CESifo WORKING PAPERS

9476
2021

December 2021

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
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CESifo *Working Paper No. 9476*

Evaluating Marginal Internalities: A New Approach

Abstract

This paper develops a new sufficient statistic approach for estimating the marginal internality from sin good consumption. It models a biased consumer who faces uncertain health harms and receives mandatory health insurance. I show that the marginal internality can be identified by observing how sin good demand reacts to changes in health insurance coverage. The method does not require to recover the true willingness to pay for the sin good or to elicit consumers' biases using surveys. I calibrate the model to sugary drinks consumption. My results are consistent with studies that use survey-based measures of biases.

JEL-Codes: D110, D620, H210, H310, I120, I130, I180.

Keywords: marginal internality, self-control, biased beliefs.

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December 6, 2021
I would like to thank Juho Alasalmi, Davide Dragone, Andreas Gerster, Dylan Moore, Daniel Reck, Marco Runkel, Renke Schmacker, Martin Siegel, and participants at the 2021 ZEW Public Finance Conference, the 13th Meeting of the German Health Economics Association (DGGÖ), 2021 CESifo Area Conference on Public Economics, the 77th Annual Congress of the International Institute of Public Finance (IIPF), and the 114th National Tax Association (NTA) Annual Conference on Taxation for helpful comments. The usual disclaimer applies.

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 (Allcott et al., 2019b). If a consumer fails to fully consider these costs, either because of incomplete 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 sufficient statistic method for estimating the marginal internality. As a starting point, I develop a two-period model under uncertainty, where sin good consumption in period one increases the probability of falling sick in period two. A consumer exhibits both present-bias and biased beliefs about the probability of illness. The government provides mandatory health insurance and taxes the sin good.

To identify the marginal internality, I first derive the sin good demand's insurance coverage elasticity. It is determined by the effects of coverage on (i) out-of-pocket costs in the sick state, (ii) the insurance premium, and (iii) the marginal internality. By estimating the part of the observed elasticity that can be attributed to (i) and (ii), I can isolate the third effect. Moreover, I show that the product of the third effect and the money-metric utility loss from sickness gives the money-metric marginal internality.

Most importantly, my approach does not require measuring present-bias, consumers' beliefs, and true willingness to pay for the sin good. Instead, the sufficient statistic formula contains the observed elasticities with respect to insurance coverage, income, and prices, the money-metric utility loss in the sick state, and several other parameters. Furthermore, I derive three different methods of identifying the marginal internality that differ in the structural assumptions necessary to estimate them.

Another method for measuring the marginal internality is the "counterfactual normative consumer" approach. Allcott et al. (2019a) use it to quantify the behavioral bias in SSBs' consumption. First, they observe consumer behavior from homescan panel data and use surveys to estimate consumers' nutrition knowledge and self-control. Then, they create nutritional and self-control bias indexes 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 money-metric marginal internality is the compensated price increase that leads consumers to choose this hypothetical consumption level.

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 estimate the same bias using different data.

Furthermore, my model differs from the theoretical literature on sin good consumption, which usually 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. 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.[1] 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 addresses the ex-ante moral hazard of health insurance, which constitutes an externality. Moreover, the model predicts an optimal health insurance coverage equal to 84% of medical costs, which is close to the empirically observed coverage of about 85% (Finkelstein et al., 2013).

Furthermore, Section 5 extends the model. First, I take into account the crowding out of private insurance by public coverage. This extension does not affect the results. Second, I consider multiple sin goods. In this case, the health insurance elasticities of

[1]One ounce is approximately equal to 30 ml.

all sin goods determine the marginal internality of each good. 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 slightly. Third, I allow life expectancy to decrease in the sick state of nature. This extension also has a small (but positive) effect on the results.

This paper is related to the literature that quantifies behavioral biases. A standard approach is to compare consumers' observed (biased) willingness to pay to their true willingness to pay (Chetty, 2015). This is the approach of Allcott et al. (2019a). Also, Chetty et al. (2009) and Taubinsky and Rees-Jones (2017) apply this method to tax salience, and Allcott and Taubinsky (2015) apply it to biases in the valuation of energy efficiency. My method differs because it does not require a derivation of the true willingness to pay.

Moreover, other approaches can be used to measure self-control. In the case of sin goods, one could measure the individual health costs and use an estimate of present-bias from another domain to quantify the internality (Allcott et al., 2019b). One deficiency of this approach is that self-control may differ across domains (Attema et al., 2018; Allcott et al., 2019b).[2] However, sin good consumers likely suffer from both self-control problems and incomplete information. Hence, my method is better suited to estimate the marginal internality for sin goods than approaches that focus only on self-control.

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 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.

[2]Another way to measure self-control is comparing choices for immediate consumption versus consumption choices made in advance (see, e.g., Read and van Leeuwen, 1998). However, this method cannot quantify the bias in monetary units (Allcott et al., 2019b).

Section 3 derives the estimation method. Section 4 describes the calibration 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 one with an exogenous income Y_1. In the same period, she consumes a numèraire 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 as a lump-sum transfer $\ell = \tau X$. The individual also finances mandatory health insurance at a premium P. The pre-tax price of X is exogenous and equal to p. Thus, the period one budget constraint is

$$Y_1 + \ell = Z_1 + (p + \tau)X + P. \tag{1}$$

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.[3] Moreover, the individual purchases the numèraire good in quantity Z_2^i for $i = s, h$. In the case of illness, the individual faces exogenous treatment costs M, and insurance covers an amount I of these costs.[4] Thus, the second period budget constraint is

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

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

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

[3]By assumption, in period one the individual is healthy and has a health level H^h.

[4]In 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.

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

The agent derives utility from sin good consumption, numèraire 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 $U_Z^i > 0 > U_{ZZ}^i, U_H^i > 0$.[5] 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). Thus, the agent's expected utility EU is given by

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

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 biased beliefs regarding the probability $\pi(X)$. 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 incomplete nutrition knowledge.

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

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

where $\widehat{\pi}(X)$ and $1 - \widehat{\pi}(X)$ are the perceived probabilities of being sick and healthy, and $\beta \in (0, 1]$ represents present-bias.[6] Whether $\widehat{\pi}(X) \gtreqless \pi(X)$ is empirically unclear. Smokers overestimate lung cancer risk (Viscusi, 1990) but underestimate lung cancer mortality risk (Ziebarth, 2018). Also, individuals overestimate their own heart disease and diabetes risks (Belot et al., 2020).[7]

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, 2006; DellaVigna

[5]Capital letter subscripts denote partial derivatives.

[6]The modelling approach to biased beliefs follows Spinnewijn (2015) who develops and applies such a model to unemployment insurance. My model allows both for what Spinnewijn defines as *baseline bias* ($\widehat{\pi}(X) \neq \pi(X)$), and *control bias* ($\widehat{\pi}'(X) \neq \pi'(X)$).

[7]Carrillo and Mariotti (2000) show that overestimation of risk can be strategically used by present-biased individuals as a commitment device.

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

$$\tau^{\xi} := \frac{\partial P}{\partial X} = \frac{\pi'(X)I}{1+r}. \tag{6}$$

Then, the socially optimal consumption level, X^*, is determined by

$$\begin{aligned}\frac{\partial EU^{SP}}{\partial X} &= -U_Z^1(Z_1, H^h, X^*)[p + \tau^{\xi}] + U_X^1(Z_1, H^h, X^*) \\ &\quad + \delta\pi'(X^*)\left[U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)\right] = 0,\end{aligned} \tag{7}$$

where the superscript ^{SP} indicates the social planner's choice. According to (7), X^* is determined by four terms. First, an increase in sin good demand lowers the period one numèraire 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

$$\frac{\partial \widehat{EU}}{\partial X} = \left.\frac{\partial EU^{SP}}{\partial X}\right|_{X=\widehat{X}} + U_Z^1(Z_1, H^h, \widehat{X}) \cdot \left[-\tau + \tau^{\xi} + \tau^b\right] = 0, \tag{8}$$

where

$$\tau^b := \delta[\beta\widehat{\pi}'(X) - \pi'(X)]\frac{[U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)]}{U_Z^1(Z_1, H^h, X)}. \tag{9}$$

There are three differences between (8) and (7). First, the individual considers the government's transfer to be exogenous and, thus, perceives the sin good price to be $p+\tau$. Hence, the tax rate τ emerges with a negative sign in (8). 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 (8). Third, the individual misperceives the marginal probability of illness. This creates an internality. The term τ^{b} denotes the money-metric marginal internality. 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 estimating τ^{b}, it is helpful to first derive the optimal tax τ^{*} and insurance coverage I^{*}. The social planner maximizes the expected utility EU, taking into account the consumption's reaction to policy changes, i.e., $\widehat{X}(\tau, I)$, determined by (8). The first-order conditions are (see Appendix A):

$$\tau^{*} = \tau^{b} + \tau^{\xi}, \tag{10}$$

$$U_{Z}^{1}(Z_1, H^{h}, X) = \delta(1+r)U_{Z}^{s}(Z_2^{s}, H^{s}). \tag{11}$$

According to (10), a tax rate equal to the sum of the Pigouvian and behavioral wedges is optimal. This result is well-known (see, e.g. Allcott et al., 2019a; Farhi and Gabaix, 2020).[8] Moreover, I^{*} optimally redistributes risk between the (healthy) first period and the sick state in period two.

3 Estimating the marginal internality

According to (9), health insurance affects τ^{b}. A higher coverage I raises consumption Z_2^{s} and thus lowers the numerator of (9). Hence, the marginal internality, measured in utility

[8] If there are heterogeneous 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).

units, $U_Z^1(\cdot)\tau^b$, is decreasing in the insurance coverage.

To estimate τ^b, I first totally differentiate (8) with respect to sin good demand X and the coverage I. Define $q \equiv p + \tau$ as the sin good's after-tax price. The total differential can be expressed as (see Appendix A.1):

$$\epsilon_{X,I} = -\epsilon_{X,q}^{C}\Bigg\{ \underbrace{\delta\pi'(X)\frac{U_Z^s(\cdot)}{U_Z^1(\cdot)}}_{\text{out-of-pocket costs}\downarrow} + \underbrace{\frac{\pi(X)}{1+r}\frac{\epsilon_{X,Y_1}}{\epsilon_{X,q}^{C}}}_{\text{insurance premium}\uparrow} + \underbrace{\frac{1}{U_Z^1(\cdot)}\frac{\partial\left[U_Z^1(\cdot)\tau^b\right]}{\partial I}}_{\text{marginal internality}\downarrow} \Bigg\}, \tag{12}$$

where

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

Equation (12) determines the impact of insurance coverage on $\widehat{X}$, given by $\epsilon_{X,I}$, as a function of three effects.[9] First, higher insurance coverage lowers the out-of-pocket costs in the sick state, thus reducing the perceived health costs and increasing sin good demand.[10] Second, it raises the insurance premium, which lowers the disposable income in period one. This effect reduces $\epsilon_{X,I}$ if X is a normal good, i.e., if its income elasticity is positive. Third, higher insurance coverage reduces the marginal internality, which lowers sin good demand. This effect is given by

$$\frac{1}{U_Z^1(\cdot)}\frac{\partial\left[U_Z^1(\cdot)\tau^b\right]}{\partial I} = \delta[\beta\widehat{\pi}' - \pi']\frac{U_Z^s(\cdot)}{U_Z^1(\cdot)} = \frac{U_Z^s(\cdot)}{U^s(\cdot) - U^h(\cdot)}\tau^b. \tag{13}$$

Because the right-hand side of (13) is proportional to the behavioral wedge, τ^b, we can solve (12) for τ^b and derive the following expression:

$$\tau^b = \underbrace{-\frac{U^s(\cdot) - U^h(\cdot)}{U_Z^s(\cdot)}}_{\substack{\text{(current) monetary value of}\\ \text{utility loss due to sickness}}} \left[\frac{\epsilon_{X,I}}{\epsilon_{X,q}^{C}} + \underbrace{\frac{\delta\pi'(X)U_Z^s(\cdot)}{U_Z^1(\cdot)}}_{\text{out-of-pocket costs}\downarrow} + \underbrace{\frac{\pi(X)}{1+r}\frac{\epsilon_{X,Y_1}}{\epsilon_{X,q}^{C}}}_{\text{insurance premium}\uparrow}\right]. \tag{14}$$

[9] As a fourth effect, the expansion of public insurance coverage may crowd out private insurance (Cutler and Gruber, 1996). I consider this effect explicitly in an extension in Section 5.

[10] This term is multiplied by $-\epsilon_{X,q}^{C}$, which is positive according to (A.7).

If the individual is rational, then $\epsilon_{X,I}$ would be completely determined by the effects of I on out-of-pocket costs and insurance premium, and the terms in brackets in (14) would sum up to zero. However, if the individual maximizes $\widehat{EU}$, then the terms in brackets sum up to the negative of the change in the marginal internality. Because this effect is proportional to τ^b as defined in (13), we can multiply it by the money-metric utility loss in the sick state and thus estimate the behavioral wedge.

Importantly, the right-hand side of (14) does not explicitly contain the degree of present-bias β, the perceived probability $\widehat{\pi}(X)$, the marginal utility $U_X(\cdot)$ or their derivatives. However, it contains the marginal utility of income in period one, $U_Z^1(\cdot)$, which may depend on the sin good X. Thus, to estimate (14), one needs to make assumptions about the utility function. I consider three possible approaches.

Suppose first that period one utility takes the form $U^1(Z_1, H^h, X) = U^h(Z_1, H^h) + V(X)$, 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 (14).

Second, we may wish to estimate (14) without making any assumptions about first period utility. This is possible, if one assumes that health insurance is optimal. To see this, insert (11) in (14) to get

$$\tau^b(I = I^*) = -\frac{U^s(\cdot) - U^h(\cdot)}{U_Z^s(\cdot)} \left[\frac{\epsilon_{X,I}}{\epsilon_{X,q}^C} + \frac{\pi'(X)}{1+r} + \frac{\pi(X)}{1+r} \frac{\epsilon_{X,Y_1}}{\epsilon_{X,q}^C} \right]. \tag{15}$$

To estimate (15), one still needs to make structural assumptions about second-period utility. There are two possible approaches to calibrating the terms in front of brackets in (15). First, one may assume a state-dependent utility function of the form considered by Finkelstein et al. (2013) who empirically estimate negative 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 De Nardi et al. (2010) who do not find evidence for state dependence. In this case, $U^i(Z, H) = U(Z, H)$ for $i = s, h$. A first-order Taylor approximation gives

$$U(Z_2^h, H^h) \approx U(Z_2^s, H^s) + U_Z(Z_2^s, H^s) \cdot (Z_2^h - Z_2^s) + U_H(Z_2^s, H^s) \cdot (H^h - H^s). \tag{16}$$

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, (15) and (16) together give

$$\tau^b(I = I^*) \approx \big[M - I + \text{MRS} \cdot (H^h - H^s)\big] \left[\frac{\epsilon_{X,I}}{\epsilon^C_{X,q}} + \frac{\pi'(X)}{1+r} + \frac{\pi(X)}{1+r}\frac{\epsilon_{X,Y_1}}{\epsilon^C_{X,q}}\right]. \tag{17}$$

Equation (17) approximates the money-metric utility loss in the sick state as the sum of out-of-pocket costs and the health loss's monetary value. I summarize the results in the following proposition.

Proposition 1. *The money-metric marginal internality τ^b can be determined using* (14) *without information on present-bias β and beliefs $\widehat{\pi}(X)$.*

(i) If first-period utility is of the form $U^1(Z_1, H^h, X) = U^h(Z_1, H^h) + V(X)$, then (14) *can be estimated without additional assumptions about $V(X)$.*

(ii) If health insurance is optimal, then τ^b can be estimated using (15) *and without any assumptions regarding first-period utility $U^1(Z_1, H^h, X)$.*

(iii) If health insurance is optimal and second-period utility is state-independent, then τ^b can be approximated using (17).

Hence, all three approaches considered above do not require data on the true preferences for the sin good. Moreover, all elasticities that appear in (14), (15), and (17) are the observed elasticities and not the counterfactual elasticities of a hypothetical normative consumer. Hence, this approach can be applied without knowing the true willingness to pay for the sin good.

In the next section, I calibrate the model to SSB consumption, and estimate τ^b for all three cases from Proposition 1. Allcott et al. (2019a) also apply the counterfactual normative consumer approach to sugary drinks. Hence, their estimates can serve as a benchmark for evaluating this paper's results.

4 Calibration

Consider Proposition 1(i). The first step is to specify the state-dependent utility function. Following Finkelstein et al. (2013, 2019), I define U^i as

$$U^i(Z^i, H^i) = (1 + \varphi \mathbb{1}_{i=s}) \frac{Z^{i\,1-\gamma}}{1-\gamma} + \phi H^i, \tag{18}$$

where $\gamma > 0$ is the degree of risk aversion, $\mathbb{1}_{i=s}$ is an indicator variable that equals one in the sick state and zero otherwise. Thus, illness lowers the marginal utility of consumption (negative state dependence) if $\varphi < 0$. The case $\varphi > (=)0$ denotes positive (zero) state dependence. Moreover, health has a constant marginal utility given by $\phi > 0$.[11]

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 correspond to the average duration of SSB consumption prior to the onset of sickness. To the best of my knowledge, no studies 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. Using the same age cutoff value, 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 from 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 $Y_1 = \$68,000/2.48 \approx \$27,400$

[11] Finkelstein et al. (2013) define H^i as a function of health expenditures. Because the health costs are fixed in my model, I do not need to specify the health function. Finkelstein et al. (2019) consider a special case of the utility function in (18) where $\varphi = 0$.

(all calibration parameters are reported in Table 1).

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

$$Y_1 + \ell = Z_1 + (p + \tau)X + P + (\widetilde{T} + \sigma)Y_1, \tag{19}$$

where $\widetilde{T}$ denotes other tax and social security contributions as a proportion of income, and σ is the savings rate. Because both $\widetilde{T}$ 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, 2021). According to this data, during 2006–2016, disposable income minus savings is 82.97% of gross income. Therefore, I set $\widetilde{T}$ and σ such that the proportion of income spent on consumption equals 83%; that is, $(Z_1 + pX)/Y_1 = [1 - P/Y_1 - \widetilde{T} - \sigma] = 0.83$. 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 the number of (12-ounce) servings per year, and convert the liter price to $q = \$0.405$ per serving. Because there is no federal SSB tax in the U.S., I also set $p = q$.

Moreover, the average respondent of Allcott et al. (2019a) consumes 87.70 liters of SSBs per year, which equals 247.12 servings. 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 equals ≈ 400 servings per year. Hence, NHANES respondents report much higher consumption. As a central value, I set consumption at the average of both estimates: $X = 325$. 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 $\rho > 0$ 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. Because total expenditures fall relatively fast after the age of 50, they are around 20% lower at age 75 compared to 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, they estimate that the ratio of (food) consumption to expenditure increases 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 consumption declines less than expenditures at old ages. Because in my model period one (two) represents age before (after) 50, I choose $\rho = 1$ as a central value.

Table 1: Benchmark parameter values.

Parameter	Benchmark	Range
A. Preference Parameters		
γ:	3	[2,4]
φ:	-0.1	[-0.4,0.2]
ϕ:	$6.38 \cdot 10^{-9}$	$[4.25 \cdot 10^{-9}, 1.28 \cdot 10^{-8}]$
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		
q (\$/12-ounce serving):	0.405	–
X (servings/year):	325	[200,400]
$\epsilon^C_{X,q}$:	-3.43	[-3.7,-3.2]
$\epsilon_{X,I}$:	0	$[-6.7 \cdot 10^{-5}, 3.3 \cdot 10^{-5}]$
$\epsilon_{X,Y_1} Y_1$:	0.2	[0.197,0.34]
C. Health, Insurance and Costs		
$\pi(X)$:	0.5	$[0.4, 0.6]$
$\pi'(X)$:	$4.18 \cdot 10^{-5}$	$[2.09 \cdot 10^{-5}, 6.27 \cdot 10^{-5}]$
m:	0.236	$[0.18, 0.29]$
b:	0.851	$[0.79, 1]$
$1 + r$:	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		
Y_1:	\$27,400	–
ρ:	1	[0.9,1.05]
$\widetilde{T} + \sigma$:	0.125	–

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). De 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) lowers marginal utility by $10\% - 25\%$. In a calibration, 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 ($\varphi > 0$). De 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).[12]

To estimate the marginal utility from health, ϕ, I follow Finkelstein et al. (2019). Their approach consists of three steps. 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. Third, to estimate the MRS for a given subpopulation, one needs to adjust the representative MRS for differences in the marginal utility of consumption, according to MRS(Y) =MRS$(\overline{Y}) \cdot (Y/\overline{Y})^{\gamma}$, where Y is the income of the subpopulation and $\overline{Y}$ is the average income. Finkelstein et al. (2019) use VSLY = MRS $(\overline{Y})$ = \$100,000 as a consensus value for the U.S. population, which I also apply here.[13]

Because SSB consumption is higher among the poor (Allcott et al., 2019a), we also need to adjust the MRS for the subpopulation 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 status of

[12]Using European data, Kools and Knoef (2019) also find evidence for positive state dependence.

[13]Finkelstein 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.

the U.S. population. It also provides dietary data, which can be used to divide the survey participants into SSB consumers and non-consumers.[14] While NHANES reports income in bins, it gives the exact ratio of family income to the poverty threshold up to a value of 5.00 (values above 5 are coded as 5.00 due to disclosure concerns). I estimate an average family income ratio equal to 2.69 and 2.954 for adult (age ≥ 18) SSB consumers and the general adult population, respectively. Thus, the average income of SSB consumers is $2.69/2.954 \approx 91\%$ 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 (18) and (2), we get $\phi = \text{MRS} \cdot Y_2^{-\gamma}$. Inserting the values of all variables on the right-hand side gives $\phi \approx 6.38 \cdot 10^{-9}$.

However, VSLY has a large range of estimates (Viscusi, 2018). The results depend on the method of elicitation (Hirth et al., 2000) and 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).[15] Hence, Lindhjem et al.'s (2011) VSLY estimate 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 ($\approx 0.91^3 \cdot 200,000$).[16]

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

[15]To derive VSLY=\$200,000, I first convert the VSL in 2016 dollars, which gives VSL$\approx$ 4,76 million. Then, I follow Viscusi (2014) to estimate VSLY for a given VSL according to VSLY $= r\text{VSL}/(1-(1+r)^{-L})$ where r is the interest rate and L is life expectancy. Using the standard values $r = 0.03$ and $L = 40$ (Hirth et al., 2000), I get VSLY$\approx \$200,000$.

[16]Studies using occupational data find even larger VSL estimates of about \$8.1 million (Viscusi, 2018). However, Lindhjem et al. (2011) show that VSL is context-specific and about half as large in the health domain compared to other domains. Also, stated-preference elicitation of the willingness to pay for QALY usually finds estimates close to the lower bound of \$50,000 (King et al., 2005).

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 (as in Finkelstein et al., 2013). Second, I apply the mapping of self-assessed health to QALYs from Finkelstein et al. (2019) to the answers to the self-assessed health question: "Would you say your health in general is excellent, very good, good, fair, or poor?".

In measuring chronic diseases, I focus on the following seven conditions: arthritis, hypertension, cancer, chronic obstructive pulmonary disease (COPD), coronary heart disease, diabetes, and stroke. These are the same seven diseases 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 are linearized standard errors that take into account the complex cluster design and sampling weights of NHANES (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($= H^h$).

Both the annual discount and interest rates are set at a standard value of 3%. Thus, $1 + r = (1 + 0.03)^T, \delta = 1/(1 + 0.03)^T$. The sensitivity analysis varies them over the interval $[0.01, 0.05]$ separately.

Next, I express the medical expenditures as a proportion m of the non-medical second period spending, $M = mZ_2^s$, and the coverage 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.

Table 2: 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)	30.0 (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

C. QALY[a]	
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: NHANES 1999–2018 (CDC, 2021).

[b] Source: Mapping from self-assessed health to QALY from Finkelstein et al. (2019).

(Marginal) Probability of Sickness. To estimate the marginal probability $\pi'(X)$, I use the fact that it partially determines the marginal externality τ^{ξ} (see Equation (6)). 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 discounted marginal medical costs of one serving are given by

$$\frac{\partial}{\partial X}\frac{\pi(X)M}{1+r} = \frac{\pi'(X)M}{1+r}.$$

Using $M = mZ_2^s, I = bM$, Equation (2), and $Y_2 = \rho(Z_1 + pX)$, we get

$$\frac{\partial}{\partial X}\frac{\pi(X)M}{1+r} = \frac{\pi'(X)m\rho(Z_1 + pX)}{(1+r)[1+m(1-b)]}. \tag{20}$$

All parameters in (20) except for $\pi'(X)$ are known. Similarly to Allcott et al. (2019a), I use Wang et al.'s (2012) estimate of a marginal cost of one cent per ounce in the U.S.

Because one serving contains 12 ounces, I equate the right-hand side of (20) to \$0.12 and solve for $\pi'(X)$. The resulting estimate is $\pi'(X) = 4.18 \cdot 10^{-5}$.

However, there is uncertainty in the above estimate because its value depends on all other parameters in (20). To consider this uncertainty in the sensitivity analysis, I vary $\pi'(X)$ by one-half in each direction, i.e., I set $\pi'(X) \in [2.09 \cdot 10^{-5}, 6.27 \cdot 10^{-5}]$.

The probability of sickness $\pi(X)$ can, in principle, be evaluated as the share of individuals with at least two chronic conditions among the SSB consumers in the NHANES dataset. Using the same data as in Table 2, this proportion is 42.5% among the SSB consumers aged at least 50 (not reported in Table 2). This estimate is less than the 46.3% classified as sick among all individuals in this age category (see Table 2). The likely reason is that sickness may induce SSB consumers to stop consuming. Thus, 42.5% likely underestimates $\pi(X)$. The true probability should also be greater than the average from Table 2 because of the positive marginal probability $\pi'(X)$. Hence, I follow Finkelstein et al. (2013) and set $\pi(X) = 0.5$ as a central estimate. Because of the uncertainty in $\pi(X)$'s value, I consider the range $\pi(X) \in [0.4, 0.6]$ in the sensitivity analysis. This variation affects the results only minimally.[17]

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 (12), $\epsilon^C_{X,q}$ denotes the semi-elasticity and thus equals $\epsilon^C_{X,q} = -1.39/q = -1.39/0.405 \approx -3.43$. 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 soda. 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) 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.

[17] Together, the parameter values give a health insurance contribution equal to approximately 4.5% of income, i.e., $P \approx 0.045 Y_1$. Hence, the sum of tax payments and savings is $\widetilde{T} + \sigma \approx 1 - 0.83 - 0.045 = 0.125$.

However, Cotti et al. (2019) find that the reform reduced smoking, while He et al. (2020) find a positive effect on the purchases of diet soda. Therefore, the null effects are likely not driven by a lack of salience. Therefore, I set $\epsilon_{X,I} = 0$ as a benchmark estimate and consider other values in the sensitivity analysis.[18]

4.1 Results

Row (1) in Table 3 reports the results from Proposition 1(i), where first-period utility is additively separable. The behavioral wedge τ^b, estimated using (14), 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/ounce. Second, I insert τ^b in (9) to derive the effectively perceived marginal probability $\beta\widehat{\pi}'(X)$. It equals only 0.026 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, $\beta\widehat{\pi}'(X)$ increases in the extensions in the next section. The marginal externality is $\tau^\xi = 0.851$ cents/ounce (the same as in Allcott et al. (2019a)).

Moreover, I derive the optimal tax τ^* and insurance coverage b^*, using (10) and (11). Even though Equation (11) determines I^*, we can solve it for $b^* = I^*/M$ because of the exogeneity of the medical costs, M. To derive τ^*, I assume that $\beta\widehat{\pi}'(X)/\pi'(X)$ is constant. Thus, varying the policy parameters affects τ^b. However, these effects are small. The optimal tax is $\tau^* = 1.94$ cents/ounce, while the optimal insurance coverage $b^* = 0.84$ is very close to the observed value $b = 0.851$ (Finkelstein et al., 2013).

Table 3: Results from the benchmark calibration.

	τ^{b} [a]	$\frac{\beta\widehat{\pi}'(X)}{\pi'(X)}$	τ^{ξ} [a]	τ^{*} [a]	b^*
(1) Proposition 1(i)	1.08	0.026	0.851	1.94	0.84
(2) Proposition 1(ii)	1.1	0.025	0.851	1.951	–
(3) Proposition 1(iii)	1.32	0.025	0.851	2.171	–

[a] Expressed in cents per ounce.

[18] Public insurance coverage may crowd out private insurance. Both Cotti et al. (2019) and He et al. (2020) observe the change in soda demand after such crowding out may have taken place. As I show in an extension in Section 5, this is the correct elasticity to be used in the presence of crowding out.

Row (2) in Table 3 presents the estimate of τ^b according to (15), i.e., under the assumption that the observed value of b is optimal (Proposition 1(ii)). Here, first period utility is not specified. Hence, it is not possible to determine the optimal level of health insurance. The behavioral wedge increases slightly to $\tau^b = 1.1$. The remaining results are almost identical to case (i).[19]

The last row of Table 3 considers Proposition 1(iii), where τ^b is approximated by (17). Here, no assumption about utility is made apart from it being state-independent. In this case, the estimated behavioral wedge is larger and equal to 1.32 cents per ounce.

4.2 Sensitivity Analysis

Figure B.1 in Appendix B reports the first set of sensitivity analyses. The blue, orange, and green curves in Figure B.1 correspond to τ^b estimated according to cases (i), (ii), and (iii) from Proposition 1, respectively. Panels (a) and (b) show the effects of varying $\pi(X)$ and $\pi'(X)$, respectively. A change in $\pi(X)$ only marginally affects the estimated behavioral bias, while the marginal probability has a more pronounced effect. In fact, τ^b varies almost proportionately with $\pi'(X)$. Increasing $\pi'(X)$ by one-half raises the estimated τ^b by about one-half, and vice versa.

Next, I vary the monetary value of QALYs (MRS), and thus the marginal utility from health, ϕ. Higher MRS raises the utility loss from sickness. Hence, τ^b is increasing in MRS (panel (c) in Figure B.1). In the case MRS=\$150,000, the estimated marginal internality lies between 2.22 and 2.49 cents per ounce.

Panel (d) varies the state dependence parameter φ.[20] In case (i), the effect on τ^b is insignificant. Higher φ lowers the utility loss of sickness and also strengthens the effect of out-of-pocket costs on sin good demand (second term in brackets in (14)). These effects largely cancel out. Because the second effect is missing in case (ii), τ^b is declining in φ. In case (iii), φ has a zero effect by assumption.

[19] In rows (2) and (3) of Table 3, period one utility is unspecified. Hence, it is not possible to derive the effects of changes in τ and b on τ^b. Thus, τ^* is derived by summing τ^b and τ^ξ.

[20] Following 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.

Next, I vary b from 0.79 to 1 in panel (e). 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, $b = 0.79$ holds for the uninsured and is the lowest bound for coverage. The effect of b is minimal. Thus, the assumption in cases (*ii*) and (*iii*) of optimal health insurance seems not to affect the numerical results.

Next, I consider different values for the semi-elasticity $\epsilon_{X,I}$ (panel (f)). While both Cotti et al. (2019) and He et al. (2020) find statistically insignificant changes in demand following the ACA Medicaid expansion, both papers report negative point estimates. He et al. (2020) find an insignificant reduction in SSB demand of 6.135 ounces per household per month, which amounts to a 3% decline (relative to pre-Medicaid expansion demand of 200.387 ounces). Cotti et al. (2019) report an insignificant reduction in the monthly household carbonated beverages purchases of 16.215 ounces. This is a reduction of 4.28% relative to average purchases of 378.877 ounces per month (Cotti et al. (2019) do not differentiate between regular and diet soda).

The semi-elasticity $\epsilon_{X,I}$ is defined as $\epsilon_{X,I} = (dX/X)(1/dI)$. The first term, dX/X, is the relative change in demand. The term dI is the change in insurance coverage. Sommers et al. (2017) find that the ACA lowered the annual out-of-pocket costs of previously uninsured households by \$337. Because this estimate is average over healthy and sick individuals, in the model, it amounts to the change in expected coverage $d\pi I = \pi dI =$ \$337. Setting $dI = 337/\pi$, using $\pi = 0.5$ from Table 1 and letting dX/X vary from -5% (less than the lowest point estimate) to 2.5%, we get $\epsilon_{X,I} \in [-7.4 \cdot 10^{-5}, 3.7 \cdot 10^{-5}]$. Panel (f) from Figure B.1 shows the effect of varying $\epsilon_{X,I}$ in this range. At the lowest end (5% reduction in demand), the behavioral wedge is 2.12-2.57 cents/ounce. Thus, higher τ^b is required to explain a lower insurance elasticity.

Figure B.2 in Appendix B presents the impact of changes in other parameter values. Panels (a), (b), and (c) show that τ^b is largely unaffected by changes in the medical expenditures ratio m, risk aversion γ, and SSB consumption X. Panels (d), (e), and (f) vary the yearly discount and interest rates, and time between periods, respectively. Higher discounting (and discounting over more years) lowers the marginal internality slightly. Panels (g) and (h) vary the elasticities ϵ_{X,Y_1} and $\epsilon^C_{X,q}$ (according to the range of estimates in Allcott et al. (2019a)). Neither elasticity affects τ^b. Lastly, panel (i) shows that the degree of consumption smoothing ρ also has a small impact on τ^b.

5 Extensions

5.1 Private Insurance

Here, I consider explicitly the possibility that the individual also has private health insurance, which may be crowded out by public coverage. Suppose the individual purchases private coverage I_{pr} at a premium P_{pr} that is determined by a zero-profit condition $P_{pr} = \pi(X)I_{pr}/(1+r)$ on a competitive insurance market. As in Chetty and Saez (2010), private insurance is not chosen optimally to maximize the true expected utility EU. While private insurance demand is a discrete choice, I again follow Chetty and Saez (2010) and define it as the continuous function $I_{pr}(I)$.

Define the crowding out of private by public coverage as $\eta \equiv I'_{pr}(I) \in (-1, 0]$. The corner case of no crowding out is considered in the main model. The second corner case of perfect crowding out ($\eta = -1$) is excluded because it is empirically implausible. Cutler and Gruber (1996) estimate $\eta = -0.5$.

To solve the model, define the total insurance coverage as $\widetilde{I}(I) = I + I_{pr}(I)$. Next, substitute $\widetilde{I}(I)$ for I in Equations (2) and (3), such that (3) gives the overall insurance expenditures. Taking into account $\widetilde{I}' = 1+\eta > 0$, it is straightforward to solve the model analogously to Sections 2 and 3. The optimal policies from Equations (10)-(11) remain unchanged (with the difference that now (11) implicitly determines overall insurance $\widetilde{I}$). Equations (14), (15), and (17) that form Proposition 1 also remain unchanged with one main difference. The elasticity $\epsilon_{X,I}$ is replaced by the elasticity $\epsilon_{X,\widetilde{I}} = \epsilon_{X,I}/(1+\eta)$. That is, in the presence of crowding out, one needs to consider the observed elasticity after (possible) crowding out has taken place. This is the elasticity that Cotti et al. (2019) and He et al. (2020) observe and is used in the calibration in Section 4. Moreover, here I is replaced by $\widetilde{I}(I)$ in the individual budget constraints and in Equation (17). However, insurance coverage is already calibrated to be approximately 85% of medical costs ($b = 0.851$), which holds for the representative insured individual in the U.S. (Allcott et al., 2019a). Hence, crowding out of private insurance does not affect the calibration results.

5.2 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 $\mathbf{X} = (X^1, \ldots, X^n)$. The corresponding price vector is $\mathbf{q} = (q^1, \ldots, q^n)$, where $q^i = p^i + \tau^i$ for $i = 1, \ldots, n$. The first period budget constraint becomes

$$Y_1 + \ell = Z_1 + \mathbf{q}'\mathbf{X} + P, \tag{21}$$

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

$$EU = U^1(Z_1, H^h, \mathbf{X}) + \delta \left\{ \pi(\mathbf{X}) U^s(Z_2^s, H^s) + [1 - \pi(\mathbf{X})] U^h(Z_2^h, H^h) \right\}. \tag{22}$$

The perceived utility $\widehat{EU}$ is defined analogously. The individual maximizes her perceived expected utility over X^i for $i = 1, \ldots, n$. Denoting the respective marginal internalities as τ_i^b, Appendix C derives the following expression:

$$\tau_i^b = -\frac{U^s(\cdot) - U^h(\cdot)}{U_Z^s(\cdot)} \left[E_1^i + \frac{\delta \pi_{X^i} U_Z^s(\cdot)}{U_Z^1(\cdot)} + \frac{\pi(\mathbf{X})}{1+r} E_2^i \right], \tag{23}$$

where E_1^i and E_2^i are defined in (C.11) and (C.15) in Appendix C. The term E_1^i contains all semi-elasticities ϵ_{X^k,q^j}^C and $\epsilon_{X^j,I}$ for $k, j = 1, \ldots, n$, while E_2^i contains all semi-elasticities ϵ_{X^k,q^j}^C and ϵ_{X^j,Y_1}. The term E_1^i has the following interpretation. If the goods are substitutes or complements, then the health insurance elasticities are jointly determined and we need to consider all of them in estimating τ_i^b. The term E_2^i includes all income and price elasticities for analogous reasons. Equation (23) is the equivalent of (14) from the main model (and collapses to (14) when $n = 1$). Furthermore, it is straightforward to derive the analogue of Proposition 1 in the case of multiple sin goods from (23) following the same steps as in Section 3.

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 (23) if it is a substitute or complement to SSBs. Interestingly, a good need not be itself a sin good 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.[21] They find only two nonzero cross-price elasticities. First, SSBs are substitutes with diet drinks (cross-price elasticity $\approx$ 0.25). Second, SSBs are slight complements with canned, dry fruit (cross-price elasticity $\approx$ -0.19).

Cotti et al. (2019) show that the expenditures on candy, cookies, and snacks were not affected by the ACA. Hence, the demand for canned, dry fruits is unlikely to respond to changes in insurance coverage. However, the ACA raised diet soda demand of eligible households by 8.93 ounces per household per month (He et al., 2020). Therefore, I include only diet soda as a second good in calibrating the SSBs' behavioral wedge.

I describe in detail the derivation of all parameter values in Appendix C.2. The results from estimating Equation (23) for SSBs are reported in Table C.1. The SSBs' marginal internality declines to 0.88, 0.91, and 1.10 cents per ounce in cases (*i*), (*ii*), and (*iii*), respectively. The reason is that substitutability to diet soda explains part of the SSBs' zero health insurance elasticity that was previously attributed to the marginal internality. Moreover, the estimated proportion of the marginal probability that individuals take into account increases to around $19 - 20\%$ in all three cases. Furthermore, the optimal health insurance remains almost unchanged and is given by $b^* = 0.83$.

5.3 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). Smoking lowers LE by six years (Gruber and Köszegi, 2004). SSB consumption is associated with higher mortality risk (Malik et al., 2019), and one SSB lowers LE by 7.95 minutes of healthy life (Stylianou et al., 2021).

To integrate these effects in the model, define the ratio of LE in the sick state to LE when healthy as $\mu \in [0, 1)$. Thus, prior to the resolution of uncertainty at the beginning of period two, expected LE is a proportion $\mu\pi + (1 - \pi)$ of the healthy LE. Moreover,

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

expected utility (4) changes to

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

The perceived expected utility $\widehat{EU}$ is changed analogously.

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

Calibration. To simulate the model, we need an estimate of the relative LE μ. The marginal effect of SSB demand on LE at the beginning of period two relative to the LE in the healthy state is $\pi'(X)[\mu - 1]$. Suppose that the SSB's marginal LE effect equals the average effect. Stylianou et al.'s (2021) result of 7.95 minutes of healthy LE losses per SSB serving translate into $1.513 \cdot 10^{-5}$ healthy years lost per serving. To derive the relative LE loss, $\pi'(X)[\mu - 1]$, I divide the absolute loss by LE at the beginning of period two. By assumption, period two is representative for age ≥ 50. In the U.S., life expectancy at the age of 50 was 31.7 years in 2018 (Arias and Xu, 2020). Thus, we have

$$\pi'(X)[\mu - 1] = -\frac{1.513 \cdot 10^{-5}}{31.7}. \quad (25)$$

Using $\pi'(X)$ from Table 1, I get $\mu = 0.988$. To estimate the model with one sin good, I additionally use the parameter values from Table 1. The estimates for τ^b are equal to 1.18 and 1.22 cents/ounce for cases (i) and (ii), respectively (see Table C.2 in Appendix C.3). These estimates are slightly higher than those from Table (3) because LE effects augment the sin goods' health costs. Introducing LE effects in the model with two sin goods, the SSB's marginal internality becomes 0.96 and 1.02 cents/ounce, respectively. Thus, the last two extensions have small and largely offsetting effects on τ^b. Finally, LE effects lower the benefits of health insurance and reduce slightly b^* to 0.81-0.82.

6 Conclusion

This paper exploits the relationship between health insurance and the marginal internality of sin goods consumption to estimate the latter. The derived approach does not require surveys to elicit individuals' beliefs and self-control, and does not need an estimate of the consumers' true willingness to pay. 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 consumer approach.

Furthermore, this paper's method can be applied to other sin goods, such as alcohol and cigarettes. To the best of the author's knowledge, there is no study that measures the marginal internalities from alcohol and cigarettes in the presence of both self-control problems and biased beliefs.

Moreover, while this paper focuses on sin goods, its method can also measure 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 method 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 Equations (10), (11), and (12)

To derive (10) and (11), first rewrite (8):

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

Equation (A.1) determines implicitly the sin good demand as a function of τ and I: $\widehat{X}(\tau, I)$. The social planner maximizes the expected utility (4) taking into account (3),

$\ell = \tau X$, and $\widehat{X}(\tau, I)$. The first-order conditions are

$$\frac{\partial EU}{\partial \tau} = \left\{ -U_Z^1(\cdot)(p + \tau^{\xi}) + U_X^1(\cdot) + \delta\pi'(\widehat{X})[U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)] \right\} \frac{d\widehat{X}}{d\tau} = 0, \quad \text{(A.2)}$$

$$\frac{\partial EU}{\partial I} = \left\{ -U_Z^1(\cdot)(p + \tau^{\xi}) + U_X^1(\cdot) + \delta\pi'(\widehat{X})[U^s(Z_2^s, H^s) - U^h(Z_2^h, H^h)] \right\} \frac{d\widehat{X}}{dI}$$
$$- U_Z^1(Z_1, H^h, X)\frac{\pi(\widehat{X})}{1+r} + \delta\pi(\widehat{X})U_Z^s(Z_2^s, H^s) = 0. \quad \text{(A.3)}$$

Solving (A.1) for $U_X^1(\cdot)$, inserting the resulting expression in (A.2) and simplifying gives (10). From (A.2), the first row of (A.3) equals zero. Thus, (A.3) simplifies to (11).

A.1 Derivation of Equation (12)

Start by deriving the slope of uncompensated demand, $d\widehat{X}/dq$, and 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

$$\frac{d\widehat{X}}{dq} = \frac{U_Z^1(\cdot) - \widehat{X}[U_{ZZ}^1(\cdot)q - U_{XZ}^1(\cdot)]}{\partial^2\widehat{EU}/\partial X^2}, \quad \text{(A.4)}$$

$$\frac{d\widehat{X}}{dY_1} = \frac{U_{ZZ}^1(\cdot)q - U_{XZ}^1(\cdot)}{\partial^2\widehat{EU}/\partial X^2}, \quad \text{(A.5)}$$

where

$$\frac{\partial^2\widehat{EU}}{\partial X^2} = U_{ZZ}^1 q\left[p + \tau^{\xi}\right] + U_{XX}^1 - U_{XZ}^1(p+q) + \delta\beta\widehat{\pi}''(X)[U^s - U^h] < 0. \quad \text{(A.6)}$$

The second-order condition of the individual maximization problem requires that (A.6) is negative. Using the Slutsky equation, we can find the slope of compensated demand, that I define as $\widehat{X}^C$:

$$\frac{d\widehat{X}^C}{dq} = \frac{d\widehat{X}}{dq} + \widehat{X}\frac{d\widehat{X}}{dY_1} = \frac{U_Z^1(Z_1, H^h, X)}{\partial^2\widehat{EU}/\partial X^2} < 0. \quad \text{(A.7)}$$

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

$$0 = \frac{\partial^2\widehat{EU}}{\partial X^2}d\widehat{X} + \left\{ \delta\pi' U_Z^s(Z_2^s, H^s) + \frac{\pi(X)}{1+r}[qU_{ZZ}^1(\cdot) - U_{XZ}^1(\cdot)] + \frac{\partial\left[U_Z^1(\cdot)\tau^b\right]}{\partial I} \right\} dI. \quad \text{(A.8)}$$

Multiplying (A.8) with $1/dI$ and using the definition of $\epsilon^C_{X,q}$ from Section 3 together with (A.7), we get

$$0 = \frac{U^1_Z(\cdot)}{\epsilon^C_{X,q}\widehat{X}}\frac{d\widehat{X}}{dI} + \left\{\delta\pi' U^s_Z(Z^s_2, H^s) + \frac{\pi(X)}{1+r}[qU^1_{ZZ}(\cdot) - U^1_{XZ}(\cdot)] + \frac{\partial\left[U^1_Z(\cdot)\tau^b\right]}{\partial I}\right\}. \quad \text{(A.9)}$$

Next, we use the definition of $\epsilon_{X,I}$ and rearrange (A.9) to get

$$\frac{\epsilon_{X,I}}{\epsilon^C_{X,q}} = -\left\{\delta\pi'\frac{U^s_Z(Z^s_2, H^s)}{U^1_Z(\cdot)} + \frac{\pi(X)}{1+r}\frac{qU^1_{ZZ}(\cdot) - U^1_{XZ}(\cdot)}{U^1_Z(\cdot)} + \frac{1}{U^1_Z(\cdot)}\frac{\partial\left[U^1_Z(\cdot)\tau^b\right]}{\partial I}\right\}. \quad \text{(A.10)}$$

Lastly, we use Equations (A.5) and (A.7) to derive

$$\frac{qU^1_{ZZ}(\cdot) - U^1_{XZ}(\cdot)}{U^1_Z(Z_1, H^h, X)} = \frac{\epsilon_{X,Y_1}}{\epsilon^C_{X,q}}. \quad \text{(A.11)}$$

Together, (A.10) and (A.11) give Equation (12).

B Calibration

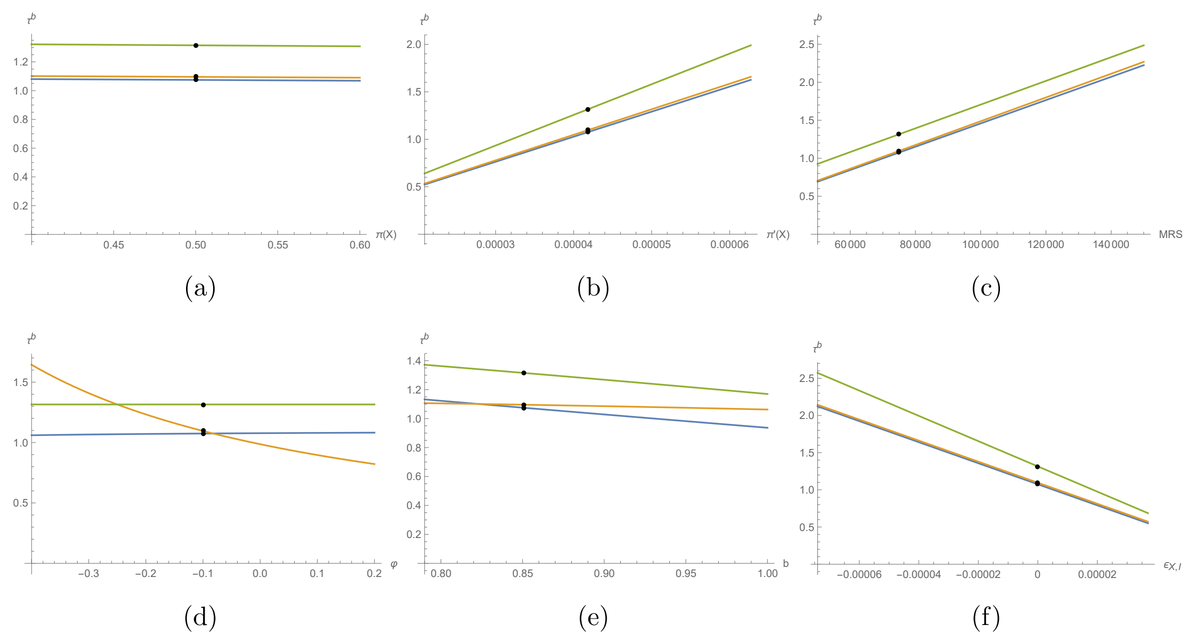

Figure B.1: The behavioral wedge τ^b estimated according to case (*i*) (blue), case (*ii*) (orange), and case (*iii*) (green) as a function of the probability of sickness $\pi(X)$ (panel (a)), marginal probability $\pi'(X)$ (panel (b)), MRS (panel (c)), degree of state dependence φ (panel (d)), health insurance coverage b (panel (e)), and insurance elasticity $\epsilon_{X,I}$ (panel (f)). Dots indicate the benchmark estimates.

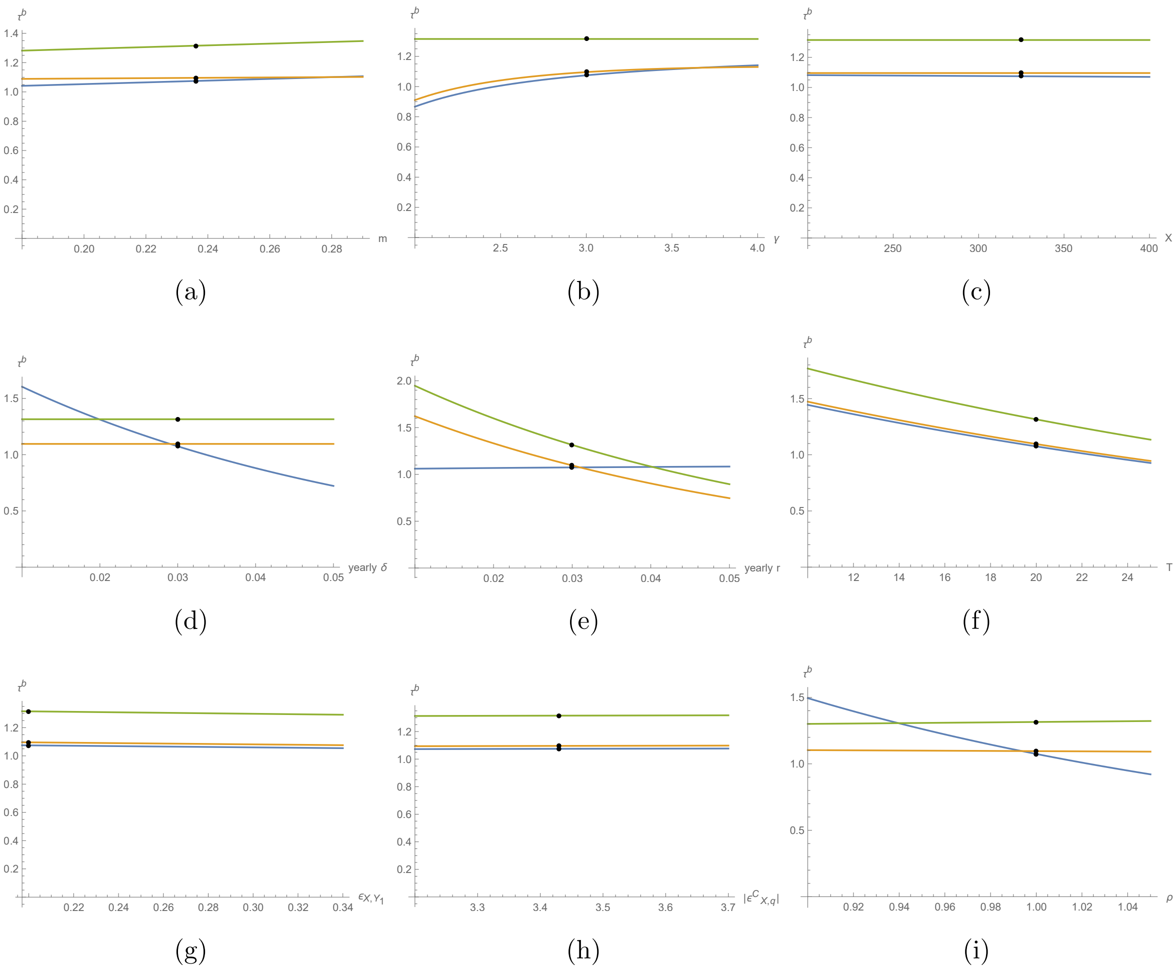

Figure B.2: The behavioral wedge τ^b according to case (i) (blue), case (ii) (orange), and case (iii) (green) as a function of health costs m (panel (a)), risk aversion γ (panel (b)), SSB consumption X (panel (c)), yearly discount rate (panel (d)), yearly interest rate (panel (e)), time between periods T (panel (f)), income semi-elasticity ϵ_{X,Y_1} (panel (g)), compensated price semi-elasticity $|\epsilon^C_{X,q}|$ (panel (h)), and degree of consumption smoothing ρ (panel (i)). A dot indicates the benchmark estimate.

C Extensions

C.1 Multiple Sin Goods

Here, I derive Equation (23). The first-order condition with respect to good X^i is:

$$\frac{\partial \widehat{EU}}{\partial X^i} = -U^1_Z[Z_1, H^h, \mathbf{X}][p^i + \tau^i] + U^1_{X^i}(Z_1, H^h, \mathbf{X})$$

$$+\,\delta\pi_{X^i}(\mathbf{X})\left[U^s(Z_2^s,H^s)-U^h(Z_2^h,H^h)\right]+U_Z^1[Z_1,H^h,\mathbf{X}]\tau_i^b=0, \tag{C.1}$$

where the behavioral wedge τ_i^b is defined as

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

Next, we use the system of n first-order conditions to derive the slopes of compensated demand similarly to Appendix A.1. Define

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

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

$$\frac{d\widehat{X}^i}{dY_1}=\sum_{j=1}^{n}\frac{(-1)^{j+i}[q^jU_{ZZ}^1(\cdot)-U_{X^jZ}^1(\cdot)]|\mathbf{M_{ji}}|}{|\mathbf{J}|}, \tag{C.4}$$

$$\frac{d\widehat{X}^{i\,C}}{dq^i}=\frac{U_Z^1(\cdot)|\mathbf{M_{ii}}|}{|\mathbf{J}|}, \tag{C.5}$$

$$\frac{d\widehat{X}^{i\,C}}{dq^j}=\frac{(-1)^{j+i}U_Z^1(\cdot)|\mathbf{M_{ji}}|}{|\mathbf{J}|}. \tag{C.6}$$

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

$$\Delta^i := \frac{\partial^2\widehat{EU}}{\partial X^i\partial I}=\delta\pi_{X^i}U_Z^s(Z_2^s,H^s)+\frac{\pi}{1+r}[q^iU_{ZZ}^1(\cdot)-U_{X^iZ}^1]+\frac{\partial\left[U_Z^1(\cdot)\tau_i^b\right]}{\partial I}. \tag{C.7}$$

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

$$\frac{d\widehat{X}^i}{dI}=\sum_{j=1}^{n}\frac{(-1)^{j+i}(-\Delta^j)|\mathbf{M_{ji}}|}{|\mathbf{J}|},\quad i=1,\dots,n. \tag{C.8}$$

Defining the semi-elasticities $\epsilon_{X^i,I}$ and $\epsilon^C_{X^i,q^j}$ analogously to Section 2 and using Equations (C.5), (C.6), and (C.8), we get

$$U_Z^1(\cdot)\epsilon_{X^i,I}=-\sum_{j=1}^{n}\epsilon^C_{X^i,q^j}\Delta^j,\quad i=1,\dots,n. \tag{C.9}$$

Thus, we have derived a system of n linear equations in Δ^j that we can solve for Δ^j. In matrix form, (C.9) can be represented as

$$-U_Z^1(\cdot)\epsilon_{\mathbf{X},\mathbf{I}} = \mathbf{S}\boldsymbol{\Delta}, \tag{C.10}$$

where $\mathbf{S}$ is the $n \times n$ matrix containing all $\epsilon^C_{X^i,q^j}$ for $i, j = 1, \ldots, n$, $\boldsymbol{\Delta} = (\Delta^1, \ldots, \Delta^n)$ and $\epsilon_{\mathbf{X},\mathbf{I}} = (\epsilon_{X^1,I}, \ldots, \epsilon_{X^n,I})$. Using Cramer's rule, we can solve (C.10) for Δ^i:

$$\Delta^i = -E_1^i U_Z^1(\cdot), \quad \text{where} \quad E_1^i \coloneqq \frac{1}{|\mathbf{S}|}\sum_{j=1}^{n}(-1)^{j+i}|\mathbf{S_{ji}}|\epsilon_{X^j,I}, \tag{C.11}$$

and $\mathbf{S_{ji}}$ is the matrix left after removing the jth row and ith column from $\mathbf{S}$.

Moreover, we can divide (C.4) by $\widehat{X}^i$ from both sides, use the definitions of ϵ_{X^i,Y_1} and $\epsilon^C_{X^i,q^j}$, as well as (C.6) to derive

$$\epsilon_{X^i,Y_1} = \sum_{j=1}^{n}\epsilon^C_{X^i,q^j}\frac{[q^j U^1_{ZZ}(\cdot) - U^1_{X^jZ}(\cdot)]}{U_Z^1(\cdot)}, \quad i = 1, \ldots, n. \tag{C.12}$$

Define

$$E_2^j \coloneqq \frac{[q^j U^1_{ZZ}(\cdot) - U^1_{X^jZ}(\cdot)]}{U_Z^1(\cdot)}. \tag{C.13}$$

Then, the n equations from (C.12) can be written in matrix form as

$$\epsilon_{\mathbf{X},\mathbf{Y_1}} = \mathbf{S}\mathbf{E_2}, \tag{C.14}$$

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

$$E_2^i = \frac{1}{|\mathbf{S}|}\sum_{j=1}^{n}(-1)^{j+i}|\mathbf{S_{ji}}|\epsilon_{X^j,Y_1}. \tag{C.15}$$

Finally, putting (C.7), (C.11), (C.13), and (C.15) together, and taking (13) in the case of n sin goods into account, we get Equation (23).

C.2 Calibration with regular and diet soda

Index the two types of drinks as $i = d, r$, where d labels diet soda and r regular soda. For the calibration in Section 5.2, we need the semi-elasticities $\epsilon_{X^i,I}$ and $\epsilon^C_{X^i,q^j}$ for $i, j = d, r$. Table 1 already lists $\epsilon_{X^r,I} = 0$ and $\epsilon^C_{X^r,q^r} = -3.43$.

To determine the health insurance semi-elasticity of diet soda, $\epsilon_{X^d,I}$, I use He et al.'s (2020) results. 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 $\approx 7.8\%$ increase. The semi-elasticity $\epsilon_{X^d,I}$ is equal to $(dX^d/X^d)(1/dI)$. Using $dX^d/X^d = 0.078$ and $dI = \$337/\pi$ as in Section 4, we get $\epsilon_{X^d,I} = 1.16 \cdot 10^{-4}$.

Next, I turn to the price elasticities. While Allcott et al. (2019a) 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 semi-elasticities. Therefore, I additionally use results from Zhen et al. (2014) and Harding and Lovenheim (2017).

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

$$\frac{d\widehat{X^i}^C}{dq^j} = \frac{d\widehat{X^i}}{dq^j} + \widehat{X^j}\frac{d\widehat{X^i}}{dY_1}, \tag{C.16}$$

Multiply both sides of (C.16) by $q^j/\widehat{X^i}$ to get

$$\nu^C_{X^i,q^j} = \nu_{X^i,q^j} + \xi^j \nu_{X^i,Y_1}, \tag{C.17}$$

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 $\xi^r = 0.0026$.[22] 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.[23] Taking the average, I derive $\xi^d = 0.74\xi^r \approx 0.002$. Using (C.17), I find the compensated elasticities: $\nu^C_{X^d,q^d} = -0.9527, \nu^C_{X^d,q^r} = 0.2484$.

Moreover, 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.17) to derive $\nu^C_{X^r,q^d} = 0.103$.

[22] Table 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.

[23] Zhen et al. (2014) divide their sample in 7,936 low- and 19,704 high-income households. I calculate the average expenditure shares for both groups. Harding and Lovenheim (2017) report spending on diet and regular soda as a proportion of food expenditures in their Table 1.

Finally, to get the compensated semi-elasticities, we need to divide $\nu^C_{X^i,q^j}$ by q^j. While Allcott et al. (2019a) do not report q^d, Zhen et al. (2014) find identical prices for diet and regular soda[24], while Harding and Lovenheim (2017) find diet soda to be 38% more expensive on average (see their Table 1). Taking the average of the estimated relative prices, I set $q^d = 1.19q^r = \$0.482$ per serving.

Together, the estimates of $\nu^C_{X^i,q^j}$ and q^j give the following compensated semi-elasticities:

$$\epsilon^C_{X^d,q^d} = -1.977, \tag{C.18}$$

$$\epsilon^C_{X^d,q^r} = 0.613, \tag{C.19}$$

$$\epsilon^C_{X^r,q^d} = 0.214. \tag{C.20}$$

Together with $\epsilon^C_{X^r,q^r} = -3.43$ from Table 1 and $\epsilon_{X^d,I} = 1.16 \cdot 10^{-4}$, we have all elasticities required for the calibration of (23) in the case of two sin goods.

Table C.1: Results for τ^b_r in the case of two sin goods (SSB and diet soda).

	$\tau_r^{b\,a}$	$\frac{\beta\widehat{\pi}_{X^r}}{\pi_{X^r}}$	$\tau_r^{\xi\,a}$	$\tau^{r*\,a}$	b^*
A. Proposition 1 *(i)*	0.88	0.195	0.851	1.73	0.83
B. Proposition 1 *(ii)*	0.91	0.188	0.851	1.761	–
C. Proposition 1 *(iii)*	1.10	0.188	0.851	1.951	–

[a] Expressed in cents per ounce.

[24] 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.

C.3 Calibration with life expectancy effects

Table C.2: Results in the case of LE effects.

	τ^{b}[a]	$\frac{\beta\widehat{\pi}'(X)}{\pi'(X)}$	τ^{ξ}[a]	τ^{*}[a]	b^*
A. Proposition 1 (i)					
Model with one sin good	1.18	0.026	0.851	2.04	0.824
Model with two sin goods	0.96	0.197	0.851	1.82	0.814
B. Proposition 1 (ii)					
Model with one sin good	1.22	0.025	0.851	2.071	–
Model with two sin goods	1.02	0.189	0.851	1.871	–

[a] Expressed in cents per ounce.