Parameters	(1) LC Incidence	(2) LC Progression	(3) Other Health Condition	(4) Mortality
Age	-0.11	1.04	1.32	0.81
Smoking History	0.82	0.07	0.04	—
Currently Smoking	-0.58	0.88	0.24	—
LC Treatment	—	-5.19	—	—
Early-Stage LC	—	—	—	2.35
Late-Stage LC	—	—	—	4.19
Other Health Condition	—	—	—	0.69
Intercept	-8.18	-12.93	-7.68	-6.91

Notes: This table presents calibrated parameters governing how underlying health states evolve over time in the model. These parameters are reported as the coefficients on logistic regressions predicting each of the outcomes indicated in columns (1) through (4). Smoking history is measured in 10 pack-year units, and age is measured in decades above age 40. Parameters are calibrated to match empirical incidence of cancer and its progression based on the NLST, SEER cancer incidence data, and previous work (Darden et al., 2018).

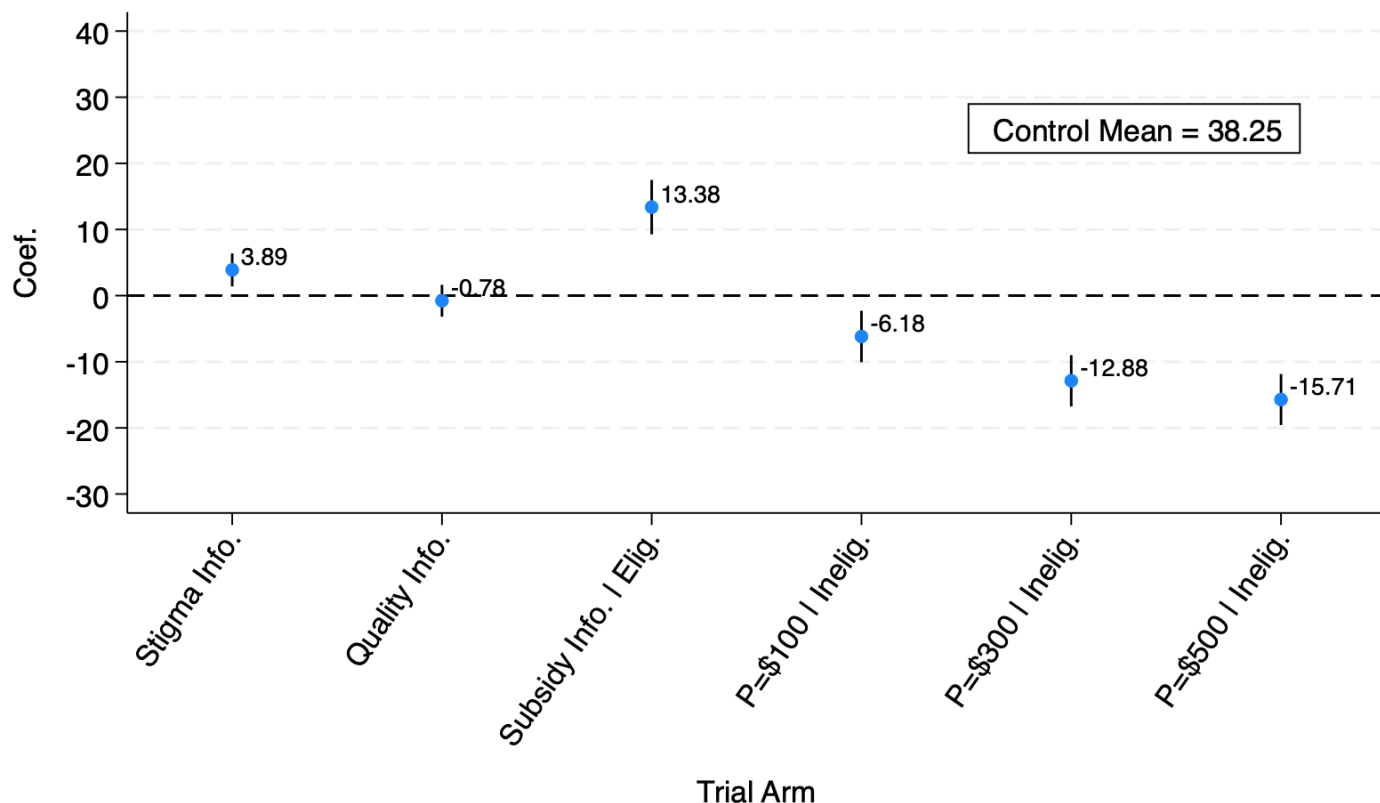
Table 3: Counterfactual Simulation Results

Counterfactual	% Experiencing Increase In						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Screening	Quitting Years	Cancer-Free Years	Late-Stage Cancer-Free Years	YOL Gained	Utility Gained	% Benefiting
Panel A: Screening Prices							
Free Screening	50.9%	26.7%	0.5%	0.03%	0.6%	5.1%	100.0%
Panel B: USPSTF Eligibility Requirements							
Age: 50 to 45	0.7%	29.7%	0.6%	0.03%	0.7%	2.0%	99.9%
History: 20 to 10	5.8%	28.5%	0.7%	0.03%	0.8%	1.9%	99.9%
Panel C: Targeting Based on Preferences							
No Pessimism	4.8%	3.5%	0.04%	0.003%	0.05%	0.3%	43.7%
No Stigma	4.2%	3.5%	0.04%	0.003%	0.06%	0.2%	47.5%
Eliminating Both	7.5%	5.9%	0.07%	0.004%	0.09%	0.5%	69.9%

Notes: All results are for outcomes between ages 40 and 100. Column (1) indicates percentage changes in the average screening rate at the individual-year level. Columns (2) through (5) estimate the percentage of individuals with increases in years without smoking, years without (any) cancer, years without late-stage cancer, and years of life, respectively. Finally, column (6) reports percentage differences in discounted lifetime utility (calculated at age 40), while column (7) indicates the percentage of the sample with a positive net utility change as a result of the policy. Baseline simulations include eliminating all screening prices, changing USPSTF eligibility criteria (and imposing a screening price of \$300 outside these criteria) and reassigning individual types. Computed with simulated dataset of 1,000,000 respondents.

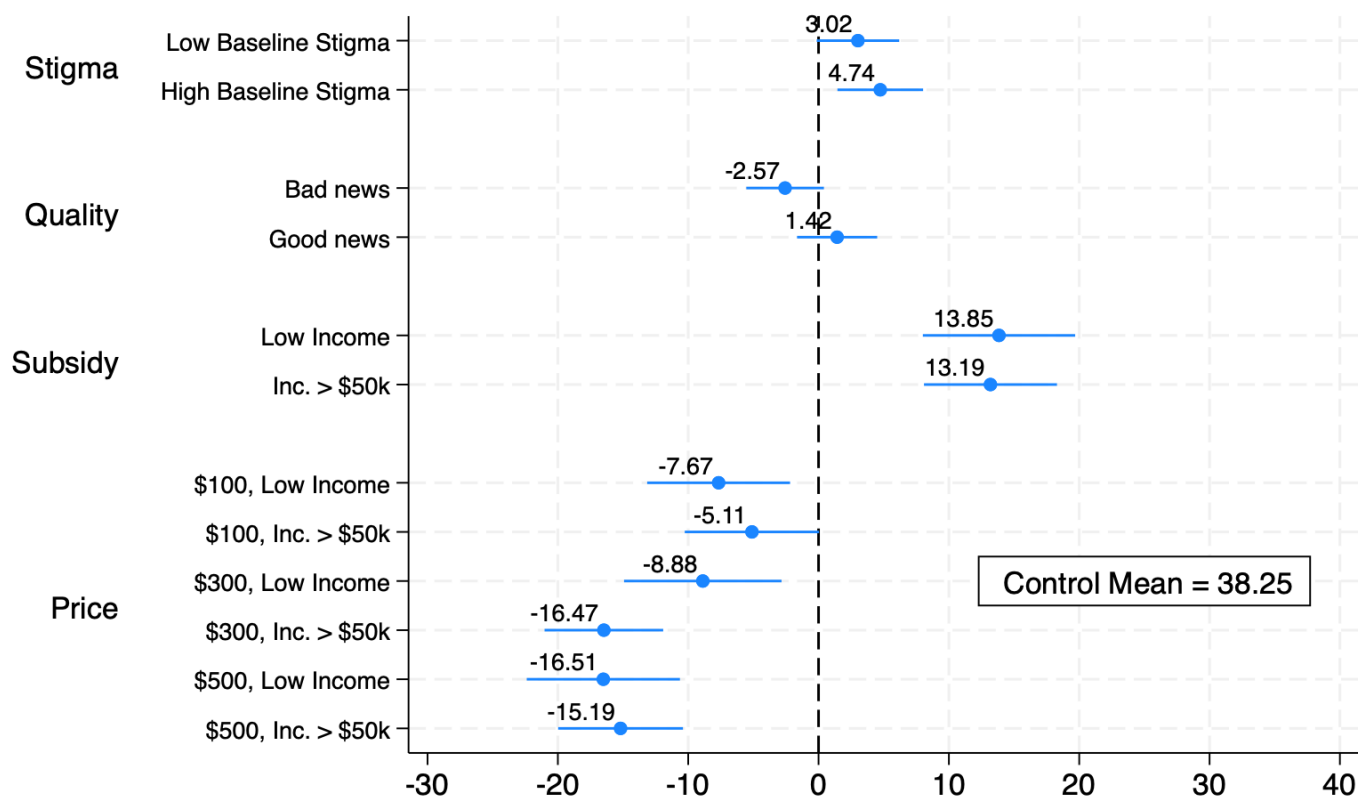
9 Figures

Figure 1: Experimental Effects on Intent to Screen



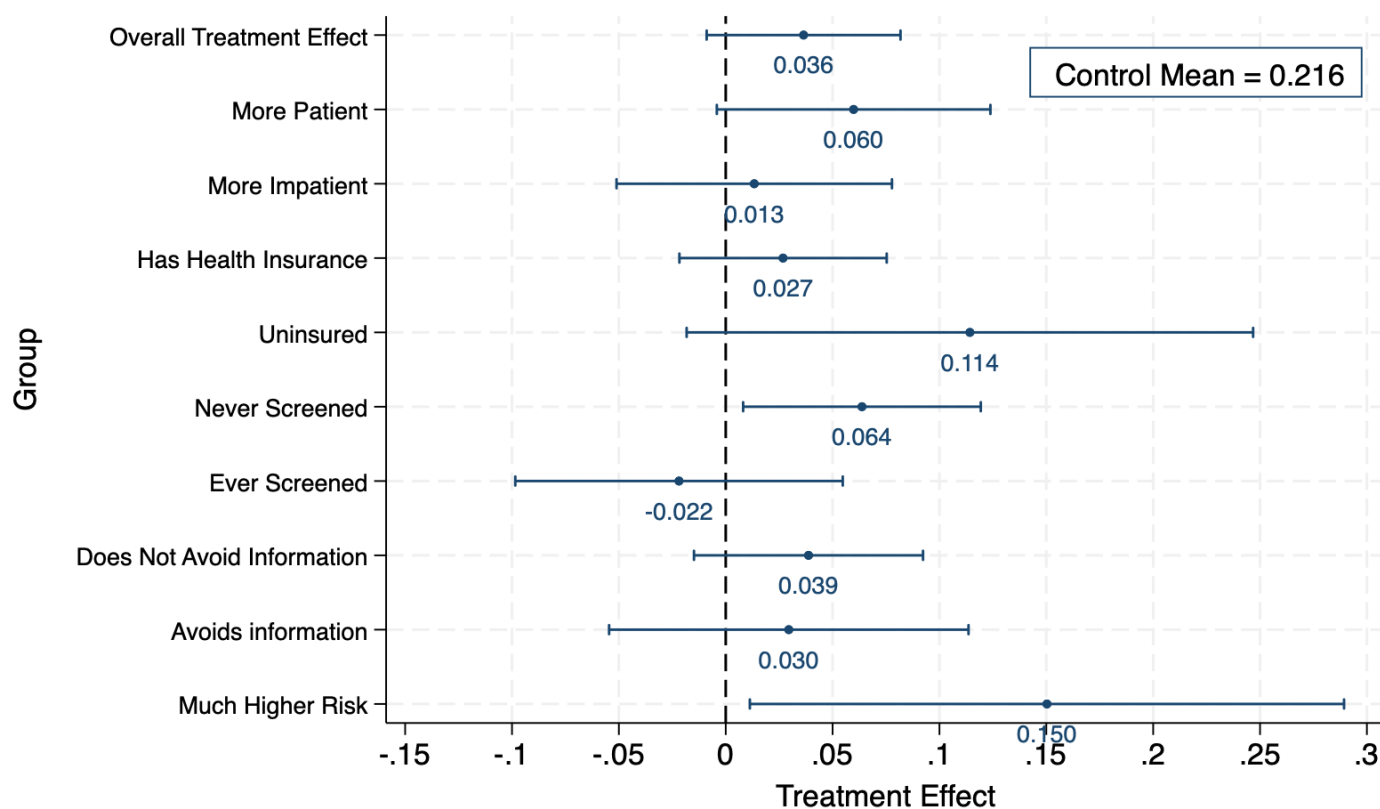
Notes: The Figure presents experimental effects from regressions of the intention to screen in the next year on binary variables for each treatment arm relative to the baseline, neutral framing of the intention to screen question. Treatment arms include receiving information about nonjudgmental screening staff (stigma), the observed false positive rate (quality info) and prices. If randomized to the price arm, eligible respondents received information about their eligibility; ineligible respondents received a price quote between \$100 and \$500. Coefficients are conditional on baseline characteristics in Table 1. Confidence intervals reflect robust standard errors. $n = 3,912$.

Figure 2: Heterogeneous Effects on Intent to Screen



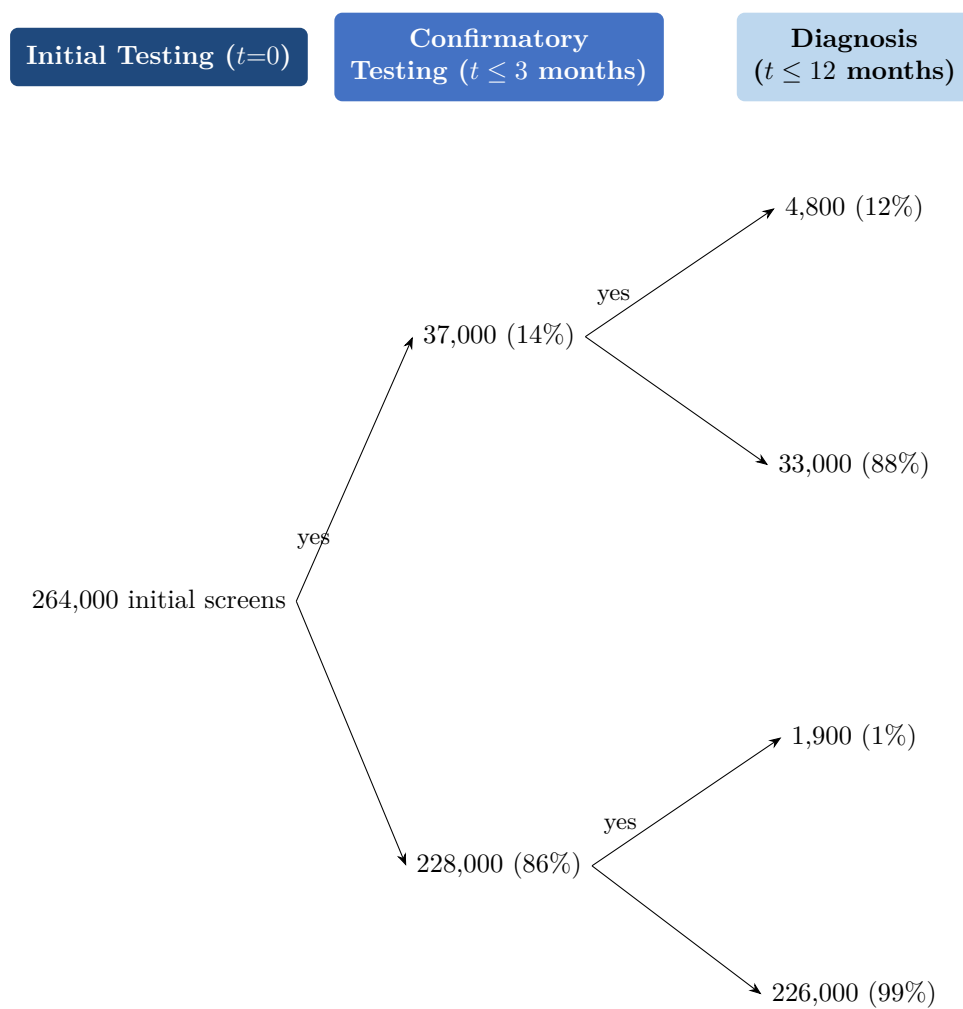
Notes: The Figure presents experimental effects from regressions of the intention to screen in the next year on binary variables for each treatment arm relative to the baseline, neutral framing of the intention to screen question. Each treatment arm indicator is interacted with relevant, baseline heterogeneity. High stigma indicates agreement with at least one of the stigma questions. Good news implies that the quality information treatment presented a lower false positive rate relative to baseline expectations. Price/subsidy effects are allowed to vary by whether baseline household income was less than \$50k. Coefficients are conditional on baseline characteristics in Table 1. Confidence intervals reflect robust standard errors. $n = 3,912$.

Figure 3: Intention to Quit Among Smokers



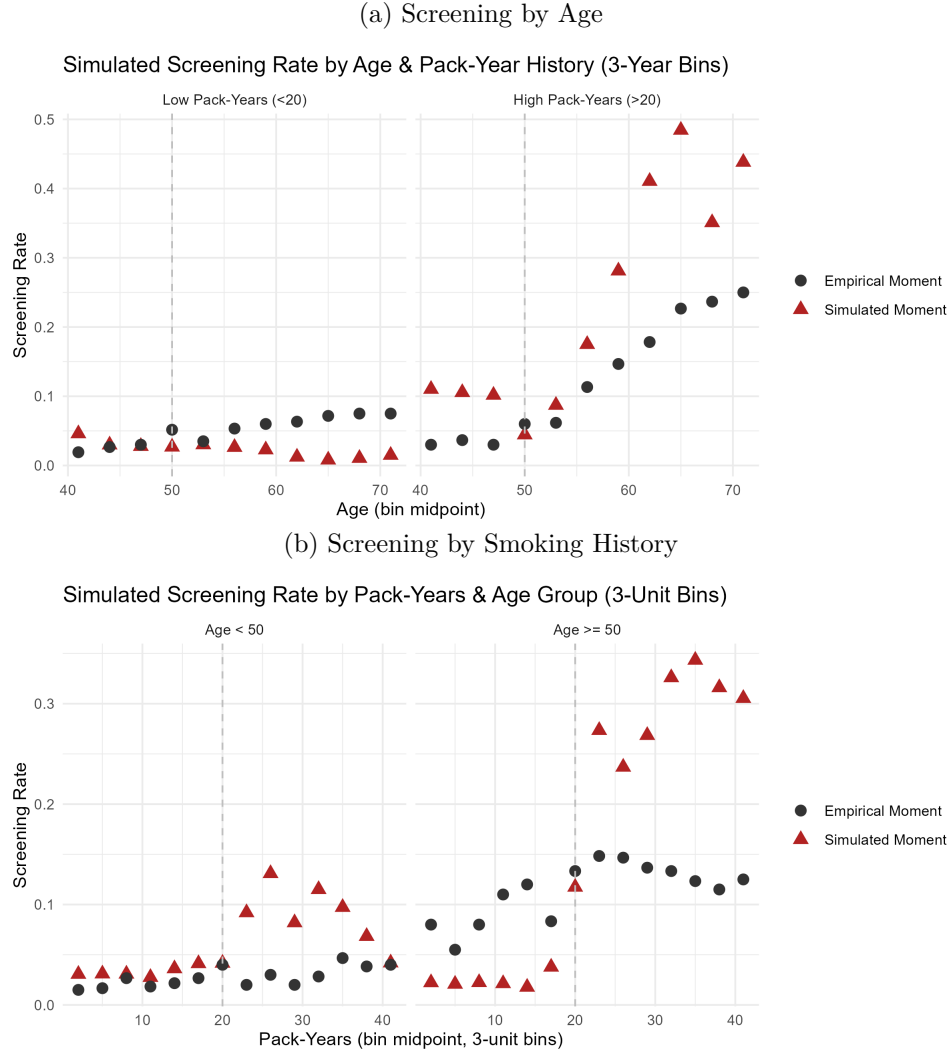
Notes: The Figure presents experimental effects on intention to quit smoking among smokers. Coefficients are treatment effects of the “clean scan” treatment group relative to the control. Coefficients are conditional on baseline characteristics in Table 1. Confidence intervals reflect robust standard errors. $n = 1,342$.

Figure 4: LDCT Screening in Truveta



Notes: The Figure presents data from our analysis of Truveta EHR data.

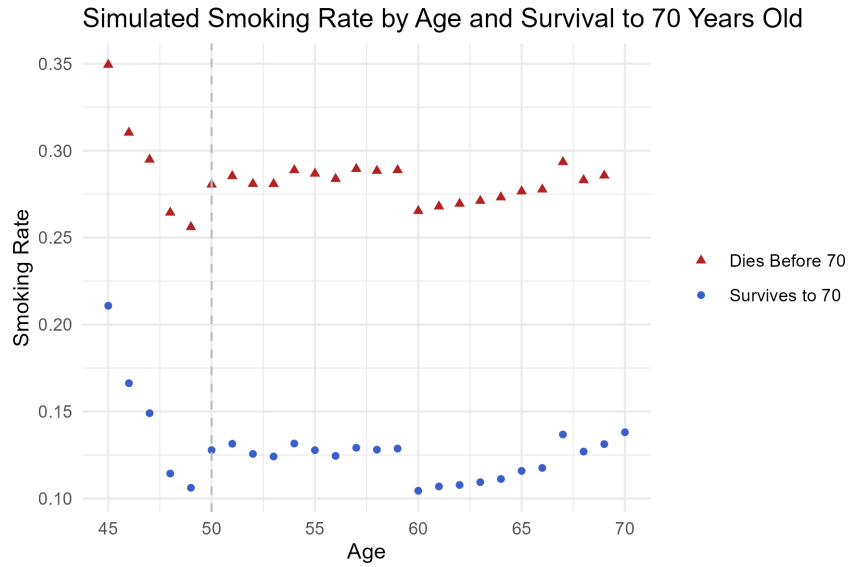
Figure 5: Model Fit: Screening by Age & Smoking History



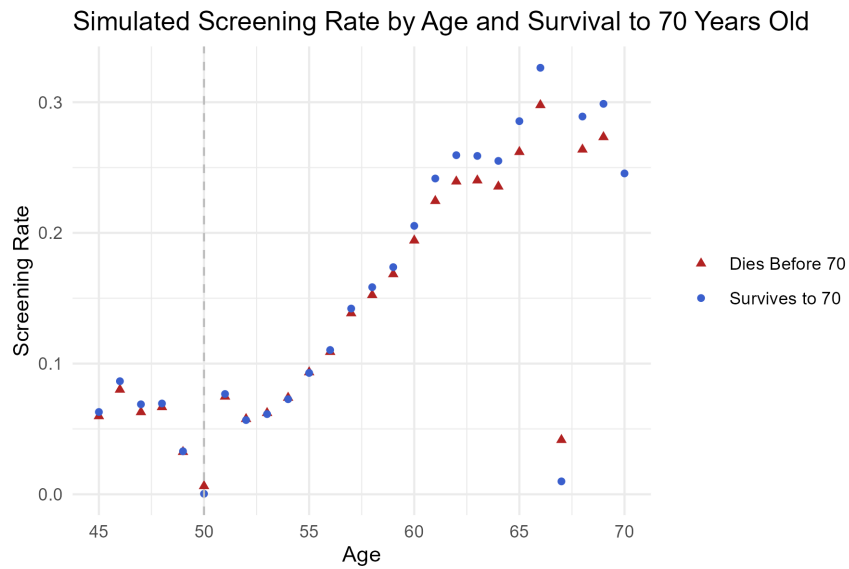
Notes: This figure plots empirical and simulated moments tracking average lung cancer screening rates. Empirical moments come from the BRFSS study (Darden and Hoagland, 2025). Sample is stratified by age and smoking history in each panel. We report binscatters averaging over 3 year or 3 pack-year increments.

Figure 6: Screening & Smoking Decisions by Survival to Age 70

(a) Smoking

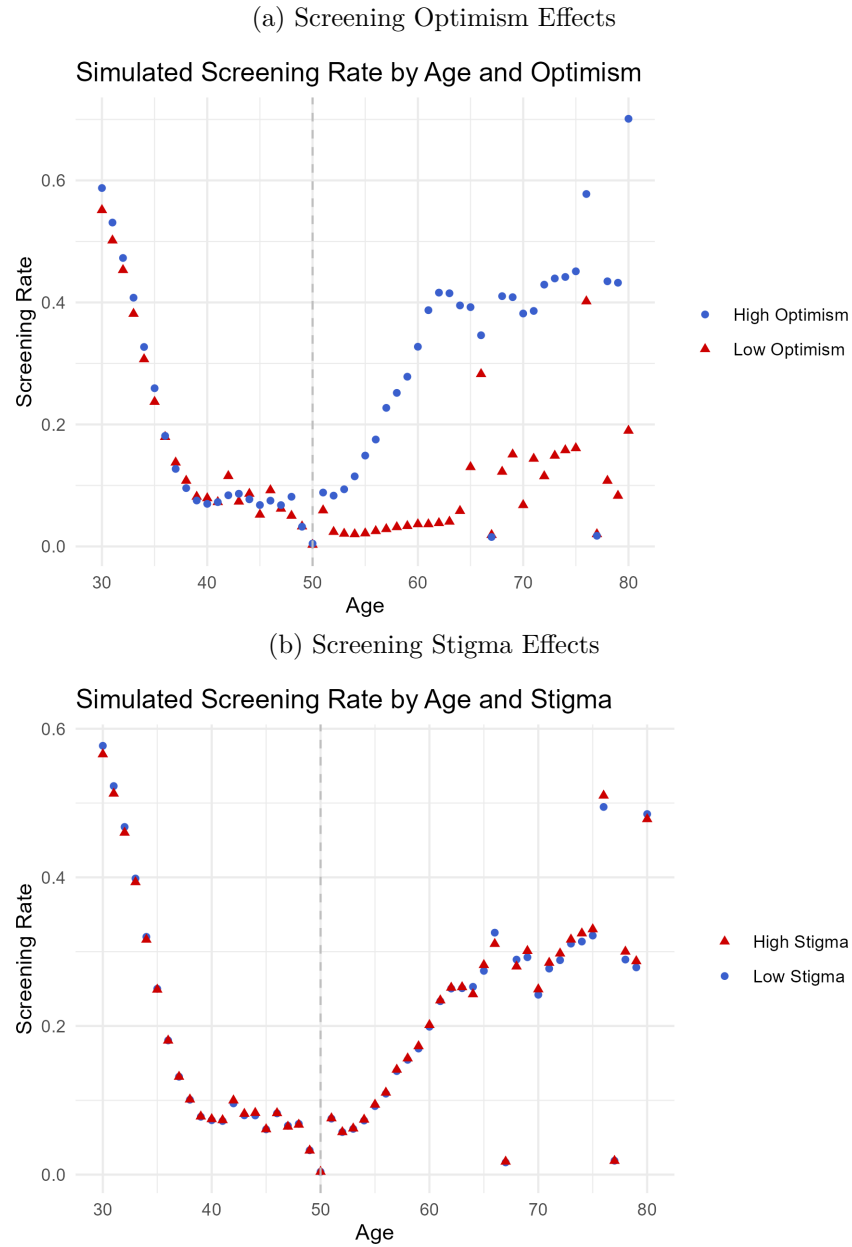


(b) Screening



Notes: This figure plots simulated smoking and screening behaviors by age for two groups in the model: those whose simulated behaviors result in death before age 70, and those who survive to at least age 70.

Figure 7: Optimism & Stigma Effects on Screening Decisions



Notes: This figure plots simulated screening behaviors by age across individual types in the model. Specifically, we compare individuals with high or low optimism about screening quality in panel (a), and those with high or low screening stigma in panel (b).

Figure 8: Counterfactual Simulation: Effect of Universal Screening at Age 45



Notes: Figures plot results from a counterfactual simulation comparing baseline choices to a world where universal screening takes place at age 45. Each panel indicates how this simulation affects key outcomes, including smoking, cancer development, and mortality. In panel (a), the average rate and conditional amount of gained years of smoking cessation is shown for those who were current smokers before the universal screening (age 44); in panel (b), the average rate and conditional amount of gained years without cancer is shown for the same population. In panel (c), we restrict only to those who were current smokers at age 44 and those who gained additional years without cancer, and plot the average rate and conditional amount of added years of life gained from the policy.

Endogenous Screening and Health Behaviors: APPENDIX*

Michael Darden and Alex Hoagland

June 3, 2026

Abstract

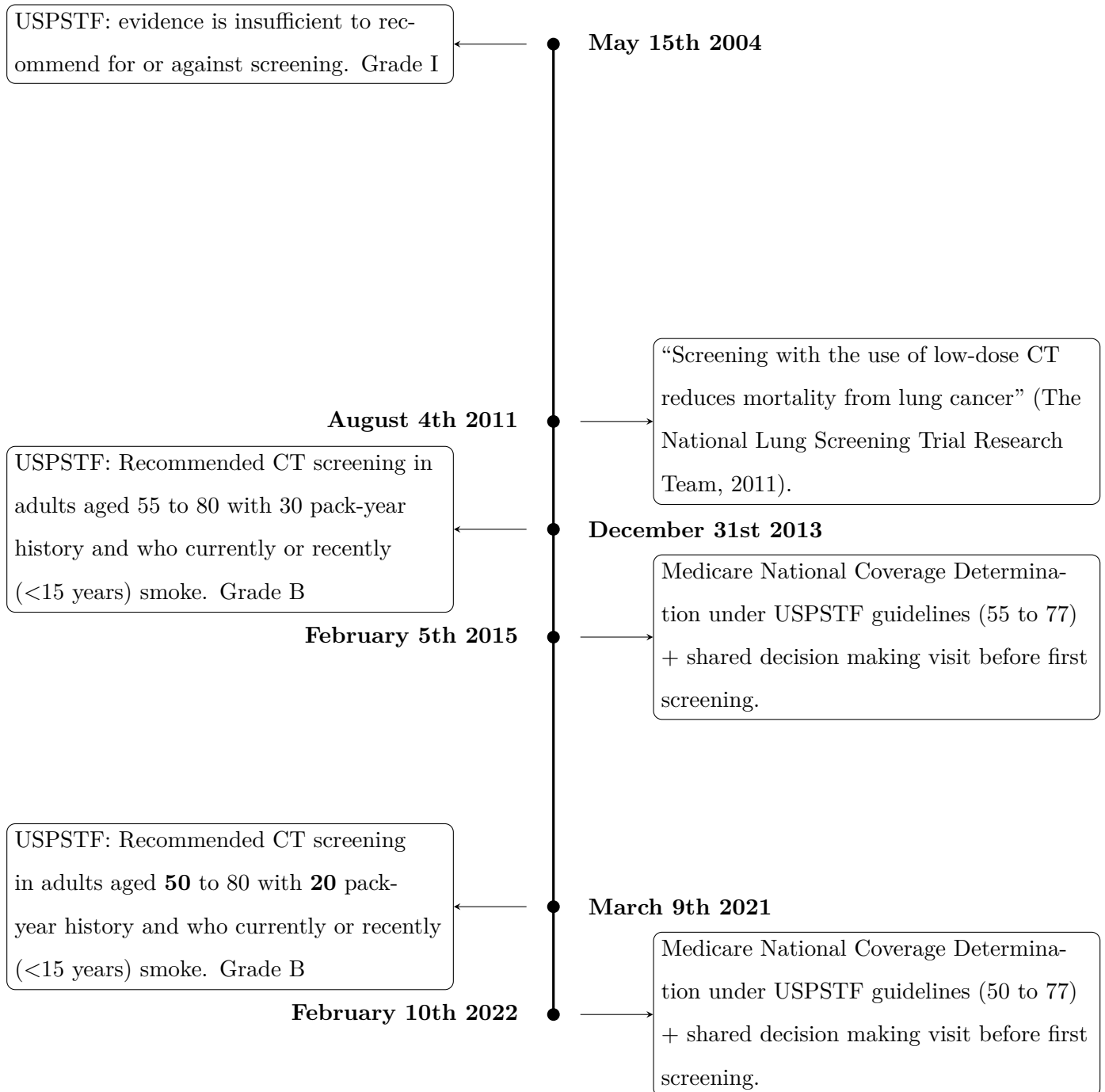
Keywords:

JEL Classification:

*Darden: Johns Hopkins University Hoagland: University of Toronto

1 Policy Environment

Timeline of Policy Changes



2 Survey & Experimental Design

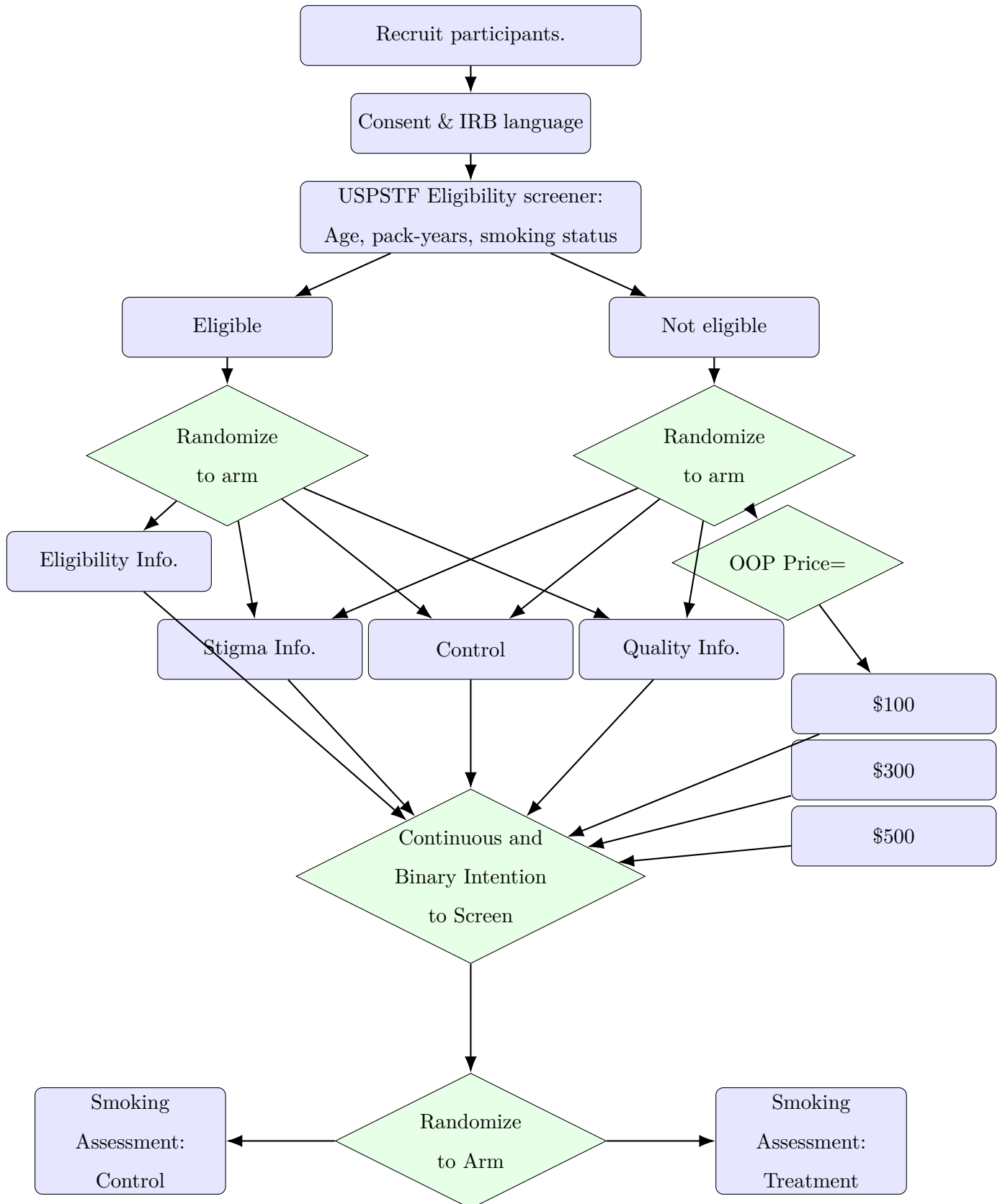


Table 1: Sample Construction

	Count
Attempted Survey	4,000
Completed Survey	3,996
ReCaptcha ≥ 0.5	3,925
Non-missing Experimental Data	3,912

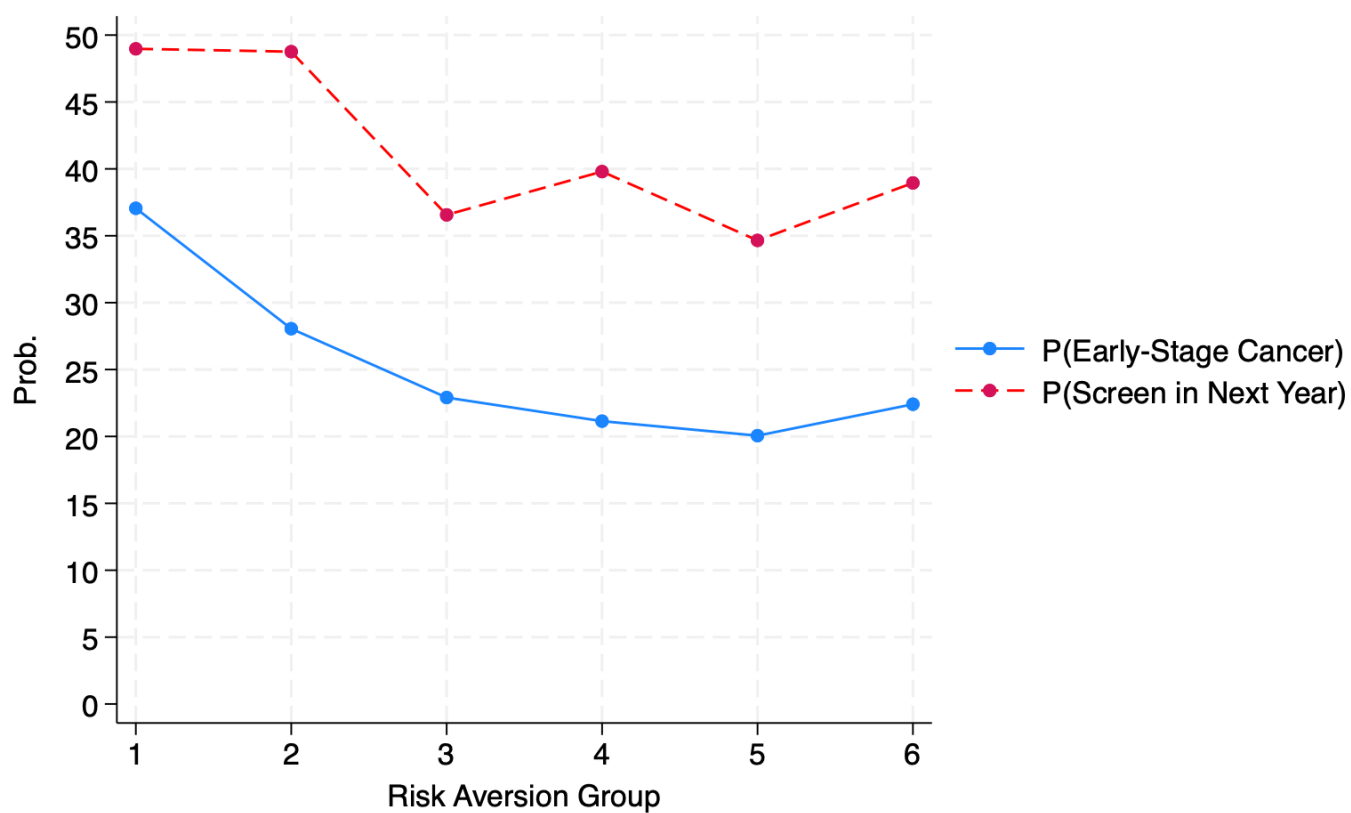
Notes: Analysis sample construction from the lung cancer screening survey. The survey was built on Qualtrics and run on Prolific from November 20th, 2025 through February 15th, 2026. The ReCaptcha score is a summary measure of whether respondent behavior is consistent with a real person. Scores less than 0.5 are associated with bot behavior. See Qualtrics [fraud detection](#) for more information.

Table 2: Survey vs. 2022 BRFSS

	Survey n=3,912	BRFSS 2022 n=125,540
Age in Years	52.30	57.98
Female	0.62	0.46
Race		
White	0.83	0.71
Black	0.07	0.09
Other	0.10	0.19
Health Insurance		
Employer-sponsored plan (own or spouse)	0.41	0.34
Individual Plan (e.g., ACA Marketplace Plan)	0.12	0.08
Medicaid	0.18	0.32
Medicare	0.17	0.09
Other Insurance.	0.04	0.11
Uninsured	0.08	0.07
Income		
Less than \$25,000	0.16	0.20
\$25,000-\$49,999	0.24	0.25
\$50,000-\$99,999	0.35	0.27
\$100,000-\$199,999	0.21	0.05
More than \$200,000	0.04	0.05
Pack-Years	27.78	21.95
Current Smoking Behavior		
Currently Smoke Cigarettes.	0.34	0.35
Recently Smoked Cigarettes (within the last 15 years).	0.37	0.25
Smoked Cigarettes, but more than 15 years ago.	0.29	0.40
Lung Cancer Screening		
Never.	0.73	0.84
Yes, but not in the past year.	0.16	0.08
Yes, in the past year.	0.11	0.08

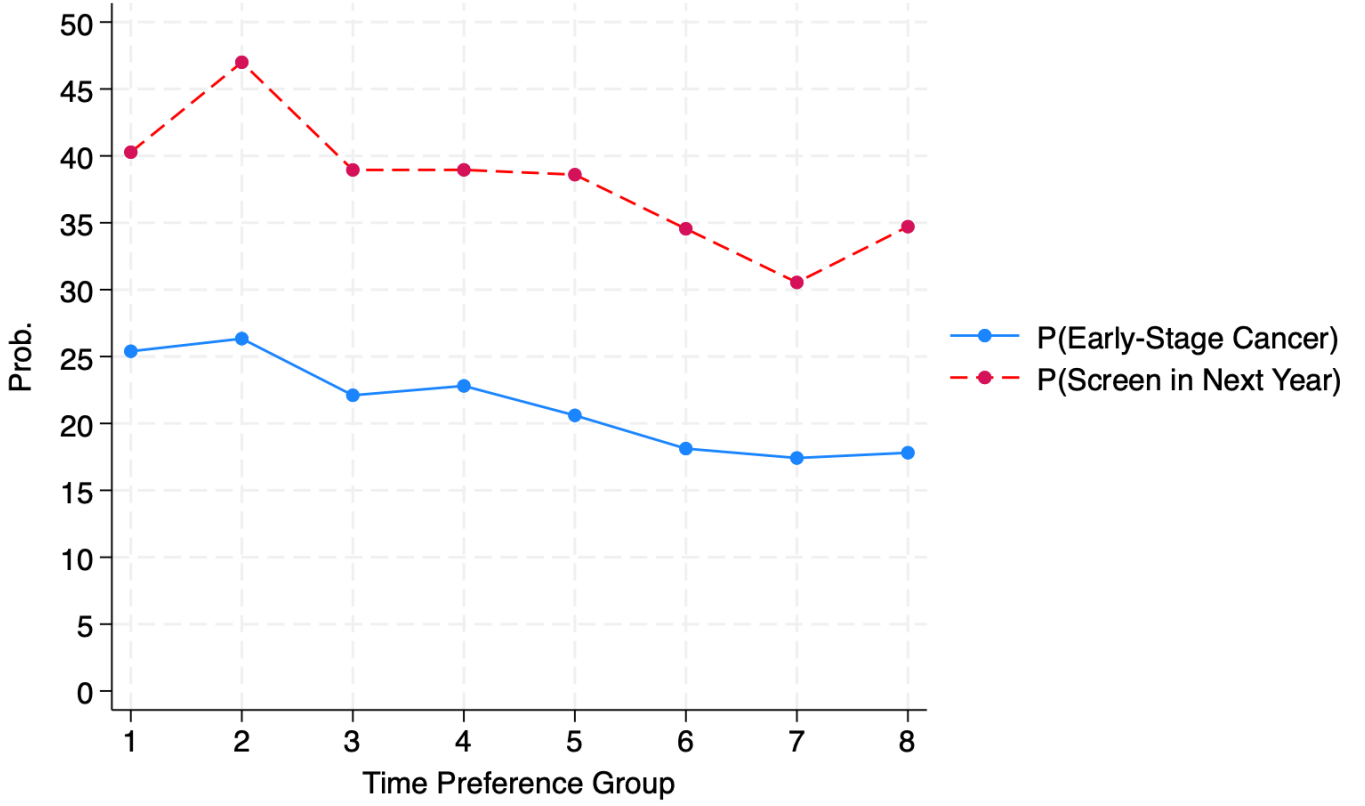
Notes: Table 2 presents overall means from our survey and from the 2022 BRFSS. As with our survey, we restrict attention to BRFSS respondents who were over the age of 40 and had some smoking history (125,540/445,132).

Figure 1: Cancer Beliefs by Risk Preference



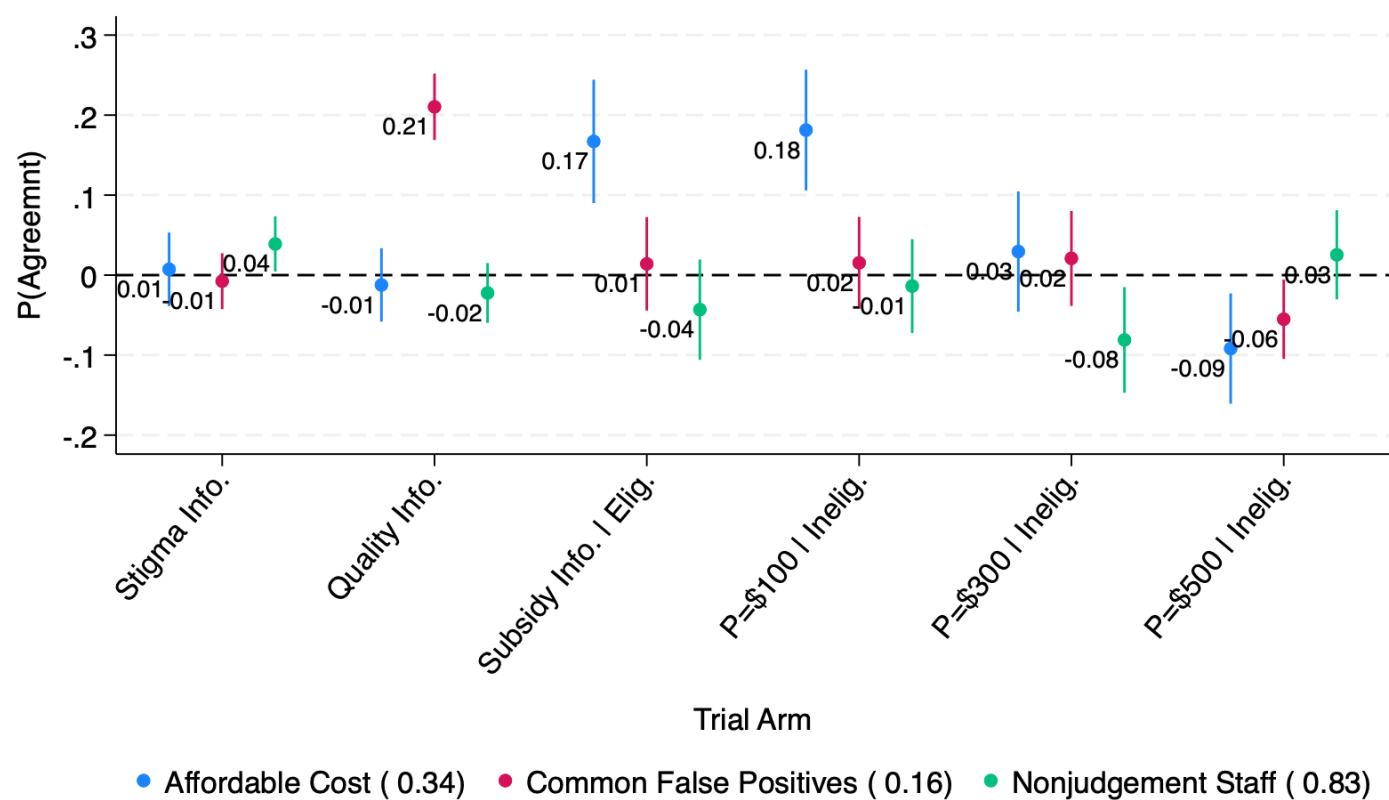
Notes: The figure presents the mean belief of early-stage lung cancer and intention to screen by risk preference group. Risk preference groups 1 through 6 reflect a CRRA risk aversion parameter in the following respective bounds: $[0, 0.3)$, $[0.3, 1)$, $[1, 2)$, $[2, 3.76)$, $[3.76, 7.53)$, $[7.53, \infty)$

Figure 2: Cancer Beliefs by Risk Preference



Notes: The figure presents the mean belief of early-stage lung cancer and intention to screen by time preference group. Time preference groups 1 through 8 reflect a time consistent discount factor in the following respective bounds: $[0, 0.476)$, $[0.476, 0.495)$, $[0.495, 0.541)$, $[0.541, 0.649)$, $[0.649, 0.8)$, $[0.8, 0.893)$, $[0.893, 0.943)$, $[0.943, 1]$.

Figure 3: Comprehension Checks



Notes: The Figure presents regression coefficients of three comprehension check binary variables on binary variables for the treatment arms. The dependent variable is whether the respondent agrees that a.) screening is affordable, b.) false positive are common, and c.) screening staff are nonjudgmental. Confidence intervals reflect robust standard errors. $n = 3,268$.

3 Solution

Derivation of Screening Belief Threshold If the person does not screen, current utility is just the no-screen utility, and next period belief is

$$b_{t+1}^N = \tilde{b}_t + (1 - \tilde{b}_t)\pi_{12}.$$

Hence,

$$Q^N(\tilde{b}_t) = u_t^N(x_t) + \beta \mathbb{E} \left[(1 - P(D_{t+1} = 1))V(\Gamma_{t+1}) \mid b_{t+1} = b_{t+1}^N, x_t \right].$$

Here $u^N(x_t)$ is the per-period utility holding the smoking choice fixed.

On the other hand, if the person screens, expected utility in the current period averages over: whether there is cancer or not, weighted by $\tilde{b}_t$, and screening outcomes, weighted by subjective test beliefs (ρ, λ) . We can therefore define

$$Q^S(\tilde{b}_t) = (1 - \tilde{b}_t) \left[(1 - \lambda)M_0^- + \lambda M_0^+ \right] + \tilde{b}_t \left[(1 - \rho)M_1^- + \rho M_1^+ \right],$$

where we define objects:

- M_0^- : value if true state is no cancer and the screen is negative
- M_0^+ : value if true state is no cancer and the screen is positive (false positive, then confirmatory testing)
- M_1^- : value if there is cancer and the screen is negative (false negative)
- M_1^+ : value if there is cancer and the screen is positive (true positive, then confirmatory testing and treatment)

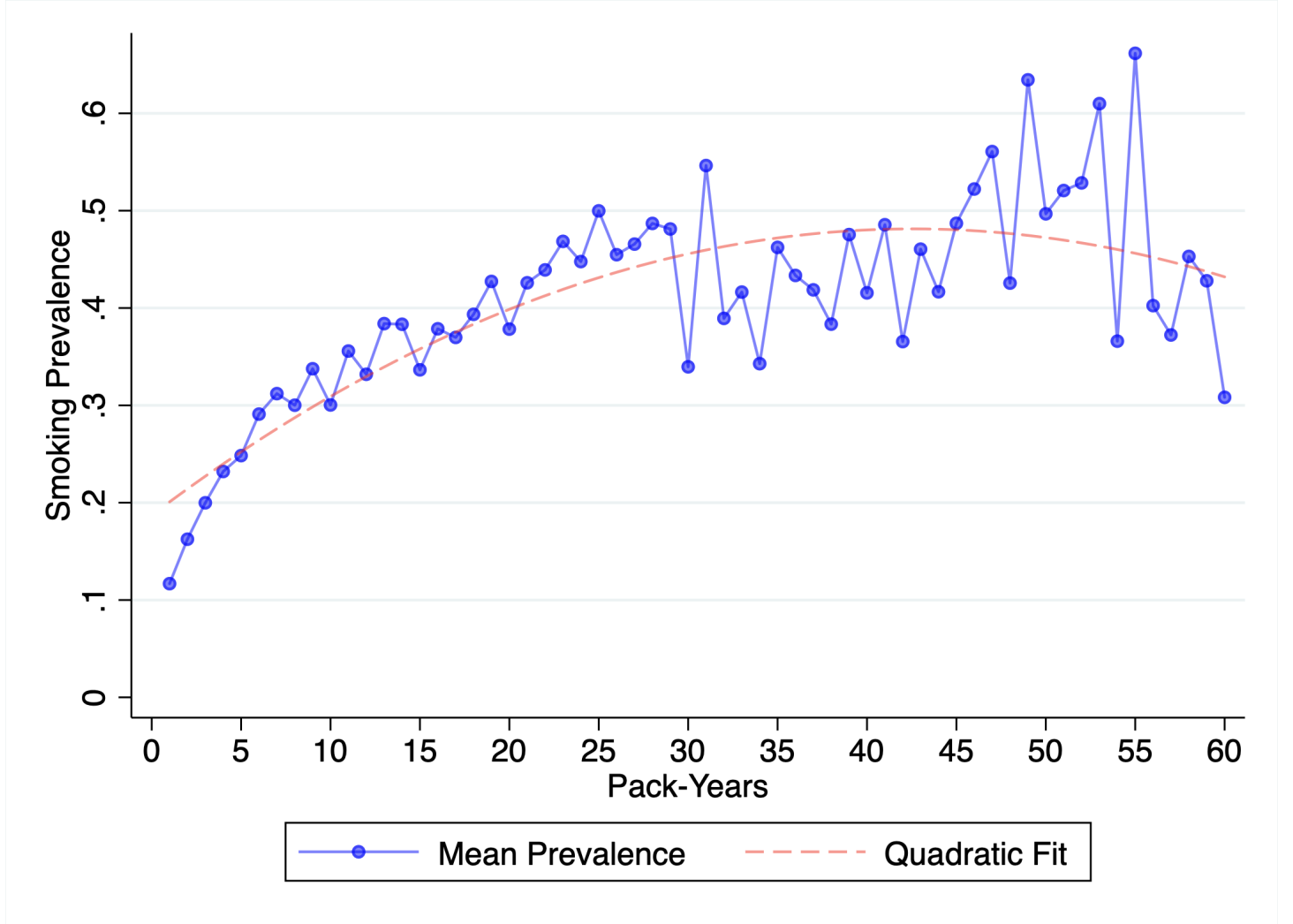
Given this, we can define the screening gain as

$$\Delta(\tilde{b}_t) \equiv Q^S(\tilde{b}_t) - Q^N(\tilde{b}_t).$$

This implicitly defines a belief threshold, $\bar{b}$, as the solution to $\Delta(\bar{b}) = 0$. Any belief above this threshold will trigger screening.

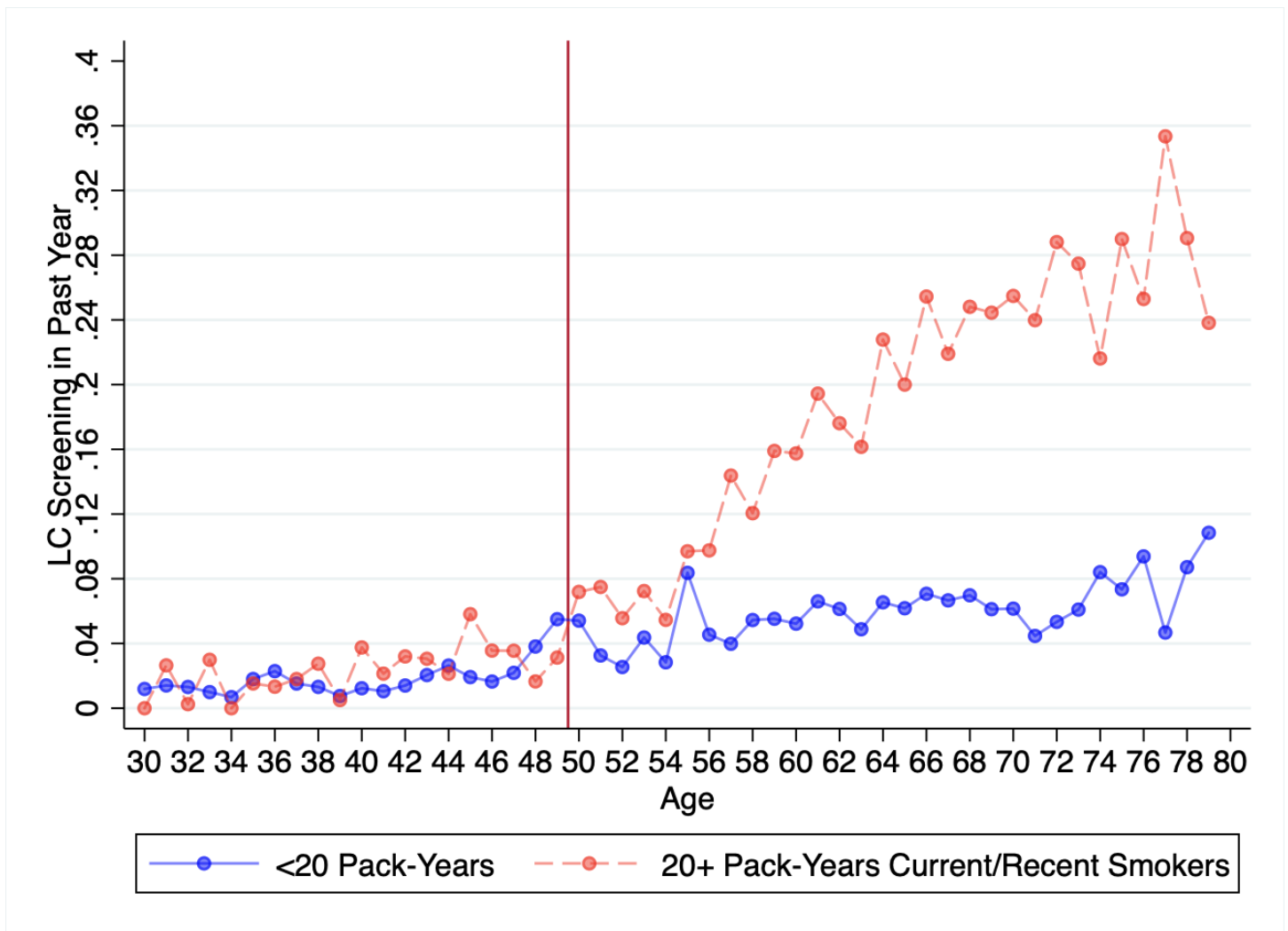
4 Behavioral Risk Factor Surveillance System

Figure 4: BRFSS Analysis: Smoking Prevalence by Pack-Years



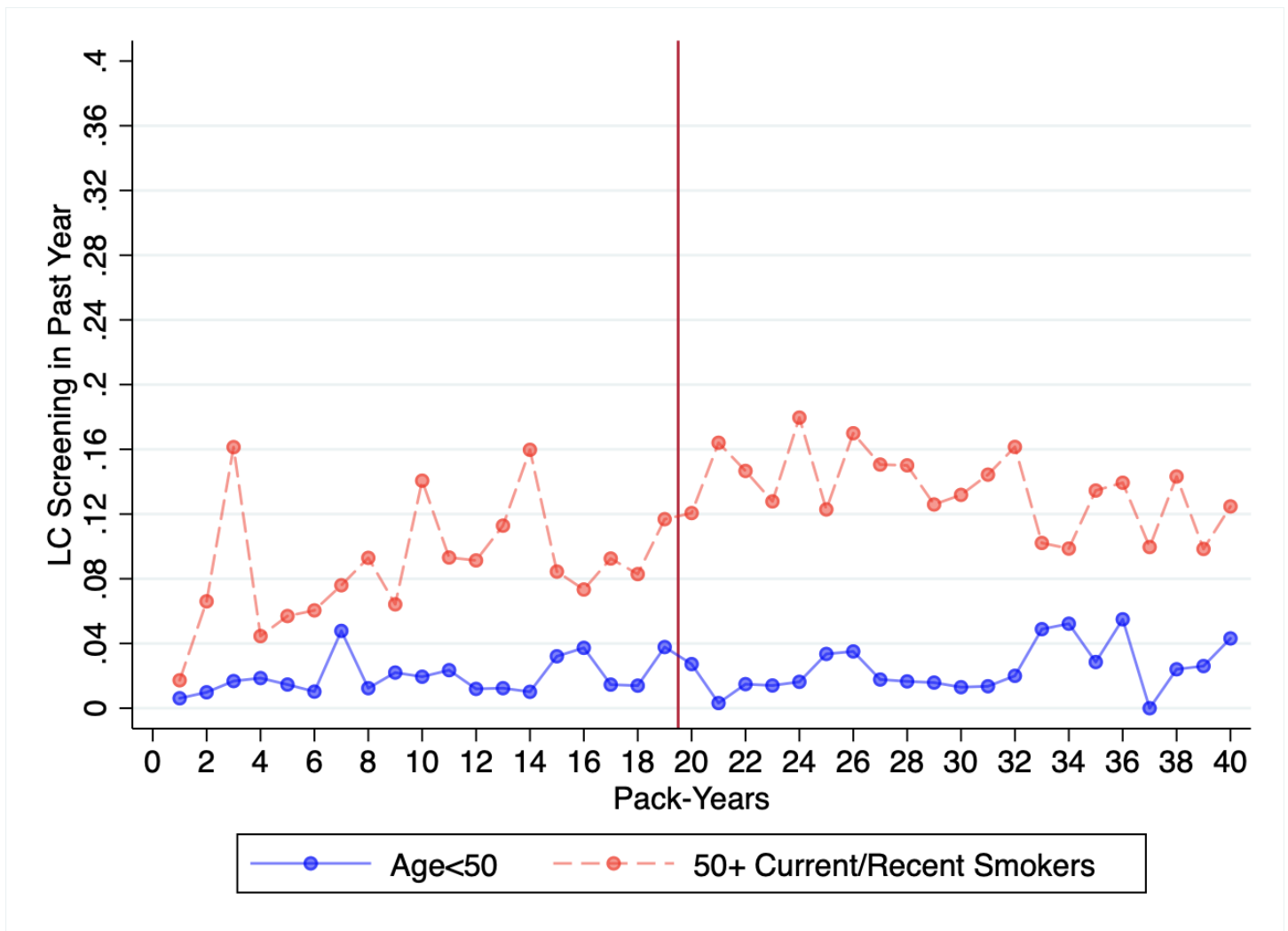
Notes: Figure plots smoking prevalence by the number of pack-years of smoking history as calculated by BRFSS. The best-fit quadratic line informs our utility parameters $\gamma_1 - \gamma_3$.

Figure 5: BRFSS Analysis: Screening by Age



Notes: .

Figure 6: BRFSS Analysis: Screening by Pack-Years



Notes: .

5 Additional Figures and Tables

Table 3: Estimated Model Parameters

Parameters	Symbol	(1)	(2)	(3) (*)
Panel A: Utility Function, No Late Stage Cancer ($\theta < 3$)				
Smoking	γ_1	-\$6,240 ()	-\$9,008	-\$3,852.88
Smoking $\times$ history	γ_2	\$606 ()	\$995	\$680.91
Smoking $\times$ history ²	γ_3	\$0.94 ()	\$0.64	\$0.94
Utility loss, OOP	γ_5	-\$466 ()	-\$447	-\$1.29
Symptom cost	γ_6	-\$344 ()	-\$961	-\$168.66
Panel B: Utility Function, Late Stage Cancer ($\theta = 3$)				
Smoking	γ_1	-\$4,846 ()	-\$80.44	-\$142.76
Smoking $\times$ history	γ_2	\$1,580 ()	\$9,656	\$9,938.64
Smoking $\times$ history ²	γ_3	\$0.56 ()	\$0.05	\$0.03
Panel C: Other Parameters				
Screening disutility, reference	$\gamma_{4,0}$	-\$615 ()	-\$41.88	-\$989.27
Additional disutility, high stigma	$\gamma_{4,1}$	-\$21.73 ()	-\$80.19	-\$80.69
Additional disutility, low optimism	$\gamma_{4,2}$	-\$4,600 ()	-\$61.88	-\$5,780.75
Additional disutility, high stigma $\times$ low optimism	$\gamma_{4,3}$	-\$0.34 ()	-\$964	-\$170.04
Panel D: Initial Beliefs				
Average	$\bar{b}_0$	0.109	0.001	0.031
Median		0.080	0.000	0.022
SD		0.099	0.002	0.031

Notes: This table presents estimated model parameters following Section ?? . Model is estimated via two-step GMM using an optimized warm start based on XGBoost models and refined using stochastic gradient descent. Coefficients are expressed in thousands of dollars. [Standard errors forthcoming]

References

The National Lung Screening Trial Research Team (2011). Reduced lung-cancer mortality with low-dose computed tomographic screening. New England Journal of Medicine, 365(5):395–409.