

Evaluating Marginal Internalities: a new Approach¹

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Abstract

Consumers of sin goods often partially ignore the health costs of consumption and thus impose an externality on themselves. This paper develops a new method for the estimation of the marginal externality. It uses a model of a biased sin good consumer who faces uncertain health harms and receives mandatory health insurance. It shows that the marginal externality can be identified by observing how sin good demand reacts to changes in health insurance coverage. I calibrate the model to sugary drinks consumption. My results are consistent with measurements from surveys that directly elicit consumers' biases.

Key Words: money-metric marginal externality, present bias, biased beliefs, health insurance, sin tax

JEL Codes: D11, D15, D62, H21, H31, I12, I13, I18

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1 Introduction

To consume sin goods rationally is not an easy task. Consider, e.g., an individual who chooses whether to drink a sugar-sweetened beverage (SSB). A rational choice would weigh the instant pleasure of consumption against potential future health costs. The health harms of SSB consumption include, among others, an increase in the risk of type II diabetes and coronary heart disease. If a consumer fails to fully consider these costs, either because of imperfect knowledge or lack of self-control, she imposes an internality on herself. Behavioral welfare analysis requires a measure of the money-metric marginal internality (Allcott et al., 2019b).

This paper derives a new method for the estimation of the marginal internality. As a starting point, I develop a simple two-period model under uncertainty, where sin good consumption in period one increases the probability of falling sick in period two. A representative consumer exhibits both present-bias and biased beliefs regarding the probability of illness. Furthermore, the government provides mandatory health insurance and taxes the sin good.

My main insight is that the health insurance elasticity of sin good demand is (partially) determined by the effect of insurance on the marginal internality. To identify the marginal internality, I first divide the determinants of the health insurance elasticity into rational factors and factors that depend on the behavioral bias. The latter is proportional to the money-metric marginal internality. Then, I estimate the part of the observed elasticity that can be attributed to rational factors. The remaining part gives an estimate of the marginal internality. Moreover, I derive three different methods of identifying the marginal internality that differ in the structural assumptions necessary to estimate them.

An alternative method for estimating the money-metric marginal internality is the so-called “counterfactual normative consumer” approach. Allcott et al. (2019a) apply this method to measure and quantify the behavioral bias in SSBs’ consumption.¹ To do so, they observe consumer behavior from homescan panel data and use surveys to estimate the nutrition knowledge and self-control of consumers. The surveys allow them

¹Earlier work that has used the counterfactual normative consumer approach to compare informed with uninformed choices includes Bartels (1996), Levitt and Syverson (2008), Bronnenberg et al. (2015), Handel and Kolstad (2015), Johnson and ReHAVI (2016).

to create indexes of nutritional and self-control bias and estimate the correlation between consumption and these biases. By assuming that the conditional correlation between bias and consumption measures the causal effect of bias on consumption, they can estimate the hypothetical consumption of a counterfactual normative consumer (Allcott et al., 2019b). The compensated price increase that leads a consumer to choose this hypothetical consumption level is the money-metric marginal internality.

Compared to the counterfactual normative consumer approach, my method has the advantage of not requiring survey data on the knowledge and self-control of consumers. Thus, it is not affected by possible measurement errors in these surveys. However, it requires other measurements such as, e.g., the health insurance elasticity of sin good demand. Hence, the two approaches are complementary because they measure the same behavioral bias using different data.

Furthermore, my model differs from the theoretical literature on sin good consumption, which takes a reduced-form approach. This approach originates from the seminal paper of O’Donoghue and Rabin (2006), where the health harms are represented by a reduced-form increasing function of the sin good intake. Allcott et al. (2019a) also consider a (more general) reduced-form model. However, this approach does not allow to study the effects of health insurance on the marginal internality. By developing a model under uncertainty, where sin good consumption raises the probability of future health harms, I can study these effects and derive the evaluation method.

Moreover, I calibrate the model to SSB consumption. My central estimates of the marginal internality lie between 1.08 and 1.32 cents per ounce, depending on the different structural assumptions made in estimating it. These results are consistent with the estimates of Allcott et al. (2019a) that have a lower and upper bound of 0.91 and 2.1 cents per ounce, respectively. Additionally, the optimal tax rate is equal to 1.94-2.17 cents per ounce. This tax rate also takes the ex-ante moral hazard of health insurance into account, which constitutes an externality. Furthermore, the model predicts an optimal health insurance coverage equal to approximately 84% of medical costs, which is close to the empirically observed coverage of about 85% (Finkelstein et al., 2013).

Furthermore, Section 6 extends the model. First, I consider multiple sin goods. In this case, the marginal internality of one sin good depends in addition on the compensated

price, health insurance, and income elasticities of all goods. I extend the calibration to a setting of two goods, where the second good is diet soda. The reason is that diet soda is a substitute for SSBs (Allcott et al., 2019a) and its demand reacts to changes in health insurance coverage (He et al., 2020). The substitutability to diet soda lowers the estimated marginal internality. Second, I allow life expectancy to decrease in the sick state of nature. This extension has a positive effect on the results that largely offsets the impact of substitutability to diet soda.

This paper is related to the literature that quantifies behavioral biases. Apart from the method developed in this paper and the counterfactual normative consumer approach, both of which quantify marginal internalities stemming from lack of self-control and imperfect information, other approaches measure each source of bias separately. In the case of self-control, one could measure the individual health costs and use an estimate of self-control from another domain to quantify the marginal internality. One deficiency of this approach is that self-control may differ across domains (Attema et al., 2018; Allcott et al., 2019b).² In the case of biased beliefs, one can compare the consumers' willingness-to-pay for a good before and after information provision (see, e.g., Allcott and Taubinsky, 2015, for an application of this approach to biases in the valuation of energy efficiency).³

However, sin good consumers likely suffer from both self-control problems and imperfect information. Hence, my method is better suited to estimate the marginal internality for sin goods than the approaches that elicit only one type of bias.

Moreover, my approach is conceptually similar to Chetty's (2006) method of estimating risk aversion. Chetty (2006) estimates the coefficient of risk aversion by deriving the wage rate's comparative static effect on optimal leisure. He shows that risk aversion is one of the determinants of labor supply's wage elasticity and uses estimates of this elasticity to derive the underlying risk aversion coefficient. Similarly, I derive the health insurance's comparative static effect on sin good demand and show that it depends on

²Another approach to the measurement of self-control is comparing choices for immediate consumption versus consumption choices made in advance (see, e.g., Read and van Leeuwen, 1998). While this approach can detect a lack of self-control, it cannot quantify the bias in monetary units (Allcott et al., 2019b).

³Furthermore, Gerster and Kramm (2020) show that consumption decisions may be informative about biases, and a social planner could use this information to target biased consumers using a non-linear tax. They apply their method to the analysis of optimal subsidies for energy efficiency.

the behavioral bias. Furthermore, I exploit empirical estimates of the health insurance elasticity to derive the sin good's marginal internality.

The rest of the paper is structured as follows. In Section 2, I present the model. Section 3 derives the method of estimating the marginal internality. Section 4 describes the calibration approach and results. Section 5 extends the model, and Section 6 concludes.

2 The Model

Consider a representative individual who lives for two periods $t = 1, 2$. She starts period 1 with an exogenous income Y_1 . In the same period, she consumes a numéraire good Z in the amount Z_1 and a sin good X . The sin good may represent any good with negative long-term health effects, such as unhealthy food, alcohol, cigarettes. The government taxes X at a rate τ and returns the tax revenues to the individual as a lump-sum transfer $\ell = \tau X$. The individual also finances mandatory health insurance at a premium P . Without loss of generality, the net price of X is exogenous and equal to p . Thus, the period one budget constraint is

$$Y_1 + \ell = Z_1 + (p + \tau)X + P. \quad (1)$$

Income in period two is also exogenous and is denoted by Y_2 . Furthermore, the individual falls sick in period two with probability $\pi(X) \in (0, 1)$ where $\pi'(X) > 0$. Thus, risky health behavior increases the probability of illness. Denote the individual's health by H^i , where $i = s, h$ denotes the sick and healthy state, respectively.⁴ Moreover, the individual purchases the numéraire good in quantity Z_2^i for $i = s, h$. In the case of illness, the individual faces exogenous treatment costs M , and insurance pays an indemnity equal to I .⁵ Thus, the second period budget constraint is

$$Y_2 = \begin{cases} Z_2^s + M - I, & \text{if sick,} \\ Z_2^h, & \text{if healthy.} \end{cases} \quad (2)$$

⁴By definition, in period one the individual is healthy and has a health level H^h .

⁵In general, the health level H^s is a function of the treatment expenditures M . However, the model treats, without loss of generality, M as exogenous. Hence, the health level H^s is also exogenous.

The insurer invests the first period insurance premium P on the capital market and earns an exogenous interest rate r . The premium is actuarially fair and thus given by

$$P = \frac{\pi(X)I}{1+r}, \quad (3)$$

where $\pi(X)I$ denotes the expected insurer's costs in period two.

The agent derives utility from sin good consumption, numéraire consumption, and health. First period utility is given by a well-behaved function $U^1(Z_1, H^h, X)$, which is increasing in all its arguments. In period two, utility is $U^i(Z_2^i, H^i)$ for $i = s, h$, where $U_Z^i > 0 > U_{ZZ}^i, U_H^i > 0$.⁶ The superscript i in $U^i(\cdot)$ indicates utility's state-dependence, defined as the health's impact on the marginal utility of consumption (Finkelstein et al., 2009). Finkelstein et al. (2013) find empirical evidence for negative state-dependence. Thus, the agent's expected utility EU is given by

$$EU = U^1(Z_1, H^h, X) + \delta \{ \pi(X)U^s(Z_2^s, H^s) + [1 - \pi(X)]U^h(Z_2^h, H^h) \}, \quad (4)$$

where $\delta \in (0, 1]$ is a time discount factor.

The individual may, however, not maximize her true expected utility. There are two possible reasons for such behavior. First, the individual may have self-control problems. I follow the standard approach in the literature and model lack of self-control in the form of present-bias (Laibson, 1997). Furthermore, the individual may have full self-control but biased beliefs (imperfect information) regarding the probability $\pi(X)$ (see, e.g., Cremer et al., 2016, for a model of sin good consumption with biased beliefs). Allcott et al. (2019a) develop a general model under certainty where both biases emerge as special cases. They also survey SSB consumers and find evidence for both self-control problems and imperfect nutrition knowledge.

Denote the perceived expected utility as \widehat{EU} and define it as

$$\widehat{EU} = U^1(Z_1, H^h, X) + \delta\beta \{ \widehat{\pi}(X)U^s(Z_2^s, H^s) + [1 - \widehat{\pi}(X)]U^h(Z_2^h, H^h) \}, \quad (5)$$

where $\widehat{\pi}(X)$ and $1 - \widehat{\pi}(X)$ are the perceived probabilities of the sick and healthy states of nature, and $\beta \in (0, 1]$ is a quasi-hyperbolic discount factor.⁷

⁶Capital letter subscripts denote partial derivatives.

⁷The modelling approach to biased beliefs follows Spinnewijn (2015) who develops and applies such a model to unemployment insurance.

Following the present-bias literature, the social planner is paternalistic and views EU as the true long-term utility of the individual (O'Donoghue and Rabin, 2003, 2006; DellaVigna and Malmendier, 2004). Next, I first derive the socially optimal consumption level X^* (that maximizes EU) and then the agent's sin good demand \widehat{X} (that maximizes the perceived utility \widehat{EU}).

2.1 Benchmark consumption

Suppose that a social planner chooses X to maximize the individuals' expected long-term utility (4). She takes into account the public budget constraint $\ell = \tau X$ and the health insurance premium's determination, defined by (3). Thus, the social planner solves

$$\begin{aligned} \max_X \quad EU &= U^1 [Y_1 + \tau X - (p + \tau)X - P(X), H^h, X] \\ &+ \delta \{ \pi(X)U^s [Y_2 - M + I, H^s] + [1 - \pi(X)]U^h [Y_2, H^h] \}. \end{aligned} \quad (6)$$

Define the effect of sin good consumption on the insurance premium as

$$\tau^\xi := \frac{\partial P}{\partial X} = \frac{\pi'(X)I}{1 + r}. \quad (7)$$

Then, the socially optimal consumption level is given by

$$\begin{aligned} \frac{\partial EU^{SP}}{\partial X} &= -U_Z^1(Z_1, H^h, X^*)[p + \tau^\xi] + U_X^1(Z_1, H^h, X^*) \\ &+ \delta \pi'(X^*) [U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)] = 0, \end{aligned} \quad (8)$$

where the superscript SP indicates the social planner's choice. According to (8), X^* is determined by four terms. First, an increase in sin good demand lowers the period one numéraire consumption and, thus, utility by $U_Z^1(\cdot)p$. Second, it raises the probability of illness and, thus, drives the health insurance premium up by τ^ξ . The resulting marginal utility loss is $U_Z^1(\cdot)\tau^\xi$. Third, the sin good's marginal utility is $U_X^1(\cdot)$. Lastly, the higher probability of illness lowers the expected second period utility if $U^s < U^h$.

2.2 Sin good demand

The consumer determines sin good demand \widehat{X} by maximizing the perceived expected utility \widehat{EU} , taking as given the lump-sum transfer ℓ and health insurance premium P .

The first-order condition is given by

$$\frac{\partial \widehat{EU}}{\partial X} = \frac{\partial EU^{SP}}{\partial X} \Bigg|_{X=\widehat{X}} + U_Z^1(Z_1, H^h, \widehat{X}) \cdot [-\tau + \tau^\xi + \tau^b] = 0, \quad (9)$$

where

$$\tau^b := \delta[\beta\widehat{\pi}'(X) - \pi'(X)] \frac{[U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)]}{U_Z^1(Z_1, H^h, X)}. \quad (10)$$

There are three differences between (9) and (8). First, the individual considers the government's transfer to be exogenous and, thus, perceives the gross sin good price to be $p + \tau$. Hence, the tax rate τ emerges with a negative sign in (9). Second, the individual neglects the impact of her consumption on the health insurance premium. This is the ex-ante moral hazard of health insurance and constitutes an externality (Arnott and Stiglitz, 1986). The marginal externality is given by τ^ξ in (9). Third, the individual misperceives the marginal probability of illness. This creates an internality. The term τ^b denotes the money-metric marginal internality.⁸ Following Farhi and Gabaix (2020), I refer in the subsequent analysis to the marginal externality τ^ξ and marginal internality τ^b as Pigouvian wedge and behavioral wedge, respectively.

2.3 Optimal tax and insurance

Before we turn to the estimation of τ^b , it is helpful to first derive the optimal tax τ^* and insurance indemnity I^* . The social planner maximizes the expected utility EU , given by (6), taking into account the reaction of consumption to policy changes, i.e., $\widehat{X}(\tau, I)$, determined by (9). The social planner's first-order conditions are:

$$\tau^* = \tau^b + \tau^\xi, \quad (11)$$

$$U_Z^1(Z_1, H^h, X) = \delta(1+r)U_Z^s(Z_2^s, H^s), \quad (12)$$

where (12) determines implicitly I^* . According to (11), a tax rate equal to the sum of the Pigouvian and behavioral wedges is optimal. This result is well-known from the existing

⁸The term τ^b is a money-metric because it is defined as the ignored marginal utility loss, divided by the marginal utility of income, $U_Z^1(\cdot)$ (see Equation (10)).

literature (see, e.g. [Allcott et al., 2019a](#); [Farhi and Gabaix, 2020](#); [Wang et al., 2020](#)).⁹ Moreover, I^* optimally redistributes risk between the (healthy) first period and the sick state in period 2.

3 Estimating the marginal internality

According to (10), health insurance affects τ^b . A higher coverage I raises consumption Z_2^s and thus lowers the numerator of (10). Hence, the marginal internality, measured in utility units, $U_Z^1(\cdot)\tau^b$, is decreasing in the insurance coverage.

To estimate τ^b , I first totally differentiate (9) with respect to sin good demand X and the indemnity I . Define $q \equiv p + \tau$ as the sin good's gross price. In Appendix A, I show that the total differential can be expressed as

$$\frac{\epsilon_{X,I}}{\epsilon_{X,q}^C} = - \left\{ \delta\pi' \frac{U_Z^s(Z_2^s, H^s)}{U_Z^1(\cdot)} + \frac{\pi(X)}{1+r} \frac{\epsilon_{X,Y_1}}{\epsilon_{X,q}^C} + \frac{1}{U_Z^1(\cdot)} \frac{\partial [U_Z^1(\cdot)\tau^b]}{\partial I} \right\}, \quad (13)$$

where

- $\epsilon_{X,I} := \frac{d\widehat{X}}{dI} \frac{1}{\widehat{X}}$ = the semi elasticity of sin good demand with respect to I ,
- $\epsilon_{X,q}^C := \left[\frac{d\widehat{X}}{dq} + \widehat{X} \frac{d\widehat{X}}{dY_1} \right] \frac{1}{\widehat{X}}$ = the compensated price semi elasticity of sin good demand,
- $\epsilon_{X,Y_1} := \frac{d\widehat{X}}{dY_1} \frac{1}{\widehat{X}}$ = the income semi elasticity of sin good demand.

Equation (13) has the following interpretation. It determines the impact of insurance coverage on \widehat{X} , given by $\epsilon_{X,I}$. If the individual maximizes the true expected utility, EU , then the elasticity $\epsilon_{X,I}$ would be fully determined by the first two terms in curly brackets on the right-hand side of (13). However, if the individual maximizes the perceived expected utility, \widehat{EU} , then insurance would additionally affect sin good demand through its impact on the behavioral wedge (the third term in curly brackets). This effect is given by

$$\frac{\partial [U_Z^1(\cdot)\tau^b]}{\partial I} = \delta[\beta\widehat{\pi}' - \pi'] U_Z^s(Z_2^s, H^s) = \frac{U_Z^s(Z_2^s, H^s) U_Z^1(\cdot)}{U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)} \tau^b. \quad (14)$$

⁹If there are heterogenous individuals and the government also has redistributive or revenue-raising motives for taxation, then τ^ξ and τ^b are not the only sufficient statistics for τ^* ([Allcott et al., 2019a](#); [Farhi and Gabaix, 2020](#)).

Because the right-hand side of (14) is proportional to the behavioral wedge, τ^b , we can solve (13) for τ^b and derive the following expression:

$$\tau^b = -\frac{U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)}{U_Z^s(Z_2^s, H^s)} \left\{ \frac{\epsilon_{X,I}}{\epsilon_{X,q}^C} + \frac{\delta\pi'(X)U_Z^s(Z_2^s, H^s)}{U_Z^1(Z_1, H^h, X)} + \frac{\pi(X)\epsilon_{X,Y_1}}{1+r}\frac{1}{\epsilon_{X,q}^C} \right\}. \quad (15)$$

If the individual has full self-control and correct beliefs, then the terms in curly brackets in (15) would sum up to zero. However, if the individual maximizes \widehat{EU} , then the terms in curly brackets sum up to the negative of the indemnity's impact on τ^b . Because this effect is proportional to τ^b , we can simultaneously isolate the behavioral wedge.

The most important feature of Equation (15) is the following. Its right-hand side does not explicitly contain the degree of present-bias β , as well as the perceived probability $\widehat{\pi}(X)$, or its derivatives. However, it does contain the marginal utility of income in period one, $U_Z^1(\cdot)$, which may depend on the sin good X . Thus, to estimate (15), one needs to make assumptions about the utility function. I consider three possible approaches.

Suppose first that period one utility is additively separable, i.e., $U^1(Z_1, H^h, X) = U^h(Z_1, H^h) + V(X)$, where $U^h(\cdot)$ is the same as the period two utility function in the healthy state and $V'(X) > 0 > V''(X)$. In this case, $U_Z^1 = U_Z^h(Z_1, H^h)$ and is independent of X . Thus, no further assumptions about $V(X)$ are necessary to estimate (15).

Second, we may wish to estimate (15) without making any assumptions about first period utility. This is possible, if one assumes that health insurance is chosen optimally. To see this, insert (12) in (15) to get

$$\tau^b(I = I^*) = -\frac{U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)}{U_Z^s(Z_2^s, H^s)} \left\{ \frac{\epsilon_{X,I}}{\epsilon_{X,q}^C} + \frac{\pi'(X)}{1+r} + \frac{\pi(X)\epsilon_{X,Y_1}}{1+r}\frac{1}{\epsilon_{X,q}^C} \right\}. \quad (16)$$

To estimate (16), one still needs to make structural assumptions about second-period utility. There are two possible approaches to calibrating the terms in front of curly brackets in (16). First, one may assume a state-dependent utility function of the form considered by Finkelstein et al. (2013) who empirically estimate the degree of state dependence.

Second, one may assume there is no state dependence. While this assumption contradicts Finkelstein et al. (2013), it is in line with the results of Nardi et al. (2010) who do not find evidence for state dependence. Moreover, Finkelstein et al. (2019) perform a welfare analysis of Medicaid without considering state dependence. In this case,

$U^s(Z, H) = U^h(Z, H) \equiv U(Z, H)$. Then, first-order Taylor approximation gives

$$U(Z_2^h, H^h) \approx U(Z_2^s, H^s) + U_Z(Z_2^s, H^s) \cdot (Z_2^h - Z_2^s) + U_H(Z_2^s, H^s) \cdot (H^h - H^s). \quad (17)$$

From (2), $Z_2^h - Z_2^s$ is equal to the copayment $M - I$. Moreover, following [Finkelstein et al. \(2019\)](#), one can measure H^i on a cardinal utility scale in units of quality adjusted life years (QALYs). Additionally, the marginal rate of substitution, $MRS \equiv U_H/U_Z$, gives the QALYs' monetary value and is well-estimated in the empirical literature. Thus, (16) and (17) together give

$$\tau^b(I = I^*) \approx [M - I + MRS \cdot (H^h - H^s)] \left\{ \frac{\epsilon_{X,I}}{\epsilon_{X,q}^C} + \frac{\pi'(X)}{1+r} + \frac{\pi(X)}{1+r} \frac{\epsilon_{X,Y_1}}{\epsilon_{X,q}^C} \right\}. \quad (18)$$

Equation (18) approximates the behavioral wedge under the assumptions of optimal health insurance and state-independent utility. Its advantage is that it does not require any additional assumptions about utility. I summarize the results in the following proposition.

Proposition 1. *The money-metric marginal internalality τ^b can be determined using (15) without any information regarding present-bias β and the beliefs $\hat{\pi}(X)$.*

- (a) *If, additionally, first-period utility is of the form $U^1(Z_1, H^h, X) = U^h(Z_1, H^h) + V(X)$, then (15) can be estimated without additional assumptions regarding $V(X)$.*
- (b) *If health insurance is optimal, then τ^b can be estimated using (16) and without any assumptions regarding first-period utility $U^1(Z_1, H^h, X)$.*
- (c) *If health insurance is optimal and second-period utility is state-independent, then τ^b can be approximated using (18).*

In the next section, I calibrate the model to SSB consumption. The calibration estimates τ^b for all three cases from Proposition 1.

4 Calibration

Here, I focus on sugary drinks. [Allcott et al. \(2019a\)](#) have also applied the counterfactual normative consumer approach to SSB consumption. Hence, their estimates can serve as a benchmark for the evaluation of this paper's results.

Consider case (a) from Proposition 1. The first step is to specify the state-dependent utility function U^i . Following [Finkelstein et al. \(2013\)](#), I define utility U^i as

$$U^i(Z^i, H^i) = (1 + \varphi \mathbb{1}_{i=s}) \frac{Z^{i1-\gamma}}{1-\gamma} + \phi H^i, \quad (19)$$

where $\gamma > 0$ is the degree of risk aversion, $\mathbb{1}_{i=s}$ is an indicator variable that equals one in the sick state of nature and zero otherwise. Therefore, illness lowers the marginal utility of consumption (negative state dependence) if $\varphi < 0$. The condition $\varphi > (=)0$ denotes positive (zero) state dependence. Furthermore, health has a constant marginal utility given by $\phi > 0$.¹⁰

[Finkelstein et al. \(2013\)](#) calibrate their model such that each period lasts a year and the periods are 25 years apart. In the case of SSB consumption, the time between the periods should be chosen according to the average duration of SSB consumption prior to the onset of sickness. To the best of my knowledge, there are no studies that measure it. However, in the case of obesity, a duration of at least ten years is associated with a significantly higher risk of type II diabetes ([Luo et al., 2020](#)), while the risk of all obesity-related cancers increases with duration until it reaches 20 years and then plateaus ([Arnold et al., 2016](#)). As a central value, I define the time between the periods as $T = 20$ years, and vary it in the sensitivity analysis to 10 and 25 years.

Moreover, [Finkelstein et al. \(2013\)](#) use data from the Health and Retirement Study (HRS), and estimate empirically the value of φ for the U.S. population aged at least 50. Therefore, I assume the first and second periods to be representative years from young adulthood (age < 50) and old adulthood (age ≥ 50), respectively.

Income and Expenditures. [Allcott et al. \(2019a\)](#) use Nielsen Homescan data over the period 2006-2016. To make my estimates comparable to theirs, I parametrize the period one SSB consumer to match their average consumer. They report average household income, expressed in 2016 dollars, equal to \$68,000 and mean household size of 2.48 adult equivalents. Therefore, I fix the period one individual income at $Y_1 = \$68,000/2.48 \approx \$27,400$ (all calibration parameters are reported in Table 1).

¹⁰Additionally, [Finkelstein et al. \(2013\)](#) define H^i as a CRRA function of the health expenditures. Because the health costs are fixed in this model, we do not need to specify the health function. [Finkelstein et al. \(2019\)](#) consider a special case of the utility function in (19) by setting $\varphi = 0$.

However, the household income reported by [Allcott et al. \(2019a\)](#) is gross income, while in my model, it equals the sum of expenditures and health insurance contribution. Therefore, I extend the first period budget constraint for the purpose of calibration to

$$Y_1 + \ell = Z_1 + (p + \tau)X + P + (\tilde{T} + \sigma)Y_1, \quad (20)$$

where \tilde{T} denotes other tax and social security contributions as a proportion of income and σ is the savings rate. Because both \tilde{T} and σ are exogenous to the model, they do not affect the previous analysis. Tax payments and savings can be found in the data on personal income and its decomposition (Table 2.1.) from the Bureau of Economic Analysis ([BEA, 2020](#)). According to this data, for the period 2006-2016, disposable income minus savings is 82.97% of gross income. Therefore, I set \tilde{T} and σ such that the proportion of income spent on consumption equals 83%; that is, $(Z_1 + pX)/Y_1 = [1 - P/Y_1 - \tilde{T} - \sigma] = 0.83$. I determine the health insurance premium P later.

Furthermore, [Allcott et al. \(2019a\)](#) measure the average SSB price to be \$1.14 per liter. I express the quantity consumed X as servings per year (one serving is equal to 12-ounce), and convert the liter price to $q = \$0.405$ per serving.

Moreover, the average respondent of [Allcott et al. \(2019a\)](#) consumes 87.70 liters of SSBs per year, which equals 247.12 servings per year. However, the average U.S. adult consumes 154 calories of SSBs per day according to data from the National Health and Nutrition Examination Survey (NHANES) from 2009-2016 ([Allcott et al., 2019b](#)). Using a conversion rate of 140 calories per serving, this estimate is equal to ≈ 400 servings per year. Hence, NHANES respondents report around 50% higher consumption. As a central value, I set $X = 247.12$. The sensitivity analysis considers $X \in [200, 400]$.

Second-period income Y_2 is equal to consumption in that period. Express it as a proportion of first-period consumption, that is, $Y_2 = \rho(Z_1 + pX)$, where $\rho > 0$. Thus, ρ can be interpreted as the degree of consumption smoothing. [Fernández-Villaverde and Krueger \(2007\)](#) analyze Consumer Expenditure Survey data and find total expenditures to be hump-shaped with a maximum at age around 50, where they reach about 30% higher level compared to age 22. Because total expenditures fall relatively fast after the age of 50, at age 75 expenditures are around 20% lower than at age 22. While this data points toward $\rho < 1$, [Aguiar and Hurst \(2007\)](#) show that expenditures may differ considerably from consumption. Using scanner data, they show that prices paid are constant until the

age of 49 and start declining afterward, reaching a 3.9% lower level in the early seventies. Moreover, [Aguiar and Hurst \(2007\)](#) use data from the American Time Use Survey (ATUS) to estimate home production and food consumption. The ratio of (food) consumption to expenditure starts to increase after the age of 49 and reaches a 20% higher level for 65-74-year-olds compared to 25-29-year-olds. This is (partial) evidence that total consumption declines less than total expenditures at old ages. Because in my model period one (two) represents age before (after) 50, I choose $\rho = 1$ in the benchmark case.

Preference Parameters. The literature with health-dependent utility functions commonly sets risk aversion at $\gamma = 3$ (see, e.g., [Finkelstein et al., 2013, 2019](#); [Kools and Knoef, 2019](#)). However, [Chetty and Saez \(2010\)](#) choose $\gamma = 2$ to estimate the optimal public health insurance in a similar model (citing [Chetty's \(2006\)](#) estimate of γ). [Nardi et al. \(2010\)](#) use the Assets and Health Dynamics of the Oldest Old (AHEAD) data set and estimate $\gamma = 3.8$. I choose $\gamma = 3$ as the central value.

Following [Finkelstein et al. \(2013\)](#), I define an individual to be sick in period two, if she has more than the median number of chronic diseases in the population aged over 50. For this population, [Finkelstein et al. \(2013\)](#) find that a one-standard-deviation increase in the number of diseases (equal to 0.65 diseases) leads to a 10% – 25% reduction in marginal utility. Moreover, in a calibration exercise [Finkelstein et al. \(2013\)](#) set $\varphi = -0.2$ and let it vary between -0.4 and zero. However, [Lillard and Weiss \(1997\)](#) and [Edwards \(2008\)](#) find evidence for positive state-dependence ($\varphi > 0$). [Nardi et al. \(2010\)](#) do not find statistically significant state-dependence. In the benchmark case, I take the lower bound of [Finkelstein et al.'s \(2013\)](#) findings and set $\varphi = -0.1$. The sensitivity analysis allows positive (up to 0.2), zero and more negative values of φ (down to -0.4).¹¹

To estimate the marginal utility from health, ϕ , I follow [Finkelstein et al. \(2019\)](#). Their approach is the following. First, one defines H^i in units of QALYs. Second, one converts the QALYs in consumption units by equating the marginal rate of substitution of health for consumption (MRS) to the value of a statistical life year, VSLY. [Finkelstein et al. \(2019\)](#) use $VSLY = MRS = \$100,000$ as a consensus value for the U.S. population.

¹¹[Kools and Knoef \(2019\)](#) also find evidence for positive state-dependence. However, they use European data and explain the difference from [Finkelstein et al.'s \(2013\)](#) results with differences in preferences between the U.S. and European populations.

Moreover, to estimate the MRS for a given subpopulation, one needs to adjust the estimated MRS for differences in the marginal utility of consumption, according to $MRS(Y) = MRS(\bar{Y}) \cdot (Y/\bar{Y})^\gamma$, where Y is the income of the subpopulation and \bar{Y} is the average income (Finkelstein et al., 2019).¹²

Because SSB consumption is higher among the poor (Allcott et al., 2019a), we also need to adjust the MRS for the population of SSB consumers. Here, and later in the analysis, I use ten waves of the NHANES data from 1999-2018. NHANES is a biannual, cross-sectional representative survey that collects data on the health and nutritional status of the U.S. population. It also provides dietary data, which can be used to divide the survey participants into SSB consumers and non-consumers. While NHANES reports income in bins, it gives the exact ratio of family income to the poverty threshold for each respondent. I estimate an average family income ratio equal to 2.69 and 2.953 for adult (age \geq 18) SSB consumers and the general adult population, respectively.¹³ Thus, the average income of SSB consumers is $2.69/2.953 \approx 91\%$ of mean adult income. Hence, the MRS of an SSB consumer is given by $MRS = (0.91)^3 \cdot \$100,000 \approx \$75,000$.

Defining the marginal rate of substitution in the healthy state as $MRS = \phi/Y_2^{-\gamma}$ according to (2) and (19), we get $\phi = MRS \cdot Y_2^{-\gamma}$. Inserting the values of all variables on the right-hand side gives $\phi \approx 6.38 \times 10^{-9}$.

However, VSLY has a large range of estimates (Viscusi, 2018). The results depend on the method of VSL elicitation (Hirth et al., 2000) as well as on the risk context (Lindhjem et al., 2011). Allcott et al. (2019a) use \$50,000 as a “commonly used conservative estimate” for the monetary value of a QALY. Lindhjem et al. (2011) show in a meta-analysis that the value of statistical life (VSL) derived in health contexts is \$4 million (measured in 2005 U.S. dollars). The \$4 million VSL is equivalent to a VSLY of approximately \$200,000 (measured in 2016 dollars).¹⁴ Hence, Lindhjem et al.’s (2011) VSLY estimate

¹²Finkelstein et al. (2019) use data for low income individuals with income equal to 40% of the average, and thus set for $\gamma = 3$, and $VSLY = \$100,000$, $MRS = \$100,000 \cdot 0.4^3 \approx \$5,000$.

¹³SSB consumers are individuals who report a positive SSB consumption. To identify a drink as an SSB, I use the SSB food code classifications provided by Allcott et al.’s (2019b) replication file.

¹⁴To arrive at $VSLY = \$200,000$, I first convert the VSL value in 2016 dollars, which gives $VSL \approx 4.76$ million. Then, I use Viscusi’s (2014) approach to estimate the VSLY for a given VSL according to $VSLY = rVSL / (1 - (1 + r)^{-L})$ where r is the yearly interest rate and L is life expectancy. Using the standard values $r = 0.03$ and $L = 40$ (Hirth et al., 2000), we get the desired result.

is double the consensus value used by [Finkelstein et al. \(2019\)](#). As a lower bound in the calibration, I follow [Allcott et al. \(2019a\)](#) and set $MRS = \$50,000$, while the upper MRS bound is set equal to $\$150,000 (\approx 0.91^3 \cdot 200,000)$.

Health and Health Insurance. To express H^i in QALYs, I again use the NHANES data. First, I measure the number of chronic diseases per respondent and label a person as sick if they have more than the median number of diseases in the population. Second, I use the answers to the self-assessed health question that asks “Would you say your health in general is excellent, very good, good, fair, or poor?”, and use the mapping of self-assessed health to QALYs from [Finkelstein et al. \(2019\)](#).

In measuring chronic diseases, I focus on the following seven chronic conditions: arthritis, hypertension, cancer, chronic obstructive pulmonary disease (COPD), coronary heart disease, diabetes, and stroke. These are the same seven conditions that [Finkelstein et al. \(2013\)](#) use in their analysis. As reported in [Table 2](#), 53.7% of all respondents aged at least 50 have at most one chronic condition. The standard errors in [Table 2](#) and the remaining tables are linearized standard errors that take into account the complex cluster design and sampling weights of NHANES, and are appropriate for work with NHANES data ([Johnson et al., 2013](#)). The median number of diseases is one, and the average is 1.52. I, therefore, define a person to be healthy if they have at most one disease and sick otherwise. Using the mapping of self-assessed health to QALYs from [Finkelstein et al. \(2019\)](#), I calculate the average QALY in the NHANES data for sick and healthy individuals aged over 50. The resulting estimates are $QALY^s=0.797(= H^s)$ and $QALY^h=0.88(= H^h)$.

Similarly to [Allcott et al. \(2019a\)](#), I use [Wang et al.’s \(2012\)](#) estimates of the SSB-related medical costs. [Wang et al. \(2012\)](#) estimate the ten-year medical costs of treating SSB-related illnesses and discount these costs at an annual 3% rate. Because the role of the interest rate r in my model is also to discount the medical expenditures, I choose the same discount rate. Thus, $1 + r = (1 + 0.03)^T$.

[Finkelstein et al. \(2013\)](#) set the yearly time discount rate at 2.7%. I choose in the benchmark analysis a yearly discount rate of 3% such that the time discount and interest rates are equal. Thus, I set $\delta = 1/(1 + 0.03)^T$. The sensitivity analysis varies both the yearly interest and discount rates over the interval $[0.01, 0.05]$.

Next, express the medical expenditures as a proportion m of the non-medical second period spending, $M = mZ_2^s$, and the indemnity I as a proportion b of medical costs, $I = bM$. [Finkelstein et al. \(2013\)](#) empirically estimate m and b and find $m = 0.236, b = 0.851$. Moreover, [Cawley and Meyerhoefer \(2012\)](#) find that third parties bear 88% of the medical costs of obesity, while [Allcott et al. \(2019a\)](#) choose $b = 0.85$ to derive the marginal externality. I use [Finkelstein et al.'s \(2013\)](#) estimates of m and b as central values.

(Marginal) Probability. To estimate the marginal probability $\pi'(X)$, I follow two different approaches. The first is indirect and uses the fact that the marginal externality is partially determined by $\pi'(X)$ (see Equation (7)). Using empirical estimates of the marginal externality and all of its determinants except for the marginal probability, one can derive the value of $\pi'(X)$ consistent with these estimates. The second approach is more direct and uses the NHANES data to estimate the association between SSB consumption and the probability of being sick.

Starting with the first approach, the discounted marginal medical costs of one serving are given by

$$\frac{\partial}{\partial X} \frac{\pi(X)M}{1+r} = \frac{\pi'(X)mZ_2^s}{1+r},$$

where I used $M = mZ_2^s$. Furthermore, from (2) and $Y_2 = \rho(Z_1 + pX)$, we get $Z_2^s = \rho(Z_1 + pX)/(1 + m(1 - b))$. Thus, we have

$$\frac{\partial}{\partial X} \frac{\pi(X)M}{1+r} = \frac{\pi'(X)m\rho(Z_1 + pX)}{(1+r)[1 + m(1 - b)]}. \quad (21)$$

We have determined all parameters in (21) except for $\pi'(X)$. Similarly to [Allcott et al. \(2019a\)](#), I use [Wang et al.'s \(2012\)](#) estimate of a marginal cost of one cent per ounce. Because one serving contains 12 ounces, I equate the right-hand side of (16) to \$0.12 and solve for $\pi'(X)$. The resulting estimate is $\pi'(X) = 4.18 \times 10^{-5}$.

Table 1: Benchmark parameter values.

Parameter	Benchmark	Range
A. Preference Parameters^a		
γ :	3	[2,4]
φ :	-0.1	[-0.4,0.2]
ϕ :	6.38×10^{-9}	$[4.25 \times 10^{-9}, 1.28 \times 10^{-8}]$
δ :	$\left(\frac{1}{1.03}\right)^T$	$\left[\left(\frac{1}{1.05}\right)^T, \left(\frac{1}{1.01}\right)^T\right]$
T :	20	[10, 25]
B. SSB Demand and Price^b		
q (\$/12-ounce serving):	0.405	-
X (servings/year):	247.12	[200,400]
$\epsilon_{X,q}^C$:	-3.43	[-3.7,-3.2]
$\epsilon_{X,I}$:	0	-
$\epsilon_{X,Y_1} Y_1$:	0.2	[0.197,0.34]
C. Health, Insurance and Costs^c		
$\pi(X)$:	0.483	[0.4, 0.6]
$\pi'(X)$:	4.18×10^{-5}	$[2.8, 6.7] \times 10^{-5}$
m :	0.236	[0.19, 0.28]
b :	0.851	[0.75, 1]
$1 + r$:	1.03^T	$[1.01^T, 1.05^T]$
H^h in QALYs:	0.88	-
H^s in QALYs:	0.797	-
D. Income and Expenditures^d		
Y_1 :	\$27,400	-
ρ :	1	[0.9,1.05]
$\tilde{T} + \sigma$:	0.13	-
P :	0.04	-

^a Sources: γ, φ, δ (Finkelstein et al., 2013), ϕ (based on Finkelstein et al., 2019), T (assumption based on Finkelstein et al. (2013); Arnold et al. (2016); Luo et al. (2020)).

^b Sources: $q, X, \epsilon_{X,q}^C, \epsilon_{X,Y_1}$ (Allcott et al., 2019a), $\epsilon_{X,I}$ (Cotti et al., 2019; He et al., 2020).

^c Sources: m, b (Finkelstein et al., 2013), $\pi(X), \pi'(X)$ (author's calculation based on Wang et al. (2012) and CDC (2021)), r (Wang et al., 2012), H^h, H^s (Finkelstein et al., 2019; CDC, 2021).

^d Sources: Y_1 (Allcott et al., 2019a), \tilde{T}, σ (BEA, 2020), ρ (assumption based on Fernández-Villaverde and Krueger (2007); Aguiar and Hurst (2007)).

Table 2: Number of chronic diseases and QALYs age ≥ 50 (standard error in parentheses).

A. Number of chronic diseases^a					
	Share (%)			Median	Mean
Number of diseases	0	1	≥ 2		
	23.7 (0.45)	29.9 (0.43)	46.3 (0.58)	1	1.52 (0.015)
B. Self-assessed health^a					
Health assessment	Share (%)			QALY ^b	
Poor	5.19 (0.22)			0.401	
Fair	17.45 (0.44)			0.707	
Good	33.35 (0.48)			0.841	
Very Good	29.39 (0.59)			0.931	
Excellent	14.62 (0.44)			0.983	
Median QALY				0.841	
Mean QALY				0.842 (0.0018)	
Mean QALY among sick (≥ 2 diseases)				0.797 (0.0024)	
Mean QALY among healthy (< 2 diseases)				0.88 (0.0016)	
Observations				23,818	

^a Source: [CDC \(2021\)](#).

^b Source: [Finkelstein et al. \(2019\)](#).

However, the first approach is not informative about the reliability of its result. Therefore, I continue with the direct approach. NHANES gives cross-sectional data on both chronic conditions and SSB consumption, which can be used to determine the correlation between SSB intake and the probability of sickness. A large concern, however, with this data is reverse causality. Individuals may lower their SSB consumption after a disease is diagnosed, which would bias downwards the observed relationship between consumption and sickness. I, therefore, first look in Table 3 at different health indicators of SSB consumers and non-consumers in the NHANES dataset.

As expected, SSB consumers have worse health, as measured by QALY, compared to non-consumers, and the difference is statistically significant. However, the BMI difference between the two groups is slightly negative but not statistically significant. Moreover, SSB consumers have, on average, a lower number of chronic diseases. One likely reason for this result is reverse causality. Individuals diagnosed with chronic conditions may switch from SSBs to diet soda, and we would observe them as non-consumers.

Table 3: QALYs, BMI, and number of chronic diseases among adult (age ≥ 50) SSB consumers and non-consumers (standard error in parentheses).

Measure ^a	Mean (SSB consumers)	Mean (Non-consumers)
QALY	0.835 (0.002)	0.847 (0.002)
BMI	29.11 (0.1)	29.18 (0.1)
Number of chronic diseases	1.41 (0.02)	1.6 (0.02)
Observations	10,340	13,478

^a Source: CDC (2021).

In the following, I perform a logistic regression with a binary variable indicating whether a person has more than two chronic diseases as the dependent variable and SSB consumption on the right-hand side. To address the problem of sick individuals choosing not to consume SSBs before the survey is conducted, I include a dummy variable that equals one if an individual is an SSB consumer and zero otherwise. Thus, I estimate the following logistic model:

$$\log\left(\frac{\pi_i}{1 - \pi_i}\right) = \beta_0 + \beta_1 X_i + \beta_2 D_i + \zeta \mathbf{W}_i + \varepsilon_i, \quad (22)$$

where the index i stands for the i th individual, π_i is the probability of being sick, X_i measures the SSB consumption in servings per year¹⁵, D_i is an indicator variable that equals one if the individual reports positive SSB consumption and zero otherwise, \mathbf{W}_i is a vector of control variables that includes age, age squared, BMI, household income, education level, race/ethnicity, and gender, and ε_i is the error term. I report the results in Table 4.

The first column in Table 4 uses data for all individuals aged ≥ 50 and controls only for age and age squared. The coefficient on SSB consumption is positive and significant, in accordance with the expected adverse association between SSB consumption and the probability of being sick. The coefficient on the dummy variable for an SSB consumer is negative and significant. This result is in line with the descriptive statistics from Table 3 that indicate fewer chronic conditions among SSB consumers. It possibly shows the effect of consumers who choose not to drink SSBs after being diagnosed with chronic

¹⁵The NHANES data gives consumption in grams per day. I multiply the data by 365 (days) and divide by 370 grams per 12 ounce-serving (Van Rompay et al., 2015) to get servings per year.

conditions. The estimated marginal probability $\pi'(X)$ equals 3.66×10^{-5} and is slightly less than the estimate from the indirect approach (4.18×10^{-5}). However, the indirect approach's result is less than one standard error away from column (1)'s result. The estimated probability of sickness among the SSB consumers is around 49%. In column (2), I include all additional control variables. The results remain qualitatively unchanged. The marginal probability declines to 2.86×10^{-5} .

Table 4: Logistic Model Estimates.

	Age \geq 50 (1)	Age \geq 50 (2)	50 \leq Age \leq 60 (3)	50 \leq Age \leq 60 (4)
Variable	Coefficients			
SSB Consumption (X_i)	.000147** (.000062)	.000116* (.000069)	.000138* (.000082)	.000161** (.000081)
SSB Consumer (D_i)	-.2399*** (.059)	-.277*** (.069)	-.295*** (.103)	—
	(Marginal) Probabilities			
$\pi'(X)$.0000366** (.0000155)	.0000286* (.0000171)	.0000288* (.0000172)	.0000331** (.0000167)
$\pi(X)$.487 (.007)	.483 (.007)	.309 (.013)	.302 (.0155)
Age, age squared	Yes	Yes	Yes	Yes
BMI, household income, race/ethnicity, education, gender	No	Yes	Yes	Yes
Observations	23,791	20,751	7,395	3,677

^a Notes: Logistic regressions. Linearized standard errors of coefficients and delta-method standard errors of the (marginal) probabilities in parentheses. Regressions based on 1999–2018 NHANES data. Specification in column 1 includes all individuals age \geq 50 and controls for age and age squared. Specification in column 2 adds the control variables BMI, household income, race/ethnicity, education, and gender. Column 3 limits the population to age \geq 50 and \leq 60. Column 4 limits the population to age \geq 50 and \leq 60 and SSB consumers only. The estimated probabilities and marginal probabilities are evaluated at the mean levels of the control variables.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Moreover, it is reasonable to expect that at a very high age, most individuals are

diagnosed with chronic conditions irrespective of SSB consumption. Thus, the estimated correlation of SSB consumption and sickness would likely be mitigated by the oldest respondents. Therefore, in column (3), I restrict the sample to age above 50 and below 60. The results remain qualitatively unchanged. The predicted absolute probability of sickness declines, because the number of individuals with at least two chronic conditions is smaller in this subsample.

Lastly, column (4) presents an alternative approach, where I drop the non-consumers. Thus, the sample further declines to include only SSB consumers aged between 50 and 60. The results remain qualitatively the same and the estimated marginal probability increases to 3.31×10^{-5} .

Based on the two approaches considered above, I choose the value from the indirect approach (4.18×10^{-5}) as the central estimate for the marginal probability $\pi'(X)$, as the results from Table 4 may be biased downwards owing to reverse causality. In the sensitivity analysis, I let $\pi'(X)$ vary between 2.8×10^{-5} (the lowest estimate in Table 4) and 6.7×10^{-5} (the upper bound of $\pi'(X)$'s confidence interval in column (4)). The probability of sickness is set at $\pi(X) = 0.483$, i.e., the estimated probability for the whole population above 50 in column (2). This estimate may also be downwards biased. Therefore, I vary it between 0.4 and 0.6 later, which affects the results only minimally.¹⁶

Elasticities. Lastly, I choose the semi-elasticities. [Allcott et al. \(2019a\)](#) estimate the compensated price elasticity of sin good demand to equal -1.39 . In (13), $\epsilon_{X,q}^C$ denotes the semi-elasticity and thus equals $\epsilon_{X,q}^C = -1.39/q = -1.39/0.405 \approx -3.43$. Also, [Allcott et al. \(2019a\)](#) estimate an income elasticity of 0.2. Because ϵ_{X,Y_1} is a semi-elasticity, we get $\epsilon_{X,Y_1} Y_1 = 0.2$.

[Cotti et al. \(2019\)](#) and [He et al. \(2020\)](#) both analyze the impact of the Affordable Care Act (ACA) on the demand for SSBs. Both studies use panel data of household expenditures from the Kilts Center's Nielsen Consumer Panel and compare households eligible for a Medicaid expansion to ineligible households. [Cotti et al. \(2019\)](#) analyze the ACA's impact on the demand for carbonated drinks and find zero effects. [He et al. \(2020\)](#)

¹⁶Together, the parameter values give a health insurance contribution equal to approximately 4% of income, i.e., $P \approx 0.04Y_1$. Hence, the sum of tax payments and savings is $\tilde{T} + \sigma \approx 1 - 0.83 - 0.04 = 0.13$.

differentiate between SSBs and diet soda and find that the demand for SSBs remained unaffected by the ACA. One may worry that a lack of salience drives the null effects. However, [Cotti et al. \(2019\)](#) find that the reform reduced smoking, while [He et al. \(2020\)](#) find a positive effect on the purchase of diet soda. Therefore, the null effects are likely not driven by a lack of salience. Therefore, I set $\epsilon_{X,I} = 0$.

4.1 Results

Panel A in [Table 5](#) reports the results from case (a) in [Proposition 1](#), where first-period utility is additively separable. The behavioral wedge τ^b , estimated using [\(15\)](#), is 1.08 cents per ounce. This result is within the range of estimates of [Allcott et al. \(2019a\)](#): between 0.91 and 2.14 cents per ounce. Second, I insert τ^b in [\(10\)](#) to derive the effectively perceived marginal probability $\beta\hat{\pi}'(X)$. It equals only 0.025 times the true marginal probability. This value means that the average consumer almost fully ignores the potential health harms when making a consumption choice. However, this result is less robust and $\beta\hat{\pi}'(X)$ increases significantly in the extensions in the next section. Moreover, I estimate the marginal individual health costs to be $\tau^b/(1 - 0.025) = 1.11$ cents per ounce of SSB. The marginal externality is given by the medical costs borne by health insurance and is $\tau^\xi = 0.851$ cents per ounce (the same as in [Allcott et al. \(2019a\)](#) by assumption).

Table 5: Results from the benchmark calibration.

A. Case (a) from Proposition 1^a						
τ^b	$\frac{\beta\hat{\pi}'(X)}{\pi'(X)}$	Individual health costs	τ^ξ	τ^*	b^*	
1.08	0.025	1.11	0.851	1.94	0.842	
B. Case (b) from Proposition 1^a						
τ^b	$\frac{\beta\hat{\pi}'(X)}{\pi'(X)}$	Individual health costs	τ^ξ	τ^*	b^*	
1.096	0.025	1.12	0.851	1.95	–	
C. Case (c) from Proposition 1^a						
τ^b	$\frac{\beta\hat{\pi}'(X)}{\pi'(X)}$	Individual health costs	τ^ξ	τ^*	b^*	
1.32	0.025	1.35	0.851	2.17	–	

^a All monetary results are measured in cents per ounce.

Moreover, Panel A reports the optimal tax τ^* and insurance coverage b^* , derived from (11) and (12). Even though Equation (12) determines I^* , we can solve it for $b^* = I^*/M$ because of the exogeneity of the medical costs, M . The optimal tax is equal to the sum of Pigouvian and behavioral wedges, while the optimal insurance coverage $b^* = 0.842$ is very close to the observed value $b = 0.851$ (Finkelstein et al., 2013).

Next, in Panel B, I estimate τ^b according to (16), i.e., under the assumption that the observed value of b is optimal (case (b) from Proposition 1). Moreover, in Panel B, no assumptions about the first period utility are made. Therefore, it is not possible to determine the optimal level of health insurance. The behavioral wedge increases slightly to $\tau^b = 1.096$. The remaining results are almost identical to Panel A.

Lastly, Panel C considers case (c) from Proposition 1, where τ^b is approximated by (18). In Panel C, no assumption about utility is made apart from it being state-independent. In this case, the estimated behavioral wedge is slightly larger and equal to 1.32 cents per ounce. Hence, neglecting state dependence and approximating τ^b does not change much the estimated behavioral wedge.

4.2 Sensitivity Analysis

Figure 1 reports the effects of varying the most important parameters of the model. The blue, orange, and green curves in Figure 1 correspond to τ^b estimated according to cases (a), (b), and (c) from Proposition 1, respectively. Panels (a) and (b) show the effects of varying $\pi(X)$ and $\pi'(X)$, respectively. A higher probability affects only marginally the estimated behavioral bias. The reason is that it is multiplied by the SSB demand's income elasticity, which is very small. A higher marginal probability raises the estimated τ^b . Here, the results are more sensitive. At the upper bound of the confidence interval for $\pi'(X)$ from Table 4, column (4) (6.7×10^{-5}), τ^b is estimated at 1.75-2.13 cents per ounce.

Next, I vary the preference parameters. Higher monetary value of QALYs (MRS) increases the utility loss from sickness and thus the estimated τ^b (panel (c)). In the case MRS= \$150,000, the estimated marginal internality lies between 2.24 and 2.49 cents per ounce, while at MRS= \$50,000, τ^b equals between 0.7 and 0.93 cents per ounce. MRS is also the parameter with respect to which τ^b is most sensitive. Panel (d) shows the impact of the degree of risk aversion, which is insignificant (and exactly zero for case (c)).

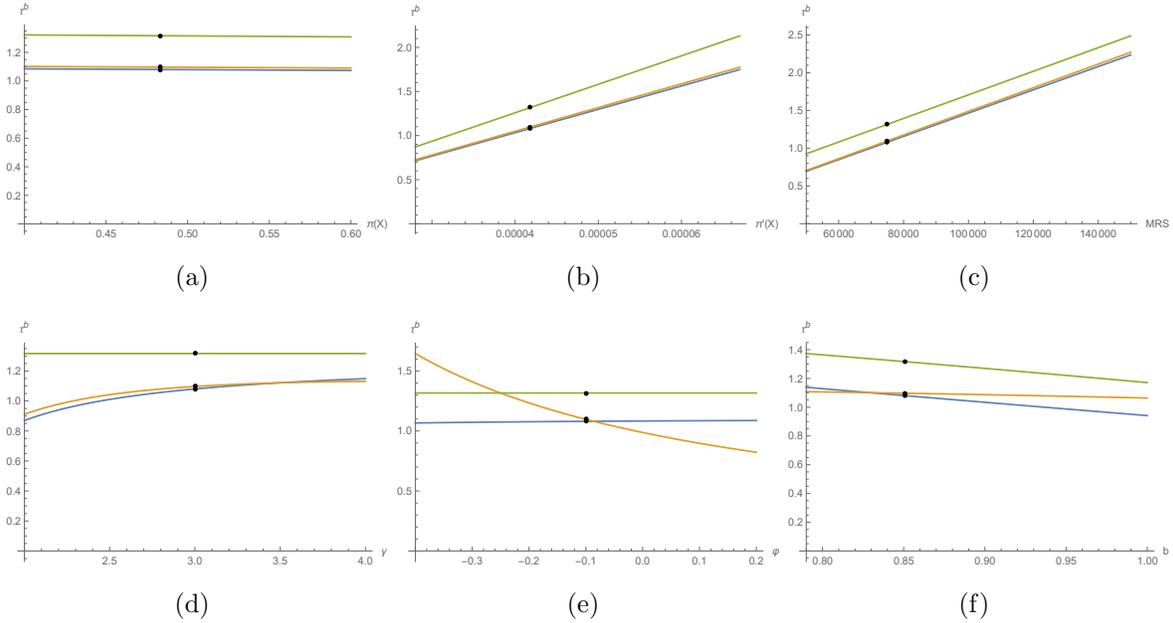


Figure 1: The behavioral wedge τ^b estimated according to case (a) (blue), case (b) (orange), and case (c) (green) as a function of the probability of sickness $\pi(X)$ (panel (a)), marginal probability $\pi'(X)$ (panel (b)), VSLY (panel (c)), risk aversion γ (panel (d)), degree of state dependence φ (panel (e)), and health insurance coverage b (panel (f)). Dots indicate the benchmark estimates.

Panel (e) varies the state dependence parameter φ .¹⁷ In case (a), the effect is insignificant because higher φ lowers the utility loss of sickness and at the same time raises the insurance elasticity that a rational consumer should exhibit. Because the second effect is missing in case (b), τ^b is declining in φ . However, in case (c), state independence is assumed away, and φ has zero effect. Most importantly, assuming both optimal health insurance and state-independence (case c) does not lead to large differences in the estimated τ^b even for large actual state dependence (e.g., when $\varphi = -0.4$). Lastly, I vary b from 0.79 to 1 in panel (f). The reason is that uninsured adults in the U.S. have out-of-pocket costs equal to 21%, with the remainder being paid by third parties (Finkelstein et al., 2019). Thus, $b = 0.79$ is the lowest bound for coverage even for the uninsured. The effect of b is minimal. Moreover, given that out-of-pocket costs do not increase above 21% for the

¹⁷Following Finkelstein et al. (2013), I keep the utility $U^s(\cdot)$ constant when varying φ such that the calibration captures only changes in the marginal utility of consumption, which is the definition of state dependence.

uninsured, the optimal b in the U.S. is likely at least 79%. Thus, the assumption in cases (b) and (c) of optimal health insurance does not seem to affect the results significantly.

Figure B.1 in Appendix B presents the impact of changes in other parameters graphically. Panel (a) shows that τ^b is affected only marginally by the proportion of medical expenditures m . Panels (b) and (c) vary the yearly discount and interest rates, respectively. Higher discounting lowers the marginal internality. Panels (d), (e), and (f) vary the SSB consumption X , as well as the income and price elasticities ϵ_{X,Y_1} and $\epsilon_{X,q}^C$ (according to the range of estimates from Allcott et al. (2019a)). Neither consumption nor the elasticities affect τ^b . Panel (g) varies the time between periods T . Higher T values lower the estimated τ^b similarly to higher discount and interest rates. Lastly, panel (h) shows that the degree of consumption smoothing ρ also has a small impact on τ^b .

5 Extensions

5.1 Multiple sin goods

If the individual consumes multiple sin goods, interactions among the internalities caused by each good are possible. To analyze such interactions, I extend the model to allow for multiple sin goods.

Suppose the individual consumes n sin goods denoted by $\mathbf{X} = (X^1, \dots, X^n)$. The corresponding gross price vector is $\mathbf{q} = (q^1, \dots, q^n)$, where $q^i = p^i + \tau^i$ for $i = 1, \dots, n$. The first period budget constraint becomes

$$Y_1 + \ell = Z_1 + \mathbf{q}\mathbf{X} + P, \quad (23)$$

where the lump-sum transfer is $\ell = \tau\mathbf{X}$. Expected utility takes the form

$$EU = U^1(Z_1, H^h, \mathbf{X}) + \delta \{ \pi(\mathbf{X})U^s(Z_2^s, H^s) + [1 - \pi(\mathbf{X})]U^h(Z_2^h, H^h) \}, \quad (24)$$

where $U^1(Z_1, H^h, \mathbf{X})$ and $\pi(\mathbf{X})$ may be any increasing or decreasing functions in X^i for $i = 1, \dots, n$ that are consistent with an interior solution to the utility maximization problem. The perceived utility \widehat{EU} is defined analogously to Equation (5). The individual maximizes her perceived expected utility over X^i for $i = 1, \dots, n$. Denoting the respective

marginal internalities as τ_i^b , Appendix C derives the following expressions:

$$\tau_i^b = -\frac{U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)}{U_Z^s(Z_2^s, H^s)} \left\{ E_1^i + \frac{\delta \pi_{X^i} U_Z^s(Z_2^s, H^s)}{U_Z^1(Z_1, H^h, \mathbf{X})} + \frac{\pi(\mathbf{X})}{1+r} E_2^i \right\} \quad (25)$$

for all $i = 1, \dots, n$, where

$$E_1^i = \frac{1}{|\mathbf{S}|} \sum_{j=1}^n (-1)^{j+i} |\mathbf{S}_{\mathbf{ji}}| \epsilon_{X^j, I}, \quad (26)$$

$$E_2^i = \frac{1}{|\mathbf{S}|} \sum_{j=1}^n (-1)^{j+i} |\mathbf{S}_{\mathbf{ji}}| \epsilon_{X^j, Y_1}, \quad (27)$$

where \mathbf{S} is an $n \times n$ matrix of all compensated semi-elasticities ϵ_{X^i, q^j}^C for $i, j = 1, \dots, n$, $\mathbf{S}_{\mathbf{ji}}$ is the matrix left after deleting the j th row and i th column from matrix \mathbf{S} , and $\epsilon_{X^j, I}$ and ϵ_{X^j, Y_1} are j 's health insurance and income semi-elasticities, respectively.

Equation (25) is the equivalent of Equation (15) in the case of multiple sin goods (and collapses to (15) when $n = 1$). It differs in the first and last terms in curly brackets. The term E_1^i has the following interpretation. If the sin goods' compensated cross-price elasticities are nonzero, then the marginal internalities of these goods interact. In this case, the n marginal internalities jointly impact the health insurance elasticity of each sin good. The term E_2^i includes all income and cross-price elasticities for similar reasons.

Furthermore, it is straightforward to derive Proposition 1 in the case of multiple sin goods from (25). The only difference is that we substitute X with \mathbf{X} .

Calibration. To simulate the model with multiple sin goods, one must initially choose the appropriate goods. A (sin) good is appropriate to be included if it affects the results from the previous section. A good affects (25) if it is a substitute or complement to SSBs. Interestingly, a good need not be itself a sin good for it to be appropriate for consideration. The reason is that even if a good $j \neq i$ has a zero behavioral wedge ($\tau_j^b = 0$), it might still affect τ_i^b , if the compensated cross-price elasticities are nonzero.

Allcott et al. (2019a) determine the SSB price's effects on the demand for 12 groups of potential sin goods.¹⁸ They find only two nonzero cross-price elasticities. First, SSBs

¹⁸The 12 groups include alcohol, diet drinks, fruit juice, baked goods, baking supplies, breakfast foods, candy, canned, dry fruit, desserts, sauces, sweeteners, tobacco.

are substitutes with diet drinks (cross-price elasticity ≈ 0.25). Second, SSBs are slight complements with canned, dry fruit (cross-price elasticity ≈ -0.19).

I do not expect the demand for canned, dry fruits to respond sufficiently to changes in insurance coverage. The reason for this conjecture are [Cotti et al.'s \(2019\)](#) results, who show that candy, cookies, and snacks demands were not affected by the ACA. Therefore, I do not consider them in the remaining analysis. However, [He et al. \(2020\)](#) find the demand for diet soda to be increasing in insurance coverage. Specifically, they find a statistically significant positive effect with a point estimate equal to 8.93 ounces per household per month. Given an initial monthly demand of 113.7 ounces per household, this change corresponds to an approximately 7.8% increase. Therefore, in this section, I include diet soda as a second good in calibrating the SSBs' behavioral wedge.

Index the two types of drinks as $i = d, r$, where d labels diet soda and r regular soda. To determine the health insurance semi-elasticity of diet soda, $\epsilon_{X^d, I}$, denote the observed change in demand from [He et al. \(2020\)](#) as:

$$\frac{\Delta X^d}{X^d} = 0.078. \quad (28)$$

The semi-elasticity $\epsilon_{X^d, I}$ is defined as $\epsilon_{X^d, I} = (dX^d/dI)(1/X^d)$. Assume $dX^d/X^d \approx \Delta X^d/X^d$. Therefore, to derive $\epsilon_{X^d, I}$ from (28), we need to divide it by the change in insurance coverage dI . Because (28) is the demand response to the ACA's implementation, we need an estimate of the change in insurance coverage for the average eligible household.

[Sommers et al. \(2017\)](#) find that the ACA lowered the annual out-of-pockets costs of previously uninsured households by \$337. Setting $dI = \$337$, we get

$$\epsilon_{X^d, I} \approx \frac{1}{dI} \frac{\Delta X^d}{X^d} = 2.31 \times 10^{-4}. \quad (29)$$

I describe in detail the derivation of all additional semi-elasticities in Appendix C.1. The results from estimating Equation (25) for SSBs in the case of two goods (SSBs and diet soda) are reported in Table 6. The benchmark estimates decline to 0.72, 0.73, and 0.88 cents per ounce in cases (a), (b), and (c), respectively. Moreover, because this extension does not affect the individual health costs, the estimated proportion of the health costs that individuals take into account increases to 35% in all three cases. Furthermore, the optimal health insurance remains almost unchanged and is given by $b^* = 0.839$.

Table 6: Results for SSB in the case of two sin goods (SSB and diet soda).

A. Case (a) from Proposition 1^a

τ^b	$\frac{\beta\hat{\pi}'(X)}{\pi'(X)}$	Individual health costs	τ^ξ	τ^*	b^*
0.72	0.354	1.11	0.851	1.564	0.839

B. Case (b) from Proposition 1^a

τ^b	$\frac{\beta\hat{\pi}'(X)}{\pi'(X)}$	Individual health costs	τ^ξ	τ^*	b^*
0.73	0.349	1.12	0.851	1.581	–

C. Case (c) from Proposition 1^a

τ^b	$\frac{\beta\hat{\pi}'(X)}{\pi'(X)}$	Individual health costs	τ^ξ	τ^*	b^*
0.88	0.349	1.35	0.851	1.731	–

^a All monetary results are measured in cents per ounce.

5.2 Life expectancy

In the main model, the sick state of nature lowers utility due to (i) worse health and (ii) positive medical costs. However, sickness is likely also to reduce life expectancy (LE). [DuGoff et al. \(2014\)](#) estimate LE for U.S. Medicare beneficiaries at the ages 67 and 75 as a function of the number of chronic conditions. They find LE to be monotonically decreasing in the number of diseases. I reproduce [DuGoff et al.'s \(2014\)](#) results in [Table D.1](#) in Appendix D. A disease-free 67-year-old adult has a life expectancy of 22.6 years. However, LE declines to 22.2 years with the first chronic condition, 21.7 years for two conditions, until it reaches five years for an adult with at least ten conditions. Moreover, there is direct evidence that sin good consumption lowers life expectancy. Smoking lowers LE by six years ([Gruber and Köszegi, 2004](#)); SSB consumption is associated with higher mortality risk, as measured by hazard ratios ([Malik et al., 2019](#)).

To integrate the effects of sickness on life expectancy in the model, I change the expected utility from [\(4\)](#) to

$$EU = U^h(Z_1, H^h, X) + \delta \{ \pi(X)\mu U^s(Z_2^s, H^s) + [1 - \pi(X)]U^h(Z_2^h, H^h) \}, \quad (30)$$

where $\mu \in (0, 1]$ measures the relative LE in the sick state of nature (as a proportion of the LE when healthy). The perceived expected utility \widehat{EU} is changed analogously to contain the relative LE μ in the sick state.

To solve the model, I define a new (effective) utility in the sick state: $\tilde{U}^s(\cdot) := \mu U^s(\cdot)$. Thus, the results with LE effects are identical to the results from Sections 2 and 3, when one replaces $U^s(\cdot)$ and its partial derivatives by $\tilde{U}^s(\cdot)$ (and its partial derivatives). Moreover, by definition $\mu < 1$ introduces state dependence of utility, i.e., $\tilde{U}^s(\cdot)$ differs from $U^h(\cdot)$. Hence, in the calibration of this extension, I can only consider cases (a) and (b) from Proposition 1.

Calibration. To simulate the model, we need an estimate of the relative LE μ . To the best of the author’s knowledge, no study measures the effect of SSB consumption on life expectancy (Malik et al. (2019) estimate the hazard ratios of mortality associated with different consumption levels). However, because the calibration procedure defines the sick state according to the number of chronic diseases, we can use DuGoff et al.’s (2014) results. Moreover, the average age of the population ≥ 50 in NHANES is 63.3 years, while DuGoff et al. (2014) estimate LE at the age of 67.

Using DuGoff et al.’s (2014) results as well as the average number of diseases for the population above 50 from the NHANES data (both reported in Table D.1 in Appendix D), I calculate the average LE for adults with at most one and at least two diseases to be 22.38 and 20.51 years, respectively. Thus, I choose $\mu = 20.51/22.38 \approx 0.9165$.

To estimate the main model with one sin good, I additionally use the central parameter values from Table 1. The estimates for τ^b are equal to 1.83 and 2.03 cents/ounce for cases (a) and (b) from Proposition 1, respectively (reported in Table 7). This is higher than the estimates from Table (5) because LE effects increase the health costs of sin goods. However, when introducing LE effects in the calibration with two sin goods, the SSB’s marginal internality declines to 1.16 and 1.36 cents per ounce, respectively. Thus, the two extensions have opposite effects on τ^b that almost cancel out.

Moreover, the individual health costs increase with LE effects to around 2 cents per ounce. Finally, reduced life expectancy lowers the benefits of health insurance and hence reduces b^* to around 0.72.

Table 7: Results in the case of LE effects.

A. Case (a) from Proposition 1^a						
Model	τ^b	$\frac{\beta\hat{\pi}'(X)}{\pi'(X)}$	Individual health costs	τ^ξ	τ^*	b^*
Main model	1.83	0.027	1.88	0.851	2.67	0.723
Two sin goods	1.16	0.39	1.88	0.851	2.0	0.714
B. Case (b) from Proposition 1^a						
Model	τ^b	$\frac{\beta\hat{\pi}'(X)}{\pi'(X)}$	Individual health costs	τ^ξ	τ^*	b^*
Main model	2.03	0.026	2.09	0.851	2.88	–
Two sin goods	1.36	0.349	2.09	0.851	2.21	–

^a All monetary results are measured in cents per ounce.

6 Conclusion

This paper exploits the relationship between health insurance and the marginal internal-ity of sin goods consumption to estimate the latter. The resulting estimation method measures the money-metric marginal internality without the need for surveys to elicit individuals' beliefs and self-control. A calibration to SSB consumption shows that the new approach leads to results similar to the estimates of [Allcott et al. \(2019a\)](#), who apply a counterfactual normative approach.

Furthermore, this paper's approach can be applied to other sin goods, such as alcohol and cigarettes. To the best of the author's knowledge, no direct measurement of the marginal internalities in these contexts exist. For example, [Gruber and Köszegi \(2004\)](#) study smoking when individuals are present-biased and estimate the individual health costs. To get a measure of the money-metric marginal internality, they use values for the degree of present-bias that have been derived in other contexts. My approach could give a more direct measurement.

Moreover, while this paper focuses on sin goods, its method can also be applied to measuring behavioral biases in the demand for preventive goods. These are goods that lower the probability of future health harms, such as, e.g., sporting activities. An application to such goods would provide essential results for the guidance of public policy.

Additionally, the paper can be used to estimate heterogeneous marginal internalities

of different subpopulations, such as, e.g., low- and high-income individuals. Because the latter exhibit less bias in previous research (see, e.g., [Allcott et al., 2019a](#)), it may also be the case that they respond differently to changes in insurance coverage. Hence, a promising research agenda is the estimation of health insurance elasticities of low- and high-income households, which would allow an estimation of heterogeneous marginal internalities.

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A Derivation of Equation (13)

First, we rewrite (9):

$$\begin{aligned} \frac{\partial \widehat{EU}}{\partial X} &= -U_Z^1[Z_1, H^h, X][p + \tau] + U_X^1(Z_1, H^h, X) \\ &\quad + \delta\pi'(X) [U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)] + U_Z^1[Z_1, H^h, X]\tau^b = 0. \end{aligned} \quad (\text{A.1})$$

Next, we derive the slope of uncompensated demand, $d\widehat{X}/dq$, as well as the effect of period one income on demand, $d\widehat{X}/dY_1$. Because we are interested in uncompensated demand, consider price changes that are not compensated via the lump-sum transfer, e.g., due to net price changes; that is, $dq = dp$. Totally differentiating (A.1) and solving, we get

$$\frac{d\widehat{X}}{dq} = \frac{U_Z^1(\cdot) - \widehat{X}[U_{ZZ}^1(\cdot)q - U_{XZ}^1(\cdot)]}{\partial^2 \widehat{EU} / \partial X^2}, \quad (\text{A.2})$$

$$\frac{d\widehat{X}}{dY_1} = \frac{U_{ZZ}^1(\cdot)q - U_{XZ}^1(\cdot)}{\partial^2 \widehat{EU} / \partial X^2}, \quad (\text{A.3})$$

where

$$\frac{\partial^2 \widehat{EU}}{\partial X^2} = U_{ZZ}^1 q [p + \tau^\xi] + U_{XX}^1 - U_{XZ}^1 (p + q) + \delta\beta\widehat{\pi}''(X)[U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)]. \quad (\text{A.4})$$

The second-order condition of the individual maximization problem requires that (A.4) is negative. Using the Slutsky equation, we can find the slope of the compensated demand, that I define as \widehat{X}^C :

$$\frac{d\widehat{X}^C}{dq} = \frac{d\widehat{X}}{dq} + \widehat{X} \frac{d\widehat{X}}{dY_1} = \frac{U_Z^1(Z_1, H^h, X)}{\partial^2 \widehat{EU} / \partial X^2}. \quad (\text{A.5})$$

Now, totally differentiate (A.1) with respect to X and I , taking into account the government budget constraint $\ell = \tau X$ and the health insurance premium condition (3). Setting the total differential equal to zero, we get

$$0 = \frac{\partial^2 \widehat{EU}}{\partial X^2} d\widehat{X} + \left\{ \delta\pi' U_Z^s(Z_2^s, H^s) + \frac{\pi(X)}{1+r} [qU_{ZZ}^1(\cdot) - U_{XZ}^1(\cdot)] + \frac{\partial [U_Z^1(\cdot)\tau^b]}{\partial I} \right\} dI. \quad (\text{A.6})$$

Multiplying (A.6) with $1/dI$ and using the definition of $\epsilon_{X,q}^C$ from Section 3 together with (A.5), we get

$$0 = \frac{U_Z^1(\cdot)}{\epsilon_{X,q}^C \widehat{X}} \frac{d\widehat{X}}{dI} + \left\{ \delta\pi' U_Z^s(Z_2^s, H^s) + \frac{\pi(X)}{1+r} [qU_{ZZ}^1(\cdot) - U_{XZ}^1(\cdot)] + \frac{\partial [U_Z^1(\cdot)\tau^b]}{\partial I} \right\}. \quad (\text{A.7})$$

Next, we use the definition of $\epsilon_{X,I}$ and rearrange (A.7) to get

$$\frac{\epsilon_{X,I}}{\epsilon_{X,q}^C} = - \left\{ \delta\pi' \frac{U_Z^s(Z_2^s, H^s)}{U_Z^1(\cdot)} + \frac{\pi(X)}{1+r} \frac{qU_{ZZ}^1(\cdot) - U_{XZ}^1(\cdot)}{U_Z^h(\cdot)} + \frac{1}{U_Z^1(\cdot)} \frac{\partial [U_Z^1(\cdot)\tau^b]}{\partial I} \right\}. \quad (\text{A.8})$$

Lastly, we use Equations (A.3) and (A.5) to derive

$$\frac{qU_{ZZ}^1(\cdot) - U_{XZ}^1(\cdot)}{U_Z^1(Z_1, H^h, X)} = \frac{\epsilon_{X,Y_1}}{\epsilon_{X,q}^C}. \quad (\text{A.9})$$

Together, (A.8) and (A.9) give Equation (13).

B Calibration

Figure B.1 presents the behavioral wedge estimated according to case (a) (blue), case (b) (orange), and case (c) (green) as a function of exogenous parameters.

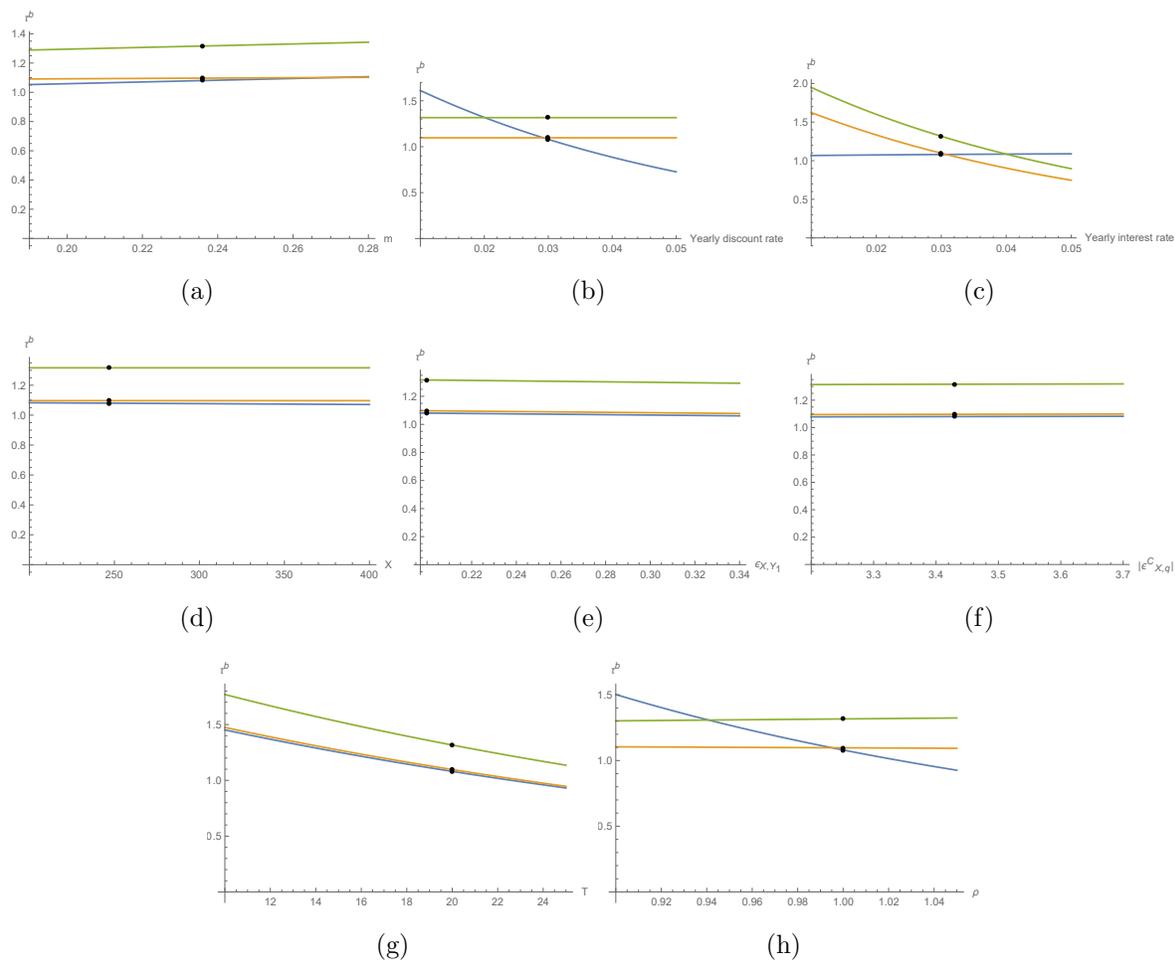


Figure B.1: The behavioral wedge τ^b as a function of the health costs m (panel (a)), insurance coverage b (panel (b)), yearly time discount and interest rates (panel (c)), yearly time discount rate δ (panel (d)), yearly interest rate r (panel (e)), SSB consumption X (panel (f)), time between periods T (panel (g)), and degree of consumption smoothing ρ (panel (h)). A dot indicates the benchmark estimate.

C Multiple Sin Goods

Here, I derive Equation (25). The first-order condition with respect to good X^i is:

$$\begin{aligned} \frac{\partial \widehat{EU}}{\partial X^i} &= -U_Z^1[Z_1, H^h, \mathbf{X}][p^i + \tau^i] + U_{X^i}^1(Z_1, H^h, \mathbf{X}) \\ &+ \delta \pi_{X^i}(\mathbf{X}) [U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)] + U_Z^1[Z_1, H^h, \mathbf{X}]\tau_i^b = 0, \end{aligned} \quad (\text{C.1})$$

where the behavioral wedge τ_i^b is defined as

$$\tau_i^b := \delta[\beta \widehat{\pi}_{X^i}(\mathbf{X}) - \pi_{X^i}(\mathbf{X})] \frac{[U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)]}{U_Z^1(Z_1, H^h, \mathbf{X})}. \quad (\text{C.2})$$

Next, we use the system of n first-order conditions to derive the slopes of compensated demand similarly to Appendix A. Use the following definitions:

$$a_{ij} := \frac{\partial^2 \widehat{EU}}{\partial X^i \partial X^j}, \quad (\text{C.3})$$

$$\mathbf{J} := \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{pmatrix}. \quad (\text{C.4})$$

Furthermore, we define as \mathbf{M}_{ij} the $(n-1) \times (n-1)$ matrix left after removing the i th row and j th column of matrix J . Then, following the same steps as in Appendix A (and using Cramer's rule), we derive the following income and compensated price effects:

$$\frac{d\widehat{X}^i}{dY_1} = \sum_{j=1}^n \frac{(-1)^{j+i} [q^j U_{ZZ}^1(\cdot) - U_{X^j Z}^1(\cdot)] |\mathbf{M}_{ji}|}{|\mathbf{J}|}, \quad (\text{C.5})$$

$$\frac{d\widehat{X}^{iC}}{dq^i} = \frac{U_Z^1(\cdot) |\mathbf{M}_{ii}|}{|\mathbf{J}|}, \quad (\text{C.6})$$

$$\frac{d\widehat{X}^{iC}}{dq^j} = \frac{(-1)^{j+i} U_Z^1(\cdot) |\mathbf{M}_{ji}|}{|\mathbf{J}|}. \quad (\text{C.7})$$

Next, we derive the comparative static effects of the indemnity I on the demands X^i for $i = 1, \dots, n$. Define

$$\Delta^i := \frac{\partial^2 \widehat{EU}}{\partial X^i \partial I} = \delta \pi_{X^i} U_Z^s(Z_2^s, H^s) + \frac{\pi}{1+r} [q^i U_{ZZ}^1(\cdot) - U_{X^i Z}^1(\cdot)] + \frac{\partial [U_Z^1(\cdot) \tau_i^b]}{\partial I}. \quad (\text{C.8})$$

Then, using again Cramer's rule, we derive the following results:

$$\frac{d\widehat{X}^i}{dI} = \sum_{j=1}^n \frac{(-1)^{j+i}(-\Delta^j)|\mathbf{M}_{ji}|}{|\mathbf{J}|}, \quad i = 1, \dots, n. \quad (\text{C.9})$$

Defining the semi-elasticities $\epsilon_{X^i, I}$ and ϵ_{X^i, q^j}^C analogously to Section 2 and using Equations (C.6), (C.7), and (C.9), we get

$$U_Z^1(\cdot)\epsilon_{X^i, I} = -\sum_{j=1}^n \epsilon_{X^i, q^j}^C \Delta^j, \quad i = 1, \dots, n. \quad (\text{C.10})$$

Thus, we have derived a system of n linear equations in Δ^j that we can solve for Δ^j . In matrix form, (C.10) can be represented as

$$\mathbf{S}\boldsymbol{\Delta} = -U_Z^1(\cdot)\boldsymbol{\epsilon}_{\mathbf{X}, \mathbf{I}}, \quad (\text{C.11})$$

where

$$\mathbf{S} := \begin{pmatrix} \epsilon_{X^1, q^1}^C & \cdots & \epsilon_{X^1, q^n}^C \\ \vdots & \ddots & \vdots \\ \epsilon_{X^n, q^1}^C & \cdots & \epsilon_{X^n, q^n}^C \end{pmatrix}, \quad (\text{C.12})$$

$\boldsymbol{\Delta} = (\Delta^1, \dots, \Delta^n)$ and $\boldsymbol{\epsilon}_{\mathbf{X}, \mathbf{I}} = (\epsilon_{X^1, I}, \dots, \epsilon_{X^n, I})$. Using Cramer's rule, we can solve (C.11) for Δ^i :

$$\Delta^i = \frac{1}{|\mathbf{S}|} \sum_{j=1}^n (-1)^{j+i} |\mathbf{S}_{ji}| (-U_Z^1(\cdot)) \epsilon_{X^j, I} = -E_1^i U_Z^1(\cdot), \quad (\text{C.13})$$

where E_1^i is defined in (26) and \mathbf{S}_{ji} is the matrix left after removing the j th row and i th column from \mathbf{S} .

Moreover, we can divide (C.5) by \widehat{X}^i from both sides, use the definitions of ϵ_{X^i, Y_1} and ϵ_{X^i, q^j}^C , as well as (C.7) to derive

$$\epsilon_{X^i, Y_1} = \sum_{j=1}^n \epsilon_{X^i, q^j}^C \frac{[q^j U_{ZZ}^1(\cdot) - U_{X^j Z}^1(\cdot)]}{U_Z^1(\cdot)}. \quad (\text{C.14})$$

Define

$$E_2^j := \frac{[q^j U_{ZZ}^1(\cdot) - U_{X^j Z}^1(\cdot)]}{U_Z^1(\cdot)}. \quad (\text{C.15})$$

Then, the n equations (C.14) for $i = 1, \dots, n$ can be written in matrix form as

$$\mathbf{S}\mathbf{E}_2 = \epsilon_{\mathbf{X}, \mathbf{Y}_1}, \quad (\text{C.16})$$

where $\mathbf{E}_2 = (E_2^1, \dots, E_2^n)$ and $\epsilon_{\mathbf{X}, \mathbf{Y}_1} = (\epsilon_{X^1, Y_1}, \dots, \epsilon_{X^n, Y_1})$. Using Cramer's rule, we can solve for E_2^i , which is given by

$$E_2^i = \frac{1}{|\mathbf{S}|} \sum_{j=1}^n (-1)^{j+i} |\mathbf{S}_{ji}| \epsilon_{X^j, Y_1}, \quad (\text{C.17})$$

Finally, putting (C.8), (C.13), (C.15), and (C.17) together, and taking (14) in the case of n sin goods into account, we get Equation (25).

C.1 Derivation of semi-elasticities for Section 5.1

For the calibration in Section 5.1, we need the compensated semi-elasticities ϵ_{X^i, q^j}^C for $i, j = d, r$. I have already listed in Table 1 the semi-elasticity $\epsilon_{X^r, q^r}^C = -3.43$ (from Allcott et al., 2019a). While Allcott et al. (2019a) also derive the uncompensated cross-price elasticities of X^d with respect to q^j for $j = r, d$, they do not report the price of diet soda, q^d that is required for the derivation of compensated elasticities from the uncompensated ones. Therefore, to derive the remaining semi-elasticities, I additionally use estimates from Zhen et al. (2014) and Harding and Lovenheim (2017), who also employ Nielsen Homescan panel data.

Denote an uncompensated price elasticity as ν_{X^i, q^j} . Allcott et al. (2019a) find $\nu_{X^d, q^d} = -0.953$, $\nu_{X^d, q^r} = 0.248$ (Table 4 in their paper). To derive a compensated elasticity from the uncompensated ones, I use the Slutsky equation

$$\frac{d\widehat{X}^i{}^C}{dq^j} = \frac{d\widehat{X}^i}{dq^j} + \widehat{X}^j \frac{d\widehat{X}^i}{dY_1}, \quad (\text{C.18})$$

where $\widehat{X}^i{}^C$ and \widehat{X}^i denote the compensated and uncompensated demand, respectively. Multiply both sides of (C.18) by q^j/\widehat{X}^i to get

$$\nu_{X^i, q^j}^C = \nu_{X^i, q^j} + \xi^j \nu_{X^i, Y_1}, \quad (\text{C.19})$$

where $\xi^j \equiv q^j X^j / Y_1$ is the expenditure share of good j and $\nu_{X^i, Y_1} \equiv (d\widehat{X}^i / dY_1)(Y_1 / \widehat{X}^i)$ is the income elasticity of good i . Allcott et al. (2019a) find $\nu_{X^d, Y_1} = 0.14$, $\nu_{X^r, Y_1} = 0.2$

and $\xi^r = 0.0026$ ¹⁹. However, [Allcott et al. \(2019a\)](#) do not report ξ^d . [Zhen et al. \(2014\)](#) and [Harding and Lovenheim \(2017\)](#) find expenditures on diet soda equal about 77% and 71% of regular soda spending, respectively.²⁰ Taking the average, we estimate $\xi^d = 0.74\xi^r \approx 0.002$. Using (C.19), we find the following compensated elasticities: $\nu_{X^d, q^d}^C = -0.9527$, $\nu_{X^d, q^r}^C = 0.2484$.

However, [Allcott et al. \(2019a\)](#) do not estimate ν_{X^r, q^d} . [Zhen et al. \(2014\)](#) and [Harding and Lovenheim \(2017\)](#) find $\nu_{X^r, q^d} = 0.004$ and $\nu_{X^r, q^d} = 0.201$, respectively. I again take the average and use (C.19) to derive $\nu_{X^r, q^d}^C = 0.103$.

Finally, to get the compensated semi-elasticities, we need to divide ν_{X^i, q^j}^C by q^j . While [Allcott et al. \(2019a\)](#) do not report q^d , [Zhen et al. \(2014\)](#) find identical prices for diet and regular soda²¹, while [Harding and Lovenheim \(2017\)](#) find diet soda to be 38% more expensive on average (see their Table 1). Taking the average of the estimates, I set $q^d = 1.19q^r = \$0.482$ per serving.

Together, the estimates of ν_{X^i, q^j}^C and q^j give the following compensated semi-elasticities:

$$\epsilon_{X^d, q^d}^C = -1.977, \tag{C.20}$$

$$\epsilon_{X^d, q^r}^C = 0.613, \tag{C.21}$$

$$\epsilon_{X^r, q^d}^C = 0.214. \tag{C.22}$$

Together with $\epsilon_{X^r, q^r}^C = -3.43$ from Table 1 and $\epsilon_{X^d, I} = 2.31 \times 10^{-4}$ from (29), we have all elasticities required for the calibration of (25) in the case of two sin goods.

¹⁹Table 2 in [Allcott et al. \(2019a\)](#) gives households' SSB purchases in liters and price per liter. Multiplying to get the SSB spending and dividing by household income, we get ξ^r .

²⁰[Zhen et al. \(2014\)](#) divide the sample in 7,936 low- and 19,704 high-income households. The expenditures on regular and diet soda are \$6.33 and \$3.55, respectively, per quarter for low-income households. High-income households spend on average \$5.53 and \$4.85 on regular and diet soda, respectively. I calculate the average expenditure shares for both groups together. [Harding and Lovenheim \(2017\)](#) report spending on diet and regular soda as proportion of food expenditures in Table 1.

²¹[Zhen et al. \(2014\)](#) find that low-income households spend \$6.33 on 333 ounces of regular soda per quarter and \$3.55 on 185 ounces of diet soda. Thus, the prices are $q^r = 6.33/333 = \$0.019$ per ounce and $q^d = 3.55/185 = \$0.019$ per ounce.

D Life expectancy

Here, I present the data for life expectancy from [DuGoff et al. \(2014\)](#) and number of chronic conditions from NHANES ([CDC, 2021](#)) in Table D.1.

Table D.1: Life Expectancy and Number of Chronic Conditions.

	Number of chronic conditions										
	0	1	2	3	4	5	6	7	8	9	10+
LE ^a :	22.6	22.2	21.7	20.1	17.9	15.4	12.8	10.3	8.4	6.9	5
% ^b :	23.4	29.3	25.8	14.2	5.3	1.6	0.34	0.03	–	–	–

^a Life expectancy (LE) at age 67 (Source: [DuGoff et al., 2014](#)).

^b Distribution of chronic conditions among adults aged at least 50 (Source: [CDC, 2021](#)).