The Life-cycle Consequences of Obesity and the Effects of Weight-Loss Drugs[1]

Jérôme Adda, Christian Dustmann and Lukas Tohoff

This version: August 2026

Abstract

We study the life-cycle consequences of excess body weight and the effects of weight-loss technologies. We develop and estimate a structural life-cycle model, using multiple large-scale U.S. datasets, which captures the effects of body weight on health, labor market outcomes, medical expenditures, partnership formation, and longevity. We find that excess body weight reduces lifetime welfare through all these channels, with health and longevity accounting for the largest share of the losses. Labor market and partnership effects play a much larger role for women than for men. Because conventional weight-control effort is costly and only weakly effective, improved weight-loss technologies generate substantial welfare gains. Willingness to pay for a permanent 10 percent reduction in body weight is highly heterogeneous, reflecting differences in health risks and financial resources. Low-price access to weight-loss treatment substantially improves health, longevity, and welfare while reducing inequality along several dimensions. Comparing alternative prescription regimes further shows that earlier preventive treatment yields substantially larger gains than restricting treatment to individuals with existing obesity-related health conditions.

JEL Codes: I12, I14, D15, J24
Keywords: Obesity; Weight-Loss Drugs; Life-Cycle Model; Health Inequality

[1] Correspondence: Jerome Adda, Bocconi University and RFBerlin, email: jerome.adda@unibocconi.it; Christian Dustmann, Department of Economics, University College London, and RFBerlin, email: c.dustmann@ucl.ac.uk; Lukas Tohoff, Humboldt-Universität zu Berlin and RFBerlin, email: lut@rfberlin.com.
We are grateful to the Rockwool Foundation for financial support. Dustmann acknowledges funding by ERC Advanced Grant 833861.

1. Introduction

Obesity is a major public health problem with substantial costs for individuals and society, and consequences for health, longevity, economic outcomes, and social integration. It is widespread in all industrialized economies and has become increasingly common in middle- and low-income countries. The emergence of GLP-1-based weight-loss drugs, which allow individuals to reduce body weight in ways previously not feasible, therefore represents a major innovation. Yet little is known about their broader economic effects and their implications for individual welfare.

This paper develops and estimates a life-cycle model to examine the consequences of obesity and the economic implications of new weight-loss technologies. Our analysis proceeds in two stages. First, we quantify how body weight affects outcomes over the life-cycle, including health, wages, employment, marriage, and longevity, and assess the contribution of each of these factors to the demand for weight reduction. Second, we evaluate how the availability of weight-loss drugs affects individual behavior and economic outcomes and assess alternative pricing and access regimes.

Our analysis combines five large-scale datasets covering the period before weight-loss drugs became widely available. The estimated model links body weight, health, longevity, employment, wages, wealth, medical expenditures, and marriage over the adult life cycle while allowing for rich heterogeneity and endogenous selection. We then use the model to quantify individuals' willingness to pay (WTP) for weight reduction, identify the mechanisms driving demand, and evaluate how expanded access to weight-loss technologies affects individual welfare and inequality across several dimensions, including wealth, lifetime utility, and longevity.

Our analysis yields three main findings. First, conventional weight-control effort is costly and weakly effective, implying that improved weight-loss technologies generate substantial

individual welfare gains. Second, excess body weight affects outcomes through multiple channels. Wage losses are economically significant, employment effects are concentrated at the hiring margin, excess weight entails substantial health losses, and marriage-market prospects decline sharply. There are pronounced gender differences, with effects on labor-market and marriage-market outcomes substantially more negative for women. Third, WTP for weight reduction is both large and highly heterogeneous. Demand is greatest among middle-aged individuals with high BMI and those already engaged in weight-control efforts, but financial resources are also a key determinant. Decomposition exercises show that the value of weight reduction is driven overwhelmingly by improvements in health and longevity, whereas labor market and marriage channels play a comparatively smaller role.

We then use the model to evaluate alternative access regimes. Weight-loss treatment is modeled as a dynamic choice: initiating treatment permanently reduces body weight by 10 percent, while discontinuation returns individuals to their latent weight trajectory. Under market-based allocation, an annual treatment cost of USD 600 leads to widespread adoption, substantial reductions in body weight, improvements in health and longevity, and sizeable individual welfare gains[2]. The largest benefits accrue to those with greater health risks, leading to reductions in several dimensions of inequality.

We further compare two prescription-based access policies that provide a free lifetime subscription to a weight-loss technology. Under the obesity-plus rule, treatment is offered only to obese individuals in poor health, reflecting current practice in many countries. Under the more preventive obesity-only rule, all obese individuals are eligible also before health deteriorates, representing a more pre-emptive approach.

[2] The annual price of USD 600 is well below current U.S. list prices for GLP-1 agonists as of 2026 but may be realistic in the medium run.

Both policies produce benefits similar in nature to market-based allocation, but their effectiveness depends critically on the eligibility rule. The preventive obesity-only policy generates higher uptake, larger BMI reductions, stronger labor market effects, and greater reduction in medical spending than the obesity-plus rule. Both policies improve health and increase life expectancy by about one year. Compared with the low-price market access, however, prescription-based allocation results in lower uptake and smaller BMI reductions, while generating broadly similar improvements in health and economic outcomes, as well as comparable reductions in wealth, lifetime utility, and longevity inequality.

Our paper contributes to the health capital and structural life cycle literatures (Grossman 1972, 2000; Ehrlich and Chuma 1990; French 2005; Scholz et al. 2006; De Nardi et al. 2010; Galama and Van Kippersluis 2019; Margaris and Wallenius 2024; Mahler and Yum 2024; Ozkan 2025; Bolt 2024; De Nardi et al. 2025; Capatina and Keane 2026). Existing structural work has primarily examined the formation of health capital, the interaction between health and economic behavior, or specific aspects of obesity. Bolt (2024), for example, studies health investments during childhood and their implications for body weight and economic inequality, while Margaris and Wallenius (2026) analyze body weight-related social norms and quantify the spillover effects of weight-loss drugs through social reference groups. Our paper is also related to papers that evaluate medical innovations while accounting for forward-looking health behavior and endogenous treatment decisions (Arcidiacono et al. 2007; Papageorge 2016; Chan et al. 2016; Cronin et al. 2025).

We complement this literature by providing an integrated analysis of how body weight shapes economic, health, and social outcomes over the adult life cycle and using this framework to evaluate the effects of medical innovation. To this end, we model body weight as a state variable that jointly affects health, longevity, labor market outcomes, marriage, and medical expenditures over the life cycle. The model incorporates latent heterogeneity in ability and body

morphology, allowing it to capture dynamic selection, heterogeneous consequences of excess weight and, in our counterfactual analyses, treatment uptake based on expected economic, health, and social returns and available financial resources. It also embeds a marriage market in which changes in body weight affect equilibrium matching through the evolving distribution of potential partners. We abstract from labor-market general equilibrium effects and instead assume competitive labor markets, reflecting our finding that the labor-market consequences of excess body weight are modest relative to its effects on health, longevity, and marriage.

Our paper also contributes to the large empirical literature documenting the consequences of excess body weight for health, medical expenditures, longevity, wages, employment, and discrimination (Cawley 2015; Rooth 2009; Kesaite and Greve 2023; Averett 2011), as well as to studies examining the relationship between health, human capital, and socioeconomic outcomes (Currie and Madrian 1999; Cutler et al. 2011; Segal et al. 2021). More recently, several studies have exploited the early diffusion of GLP-1 drugs to estimate their economic and social effects by comparing early adopters with individuals who (may) adopt later. Diamond (2026) finds substantial increases in partnership formation among initially single women and employment entry among initially non-employed women. Daysal et al. (2026) show that GLP-1 treatment reduces long-term sickness absence but has no meaningful effects on employment or income over four years. While these studies provide valuable early evidence, treatment timing may remain correlated with expected returns and unobserved characteristics.

Our analysis complements this literature by explicitly modeling treatment decisions as function of expected economic, health, and social returns, together with financial resources and unobserved heterogeneity. Rather than studying individual outcomes in isolation, we integrate the multiple channels through which body weight affects economic and social outcomes in a unified dynamic framework. Moreover, while recent studies evaluate the effects of GLP-1 drugs during their initial rollout, we use the model's structure to examine how widespread access to

effective weight-loss technologies is likely to shape economic and social outcomes over the coming years. This allows us to quantify lifetime effects and evaluate alternative pricing and prescription regimes that cannot yet be observed in the data.

The remainder of the paper is organized as follows. Section 2 describes the data and documents how BMI relates to key labor market, health, and partnership outcomes over the life cycle. Section 3 introduces a dynamic life-cycle model. Section 4 outlines the estimation strategy and the identifying variation. Section 5 presents the estimated model and decomposes the drivers of weight-loss demand. Section 6 uses counterfactual exercises to evaluate alternative allocation regimes for a weight-reducing technology. Section 7 concludes.

2. Data and Descriptives

2.1. Data

Our analysis combines five large-scale U.S. datasets: the National Health and Nutrition Examination Survey (NHANES, 1999-2023), the Panel Study of Income Dynamics (PSID, 1999-2021), the Health and Retirement Study (HRS, 1992-2022), the National Longitudinal Surveys of Youth 1979 and 1997 (NLSY79 and NLSY97), and the Medical Expenditure Panel Survey (MEPS, 1996-2022). Together, these datasets provide complementary information on body weight, health, labor market outcomes, wealth, marriage, medical expenditures, and mortality over the life cycle. The model is estimated using data from more than two decades before weight loss drugs became widely available. We use the limited post-introduction evidence on GLP-1 use only to assess the model's external validity by comparing predicted and observed adoption patterns across demographic groups. Appendix B describes the construction of the estimation samples, variable definitions, and descriptive statistics.

Our central variable is body weight, measured by *Body Mass Index* (BMI), defined as weight in kilograms divided by height in meters squared. BMI is directly measured in NHANES and self-reported elsewhere; throughout, we winsorize BMI at 15 and 50. Although BMI is an

imperfect measure of body weight, Figures B.1 and B.2 show that BMI closely tracks measured body fat, the self-perceived overweight status, and self-reported BMI, making it a reliable and consistently available proxy across datasets. NHANES is also used to construct a measure of body morphology type, based on residual variation in BMI after conditioning on observable characteristics (see Appendix B).[3]

We also exploit unique information from NHANES to construct a measure of *weight-control effort,* indicating whether respondents actively tried to lose or maintain weight during the previous twelve months. Unlike many survey measures that capture intentions, this variable records realized behavior and is primarily associated with diet and exercise. For details, see Appendix B, including Figures B.3 and B.4.

Health is measured using a harmonized indicator equal to one if respondents report being in excellent, very good, or good health. Employment, wages, and cognitive ability are drawn primarily from the NLSY and MEPS; wealth and spousal characteristics from the PSID and MEPS; medical expenditures from MEPS and HRS; and mortality from the HRS together with life tables. Marital status is observed in all datasets. Throughout the analysis, individuals are classified by gender, race (non-Hispanic White, non-Hispanic Black, Hispanic), education (high school or more), cognitive ability (high/low)[4], birth cohort (pre/post 1965), and body morphology (high/low type). Appendix B provides further details.

[3] We classify individuals into two body morphology types (in short, body types), high and low, which can be interpreted as reflecting a predisposition toward a higher and lower BMI, respectively. The classification is based on residual variation in BMI using detailed information on nutrition and behavior from the NHANES data, after accounting for diet, physical activity, and other observable characteristics. See Appendix B for full details on the construction, including Figure B.5 which shows the distribution of body types by race.

[4] We classify individuals into two ability groups, high and low, based on standardized test scores from the NLSY79 (AFQT) and its NLSY97 equivalent, which capture general cognitive aptitude. Individuals with scores above the median are classified as high ability, and those below as low ability. See Appendix B for full details on the construction.

2.2. Descriptives

We begin by documenting a set of empirical patterns that motivate the structure of our life-cycle model.

Figure 1 summarizes the relationship between BMI and labor market and partnership outcomes at prime age (36-40). Panel (a) shows that hourly wages decline with BMI for both men and women. In contrast, employment rates (Panel (b)) are relatively flat across most of the BMI distribution, with marked declines only at very low BMI levels and among the severely obese. Panel (c) reveals a striking gender difference in marital outcomes: while marriage rates are largely flat across BMI for men, they sharply decline with BMI for women. This points to an important role in the marriage market, particularly for women, and motivates modeling partnership formation jointly with labor market outcomes. Figures B.6 and B.7 show that these patterns are generally robust to alternative age ranges and dataset choices.

Figure 2 shows that total medical expenditures, including all payments for health care services regardless of payer, increase strongly and monotonically with BMI across all age groups, with a steeper gradient at older ages. In contrast, out-of-pocket expenditures, payments made directly by individuals, rise more modestly. This suggests that a substantial share of obesity-related costs is borne by insurers or the public system, weakening individual financial incentives for weight reduction while generating external costs.

Figure 3 illustrates the link between BMI, health, and mortality. Panel (a) shows that the share reporting good health declines sharply with BMI, particularly when moving from overweight (BMI above 25) to obese (BMI above 30). Panel (b) documents a strong relationship between age and five-year mortality risk, with the gap between individuals in good and poor health widening over the life cycle. Panel (c) shows that both underweight and obese individuals face elevated mortality risk, even conditional on health and demographics. These patterns suggest that BMI affects longevity both through health and through direct channels.

Finally, Figure 4 compares the distributions of residualized one-year BMI changes among respondents who report having made efforts to control their weight during the previous year and those who do not. The distributions overlap substantially. Individuals reporting weight-control effort experience neither a pronounced leftward shift nor a noticeably narrower distribution of BMI changes. Because weight-control effort is likely endogenous to idiosyncratic weight shocks, the comparison is descriptive rather than causal. Nevertheless, the substantial dispersion in BMI changes, even among those reporting efforts, motivates modeling the outcome of weight-control effort as heterogeneous and imperfectly predictable rather than deterministic.

Overall, these empirical patterns motivate four key features of our model. First, BMI is systematically related to wages, wealth accumulation, health, medical expenditures, and longevity. Second, the association between BMI and key outcomes, especially marriage and wages, exhibits strong gender differences. Third, much of the medical cost of excess body weight is borne by insurers and public programs rather than individuals. Fourth, weight-control effort appears imperfect and only weakly related to weight loss. A model of the lifetime consequences of excess body weight and the effects of weight-loss drugs must therefore jointly account for weight dynamics, health, labor market outcomes, medical spending, savings, longevity, and partnership formation within a unified life-cycle framework.

3. Model

Individuals choose consumption, weight-control effort, and marriage under uncertainty about employment, income, medical spending, health, longevity, and marital outcomes. Time is discrete, with one period corresponding to one year. Decisions depend on current body weight, health, assets, labor market status, and fixed characteristics, including gender, race, education, ability, birth cohort, and body type. The model combines standard elements of the structural life-cycle literature, such as labor income risk, medical expenditures, savings, and government

transfers (Hubbard et al. 1994, French 2005, De Nardi et al. 2010), with endogenous body weight and marriage decisions. Body weight affects health, wages, employment, medical expenditures, marriage prospects, and longevity, while health and economic resources in turn influence body weight dynamics. Individuals also take into account the population distribution of body weight when making marriage decisions, allowing sorting patterns to adjust in counterfactual environments. This framework captures the multiple channels through which excess body weight affects lifetime utility and provides a basis for evaluating how weight-loss technologies affect individual welfare.

3.1. Model Components

We now describe the main components of the model. Additional details on functional forms and the full parameterization are provided in Appendix A.2.

Employment and Wages. We assume a competitive labor market with search frictions in which wages reflect marginal productivity conditional on a match. Employment is stochastic and determined by individual fixed characteristics D_i (i.e., cohort, education, gender, race, ability, and body type), current age t_i, body weight $\mathcal{W}_{it}$, health H_{it}, marital status M_{it}, and current employment E_{it},

$$Pr(E_{it+1} = 1) = \lambda_{it+1} = \lambda(D_i, t_i, \mathcal{W}_{it}, H_{it}, M_{it}, E_{it}). \quad (1)$$

Income w_{it} depends on employment, age, and potential wages,

$$w_{it} = \gamma(E_{it}, t_i) \times \tilde{w}(D_i, t_i, \mathcal{W}_{it}, H_{it}, \tilde{\epsilon}_{it}^{w}), \quad (2)$$

where $\tilde{w}(\cdot)$ captures potential hourly wages that vary with age, body weight, health, fixed demographic characteristics, and a log-normal wage shock $\tilde{\epsilon}_{it}^{w} = \exp(\epsilon_{it}^{w} - \sigma_w^2/2)$ with $\epsilon_{it}^{w} \sim N(0, \sigma_w^2)$. The function $\gamma(\cdot)$ maps potential hourly wages into annual earnings, unemployment

benefits, or retirement benefits depending on employment status and age (details in Appendix A). Individuals retire at age 63.[5]

Health. Health $H_{it} \in \{0,1\}$ is good (1) or poor (0), and evolves according to

$$Pr(H_{it+1} = 1) = \psi_{it+1} = \psi(D_i, t_i, \mathcal{W}_{it}, A_{it}, H_{it}). \quad (3)$$

Health depends on past health, body weight, demographics, and age. Assets A_{it} (see (6) for its evolution) affect health, capturing advantages such as better housing conditions and improved access to medical knowledge and care through socioeconomic status.

Medical expenditures. Out-of-pocket medical expenditures m_{it} are given by

$$m_{it} = m(H_{it}, t_i, D_i, \tilde{\epsilon}_{it}^m). \quad (4)$$

Medical spending uncertainty enters through a log-normal shock $\tilde{\epsilon}_{it}^m = \exp(\epsilon_{it}^m - \sigma_m^2/2)$ with $\epsilon_{it}^m \sim N(0, \sigma_m^2)$. We follow De Nardi et al. (2010) and De Nardi et al. (2025) in modeling medical expenditures as a cost that depends on health, age, and demographics, without directly affecting health dynamics[6]. These expenditures reduce available resources but do not enter the transition of any other state variable, capturing financial risk while keeping the health production process parsimonious.

Longevity. The probability of surviving to the next period is

$$\pi_{it+1} = \pi(t_i, D_i, H_{it}, \mathcal{W}_{it}), \quad (5)$$

[5] Retirement benefits approximate the progressive U.S. Social Security schedule using potential earnings at older working ages. We assume that unemployment benefits are received in all non-employment periods, reflecting annual aggregation and the availability of other income support programs after unemployment insurance expires. Appendix A provides the full parameterization.

[6] We abstract from employer-sponsored health insurance. While one may expect the uninsured unemployed to face higher out-of-pocket costs, self-paid medical expenditures are in fact slightly *higher* for employed individuals in the data, conditional on age, health, and key demographics. We therefore treat medical expenditures as independent of employment status to maintain tractability without departing materially from observed spending patterns.

which depends on age, gender, race, health, and body weight. Body weight affects survival both indirectly through health and directly (see Figure 3 Panel (c)), reflecting elevated risks of potentially fatal health shocks, such as heart attacks or strokes.

Budget constraint. Assets A_{it} evolve as

$$A_{it+1} = A_{it} + \mathcal{T}(RA_{it} + w_{it}, \tau) + b_{it} - c_{it} - m_{it} \tag{6}$$

Here c_{it} is consumption, R is the rate of return on assets, and $\mathcal{T}(RA_{it} + w_{it}, \tau)$ is a progressive tax function (details in Appendix A.1).

Following Hubbard et al. (1994) and De Nardi et al. (2010), we express government transfers b_{it} as

$$b_{it} = max\{0, \underline{c} + m_{it} - (A_{it} + \mathcal{T}(RA_{it} + w_{it}, \tau))\}, \tag{7}$$

bridging the gap between individual resources, i.e., assets plus income minus medical expenditures, and a consumption floor $\underline{c}$.

Body weight. Body weight $\mathcal{W}_{it}$ follows,

$$\mathcal{W}_{it+1} = \mathcal{W}_{it} \times \mathrm{h}(x_{it}, \varrho_x) \times \tilde{\eta}_{it+1} + f(D_i, t_i, \mathcal{W}_{it}, A_{it}), \tag{8}$$

where $\mathrm{h}(x_{it}, \varrho_x) = exp\big(x_{it}\big[\mathbb{I}_{it}^{x}\alpha_1^{\mathcal{W}} + (1 - \mathbb{I}_{it}^{x})\alpha_0^{\mathcal{W}}\big]\big)$, while $x_{it} \in \{0,1\}$ denotes weight-control effort and $\mathbb{I}_{it}^{x} \sim \mathrm{Bernoulli}(\varrho_x)$ captures whether effort is successful. Conditional on effort, weight declines by α_1^W if successful and α_0^W otherwise. Guided by evidence from randomized controlled trials (see discussion in Appendix A.4), we set $\alpha_0^W = -0.005$ and $\alpha_1^W = -0.05$, corresponding to annual BMI reductions of roughly 0.5% to 5%. We estimate the success probability ϱ_x. The function $f(D_i, t_i, \mathcal{W}_{it}, A_{it})$ captures systematic drift by fixed characteristics, age, previous period's body weight, and assets; the latter captures advantages such as better housing conditions, improved access to recreational facilities, and lifestyle-related knowledge.

The body-weight shock $\tilde{\eta}_{it} = \exp\left(\eta_{it} - \sigma_\eta^2/2\right)$ is log-normal with $\eta_{it} \sim N\left(0, \sigma_\eta^2\right)$, implying zero expected weight growth from the shock, $\mathbb{E}(\tilde{\eta}_{it}) = 1$. An important implication is that the standard deviation of weight changes scales proportionally with body weight, a pattern consistent with empirical evidence showing that BMI dispersion increases with BMI. Shocks are realized before decisions, so effort can respond to realized weight changes. The state variable $\mathcal{W}_{it}$ therefore represents *post-shock body weight*. This feature allows the model to capture an empirically important feature: individuals who exert effort may still gain weight if the realized shock dominates the returns to effort.

In all datasets, BMI is self-reported, whereas NHANES provides both measured and self-reported values. We use this to correct for measurement error by modeling reported BMI as

$$\widehat{W}_{it} = W_{it} + \xi_{it}(D_i),$$

where $\xi_{it}(D_i) \sim N(\bar{\xi}(D_i), \sigma_\xi^2(D_i))$ is a group-specific measurement error, with mean and variance allowed to differ by fixed characteristics D_i. The availability of both measures in NHANES allows us to identify the magnitude of this reporting error in the estimation.

Marriage. Marriage occurs through a stochastic matching process. Let

$$\mu_{it} = \mu(D_i, A_{it}, W_{it}, H_{it}, x_{it}) \in [0,1]$$

denote the marriage quality of individual i. We first compute a raw marriage quality index as a function of fixed characteristics, assets, body weight, health, and effort. We then rank individuals by this index using observed population densities, separately by gender and age[7]. Thus, μ_{it} measures every individual's percentile rank in the marriage market relative to individuals of the same gender and age. For example, higher body weight lowers the individual percentile rank, if body weight enters μ_{it} negatively and everything else is held fixed. Other

[7] We do not include age in the marriage quality index for computational reasons. In the backward induction, marriage decisions at later ages would require reservation match qualities of potential partners at younger ages, which have not yet been solved. Since these objects are unavailable at that point, age cannot enter the matching index. We instead let life cycle patterns in marriage operate through age specific partner arrival rates. This restriction should have limited quantitative importance in our setting, since spouses are typically close in age.

determinants can offset this effect, so that higher assets or good health may compensate for the ranking disadvantage associated with excess body weight. As we outline next, a lower rank reduces the quality of achievable partners and the expected utility gain from marriage, while also affecting the probability of marriage.

In each period, a potential partner arrives with probability $\rho_{it}(t_i)$, which varies with age to capture life-cycle patterns in partner availability. Conditional on arrival, potential partner quality $\tilde{\mu}$ is drawn i.i.d. from $\tilde{\mu} \sim U[0,1]$, reflecting a large pool of potential matches.

A successful match yields a one-time payoff,

$$z(\tilde{\mu}) = \alpha_1^z \tilde{\mu}, \tag{9}$$

so that match utility is proportional to partner quality[8]. Individuals accept a match if it exceeds their reservation match quality $\underline{\mu}_{it}$[9]. Marriage is bilateral: a match occurs if both partners accept,

$$\mathbb{I}_{it,t+1}^{M} = 1\left\{\tilde{\mu} \geq \underline{\mu}_{it} \cap \mu_{it} \geq \underline{\tilde{\mu}}\right\}, \tag{10}$$

where $\mathbb{I}_{it,t+1}^{M}$ denotes the transition from single to married, and $\underline{\tilde{\mu}}$ is the potential partner's reservation match quality.

The reservation threshold of potential partners is determined endogenously. Because marriage quality summarizes all characteristics relevant for matching, bilateral marriage decisions depend only on one's own and the potential partner's quality. Rather than tracking the full distribution of partner characteristics, we characterize matching through the expected

[8] In more detail, α_1^z is scaled by discounted residual life expectancy. For simplicity, we omit this scaling and the dependence of z on t here and only present it in Appendix A.2.10. The scaling implies that the utility gain from marriage is proportional to its expected duration, capturing in a lighthearted way the "lifelong promise" of marriage. Modeling marriage gains as a one-time payoff, rather than a per-period flow, allows us to economize on the state space, as it eliminates the need to track the spouse's match quality over time.

[9] Anticipating the notation in equation (13), $\underline{\mu}_{it} = z^{-1}\left(V_t^S(\Omega_{it}) - V_t^M(\Omega_{it})\right)$, where V_t^S and V_t^M denote the value functions for single and married individuals, respectively. The reservation marriage quality can therefore be solved by backward induction.

reservation threshold conditional on marriage quality. This is sufficient to solve the model, because marriage quality is the only object that enters individual value functions and matching decisions.

A key feature of the framework is that marriage quality rankings and reservation thresholds adjust endogenously to changes in the population distribution of characteristics. As a result, counterfactual changes in body weight affect not only individual marriage prospects but also equilibrium sorting patterns in the marriage market. For example, if weight-loss technologies compress the distribution of body weight, other characteristics become relatively more important in determining match quality.

Utility. Individuals derive utility from consumption, body weight, health, and leisure, and incur disutility from exerting effort. Period utility follows a constant relative risk aversion (CRRA),

$$u_{it} = \alpha_1^u + \frac{\mathbb{C}_{it}^{1-\alpha_2^u}}{1-\alpha_2^u}, \tag{11}$$

where α_1^u captures the utility value of being alive, and effective consumption

$$\mathbb{C}_{it} = \frac{c_{it}}{\alpha_3^u} \exp[\alpha_S^u S(\mathcal{W}_{it}, t_i, D_i) + \alpha_8^u x_{it} + \alpha_9^u H_{it} + \alpha_{10}^u E_{it}]. \tag{12}$$

combines material consumption c_{it} (normalized by the fixed constant α_3^u) with multiplicative utility shifters capturing body weight, effort, health, and work. The function $S(\mathcal{W}_{it}, t_i, D_i)$ captures the disutility of excess weight. If $\alpha_S^u < 0$, this term reflects discomfort or overweight stigma, varying with age and gender.

Modeling health, effort, work, and body weight as multiplicative shifters of effective consumption implies that their marginal utility effects are proportional to consumption. This specification is chosen to remain as neutral as possible for willingness to pay (WTP) measures derived from the model later. It ensures that period WTP for weight reduction is proportional

to consumption and independent of disutility from effort, health, and work. As a result, heterogeneity in dynamic WTP is driven by the model's state transitions, such as the effects of body weight on future health, longevity, labor market outcomes, and marriage, rather than by restrictive functional form assumptions.[10]

3.2. Bellman Equations and Dynamics

Let the individual state vector be $\Omega_{it} = \{D_i, A_{it}, \mathcal{W}_{it}, H_{it}, E_{it}\}$. Conditional on the current state, individuals choose weight-control effort x_{it} and consumption c_{it}, which determines next period assets A_{it+1} through the budget constraint. Single individuals decide whether to enter marriage if a potential partner is encountered.

Value functions depend on both employment and marital status. We therefore distinguish between employed (V) and non-employed (U) individuals, as well as between singles (S) and married individuals (M). For singles, the Bellman equations are

$$\begin{aligned} V_t^S(\Omega_{it}) = \max_{x_{it}, A_{it+1}} \; & u(c_{it}, x_{it}, \Omega_{it}) \\ & + \beta \pi_{it+1} \lambda_{it+1}^{SV} \mathbb{E} \max\left[V_{t+1}^S(\Omega_{it+1}), \mathbb{I}_{it,t+1}^M (V_{t+1}^M(\Omega_{it+1}) + z(\tilde{\mu}))\right] \\ & + \beta \pi_{it+1} \left(1 - \lambda_{it+1}^{SV}\right) \mathbb{E} \max\left[U_{t+1}^S(\Omega_{it+1}), \mathbb{I}_{it,t+1}^M (U_{t+1}^M(\Omega_{it+1}) + z(\tilde{\mu}))\right], \end{aligned} \tag{13}$$

$$\begin{aligned} U_t^S(\Omega_{it}) = \max_{x_{it}, A_{it+1}} \; & u(c_{it}, x_{it}, \Omega_{it}) \\ & + \beta \pi_{it+1} \lambda_{it+1}^{SU} \mathbb{E} \max\left[V_{t+1}^S(\Omega_{it+1}), \mathbb{I}_{it,t+1}^M (V_{t+1}^M(\Omega_{it+1}) + z(\tilde{\mu}))\right] \\ & + \beta \pi_{it+1} \left(1 - \lambda_{it+1}^{SU}\right) \mathbb{E} \max\left[U_{t+1}^S(\Omega_{it+1}), \mathbb{I}_{it,t+1}^M (U_{t+1}^M(\Omega_{it+1}) + z(\tilde{\mu}))\right]. \end{aligned} \tag{14}$$

Employed individuals retain their jobs with probability λ_{it+1}^{SV}, while non-employed individuals find jobs with probability λ_{it+1}^{SU}. The expectation operator $\mathbb{E}$ integrates over all sources of

[10] Alternative specifications, such as additively separable stigma or differing curvature across utility components, would mechanically generate large WTP differences across the wealth distribution. We therefore adopt the current formulation to let model dynamics drive the results. Under plausible parameterizations, it also implies that effort and work are more burdensome at higher body weight, introducing a realistic behavioral channel linking obesity to economic outcomes. See Appendix A.5 for an extensive discussion of the utility function.

uncertainty, including employment, income, medical expenditures, health, weight dynamics, effort success, and marital matching. Individuals survive to the next period with probability π_{it+1}, while β denotes the discount factor. The term $z(\tilde{\mu})$ denotes the one-time utility gain from marriage with potential partner quality $\tilde{\mu}$, and $\mathbb{I}^{M}_{it,t+1}$ indicates whether a mutually acceptable match occurs.

Married individuals face a similar dynamic trade-off with an exogenous but race-specific probability δ that marriage ends. We refer the reader to Appendix A.2.9 for details.

3.3. Willingness to Pay for Weight Reduction

We use the model to compute individuals' WTP for a weight-loss technology. Specifically, we calculate the compensating variation that makes an individual indifferent between the current state and a counterfactual with a 10 percent lower body weight. It represents the amount of assets an individual would be willing to pay for such a reduction in weight.

Let Ω_{it} denote the current state of individual i at age t. Define the counterfactual state

$$\widetilde{\Omega}_{it} = \{D_i,\, A_{it} - WTP^{s}_{it},\, 0.9\,\mathcal{W}_{it},\, H_{it},\, E_{it}\}, \qquad s \in \{S, M\}, \tag{15}$$

where s indexes marital status. The WTP is defined by

$$V^{s}_{t}\big(\widetilde{\Omega}_{it}\big) = V^{s}_{t}(\Omega_{it}), \qquad s \in \{S, M\}. \tag{16}$$

This measure captures the private value of a persistent reduction in body weight, holding the economic environment fixed[11].

The resulting WTP is a one-time payment,

[11] In computing this WTP, we keep the value functions fixed at their estimated baseline. Individual WTP therefore abstracts from the possibility that other individuals also adopt the technology, which may shift the population distribution of BMI and thereby affect marriage rankings. In Figure 9, we also report the opposite benchmark, in which individuals expect universal adoption and the marriage market adjusts through the induced change in the population distribution. Finally, the definition above uses the notation for employed individuals. WTP for non-employed individuals is defined analogously.

$$WTP_{it}^{s} = WTP^{s}(D_i, A_{it}, \mathcal{W}_{it}, H_{it}, E_{it}, t), \qquad s \in \{S, M\}, \tag{17}$$

which varies across individuals and states. Appendix A.5 derives a first-order approximation of this WTP, making explicit that it incorporates all dynamic channels through which body weight affects lifetime utility.

We also compute an analogous WTP that accounts for potential side effects of weight-loss drugs. In this counterfactual, individuals experience both a 10 percent reduction in body weight and a 10 percent reduction in effective consumption, capturing the possibility that appetite suppression lowers the enjoyment derived from consumption.[12] The resulting WTP is the compensating reduction in assets that leaves individuals indifferent between the baseline state and this alternative state with lower body weight and lower effective consumption.

At each age, the model implies a distribution of WTP, $f_t(WTP)$. Although this is a simple compensating variation, it reflects all channels through which body weight affects individual welfare, including health, longevity, labor market outcomes, and marriage (see Appendix A.5 for an extensive discussion). The cumulative distribution function $F(\cdot)$ directly yields the demand curve for a technology that reduces body weight by 10 percent. At price p, the adoption rate is $1 - F(p)$.

Because individuals face borrowing constraints, WTP is bounded by available assets. Nevertheless, it provides a transparent measure of demand for weight reduction and a useful tool for decomposing its underlying drivers.

[12] Because utility is CRRA in effective consumption, a 10 percent reduction in effective consumption does not imply a 10 percent reduction in consumption utility. The resulting loss depends on the level of effective consumption and the curvature of the utility function and is smaller at higher consumption levels. See Appendix A.5.

4. Estimation and Identification

The model links body weight, health, employment, wages, savings, marriage, and mortality over the life cycle. Estimation therefore requires disentangling the effects of excess body weight from persistent individual heterogeneity, endogenous selection, and the dynamic interactions among health, economic outcomes, and body weight. We do so by jointly estimating all model components using moments that capture both cross-sectional and within-individual variation. Fixed heterogeneity is incorporated via latent ability and body type characteristics, while endogenous selection operates through employment, marriage, and mortality. The model also allows health and wealth to affect and be affected by body weight, reflecting the fact that these variables are both determinants and consequences of excess body weight over the life cycle. The combination of multiple data sources and life cycle moments allows us to identify the key behavioral and outcome processes and to quantify the contribution of different channels through which excess body weight affects lifetime outcomes. We now describe the estimation strategy and discuss identification in more detail.

4.1. Estimation

We estimate the parameter vector using the simulated method of moments (SMM), implemented as indirect inference (Gouriéroux et al. 1993; McFadden 1989). To address the curse of dimensionality, we solve the model and evaluate value functions on a discretized state space and interpolate between grid points, following Keane and Wolpin (1994). The body weight shock, wage uncertainty, and medical expenditure uncertainty are approximated using Gauss Hermite quadrature (see Appendix A.2 for details). We then simulate life-cycle histories and compute the same moments as in the data (e.g., regression coefficients, age profiles, and conditional gradients). Parameters are chosen to minimize the weighted distance between empirical and simulated moments, using a diagonal weighting matrix based on inverse sampling variances. Appendix A.1 provides details on the state space and numerical implementation.

Standard errors are computed using the asymptotic variance formula for SMM indirect inference estimators (Gouriéroux et al. 1993). Counterfactual standard errors are computed via a parametric bootstrap, drawing parameters from the asymptotic distribution and recomputing outcomes.

4.2. Identification

We use 319 moments to identify 156 parameters. These moments are generally based on reduced-form regressions and age profiles constructed from the datasets described above. Cross-sectional variation captures differences across individuals, while panel data (PSID and NLSY) provide within-individual variation to disentangle effects of body weight from time-invariant unobserved heterogeneity. Appendix A.3 lists the full set of moments and discusses parameter identification; here, we summarize the key sources of identification.

Employment and wages. Employment dynamics are identified from age profiles of employment, demographics, marital status, health, and body weight, as well as panel regressions of within-individual changes. Moments conditional on lagged employment separately identify job-finding and job-separation probabilities. Wage parameters are identified from age profiles, wage differentials by body weight and cohort, demographic gradients, and panel regressions of changes in wages and body weight.

Health, medical expenditures, and longevity. Health transitions are identified using moments on age profiles, BMI gradients, health persistence, and panel variation in health and body weight. Medical expenditure parameters are identified from MEPS (and HRS at older ages) using age profiles conditional on health and demographic gradients. Longevity is identified from life tables and HRS moments on mortality by age, lagged health, and demographics, as well as age-at-death differences across BMI categories.

Body weight and effort. Weight dynamics are identified from NHANES moments on levels and dispersion by age, cohort, and demographics, combined with panel evidence on within-

individual weight changes. Measurement error in BMI is identified from NHANES moments using measured and self-reported values (see Section 3.1 for details).

Marriage. Marriage parameters are identified from age profiles of marriage by body weight and gender, as well as spousal correlations in health, education, wages, and body weight at the time of marriage formation. Moments capturing the correlation between spouses' log wages are used to identify economic assortative matching. Together, these moments discipline both sorting patterns in the marriage market and the contribution of economic resources to marriage formation and match quality.

Preferences and resources. Preference parameters are identified from asset profiles (PSID) and effort behavior (NHANES), including variation over the life cycle, demographic heterogeneity, and body weight gradients. The value of statistical life is calibrated to external estimates from the literature (see Appendix A.3.9 for details).

Taken together, these moments ensure that the model matches key life-cycle profiles, the conditional gradients, and dynamic relationships. The combination of cross-sectional and panel moments strengthens identification of the effects of body weight on economic and health outcomes. Appendix A.3 describes the full set of moments intended to identify each parameter, while Figure C.1 shows how these moments respond to parameter variation in the implemented model.

4.3. Goodness of Fit

Figure 5 assesses model fit by plotting simulated against observed moments. The resulting R^2 is 0.99. Appendix C provides additional graphical comparisons of life-cycle profiles across demographic groups, and replicates the descriptive Figures 1, 2, 3, and 4 with simulated data (Figures C.2 to C.14). Overall, the model closely matches the observed evolution of body weight, effort behavior, wages, medical expenditures, and health, and replicates key patterns observed in the data.

5. The Cost of Excess Body Weight and the Demand for Weight Reduction

We begin by discussing the key parameter estimates and the implied marginal effects of excess body weight on various outcomes. We then use the model to quantify individuals' willingness to pay (WTP) for weight reduction and examine heterogeneity in demand. Finally, we decompose WTP to identify the relative importance of the health, longevity, labor market, and marriage market channels in shaping the private value of weight reduction.

5.1. Parameter Estimates and Marginal Effects of Excess Body Weight

Tables C.1 to C.11 report the full set of parameter estimates. Here, we focus on the parameters central to understanding the life-cycle consequences of excess body weight and the demand for weight reduction.

The model estimates imply that conventional weight-control effort is both costly and largely ineffective at producing substantial and sustained weight loss.[13] Together, these high costs and limited effectiveness of weight-control effort make the consequences of excess body weight particularly important. We therefore begin by quantifying its effects on health, longevity, and labor market outcomes.

Table 1 reports model-implied marginal effects of BMI on health, life expectancy, wages, employment, and marriage market ranking. Because several components of the model are nonlinear, the estimated coefficients are not directly interpretable. We therefore compute marginal effects by assigning alternative BMI values to each simulated individual while holding all other state variables fixed, and then taking population weighted averages. The resulting estimates quantify the causal effect of BMI on each outcome, holding all other determinants constant.

[13] The probability of success is estimated at 4.5 percent. The estimated utility cost of effort is −0.262, equivalent to a reduction in effective consumption of roughly one quarter. The resulting utility loss depends on the level of material consumption and the curvature of the CRRA utility function (see equations (11) and (12)). See Tables C.7 and C.11 for the parameter estimates.

The estimated relationship between BMI and health is highly nonlinear (Panel A). Relative to a BMI of 22.5, increasing BMI to 32.5 lowers the probability of being in good health one year later by 1.8 percentage points, while a further increase to 42.5 reduces it by 12.3 percentage points.[14] The implied effects on longevity are likewise substantial (Panel B): moving from a normal BMI to obese reduces life expectancy by 1.5 years, while severe obesity lowers it by 5.0 years. These findings mirror the descriptive evidence in Figure 3, which shows a steep decline in health with BMI and strong positive association between BMI and mortality even conditional on health.

The labor-market consequences of excess body weight display striking gender differences (Panel C). Wage penalties are substantially larger for women than for men and increase sharply with BMI. Relative to normal weight, women's hourly wages decline by USD 0.26 (0.9%) when overweight, USD 2.43 (8.5%) when obese, and USD 3.08 (10.7%) under severe obesity. The corresponding declines for men are USD 0.29 (0.9%), USD 0.97 (3%), and USD 1.75 (5.4%), respectively.

Employment effects likewise fall disproportionately on women and are concentrated at the hiring margin (Panels D and E). Among employed individuals, moving from a normal BMI to obesity reduces the probability to be employed one year later by 2.4 percentage points on average, 3.1 points (4%) for women compared with 1.6 points (2%) for men. Among the non-employed, the same increase in BMI lowers the probability of finding a job within the following year by 5.10 points (10.4%) for women and 3.31 points (5.8%) for men. Overall, these estimates are broadly consistent with the empirical literature documenting adverse effects of excess

[14] To place these magnitudes in context, we consider a counterfactual that eliminates differences by education by assigning low-educated individuals the employment, wage, health, and medical expenditure processes of the highly educated. Table C.13 in Appendix C reports the results. Average BMI among the low educated declines by only 0.27 points, yet the probability of good health increases by 10.42 percentage points. Thus, the education gradient in health is comparable in magnitude to the model-implied health loss associated with moving from a normal BMI to severe obesity. The same counterfactual increases assets among the low educated by 42.2 percent and life expectancy by 3.8 years, illustrating the broad life-cycle consequences of educational disparities.

weight on wages and employment, particularly for women (e.g., Cawley 2015; Rooth 2009; Diamond 2026).

The estimates above isolate the direct effect of excess body weight on life expectancy, wages, and employment, holding health constant. Excess weight also affects these outcomes indirectly by reducing the probability of good health. We quantify this mechanism by combining the estimated effect of BMI on health with the effect of health on each outcome. When moving individuals from normal BMI to severe obesity, this indirect health channel reduces life expectancy by more than three years, lowers hourly wages by about USD 0.18, and reduces employment probabilities by roughly 2 percentage points (Table C.12).

Body weight is a major determinant of marriage-market outcomes, particularly for women. Holding all other characteristics and the population distribution of potential partners fixed, moving from the normal BMI range to obesity lowers women's marriage-market ranking by 25.07 percentile points (38%), while severe obesity lowers it by 41.0 percentile points (62%, Panel F).[15] The corresponding declines for men are smaller but still substantial, at 17.13 (30%) and 27.95 percentile points (49%), respectively. These estimates imply that obesity affects not only the likelihood of marriage, as suggested by Figure 1, but also the expected quality of potential matches and, consequently, the gains from marriage, as discussed in Section 3.

Beyond body weight, education and health are the strongest determinants of marriage-market ranking (Table C.14). Weight-control effort is also associated with a substantial improvement, while race has comparatively small effects. Wealth, in contrast, matters much more for men than for women. Increasing assets from USD 20,000 to USD 100,000 raises men’s marriage-market ranking by 10.59 percentile points and increasing them to USD 500,000 raises it by 22.7 percentile points, while the corresponding effects for women are only 3.89 and 8.30 percentile

[15] We vary each determinant of marriage quality while holding all other characteristics fixed and recompute the individual's marriage quality. The resulting counterfactual is ranked relative to the baseline population, separately for men and women. Population-weighted average rank changes then measure how an individual's marriage-market rank changes when only their own characteristics change, and all potential partners remain unchanged.

points. Thus, wealth partly offsets the marriage-market disadvantage associated with excess body weight for men, whereas this compensating mechanism is much weaker for women.

Overall, the estimates reveal that excess body weight affects nearly every dimension of economic well-being. It worsens health, reduces longevity, lowers employment and wages, and substantially reduces marriage-market prospects, with labor-market and marriage-market penalties being considerably larger for women. These effects jointly determine the lifetime welfare cost of excess body weight, and, ultimately, the value individuals place on sustained weight reduction. We now turn to quantifying this value through WTP measures for permanent reductions in body weight and by decomposing the mechanisms that drive them.

5.2. Drivers of the Demand for Weight Reduction

We quantify the private value of weight reduction by computing individuals' WTP for a technology that permanently lowers body weight by 10 percent (Section 3.3). WTP is the compensating variation in assets that leaves an individual indifferent between the baseline and a counterfactual with a permanent 10 percent lower body weight. Because it incorporates all consequences of BMI, including health, labor-market outcomes, medical expenditures, marriage, and longevity, WTP provides a comprehensive measure of the private value of weight reduction. For a population representative of the U.S., average WTP amounts to USD 79,383, equivalent to a perpetual monthly payment of USD 271.[16]

This baseline measure abstracts from potential side effects. We therefore also compute an alternative WTP in which a 10 percent reduction in body weight is accompanied by a 10 percent reduction in effective consumption, as discussed in Section 3.3. This captures the possibility that appetite suppression reduces the utility derived from consumption. This utility cost is

[16] Specifically, we convert the *one-time* WTP into a *perpetual monthly* payment wtp_m using the geometric series and the model's annual discount factor, $wtp_m = WTP\,\frac{1-\beta^{1/12}}{\beta^{1/12}}$.

moderate relative to the estimated disutility of conventional weight-control effort, which is estimated to reduce effective consumption by roughly 25 percent. Even under this more conservative scenario, the average WTP remains substantial, amounting to USD 37,103, equivalent to a perpetual monthly payment of USD 126 (see Figure C.17).

5.2.1 Heterogeneity in Willingness to Pay

WTP varies widely across individuals because it reflects both the lifetime benefits of lower body weight and the financial resources available to obtain it. Figure 6 illustrates this heterogeneity by plotting coefficients from regressions of model-implied WTP on demographic characteristics and age groups (Panel (a)) and on current state variables (Panel (b)).

WTP peaks around retirement age and increases with education, ability, body type, BMI, and weight-control effort. It is lower for women and varies little by race, health, or employment status. The strongest predictor, however, is wealth: individuals with assets exceeding USD 500,000 have an average WTP roughly USD 80,000 higher than those with assets below USD 50,000. Allowing for side effects lowers WTP but leaves these patterns largely unchanged (Figure C.15).

To isolate the role of preferences from financial resources, Figure 7 recomputes WTP after assigning every individual USD 100,000 in assets. Equalizing assets shifts the WTP profile towards younger ages and slightly raises WTP for women, indicating that much of the observed heterogeneity reflects wealth rather than preferences.

Resource constraints also shape demand across racial groups. Figure C.16 in Appendix C reports predicted demand curves by race and obesity status, with and without side effects. Demand is higher among obese individuals, while side effects sharply reduce demand among the non-obese. At high prices, demand is greatest among White individuals, primarily because they have greater financial resources rather than stronger preferences for weight reduction. This again highlights an important distributional implication of market-based allocation: when

access depends on ability to pay, weight-loss technologies are adopted disproportionately by wealthier groups, potentially widening disparities in health and economic outcomes. At moderate or low prices, however, these disparities may narrow if groups with the largest obesity-related welfare losses can increasingly afford treatment. This distributional trade-off motivates the policy analysis in Section 6, where we evaluate how pricing and prescription rules affect take-up, outcomes, and inequality.

5.2.2 What Drives the Demand for Weight Reduction?

To understand what drives demand, we next decompose WTP into its underlying channels (Table 2). We remove each channel through which BMI affects lifetime utility and measure the resulting change in WTP, either one at a time, Panel A, or cumulatively, Panel B. Specifically, individuals are assigned the outcome effects associated with a normal BMI (18.5 to 25), regardless of their simulated BMI. Parameters associated with being underweight (BMI below 18.5) are left unchanged, so that variation in WTP reflects only the consequences of excess weight.

Panel A shows single-channel exclusions. The columns display the resulting counterfactual outcomes. The first row reports the baseline values for the study population, while subsequent rows show the outcomes obtained after shutting down the corresponding channel, with the percent impact for each outcome shown underneath.[17]

Health and longevity account for the overwhelming share of WTP. Removing the health channel reduces WTP by 18.1 percent and lowers weight-control effort by 31.5 percent, leading to a modest increase in BMI (Panel A). Removing the longevity channel reduces WTP by 20.7 percent.

[17] Table C.15 reports bootstrap standard errors for overall WTP and the exclusion counterfactuals. For the exclusion counterfactuals, we isolate the precision of the counterfactual change from overall sampling variation. In each bootstrap iteration, we compute the difference between the exclusion counterfactual and the baseline outcome and report the standard error of this difference.

By contrast, labor-market channels contribute less than health and longevity. Removing the wage channel raises WTP by 1.9 percent. Removing the employment channel leaves WTP unchanged at the reported precision. Although shutting down labor-market effects reduces the incentives to lose weight, it also increases lifetime earnings and therefore the ability to pay for weight reduction. The net contribution of labor market channels is therefore more subtle, as the decomposition in Section 5.2.3 shows.

Panel B reports cumulative exclusions. Eliminating the health and longevity channels together reduces WTP by 80.3 percent.[18] Shutting down the wage and employment channels in addition has little further effect. Once the marriage channel is also removed, leaving only the direct utility cost of excess weight, WTP falls below USD 10,000. Shutting down all channels reduces WTP to zero, providing a useful consistency check on the decomposition.

Figure 8 shows that the hump-shaped life-cycle profile of WTP is almost entirely explained by health and longevity. Longevity is especially important between ages 40 and 65, when changes in expected longevity strongly affect lifetime decisions, particularly savings. The health channel becomes increasingly important at older ages, while labor market and marriage market channels matter mainly earlier in life.

Overall, the decomposition shows that the private value of weight reduction is driven primarily by improvements in health and longevity. Because removing a channel also changes behavior, including weight-control effort, savings, longevity, and marriage-market outcomes, we next present additional decompositions that separate incentive effects from wealth effects, distinguish gains in healthy life from gains in longevity, and quantify the role of endogenous adjustment in the marriage market.

[18] Because WTP is determined within a dynamic, nonlinear model, the cumulative effects in Panel B need not equal the sum of the individual exclusion effects in Panel A. Jointly excluding channels also captures interactions among them.

5.2.3 Additional Decompositions

The previous decomposition identifies which channels matter but not why. We therefore perform three additional exercises. First, we separate incentive effects from wealth effects. Second, we decompose the health channel into quality-of-life and longevity components. Third, we quantify the role of endogenous adjustment in the marriage market.

Table 3 shows that removing any channel reduces incentives to lose weight (column 3). When BMI no longer lowers earnings (through either wages or employment probability), it weakens incentives to reduce weight but provides higher resources that increase the ability to pay for weight reduction (column 4). The health and longevity channels affect wealth through different mechanisms. Removing the health channel lowers average assets, consistent with weaker precautionary saving motives, whereas removing the longevity channel increases assets by extending expected lifetimes and strengthening incentives to save.

We next decompose the health channel into gains in healthy life and gains in longevity.[19] Table 4 shows that both matter but at different stages of the life cycle. Earlier in life, the value of better health arises primarily through longer expected lifetimes. At older ages, by contrast, avoiding poor health becomes the dominant source of value, while life extension contributes relatively little.

Finally, we assess equilibrium adjustment in the marriage market (Figure 9) by comparing WTP when individuals value weight reduction assuming no one else adopts the technology with WTP after allowing marriage-market rankings to adjust as if everyone adopted it. Equilibrium effects are small: even at age 30, when marriage incentives are strongest, endogenous adjustment increases WTP by less than USD 1,000.

[19] To isolate the healthy life component, we remove the effect of BMI on health while holding longevity fixed at its baseline level. The difference between this counterfactual and the full health exclusion captures the life extension component.

Taken together, these results show that the private value of weight reduction is driven mainly by health and longevity. Labor-market and marriage-market channels create incentives to reduce weight, but their quantitative importance remains modest, and wealth effects partly offset their impact on measured WTP.

More broadly, the analysis illustrates why evaluating the long-run effects of weight-loss technologies requires a structural life-cycle framework. Behavioral responses, savings, longevity, and endogenous changes in individual states interact over the life cycle, making it necessary to analyze these mechanisms jointly.

6. Counterfactual Simulations

We next use the estimated model for two counterfactual exercises. First, we evaluate broad, low-price access to an effective weight-loss technology, examining its effects on take-up, health, economic outcomes, and inequality. We then compare simulated adoption patterns with observed GLP-1 use in MEPS to assess whether the model captures the characteristics of individuals who select into treatment. Second, we compare targeted and preventive prescription regimes to quantify the trade-off between treating individuals with existing obesity-related health problems and intervening earlier to prevent them.

6.1. Effects of a Low-Price Weight-Loss Technology

6.1.1 Average Effects

We first evaluate broad access to an effective weight-loss technology (WLT). The technology reduces BMI by 10 percent while in use and can be purchased at a fixed annual price. It affects current body weight, but weight immediately returns to its latent path once treatment stops. Because adoption changes the population distribution that determines marriage-market rankings, we solve for the corresponding equilibrium iteratively. We set the annual price at USD 600, or USD 50 per month, to represent a low-price access regime. Table 5 (Column 2)

reports the aggregate effects of this market-based access, while Table C.16 presents bootstrapped standard errors for the corresponding differences from the baseline scenario.

Adoption is high, with 82.3 percent of individuals choosing the technology. This is not surprising: almost three quarters of US adults are overweight or obese, and some individuals below the overweight threshold also value weight reduction. If the WLT also reduces effective consumption by 10 percent, capturing side effects, uptake falls to 52.9 percent (Table C.18).

Broad access substantially reduces body weight. Average BMI declines by 7.6 percent, while traditional weight-control effort falls by 17.3 percent, indicating substantial substitution away from conventional methods of weight reduction.

The reduction in body weight translates into broad improvements in health and economic outcomes. Health improves, total medical expenditures fall by 6.5 percent, and life expectancy increases by more than one year.[20] The longevity gains have fiscal implications: lower non-WLT medical spending eases pressure on the health system, while longer lives increase the duration of retirement.

Labor-market gains are positive: employment rises by 0.9 percent and wages by 1.6 percent. Under our assumption of competitive labor markets, these wage gains reflect higher individual productivity, implying that low-price WLT access also increases aggregate productivity in the economy. Average consumption increases slightly, while asset holdings decline by 1.3 percent. Individual welfare gains are sizable, with flow utility increasing by 0.5 percent and lifetime utility by 1.3 percent.

Broad access also reduces inequality. The Gini coefficients for assets and lifetime utility decline by 1.3 and 6.5 percent, respectively, while inequality in longevity also falls. Although the

[20] We impute total medical expenditures from MEPS using linear regressions on demographics, age categories, BMI categories, out-of-pocket medical expenditures, and health. Total medical expenditures capture direct payments for healthcare services received during the year, including payments by individuals, private insurance, Medicare, Medicaid, and other sources.

White-Black gap in life expectancy changes little, the overall pattern suggests that broad access generates large private welfare gains while reducing both economic and health inequalities.

Overall, low-price access to effective weight-loss technology generates substantial improvements in health, longevity, and individual welfare.

6.1.2 Heterogeneity in Adoption and Outcomes

The gains from low-price access are widespread but differ across population groups (Figure 10). Adoption is high for all groups, but it is highest among individuals with high body type, higher education, and higher ability, reflecting both the expected gains from weight reduction and the resources needed to purchase the technology.

The largest improvements occur among groups with greater obesity-related health risks. Individuals with high body type experience the largest BMI reductions and the greatest decline in traditional weight-control effort. Health gains are especially large for black and older individuals, and those with high body type. Welfare gains are positive for all groups, but largest for Blacks and Hispanics, women, and individuals with high body type. Asset holdings decline more strongly among older individuals and those with high body type, consistent with reduced precautionary saving. Figure C.19 reports heterogeneity in additional outcomes and shows that women experience larger labor market gains than men, with a slightly greater increase in employment (Panel d) and a substantially larger rise in hourly wages (Panel c).

Thus, although adoption is somewhat higher among wealthier groups, the largest health and welfare gains accrue to those with the greatest losses of excess body weight. As a result, broad access reduces several dimensions of inequality.

6.1.3 A Comparison with Early GLP-1 Uptake

To assess whether the model captures who is most likely to adopt weight-loss technologies, we compare simulated uptake of the weight-loss technology with observed GLP-1 use in MEPS

2022 and 2023. The goal is not to match aggregate uptake, which depends on access frictions, insurance coverage, uncertainty, and the early stage of the market, but rather to assess whether the model correctly predicts which groups are over- or under-represented among users. Appendix B provides details.

To make the simulation broadly comparable to the early GLP-1 market, we restrict first access to random ages, focus on the first two years after treatment becomes available, impose an annual out-of-pocket price of USD 600, and allow the technology to reduce body weight by 10 percent while imposing a 10 percent reduction in effective consumption.

Figure 11 reports representation indices, defined as each group's share among users divided by its population share. The model reproduces the main qualitative selection patterns observed in the data. In both the simulation and MEPS, users are disproportionately drawn from high-BMI individuals, while those with normal weight and good health are underrepresented. The model also captures the broad age profile of uptake. The largest discrepancies concern race and older ages, where the model predicts greater representation of Black, Hispanic, and older individuals than observed. These differences likely reflect forces outside the model, including insurance coverage, physician prescribing behavior, and access frictions. Overall, the model captures the principal economic and demographic determinants of early uptake, particularly selection by BMI and health risk.

6.2 Who Should Receive Treatment? Targeted versus Preventive Access

A central policy question is whether access to weight-loss technologies should be restricted to individuals who already suffer from obesity-related health problems or whether treatment should be offered earlier as a preventive intervention. Restricting access concentrates resources on individuals with the greatest current health needs, whereas broader access may generate larger long-run gains by preventing future health deterioration.

In practice, access to weight-loss drugs is typically tied to a diagnosis of clinical obesity, which requires evidence of obesity-related health impairment rather than obesity alone (Rubino et al. 2025). Such criteria guide current policy in a wide range of countries (Chao et al. 2024), including NICE guidelines in the UK and large parts of U.S. coverage.[21]

We compare two prescription regimes. Under an obesity-plus rule, access is restricted to individuals with BMI above 30 who are in poor health. Under an obesity-only rule, all individuals with BMI above 30 are eligible regardless of health status. Eligible individuals receive the technology at zero cost and retain access even if eligibility conditions subsequently change[22]. To isolate the direct effects of the policies, individuals are assumed not to anticipate future eligibility.[23]

Table 5 (Columns 3 and 4) report the aggregate effects of the two prescription regimes, while Table C.17 presents bootstrapped standard errors for the corresponding differences from the baseline economy. Expanding eligibility from the obesity-plus rule to the obesity-only rule raises uptake from 24.9 percent to 58.0 percent. As a result, average BMI falls by 5.7 percent under obesity-only, compared with 2.5 percent under obesity-plus. Weight-control effort declines under both policies, but more strongly under the preventive regime, indicating that the technology substitutes for conventional weight-control methods.

Earlier intervention translates into larger health gains. The share of individuals in good health increases by 2.3 percent under obesity-only, compared with 1.8 percent under obesity-plus, while life expectancy increases by roughly one year under both policies. Out-of-pocket medical

[21] The "obesity-plus" logic is explicit in the UK, where NICE 2026 guidelines condition access on at least one weight-related comorbidity, and in the US, where Medicare coverage is generally limited to cases involving diabetes or cardiovascular disease. At the same time, preventive approaches are gaining attention in the policy debate, and WHO guidance does not require comorbidities for treatment. Our counterfactuals capture this central trade-off between targeted and preventive access.

[22] This assumption prevents mechanical switching around the eligibility threshold and explains why uptake can exceed the share of individuals currently classified as obese.

[23] We solve the model separately with and without access to the technology and assign policy functions based on realized eligibility. This abstracts from strategic behavior. Moreover, we abstract from reasons that may justify prescription-based access in practice, including clinical screening, safety monitoring, and restrictions on treatment when it is medically inappropriate.

expenditures change little, suggesting that most spending effects operate through total medical costs rather than direct individual payments, as already indicated by Figure 2. Total medical spending declines by 4.0 percent under obesity-plus and by 6.6 percent under obesity-only. Whether total medical expenditures, including WLT costs, ultimately rise or fall depends on the technology's procurement price.

The key difference between the two policies is timing. Under obesity-plus, many recipients have already left the labor market, whereas obesity-only reaches more individuals earlier in life. Earlier intervention therefore produces larger economic gains (columns 3 and 4). Wages rise by 1.6 percent under obesity-only, compared with 0.7 percent under obesity-plus, while employment increases by 1.0 percent rather than 0.4 percent. Lifetime utility rises under both policies. Because treatment is free, consumption increases more than under market allocation, while assets change little.

Both prescription regimes reduce inequality in assets, lifetime utility, and longevity. Welfare inequality, measured by the Gini coefficient of the value function at age 40, declines more than under market allocation (column 2) because access no longer depends on financial resources. By contrast, the reductions in asset and longevity inequality are similar to those under broad low-price access.

The central policy margin is not whether treatment is provided but when it begins. Broad market access and broad prescription-based access yield similar improvements in health, welfare, and inequality when treatment is delivered early in life. Within prescription-based allocation, however, earlier intervention is substantially more effective. Treating obesity before major health deterioration occurs yields larger gains in health, employment, wages, and medical spending than waiting until obesity-related disease has already emerged. The key trade-off is therefore not between treatment and no treatment, but between prevention and treatment after disease onset.

7. Conclusion

We develop and estimate a structural life-cycle model to study the consequences of obesity and the effects of weight-loss technologies. The model captures the effects of body weight on health, medical expenditures, labor market outcomes, marriage, and longevity, and allows us to quantify individuals' willingness to pay for weight reduction and to evaluate alternative policies governing access to treatment.

Several findings emerge from the analysis. First, the private value of weight reduction is driven primarily by improvements in health and longevity. Labor market and marriage market channels are less important. However, the adverse effects of excess body weight on wages, employment, and marriage are sizeable, and substantially larger for women. Second, because conventional weight-control efforts are costly and only modestly effective, improved weight-loss technologies generate substantial individual welfare gains. Demand varies widely across individuals, reflecting differences in both the expected returns to weight reduction and the financial resources available to obtain it. Third, broad access at a low price leads to widespread adoption and sizeable improvements in body weight, health, longevity, labor market outcomes, and individual welfare. Although uptake is somewhat higher among wealthier groups, the largest gains accrue to those with the greatest obesity-related losses, reducing several dimensions of inequality. Finally, the timing of treatment matters. Providing treatment before major health deterioration occurs generates larger improvements in health, employment, wages, and medical spending than restricting access to individuals who are already in poor health.

These findings have direct implications for the design of obesity treatment policies. Rather than focusing solely on who should receive treatment, policy should also consider when treatment is provided. At a low price, market-based access produces outcomes similar to a preventive prescription regime because it reaches individuals before substantial health deterioration. This suggests that timing may matter more than the precise allocation mechanism. Prescription-

based access may nevertheless be preferred for considerations outside the model, including preventing inappropriate use and ensuring medical screening, supervision, and advice throughout treatment.

Our analysis abstracts from several factors that may influence the long-run effects of these technologies, including specific clinical side effects, changes in diet and exercise, and broader general-equilibrium responses. Understanding these mechanisms remains an important avenue for future research. More broadly, the paper demonstrates the value of combining structural life-cycle models with rich administrative and survey data to evaluate the long-run consequences of health technologies. The framework extends naturally to other interventions that alter health risks, longevity, and economic behavior over the life cycle.

References

Arcidiacono, P., Sieg, H., & Sloan, F. (2007). Living rationally under the volcano? An empirical analysis of heavy drinking and smoking. *International Economic Review*, 48(1), 37-65.

Averett, S. L. (2011). Labor market consequences: Employment, wages, disability, and absenteeism. In J. Cawley (Ed.), *The Oxford Handbook of the Social Science of Obesity* (pp. 531–552). Oxford University Press.

Bolt, U. (2024). What is the source of the health gradient? The case of obesity. *Working Paper*.

Capatina, E., & Keane, M. (2026). Health shocks, health insurance, human capital, and the dynamics of earnings and health. *Journal of Political Economy*, 134(6), 1714-1774.

Cawley, J. (2015). An economy of scales: A selective review of obesity's economic causes, consequences, and solutions. *Journal of Health Economics*, 43, 244-268.

Chan, T. Y., Hamilton, B. H., & Papageorge, N. W. (2016). Health, risky behaviour and the value of medical innovation for infectious disease. *The Review of Economic Studies*, *83*(4), 1465-1510.

Chao, A. M., Paul, A., Hodgkins, J. V., & Wadden, T. A. (2024). A guideline-directed approach to obesity treatment. *Diabetes Spectrum*, *37*(4), 281-295.

Cronin, C. J., Forsstrom, M. P., & Papageorge, N. W. (2025). What good are treatment effects without treatment? Mental health and the reluctance to use talk therapy. *Review of Economic Studies*, *92*(3), 1699-1737.

Currie, J., & Madrian, B. C. (1999). Health, health insurance and the labor market. *Handbook of Labor Economics*, 3, 3309-3416.

Cutler, D. M., Lleras-Muney, A., & Vogl, T. (2011). Socioeconomic status and health: Dimensions and mechanisms. In S. Glied & P. C. Smith (Eds.), *The Oxford Handbook of Health Economics* (pp. 124-163). Oxford University Press.

Daysal, N. M., Fredrickson, C. J., Kristiansen, I. L., Trandafir, M., & Zhang, J. (2026). The Labor Market Impacts of GLP-1s. *National Bureau of Economic Research, No. w35475*.

De Nardi, M., French, E., & Jones, J. B. (2010). Why do the elderly save? The role of medical expenses. *Journal of Political Economy*, 118 (1), 39-75.

De Nardi, M., Pashchenko, S., & Porapakkarm, P. (2025). The lifetime costs of bad health. *Review of Economic Studies*, 92(3), 1987-2026.

Diamond, R. (2026). GLP-1-induced weight loss and the female obesity penalty. *National Bureau of Economic Research, No. w35387*.

Ehrlich, I., & Chuma, H. (1990). A model of the demand for longevity and the value of life extension. *Journal of Political Economy*, 98(4), 761-782.

French, E. (2005). The effects of health, wealth, and wages on labour supply and retirement behaviour. *The Review of Economic Studies*, 72(2), 395-427.

Galama, T. J., & Van Kippersluis, H. (2019). A theory of socio-economic disparities in health over the life cycle. *The Economic Journal*, 129(617), 338-374.

Gouriéroux, C., Monfort, A., & Renault, E. (1993). Indirect inference. *Journal of Applied Econometrics*, 8(1), 85-118.

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy*, 80(2), 223-255.

Grossman, M. (2000). The human capital model. In *Handbook of health economics* (pp. 347-408, Vol. 1). Elsevier.

Hubbard, R. G., Skinner, J., & Zeldes, S. P. (1994). Expanding the life-cycle model: Precautionary saving and public policy. *The American Economic Review*, 84(2), 174-179.

Keane, M. P., & Wolpin, K. I. (1994). The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte Carlo evidence. *The Review of Economics and Statistics*, 648-672.

Kesaite, V., & Greve, J. (2023). The impact of overweight on employment outcomes: A systematic review of the evidence. *SSRN Electronic Journal 4651508*.

Mahler, L., & Yum, M. (2024). Lifestyle behaviors and wealth-health gaps in Germany. *Econometrica*, 92(5), 1697-1733.

Margaris, P., & Wallenius, J. (2024). Can wealth buy health? A model of pecuniary and non-pecuniary investments in health. *Journal of the European Economic Association*, 22(3), 1097-1138.

Margaris, P., & Wallenius, J. (2026). Together We Tip the Scale: Social Norms and Body Mass. *Centre for Economic Policy Research* (No. 21370).

McFadden, D. (1989). A method of simulated moments for estimation of discrete response models without numerical integration. *Econometrica*, 995-1026.

Ozkan, S. (2025). Income differences and health disparities: Roles of preventive vs. curative medicine. *Journal of Monetary Economics*, *150*, 103698.

Papageorge, N. W. (2016). Why medical innovation is valuable: Health, human capital, and the labor market. *Quantitative Economics*, *7*(3), 671-725.

Rooth, D. O. (2009). Obesity, attractiveness, and differential treatment in hiring: A field experiment. *Journal of Human Resources*, 44(3), 710-735.

Rubino, F., Cummings, D. E., Eckel, R. H., Cohen, R. V., Wilding, J. P., Brown, W. A., et al. (2025). Definition and diagnostic criteria of clinical obesity. *The Lancet Diabetes & Endocrinology*, *13*(3), 221-262.

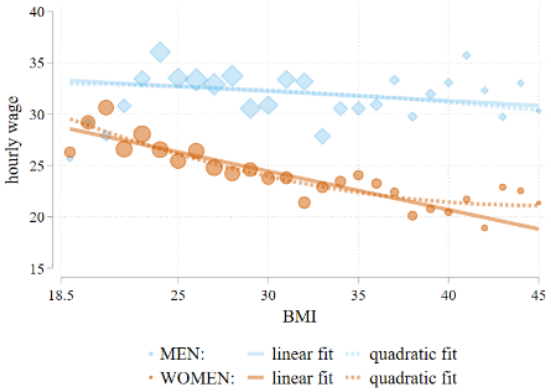
Scholz, J. K., Seshadri, A., & Khitatrakun, S. (2006). Are Americans saving "optimally" for retirement? *Journal of Political Economy*, 114(4), 607-643.

Segal, A. B., Huerta, M. C., Aurino, E., & Sassi, F. (2021). The impact of childhood obesity on human capital in high-income countries: A systematic review. *Obesity Reviews*, 22(1), e13104.

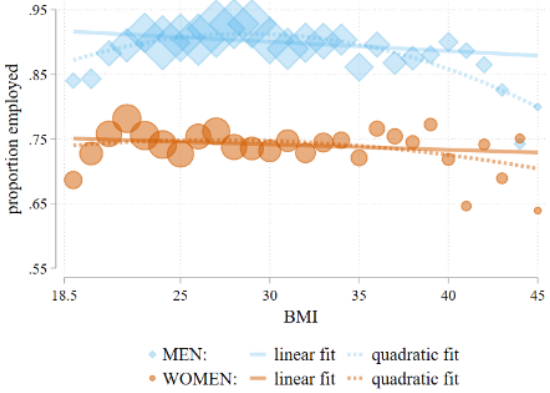
Tables and Figures

Figure 1: Hourly Wage, Employment, and Marital Status by BMI

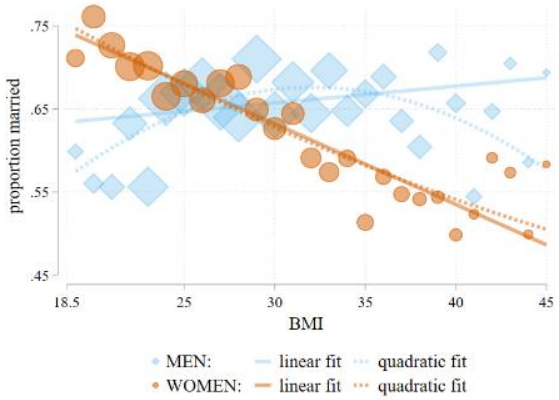
(a) Hourly wage, NLS



(b) Employment, MEPS



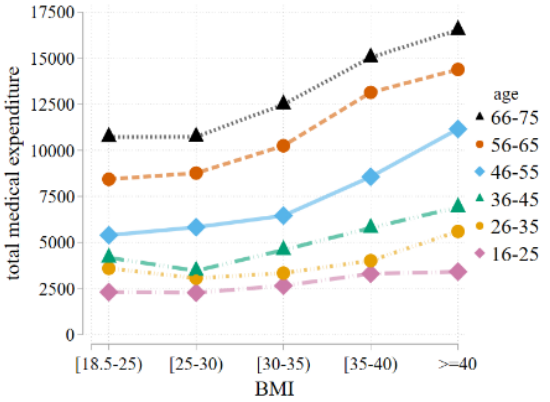
(c) Proportion married, MEPS



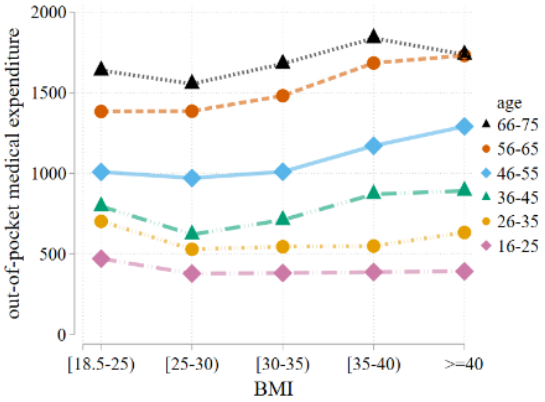
Note: The figure uses weighted MEPS and NLS data for individuals aged 36–40. The MEPS sample includes birth cohorts 1960–1986, while the NLS sample combines the NLSY79 (1957–1964) and NLSY97 (1980–1984) cohorts. Hourly wages are expressed in 2022 USD. Scatter-point size is proportional to the number of observations in each BMI bin. Appendix B presents corresponding figures for ages 30–40 and alternative datasets.

Figure 2: Medical Expenditures by BMI and Age Group

(a) Total medical expenditures



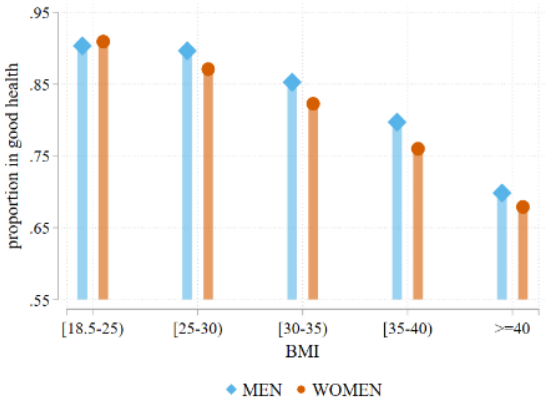
(b) Out-of-pocket medical expenditures



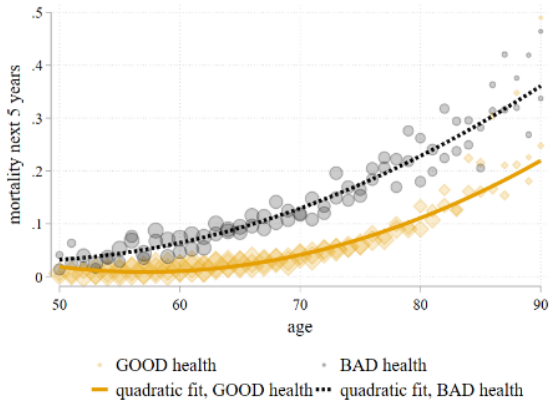
Note: The figure uses weighted MEPS data. Medical expenditures are annualized and reported in 2022 USD. Total medical expenditures include all payments for health care services, regardless of payer. Out-of-pocket expenditures include unreimbursed payments made directly by individuals or their families, including deductibles, copayments, coinsurance, and spending on uncovered services.

Figure 3: Health by BMI and Mortality by Age and BMI

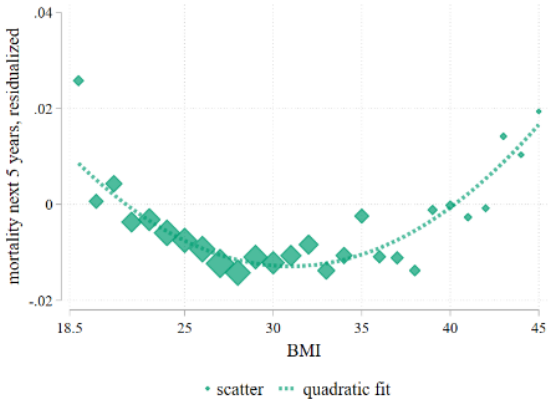
(a) Good health, MEPS



(b) Mortality by age and health, HRS

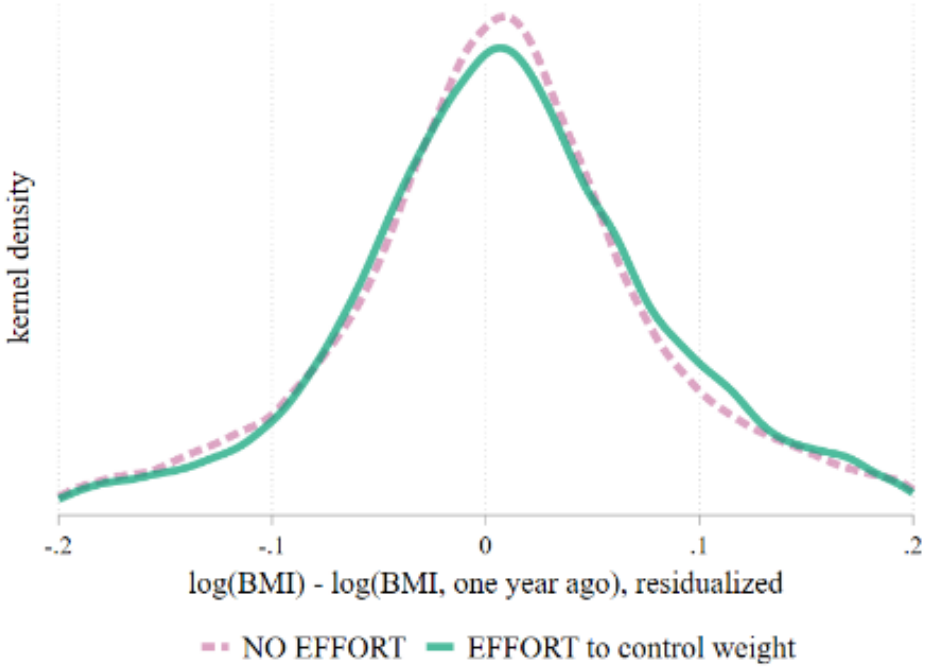


(c) Residualized mortality by BMI, HRS



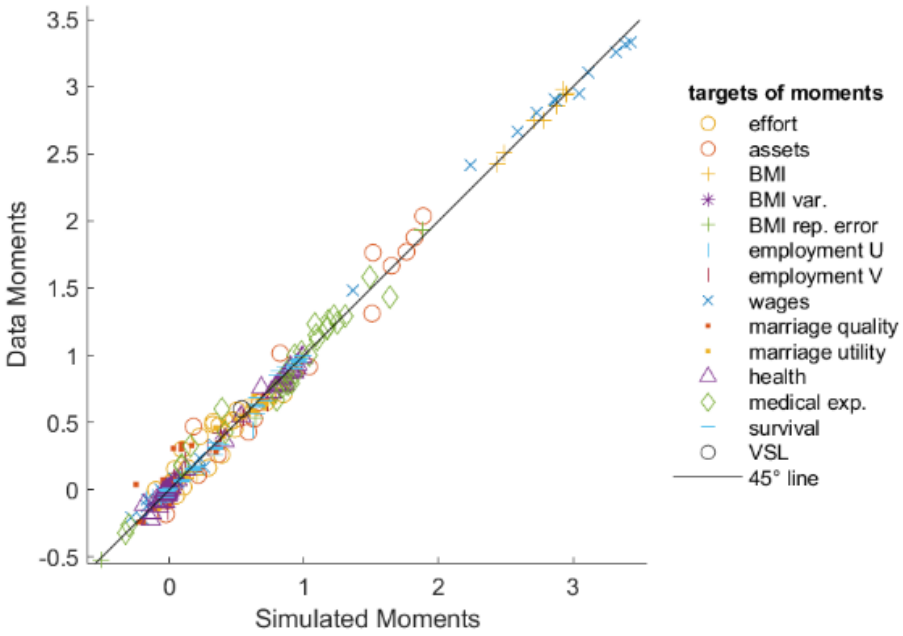
Note: Panel (a) uses weighted MEPS data, while panels (b) and (c) use weighted HRS data. Good health is an indicator equal to one if respondents report excellent, very good, or good health. Mortality is measured over the subsequent five years among individuals aged 50–90 and equals one if the respondent dies within five years of the survey date. In panel (c), mortality is residualized with respect to age-group indicators, health status, and gender. Scatter-point size in panels (b) and (c) is proportional to the number of observations in each age or BMI bin.

Figure 4: One-Year Log Change in BMI by Weight-Control Effort



Note: The figure uses weighted NHANES data. Weight-control effort is an indicator equal to one if respondents report attempting to lose or maintain weight during the previous 12 months. The outcome is the one-year log change in BMI, computed using self-reported BMI one year prior to the survey and measured BMI at the survey date. BMI changes are residualized with respect to age-group indicators, BMI-group indicators, gender, race, body type, and education. Because effort is likely endogenous to idiosyncratic weight shocks and lagged BMI is self-reported whereas current BMI is measured, the comparison is descriptive rather than causal. Densities are estimated using Gaussian kernels.

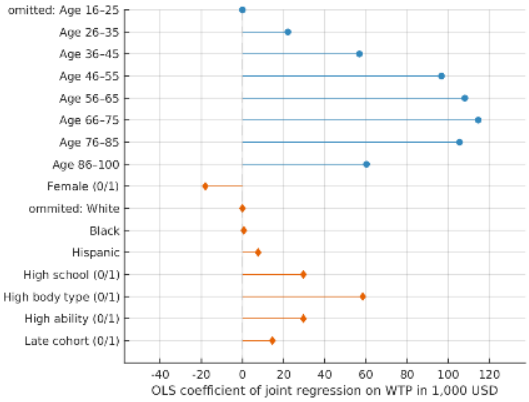
Figure 5: Simulated and Empirical Moments



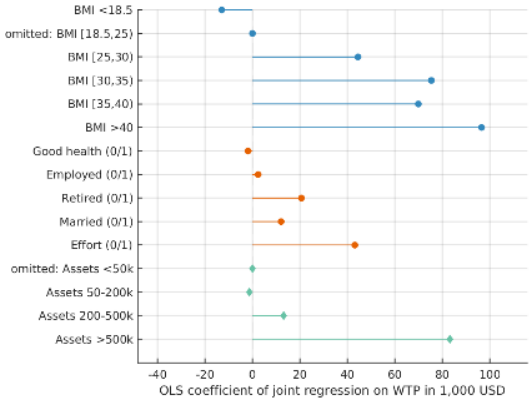
Note: The figure compares empirical and simulated moments from the estimated model. Each point corresponds to a moment included in the SMM objective function, and the 45-degree line indicates exact fit. Moments are reported in the scaled units used for estimation: BMI, wages, and age are divided by 10; medical expenditures by 1,000; log medical expenditures by 5; assets by 200,000; and the value of a statistical life (VSL) by 10,000,000.

Figure 6: WTP by Demographics and State Variables

(a) WTP by fixed demographics and age

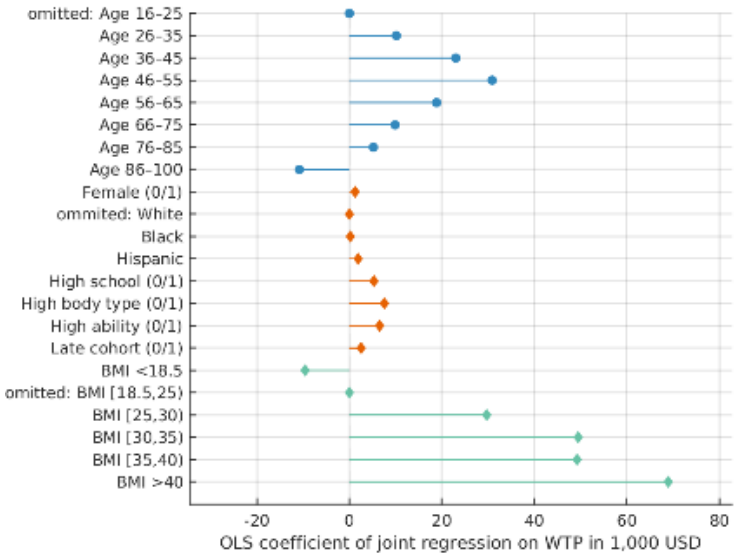


(b) WTP by current state variables



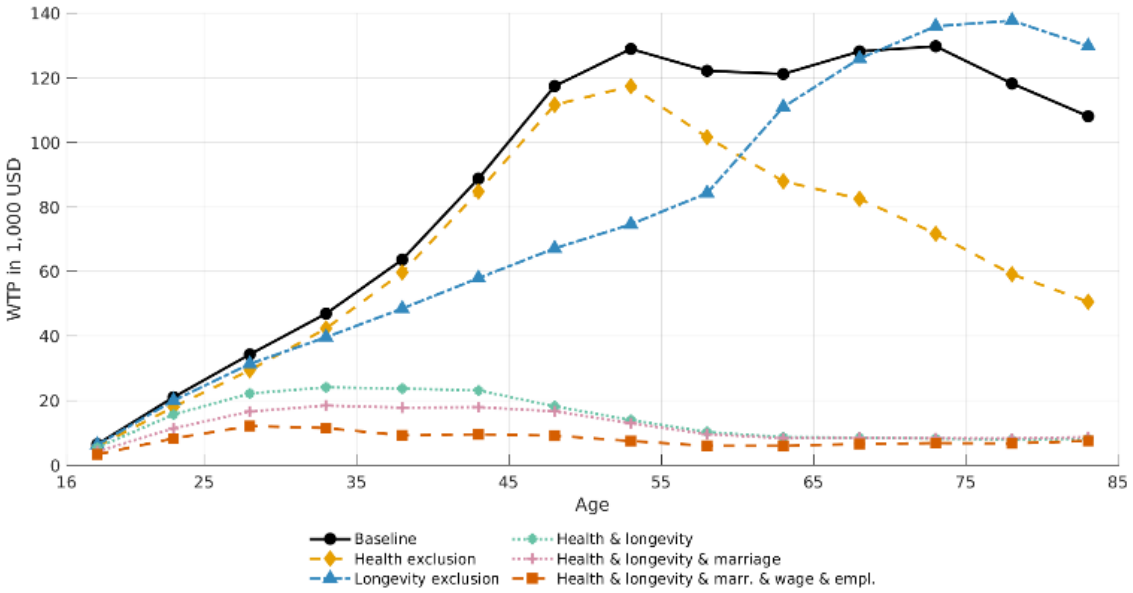
Note: The figure reports OLS coefficients from separate regressions of model-implied willingness to pay (WTP) for a technology that permanently reduces body weight by 10 percent. Simulated observations are weighted to be representative of the U.S. population. WTP is defined as the compensating reduction in current assets that makes an individual indifferent between the baseline state and a counterfactual state with 10 percent lower body weight. Panel (a) includes fixed characteristics and age-group indicators, while panel (b) includes current state variables. The figure reports coefficients from two OLS regressions, one for each panel. Within each regression, all covariates shown in the panel are included jointly. The regression constant is omitted. Dollar values are expressed in 2022 USD.

Figure 7: WTP Heterogeneity with Equal Resources



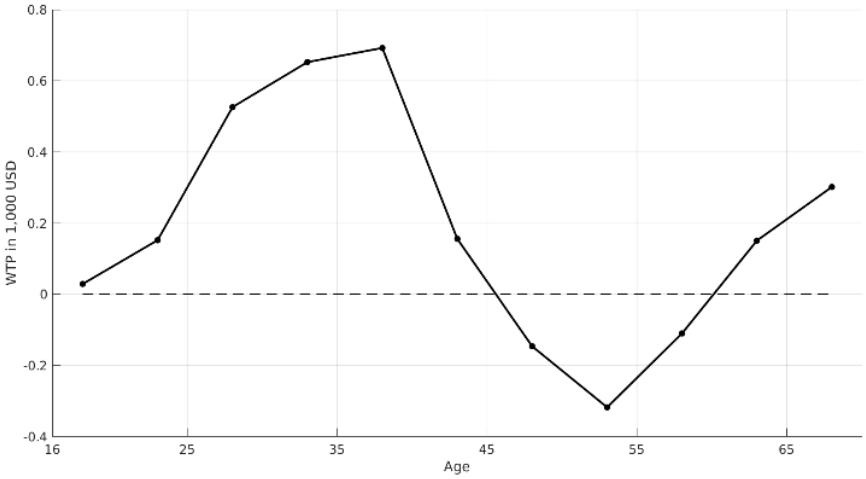
Note: The figure reports OLS coefficients from a regression of model-implied willingness to pay for a technology that permanently reduces body weight by 10 percent. Simulated observations are weighted to represent the U.S. population. Willingness to pay is computed as the compensating reduction in current assets that makes an individual indifferent between the baseline state and a counterfactual state with 10 percent lower body weight. Before computing willingness to pay, current assets are set to USD 100,000 for every simulated individual. This implies that differences in WTP are independent of individuals' current ability to pay. Expected future assets may still differ across individuals because expected income, savings, medical expenditures, and survival differ across states. Coefficients are estimated jointly, using the covariates displayed on the vertical axis. The regression constant is omitted from the figure. Dollar values are expressed in 2022 USD.

Figure 8: WTP Decomposition over the Life Cycle



Note: The figure reports age-specific averages of model-implied willingness to pay (WTP) for a technology that permanently reduces body weight by 10 percent. Simulated observations are weighted to be representative of the U.S. population. WTP is measured as the compensating reduction in current assets that leaves an individual indifferent between the baseline state and a counterfactual state with 10 percent lower body weight. The baseline series uses the estimated model, while the remaining series are generated from counterfactual models in which selected channels linking BMI to outcomes are shut down. This is done by assigning overweight and obese individuals the effects associated with the normal BMI range (18.5–25), while leaving the underweight category unchanged. Residual WTP therefore captures the direct disutility of body weight. WTP is reported in thousands of 2022 USD. Corresponding figures for men and women are reported in Appendix C.

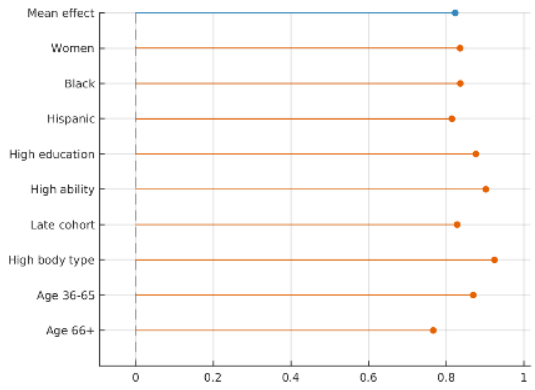
Figure 9: Endogenous Marriage Market Adjustment - WTP Gap between Universal Adoption and Baseline Expectations



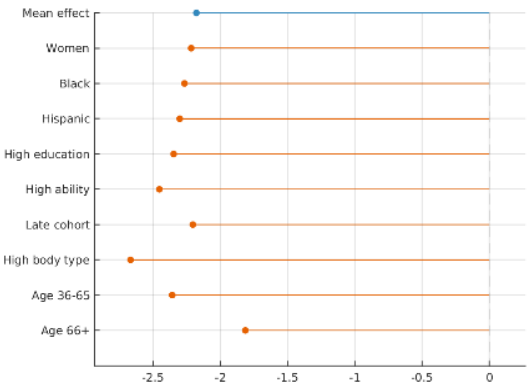
Note: The figure reports age-specific averages of model-implied willingness to pay (WTP) for a technology that permanently reduces body weight by 10 percent. Simulated observations are weighted to be representative of the U.S. population. WTP is measured as the compensating reduction in current assets that leaves an individual indifferent between the baseline state and a counterfactual state with 10 percent lower body weight. The figure plots the difference between WTP evaluated under a counterfactual population distribution in which all individuals adopt the technology and WTP evaluated under baseline expectations, where individuals assume that no one else adopts it. This difference captures the equilibrium adjustment operating through changes in the marriage market. WTP is reported in thousands of 2022 USD.

Figure 10: Uptake and Effects of Weight-Loss Technology

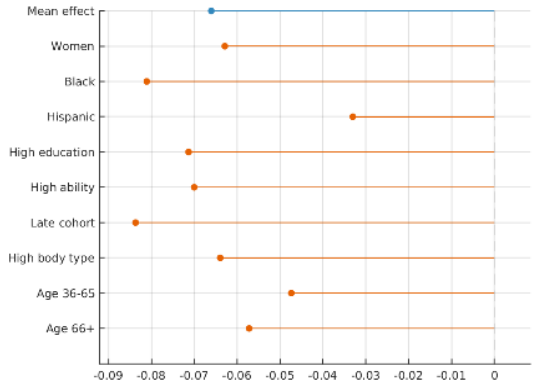
(a) WLT uptake



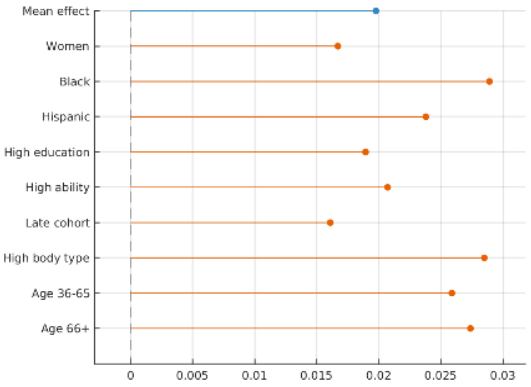
(b) BMI



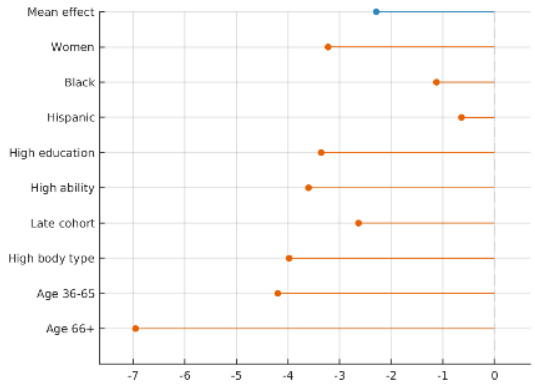
(c) Weight-control effort



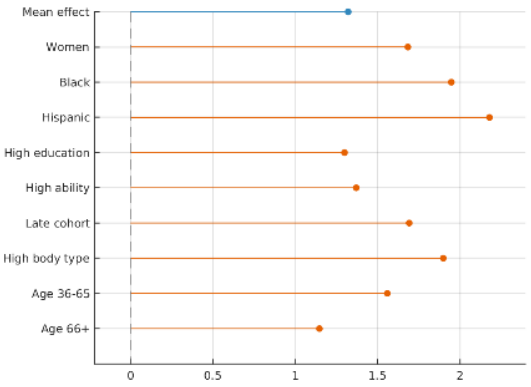
(d) Good health



(e) Assets, in 1,000 USD



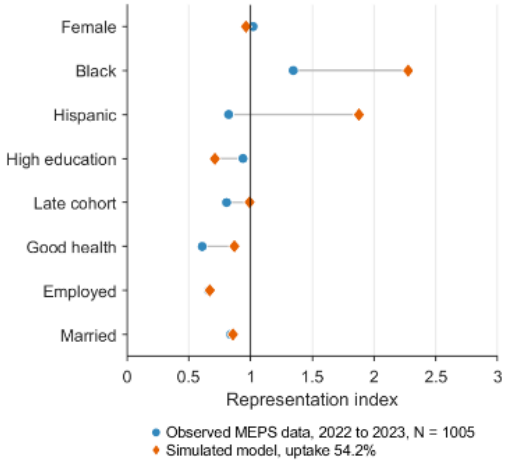
(f) Utility (Value Function)



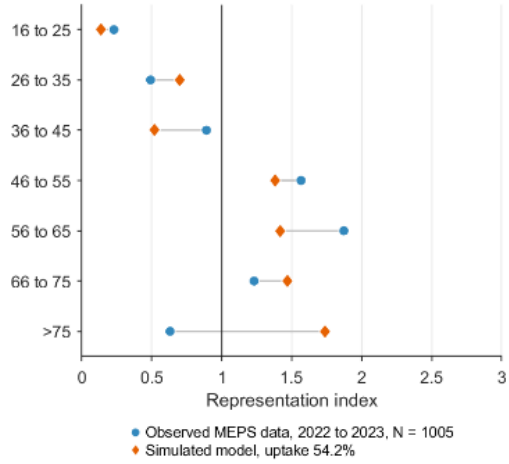
Note: The figure reports heterogeneity in the effects of a counterfactual in which a weight-loss technology is available at an annual price of USD 600. Simulated observations are weighted to be representative of the U.S. population. The technology reduces BMI by 10 percent while in use, leaves the latent BMI process unchanged, and requires continued use to maintain the reduction. Effects are measured relative to the baseline simulated economy. The blue marker reports the average effect in the population, while orange markers report unconditional subgroup averages for the demographic groups shown on the vertical axis. Panel (a) reports technology uptake. Panels (b)–(f) report effects on BMI, weight-control effort, good health, assets, and lifetime utility, respectively. Assets are reported in thousands of 2022 USD. Additional heterogeneity results are reported in Appendix C.

Figure 11: Observed GLP-1 Prescription Use and Simulated Weight Loss Technology Uptake

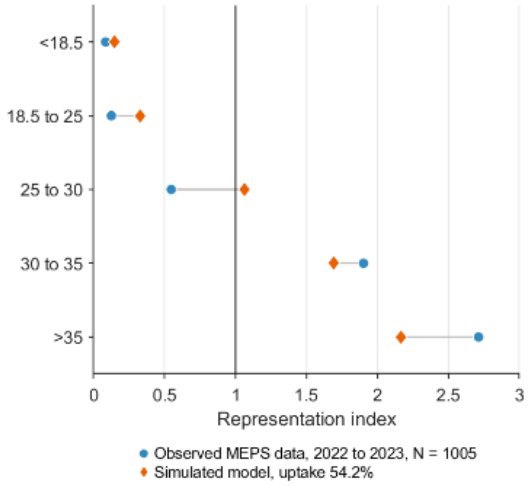
(a) Demographics



(b) Age groups



(c) BMI categories



Note: The figure compares observed and simulated GLP-1 uptake by demographic group. Observed uptake is computed from the MEPS prescription drug files for 2022 and 2023. Simulated uptake is computed from the validation exercise in which a weight-loss technology is available at an annual price of USD 600, reduces BMI by 10 percent while in use, and lowers effective consumption by 10 percent. Simulated observations are weighted to be representative of the U.S. population. The figure reports representation indices, defined as each group's share among users divided by the same group's share in the population. A value of one indicates proportional representation among users, values above one indicate over-representation, and values below one indicate under-representation. Blue circles report observed MEPS prescription data, while orange diamonds report the simulated model. Panels (a)–(c) report representation indices by demographic characteristics, age groups, and BMI groups, respectively.

Table 1: Model-Implied Marginal Effects of Excess Body Weight

	baseline level	level change relative to normal BMI *(proportional change)*		
	(1) normal BMI = 22.5	(2) overweight BMI = 27.5	(3) obese BMI = 32.5	(4) severely obese BMI = 42.5
A: Probability of good health, in percent				
average	87.99	-0.22 *(-0.3%)*	-1.80 *(-2.0%)*	-12.31 *(-14.0%)*
B: Life expectancy, in years				
average	86.03	-0.75 *(-0.9%)*	-1.53 *(-1.8%)*	-5.00 *(-5.8%)*
C: Hourly wage, in 2022 USD				
average	30.52	-0.27 *(-0.9%)*	-1.70 *(-5.6%)*	-2.42 *(-7.9%)*
women	28.67	-0.26 *(-0.9%)*	-2.43 *(-8.5%)*	-3.08 *(-10.7%)*
men	32.38	-0.29 *(-0.9%)*	-0.97 *(-3.0%)*	-1.75 *(-5.4%)*
D: Employment retention probability, in percent				
average	81.63	+0.38 *(0.5%)*	-2.37 *(-2.9%)*	-2.68 *(-3.3%)*
women	79.18	+0.41 *(0.5%)*	-3.11 (-3.9%)	-3.46 (-4.4%)
men	84.09	+0.35 *(0.4%)*	-1.62 *(-1.9%)*	-1.91 *(-2.3%)*
E: Hiring probability from non-employment, in percent				
average	53.16	-1.75 *(-3.3%)*	-4.21 *(-7.9%)*	-7.00 *(-13.2%)*
women	48.85	-1.76 *(-3.6%)*	-5.10 *(-10.4%)*	-7.87 *(-16.1%)*
men	57.49	-1.74 *(-3.0%)*	-3.31 *(-5.8%)*	-6.13 *(-10.7%)*
F: Marriage quality ranking, in percentiles				
women	65.74	-12.68 *(-19.3%)*	-25.07 *(-38.1%)*	-41.04 *(-62.4%)*
men	57.45	-9.16 *(-15.9%)*	-17.13 *(-29.8%)*	-27.95 *(-48.6%)*

Note: The table reports model-implied marginal effects of BMI on health, life expectancy, wages, employment, and marriage market ranking. Simulated observations are weighted to be representative of the U.S. population. Column 1 reports average predicted outcomes at normal BMI, evaluated at BMI 22.5. Columns 2 to 4 report level changes relative to normal BMI (and proportional changes in parantheses), evaluated at reference points for the overweight, class 1 obesity, and severe obesity categories, corresponding to BMI 27.5, 32.5, and 42.5. Gradients are computed by assigning alternative BMI values to individuals in the simulated population while holding all other state variables fixed, including health. Because several model components are nonlinear, the reported estimates are differences in average predicted outcomes rather than model coefficients. Good health, employment, and marriage market ranking are reported in percentage points. Life expectancy (16 plus the residual life expectancy at age 16) is reported in years. Wages are reported in 2022 USD per hour. Marriage market ranking is computed by recomputing individual marriage quality under each BMI assignment and ranking the resulting value relative to the baseline population, separately by gender.

Table 2: Decomposing the Drivers of Willingness to Pay and Other Outcomes

	average outcomes					
	change relative to baseline					
	(1)	(2)	(3)	(4)	(5)	(6)
	WTP	BMI	good health	effort	life exp.	assets
baseline	79.38	28.8	0.87	0.38	84.75	174.87
A: Single-Channel Exclusions						
Health	65.03	29.15	0.91	0.26	86.25	165.65
	-18.1%	*1.2%*	*5.4%*	*-31.5%*	*1.8%*	*-5.3%*
Longevity	62.96	29.14	0.86	0.26	85.96	186.42
	-20.7%	*1.1%*	*-0.7%*	*-30.7%*	*1.4%*	*6.6%*
Wages	80.93	28.81	0.87	0.38	84.81	178.92
	1.9%	*0%*	*0.1%*	*-0.9%*	*0.1%*	*2.3%*
Employment	79.38	28.81	0.87	0.38	84.8	174.35
	0%	*0%*	*0.2%*	*-0.6%*	*0.1%*	*-0.3%*
Marriage	78.03	28.89	0.86	0.37	84.68	175.08
	-1.7%	*0.3%*	*-0.3%*	*-2.6%*	*-0.1%*	*0.1%*
Body weight disutility	79.79	28.76	0.87	0.39	84.86	180.47
	0.5%	*-0.2%*	*0.2%*	*1.1%*	*0.1%*	*3.2%*
B: Cumulative Channel Exclusions						
Health & longevity	15.66	29.62	0.91	0.11	88.09	170.1
	-80.3%	*2.8%*	*5.4%*	*-71.5%*	*3.9%*	*-2.7%*
Health, long. & wages	12.76	29.61	0.91	0.11	88.11	177.09
	-83.9%	*2.8%*	*5.3%*	*-71.6%*	*4%*	*1.3%*
Health, long., wages & empl.	11.49	29.61	0.91	0.11	88.11	177.95
	-85.5%	*2.8%*	*5.3%*	*-71.6%*	*4%*	*1.8%*
Health, long., wages, empl. & marr.	8.2	29.75	0.91	0.09	88.11	178.58
	-89.7%	*3.3%*	*5.4%*	*-77.2%*	*4%*	*2.1%*
All BMI-related channels	0	29.73	0.91	0.09	88.13	183.2
	-100%	*3.2%*	*5.4%*	*-77.2%*	*4%*	*4.8%*

Note: The table reports average outcomes in the baseline simulated economy and in counterfactual economies that remove selected channels linking BMI to outcomes. Simulated observations are weighted to be representative of the U.S. population. Willingness to pay (WTP) is defined as the compensating reduction in current assets that leaves an individual indifferent between the baseline state and a counterfactual state with 10 percent lower body weight. To remove a BMI-related channel, overweight and obese individuals are assigned the effects associated with the normal BMI range (18.5–25), while parameters for BMI below 18.5 are left unchanged. Rows in italics report percentage changes relative to the baseline. WTP and assets are reported in thousands of 2022 USD. Good health and effort are indicator variables, and life expectancy (16 plus the residual life expectancy at age 16) is measured in years. Effort remains positive when all BMI channels are removed in Panel B because effort also affects outcomes through the marriage market, independently of its effect on BMI.

Table 3: Decomposing Willingness to Pay into Incentive and Wealth Effects

	(1) WTP	(2) overall effect	(3) incentive effect	(4) wealth effect
baseline	79.38	-	-	-
Single-Channel Exclusions				
Health	65.03	-14.35	-12.95	-1.40
Longevity	62.96	-16.42	-21.86	5.44
Wages	80.93	1.55	-1.20	2.75
Employment	79.38	0.00	-0.63	0.63
Marriage	78.03	-1.35	-1.13	-0.22
Body weight disutility	79.79	0.41	-2.45	2.86

Note: The table decomposes changes in model-implied willingness to pay (WTP) into incentive and wealth effects for the exclusion counterfactuals. Simulated observations are weighted to be representative of the U.S. population. WTP is defined as the compensating reduction in current assets that leaves an individual indifferent between the baseline state and a counterfactual state with 10 percent lower body weight. The overall effect is the change in WTP relative to the baseline simulated economy. The incentive effect is computed by repeating each exclusion exercise while holding asset paths fixed at their baseline values, thereby eliminating changes in current and future resources. The wealth effect is the difference between the overall and incentive effects. WTP and all decomposition terms are reported in thousands of 2022 USD.

Table 4: Healthy-Life and Life-Extension Components of Willingness to Pay

	(1) WTP at baseline	(2) WTP w/o health effects	(3) overall effect (2)-(1)	(4) effect of healthy life	(5) effect of life extension (3)-(4)
overall	79.38	65.03	-14.35	-7.37	-6.98
age: 16-25	13.96	12.09	-1.87	1.17	-3.03
age: 26-35	40.54	35.80	-4.74	3.67	-8.41
age: 36-45	76.20	72.23	-3.97	6.17	-10.13
age: 46-55	123.17	114.50	-8.67	-0.66	-8.01
age: 56-65	121.71	95.30	-26.41	-16.96	-9.44
age: 66-75	128.84	77.95	-50.88	-46.10	-4.79
age: >75	112.90	54.15	-58.75	-59.49	0.74

Note: The table decomposes the health contribution to model-implied willingness to pay (WTP) into a healthy-life component and a life-extension component. Simulated observations are weighted to be representative of the U.S. population. WTP is defined as the compensating reduction in current assets that leaves an individual indifferent between the baseline state and a counterfactual state with 10 percent lower body weight. The overall effect is the change in WTP when the BMI-related health channel is removed. The healthy-life component is computed by removing the effect of BMI on health while holding mortality fixed at its baseline level, so that changes in WTP reflect improvements in health during life rather than changes in longevity. The life-extension component is the difference between the overall and healthy-life effects. WTP and all decomposition terms are reported in thousands of 2022 USD.

Table 5: Effects of Weight-Loss Technologies under Alternative Access Regimes

		average outcomes *change relative to baseline*		
	(1)	(2)	(3)	(4)
allocation rule		Market-based	Obesity Plus	Obesity Only
	baseline	USD 600/year	BMI > 30 + poor health	BMI > 30
WLT uptake		0.823	0.249	0.58
fraction of uptakers below retirement age		0.834	0.733	0.806
BMI	28.807	26.628	28.095	27.155
		-7.6%	*-2.5%*	*-5.7%*
Effort	0.382	0.316	0.369	0.345
		-17.3%	*-3.3%*	*-9.7%*
Good health	0.865	0.885	0.88	0.885
		2.3%	*1.8%*	*2.3%*
Out-of-pocket med. exp., in USD	956.75	942.49	949.87	942.94
		-1.5%	*-0.7%*	*-1.4%*
Total med. exp., in USD (imp.)	4424.2	4135.6	4249.3	4130.9
		-6.5%	*-4.0%*	*-6.6%*
Life expectancy	84.753	85.957	85.596	85.942
		1.4%	*1.0%*	*1.4%*
Hourly wages, in USD	22.28	22.639	22.434	22.64
		1.6%	*0.7%*	*1.6%*
Employment	0.6	0.606	0.602	0.606
		0.9%	*0.4%*	*1.0%*
Consumption, in 1,000 USD	40.002	40.282	40.356	40.765
		0.7%	*0.9%*	*1.9%*
Assets, in 1,000 USD	174.87	172.58	176.55	174.42
		-1.3%	*1.0%*	*-0.3%*
Flow utility, normalized	100	100.47	100.21	100.58
		0.5%	*0.2%*	*0.6%*
Utility (value function), norm.	100	101.32	101.54	101.51
		1.3%	*1.5%*	*1.5%*
Gini of assets	0.477	0.471	0.474	0.47
		-1.3%	*-0.5%*	*-1.4%*
Gini of utility (VF), at age 40	0.033	0.031	0.03	0.031
		-6.5%	*-10.7%*	*-8.2%*
Gini of life expectancy	0.036	0.034	0.034	0.034
		-6.1%	*-6.5%*	*-6.3%*
White-Black gap in life exp.	9.883	9.868	9.821	9.828
		-0.2%	*-0.6%*	*-0.6%*

Note: The table reports average outcomes in the baseline simulated economy and in three counterfactual economies with access to a weight-loss technology. Simulated observations are weighted to be representative of the U.S. population. The technology reduces BMI by 10 percent while in use, leaves the latent BMI process unchanged, and requires continued use to maintain the reduction. In column 2, individuals may purchase the technology at an annual price of USD 600. In columns 3 and 4, eligible individuals receive access at zero cost and decide whether to adopt. Eligibility is restricted to individuals with BMI above 30 and poor health in column 3 and to all individuals with BMI above 30 in column 4. Medical expenditures exclude payments for the weight-loss technology. Total medical expenditures are imputed from MEPS and include payments by individuals, private insurers, Medicare, Medicaid, and other payers. Self-paid medical expenditures include unreimbursed payments made directly by individuals or their families. Rows in italics report percentage changes relative to the baseline. Dollar values are expressed in 2022 USD. The Gini coefficient of life expectancy uses 16 plus the residual life expectancy at age 16, and the Gini coefficient of lifetime utility is evaluated at age 40. Flow utility and lifetime utility are normalized to 100 in the baseline.

Appendix A

Codebook, Parameterization, and Identification

The Life-cycle Consequences of Obesity and the Effects of Weight-Loss Drugs

Jérôme Adda Christian Dustmann Lukas Tohoff

August 2026

A.1 Codebook

Table A.1: Codebook

Object	Description	MATLAB
Subscripts		
i	individual	i
j	spouse of individual i	j
t	age	t, Age
Choice Variables		
c_{it}	consumption	C
x_{it}	effort	X
State Variables		
$\mathcal{W}_{it}$	body weight	W, Weight
$\widehat{\mathcal{W}}_{it}$	$\mathcal{W}_{it} + \xi$, self-reported weight	
A_{it}	assets	A, Assets
H_{it}	health	H, GoodHealth
M_{it}	marriage dummy, 1=married	M, Married
E_{it}	employment dummy, 1=employed	E, Employed
D_i	demographics	D (see below)
Demographics, D_i		
Fem_i	female dummy	Gender (women/men), Female
Black_i	black dummy	Race (White/Black/hispanic), Black
Hisp_i	hispanic dummy	Race (White/Black/hispanic), Hispanic
Educ_i	high education dummy	Education (low/high), HighEduc
BT_i	high body type dummy	Body type (low/high), HighBT
Abil_i	high ability dummy	Ability (low/high), HighAbil
K_i	late cohort dummy	Cohort (early/late), LateCohort

Derived Variables		
g	age groups: 16-25, 26-35, 36-45, 46-55, 56-65, 66-75, 76-85, 86-100	AgeCat
q	weight categories, BMI: < 18.5, $[18.5, 25)$, $[25, 30)$, $[30, 35)$, $[35, 40)$, ≥ 40	WeightCat
$Alive_{it}$	dummy for individual being alive	Alive
Functions and Equations		
λ_{it+1}	employment probability	Lambda
$\widetilde{w}_{it}$	potential hourly wages	Wage
PIA_{it}	annual Social Security benefit before taxes	PIA
γ	wages to income (earnings and benefits) scale	Gamma
w_{it}	income: $\gamma \times \widetilde{w}_{it}$	Income
ψ_{it+1}	good health probability	ProbHealth
m_{it}	medical expenditures	Medical, MedExp
π_{it+1}	survival probability (1 - mortality prob.)	ProbSurv, Alive
A_{it+1}	asset evolution	nextAssets
b_{it}	government transfers	auxWageU
$\mathcal{T}$	budget equation, applying tax rate	taxRate
$\mathcal{W}_{it+1}$	body weight evolution	nextWeight
$\tilde{\eta}_{it+1}$	log normal body weight shock	Wrand
$\tilde{\epsilon}^w_{it}$	log normal wage shock	wageRN
$\tilde{\epsilon}^m_{it}$	log normal medical expenditure shock	medexpRN
ξ_{it}	BMI self-reporting error	xi
ϱ_x	probability of successful effort	varrho
μ_{it}	individual marriage quality	MU
$z(\tilde{\mu}, t)$	one-off utility from marriage quality	mMu
ρ	spouse arrival rate	rhoMu
u	utility function	Util, Utility
Fixed parameters		
β	discount factor: 0.96	Beta
$\underline{c}$	consumption floor: 5,000	MinC
γ	hourly wages to annual earnings scale: 40×52	Gamma
γ^u	share of pot. earnings when unemployed: 0.5	GammaU
γ^r_1	first Social Security replacement rate: 0.90	GammaRet1
γ^r_2	second Social Security replacement rate: 0.32	GammaRet2
γ^r_3	third Social Security replacement rate: 0.15	GammaRet3
$\bar{a}^r_1$	1st annual AIME bend point: 12,240	GammaRetA
$\bar{a}^r_2$	2nd annual AIME bend point: 73,860	GammaRetB
χ^{SS}	taxable share of Social Security benefits: 0.5	TaxSS
R	rate of return to savings: 0.05	R
δ	annual divorce rate, for Whites: 0.0151	divorceW
	annual divorce rate, for Blacks: 0.0308	divorceB
	annual divorce rate, for Hispanics: 0.0185	divorceH
t^r	retirement age: 63	AgeRet
τ	smooth progressive tax schedule	tau

	$\tau = 0.1 + (0.3 - 0.1)/(1 + \exp(-0.00005(RA_{it} + w_{it} - 100{,}000)))$	
α	parameters to be estimated	estParams (see Section A.2)
ϕ	data moments for identification and estimation	Moments (see Section A.3)
State space grids		
GridT	Age (minus starting age) grid: [0 1 2 3 ... 83 84]	Space.GridT
GridW	BMI grid: [16.5 19 22.5 27.5 32.5 37.5 42.5]	Space.GridW
GridA	Asset grid: 1000*[0 2 20 50 100 500 2000]	Space.GridA
GridH	Health grid: [0 1]	Space.GridH
GridMu	Marriage quality grid: [0 0.1 0.2 ... 0.9 1]	Space.GridMu
GridC	Consumption grid: 1000*[5 10 20 35 50 80 150]	Space.GridC
GridX	Effort grid: [0 1]	Space.GridX

Note: For the divorce rates by race we take the numbers calculated by the US National Center for Family and Marriage Research (Schweizer, 2019). Social Security benefits enter the tax base only partially, with taxable share $\chi^{SS} = 0.5$. The smooth tax function captures the progressivity of the U.S. tax and transfer system in a parsimonious way. It implies an average tax rate of about 10.4 percent at taxable income of USD 20,000, 13.6 percent at USD 70,000, and 24.6 percent at USD 120,000.

A.2 Parameterization

A.2.1 Employment retention probability

$$\begin{aligned}\lambda^V_{it+1} = \Phi((&\alpha_1^{\lambda_V}(1 - M_{it}) + \alpha_2^{\lambda_V} M_{it}) \times Fem_i \\ &+ \alpha_3^{\lambda_V} Black_i + \alpha_4^{\lambda_V} Hisp_i + \alpha_5^{\lambda_V} Educ_i + \alpha_6^{\lambda_V} K_i \times (\mathcal{W}_{it} > 30) + \alpha_7^{\lambda_V} Abil_i \\ &+ \alpha_8^{\lambda_V} t_i^{26-55} + \alpha_9^{\lambda_V} t_i^{56+} + \alpha_{10}^{\lambda_V} H_{it} + \alpha_{11}^{\lambda_V} \mathcal{W}_{it}^{<18.5} + \alpha_{12}^{\lambda_V} \\ &+ \alpha_{13}^{\lambda_V} \mathcal{W}_{it}^{[25,30)} + \alpha_{14}^{\lambda_V} \mathcal{W}_{it}^{[30,35)} + \alpha_{15}^{\lambda_V} \mathcal{W}_{it}^{\geq 35}) + \alpha_{16}^{\lambda_V} K_i + \alpha_{17}^{\lambda_V} Fem_i \times (\mathcal{W}_{it} > 30)\end{aligned} \tag{A.1}$$

Table A.2: Employment Retention Probability

Object	Description	MATLAB
$\alpha_1^{\lambda_V}$	female effect if single	estParams.alphaLambdaV(1)
$\alpha_2^{\lambda_V}$	female effect if married	estParams.alphaLambdaV(2)
$\alpha_3^{\lambda_V}$	black intercept	estParams.alphaLambdaV(3)
$\alpha_4^{\lambda_V}$	Hispanic intercept	estParams.alphaLambdaV(4)
$\alpha_5^{\lambda_V}$	high education effect	estParams.alphaLambdaV(5)
$\alpha_6^{\lambda_V}$	obesity effect for late cohort	estParams.alphaLambdaV(6)
$\alpha_7^{\lambda_V}$	high ability effect	estParams.alphaLambdaV(7)
$\alpha_8^{\lambda_V}$	age effect, age: 26-55	estParams.alphaLambdaV(8)
$\alpha_9^{\lambda_V}$	age effect, age: 56+	estParams.alphaLambdaV(9)
$\alpha_{10}^{\lambda_V}$	good health effect	estParams.alphaLambdaV(10)
$\alpha_{11}^{\lambda_V}$	body weight effect, BMI: < 18.5	estParams.alphaLambdaV(11)
$\alpha_{12}^{\lambda_V}$	constant, reference BMI: $[18.5, 25)$	estParams.alphaLambdaV(12)
$\alpha_{13}^{\lambda_V}$	body weight effect, BMI: $[25, 30)$	estParams.alphaLambdaV(13)
$\alpha_{14}^{\lambda_V}$	body weight effect, BMI: $[30, 35)$	estParams.alphaLambdaV(14)
$\alpha_{15}^{\lambda_V}$	body weight effect, BMI: ≥ 35	estParams.alphaLambdaV(15)

$\alpha_{16}^{\lambda_V}$	late cohort intercept	estParams.alphaLambdaV(16)
$\alpha_{17}^{\lambda_V}$	female obesity effect	estParams.alphaLambdaV(17)

A.2.2 Hiring probability from non-employment

$$\begin{aligned}\lambda_{it+1}^{U} = \Phi((&\alpha_1^{\lambda_U}(1-M_{it}) + \alpha_2^{\lambda_U} M_{it}) \times Fem_i \\ &+ \alpha_3^{\lambda_U} Black_i + \alpha_4^{\lambda_U} Hisp_i + \alpha_5^{\lambda_U} Educ_i + \alpha_6^{\lambda_U} K_i \times (\mathcal{W}_{it} > 30) + \alpha_7^{\lambda_U} Abil_i \\ &+ \alpha_8^{\lambda_U} t_i^{26-55} + \alpha_9^{\lambda_U} t_i^{56+} + \alpha_{10}^{\lambda_U} H_{it} + \alpha_{11}^{\lambda_U} \mathcal{W}_{it}^{<18.5} + \alpha_{12}^{\lambda_U} \\ &+ \alpha_{13}^{\lambda_U} \mathcal{W}_{it}^{[25,30)} + \alpha_{14}^{\lambda_U} \mathcal{W}_{it}^{[30,35)} + \alpha_{15}^{\lambda_U} \mathcal{W}_{it}^{\geq 35}) + \alpha_{16}^{\lambda_U} K_i + \alpha_{17}^{\lambda_U} Fem_i \times (\mathcal{W}_{it} > 30)\end{aligned} \tag{A.2}$$

Table A.3: Hiring Probability from Non-Employment

Object	Description	MATLAB
$\alpha_1^{\lambda_U}$	female effect if single	estParams.alphaLambdaU(1)
$\alpha_2^{\lambda_U}$	female effect if married	estParams.alphaLambdaU(2)
$\alpha_3^{\lambda_U}$	black intercept	estParams.alphaLambdaU(3)
$\alpha_4^{\lambda_U}$	Hispanic intercept	estParams.alphaLambdaU(4)
$\alpha_5^{\lambda_U}$	high education effect	estParams.alphaLambdaU(5)
$\alpha_6^{\lambda_U}$	obesity effect for late cohort	estParams.alphaLambdaU(6)
$\alpha_7^{\lambda_U}$	high ability effect	estParams.alphaLambdaU(7)
$\alpha_8^{\lambda_U}$	age effect, age: 26-55	estParams.alphaLambdaU(8)
$\alpha_9^{\lambda_U}$	age effect, age: 56+	estParams.alphaLambdaU(9)
$\alpha_{10}^{\lambda_U}$	good health effect	estParams.alphaLambdaU(10)
$\alpha_{11}^{\lambda_U}$	body weight effect, BMI: < 18.5	estParams.alphaLambdaU(11)
$\alpha_{12}^{\lambda_U}$	constant, reference BMI: $[18.5, 25)$	estParams.alphaLambdaU(12)
$\alpha_{13}^{\lambda_U}$	body weight effect, BMI: $[25, 30)$	estParams.alphaLambdaU(13)
$\alpha_{14}^{\lambda_U}$	body weight effect, BMI: $[30, 35)$	estParams.alphaLambdaU(14)
$\alpha_{15}^{\lambda_U}$	body weight effect, BMI: ≥ 35	estParams.alphaLambdaU(15)
$\alpha_{16}^{\lambda_U}$	late cohort intercept	estParams.alphaLambdaU(16)
$\alpha_{17}^{\lambda_U}$	female obesity effect	estParams.alphaLambdaU(17)

A.2.3 Wages

$$\begin{aligned}\widetilde{w}_{it} = \exp[&\alpha_1^w Fem_i + \alpha_2^w Black_i + \alpha_3^w Hisp_i + \alpha_4^w Educ_i + \alpha_5^w Abil_i \\ &+ \alpha_6^w K_i \times (\mathcal{W}_{it} > 30) + \alpha_7^w t_i^{26-35} + \alpha_8^w t_i^{36-45} + \alpha_9^w t_i^{46-55} + \alpha_{10}^w t_i^{56+} + \alpha_{11}^w H_{it} \\ &+ \alpha_{12}^w \mathcal{W}_{it}^{<18.5} + \alpha_{13}^w + \alpha_{14}^w \mathcal{W}_{it}^{[25,30)} + \alpha_{15}^w \mathcal{W}_{it}^{[30,35)} + \alpha_{16}^w \mathcal{W}_{it}^{\geq 35} + \alpha_{17}^w K_i \\ &+ \alpha_{18}^w Fem_i \times (\mathcal{W}_{it} > 30)] \times \tilde{\epsilon}_{it}^w \\ \text{with} \quad \tilde{\epsilon}_{it}^w = \exp&\left(\epsilon_{it}^w - \sigma_w^2/2\right) \quad \text{and} \quad \epsilon_{it}^w \sim N(0, \sigma_w^2)\end{aligned} \tag{A.3}$$

Table A.4: Hourly Wages

Object	Description	MATLAB

α_1^w	female intercept	estParams.alphaW(1)
α_2^w	black intercept	estParams.alphaW(2)
α_3^w	Hispanic intercept	estParams.alphaW(3)
α_4^w	high education effect	estParams.alphaW(4)
α_5^w	high ability effect	estParams.alphaW(5)
α_6^w	obesity effect for late cohort	estParams.alphaW(6)
α_7^w	age effect, age: 26-35	estParams.alphaW(7)
α_8^w	age effect, age: 36-45	estParams.alphaW(8)
α_9^w	age effect, age: 46-55	estParams.alphaW(9)
α_{10}^w	age effect, age: 56+	estParams.alphaW(10)
α_{11}^w	health effect	estParams.alphaW(11)
α_{12}^w	body weight effect, BMI: < 18.5	estParams.alphaW(12)
α_{13}^w	constant, reference BMI: $[18.5, 25)$	estParams.alphaW(13)
α_{14}^w	body weight effect, BMI: $[25, 30)$	estParams.alphaW(14)
α_{15}^w	body weight effect, BMI: $[30, 35)$	estParams.alphaW(15)
α_{16}^w	body weight effect, BMI: ≥ 35	estParams.alphaW(16)
α_{17}^w	late cohort intercept	estParams.alphaW(17)
α_{18}^w	female obesity effect	estParams.alphaW(18)
σ_w^2	variance of log wage shock	estParams.alphaW(19)

Hourly wages $\widetilde{w}_{it}$ are scaled to potential annual earnings using a 40 hour week and 52 weeks per year. In the PSID, the median ratio of annual earnings to hourly wages is 1977.4, which is close to our scaling factor of 2080. Employed individuals receive realized annual earnings as their income w_{it}, while non-employed individuals of working age receive a share $\gamma^u = 0.5$ of potential annual earnings as their income, reflecting unemployment benefits. We assume unemployment benefits are received in all non-employment periods. While U.S. unemployment insurance is time-limited, individuals often receive support through other programs (e.g., SNAP, tax credits) after benefits expire, and annual aggregation of employment spells makes this a reasonable approximation.

For retired individuals, benefits approximate the U.S. Social Security Primary Insurance Amount formula. We proxy annualized AIME by potential annual earnings at ages 56 and above. The bend points are the 2010 AIME bend points, expressed in 2022 USD and annualized (Social Security Administration, 2010): $\bar{a}_1^r = 12{,}240$ and $\bar{a}_2^r = 73{,}860$. Annual retirement benefits are $PIA_{it} = \gamma_1^r \min\{y_{it}^{pot}, \bar{a}_1^r\} + \gamma_2^r \min\{\max(y_{it}^{pot} - \bar{a}_1^r, 0), \bar{a}_2^r - \bar{a}_1^r\} + \gamma_3^r \max\{y_{it}^{pot} - \bar{a}_2^r, 0\}$. The exact values of all fixed parameters are provided in the codebook above. Social Security benefits enter the tax base only partially. Specifically, we set the taxable share of Social Security benefits to 0.5.

A.2.4 Health evolution

$$
\begin{aligned}
\psi_{t+1} = \Phi(&\alpha_1^\psi Black_i + \alpha_2^\psi Hisp_i + \alpha_3^\psi Educ_i \\
&+ (\alpha_4^\psi t_i^{26-35} + \alpha_5^\psi t_i^{36-55} + \alpha_6^\psi t_i^{56-75} + \alpha_7^\psi t_i^{76+}) \times Fem_i \\
&+ (\alpha_8^\psi t_i^{26-35} + \alpha_9^\psi t_i^{36-55} + \alpha_{10}^\psi t_i^{56-75} + \alpha_{11}^\psi t_i^{76+}) \times (1 - Fem_i) \\
&+ \alpha_{12}^\psi \mathcal{W}_{it}^{<18.5} + \alpha_{13}^\psi + \alpha_{14}^\psi \mathcal{W}_{it}^{[25,30)} + \alpha_{15}^\psi \mathcal{W}_{it}^{[30,35)} + \alpha_{16}^\psi \mathcal{W}_{it}^{[35,40)} + \alpha_{17}^\psi \mathcal{W}_{it}^{\geq 40} \\
&+ (\alpha_{18}^\psi + \alpha_{19}^\psi \times (\mathcal{W}_{it} > 30)) \times BT_i + \alpha_{20}^\psi H_{it} + \alpha_{21}^\psi log(A_{it} + 1))
\end{aligned}
\tag{A.4}
$$

Table A.5: Health Evolution

Object	Description	MATLAB
α_1^ψ	black intercept	estParams.alphaHealth(1)
α_2^ψ	Hispanic intercept	estParams.alphaHealth(2)
α_3^ψ	high education effect	estParams.alphaHealth(3)
α_4^ψ	age effect for women, age: 26-35	estParams.alphaHealth(4)
α_5^ψ	age effect for women, age: 36-55	estParams.alphaHealth(5)
α_6^ψ	age effect for women, age: 56-75	estParams.alphaHealth(6)
α_7^ψ	age effect for women, age: 76+	estParams.alphaHealth(7)
α_8^ψ	age effect for men, age: 26-35	estParams.alphaHealth(8)
α_9^ψ	age effect for men, age: 36-55	estParams.alphaHealth(9)
α_{10}^ψ	age effect for men, age: 56-75	estParams.alphaHealth(10)
α_{11}^ψ	age effect for men, age: 76+	estParams.alphaHealth(11)
α_{12}^ψ	weight effect, BMI: < 18.5	estParams.alphaHealth(12)
α_{13}^ψ	constant, reference BMI: $[18.5, 25)$	estParams.alphaHealth(13)
α_{14}^ψ	weight effect, BMI: $[25, 30)$	estParams.alphaHealth(14)
α_{15}^ψ	weight effect, BMI: $[30, 35)$	estParams.alphaHealth(15)
α_{16}^ψ	weight effect, BMI: $[35, 40)$	estParams.alphaHealth(16)
α_{17}^ψ	weight effect, BMI: ≥ 40	estParams.alphaHealth(17)
α_{18}^ψ	constant effect of high body type	estParams.alphaHealth(18)
α_{19}^ψ	obesity effect of high body type	estParams.alphaHealth(19)
α_{20}^ψ	persistence in health	estParams.alphaHealth(20)
α_{21}^ψ	wealth effect	estParams.alphaHealth(21)

A.2.5 Medical expenditures (out-of-pocket)

$$\begin{aligned} m_{it} = \exp[&(\alpha_1^m t_i^{16-35} + \alpha_2^m t_i^{36-55} + \alpha_3^m t_i^{56-75} + \alpha_4^m t_i^{76-85} + \alpha_5^m t_i^{86+}) \times H_{it} \\ &+ (\alpha_6^m t_i^{16-35} + \alpha_7^m t_i^{36-55} + \alpha_8^m t_i^{56-75} + \alpha_9^m t_i^{76-85} + \alpha_{10}^m t_i^{86+}) \times (1 - H_{it}) \\ &+ \alpha_{11}^m Fem_i + \alpha_{12}^m Black_i + \alpha_{13}^m Hisp_i + \alpha_{14}^m Educ_i] \times \tilde{\epsilon}_{it}^m \\ \text{with} \quad \tilde{\epsilon}_{it}^m = \exp\left(\epsilon_{it}^m - \sigma_m^2/2\right) \quad &\text{and} \quad \epsilon_{it}^m \sim N(0, \sigma_m^2) \end{aligned} \tag{A.5}$$

Table A.6: Medical Expenditures

Object	Description	MATLAB
α_1^m	age effect for good health, age: 16-35	estParams.alphaMed(1)
α_2^m	age effect for good health, age: 36-55	estParams.alphaMed(2)
α_3^m	age effect for good health, age: 56-75	estParams.alphaMed(3)
α_4^m	age effect for good health, age: 76-85	estParams.alphaMed(4)
α_5^m	age effect for good health, age: 86+	estParams.alphaMed(5)
α_6^m	age effect for bad health, age: 16-35	estParams.alphaMed(6)
α_7^m	age effect for bad health, age: 36-55	estParams.alphaMed(7)
α_8^m	age effect for bad health, age: 56-75	estParams.alphaMed(8)
α_9^m	age effect for bad health, age: 76-85	estParams.alphaMed(9)

α_{10}^m	age effect for bad health, age: 86+	estParams.alphaMed(10)
α_{11}^m	female intercept	estParams.alphaMed(11)
α_{12}^m	black intercept	estParams.alphaMed(12)
α_{13}^m	Hispanic intercept	estParams.alphaMed(13)
α_{14}^m	high education effect	estParams.alphaMed(14)
σ_m^2	variance of log medical expenditure shock	estParams.alphaMed(15)

A.2.6 Longevity

$$\begin{aligned}\pi_{it+1} = 1 - [&(\alpha_1^\pi t_i^{<56} + \alpha_2^\pi t_i^{56-65} + \alpha_3^\pi t_i^{66-75} + \alpha_4^\pi t_i^{76-85} + \alpha_5^\pi t_i^{86+}) \times (1 - H_{it}) \times Fem_i \\ &+ (\alpha_6^\pi t_i^{<56} + \alpha_7^\pi t_i^{56-65} + \alpha_8^\pi t_i^{66-75} + \alpha_9^\pi t_i^{76-85} + \alpha_{10}^\pi t_i^{86+}) \times H_{it} \times Fem_i \\ &+ (\alpha_{11}^\pi t_i^{<56} + \alpha_{12}^\pi t_i^{56-65} + \alpha_{13}^\pi t_i^{66-75} + \alpha_{14}^\pi t_i^{76-85} + \alpha_{15}^\pi t_i^{86+}) \times (1 - H_{it}) \times (1 - Fem_i) \\ &+ (\alpha_{16}^\pi t_i^{<56} + \alpha_{17}^\pi t_i^{56-65} + \alpha_{18}^\pi t_i^{66-75} + \alpha_{19}^\pi t_i^{76-85} + \alpha_{20}^\pi t_i^{86+}) \times H_{it} \times (1 - Fem_i) \\ &+ \alpha_{22}^\pi + (t \geq 50) \times (\alpha_{21}^\pi \mathcal{W}_{it}^{<18.5} + \alpha_{23}^\pi \mathcal{W}_{it}^{[25,30)} + \alpha_{24}^\pi \mathcal{W}_{it}^{[30,35)} + \alpha_{25}^\pi \mathcal{W}_{it}^{[35,40)} + \alpha_{26}^\pi \mathcal{W}_{it}^{\geq 40}) \\ &+ \alpha_{27}^\pi Black_i + \alpha_{28}^\pi Hisp_i]\end{aligned} \tag{A.6}$$

Table A.7: Longevity

Object	Description	MATLAB
α_1^π	age effect for women in bad health, age: < 56	estParams.alphaSurv(1)
α_2^π	age effect for women in bad health, age: 56-65	estParams.alphaSurv(2)
α_3^π	age effect for women in bad health, age: 66-75	estParams.alphaSurv(3)
α_4^π	age effect for women in bad health, age: 76-85	estParams.alphaSurv(4)
α_5^π	age effect for women in bad health, age: 86+	estParams.alphaSurv(5)
α_6^π	age effect for women in good health, age: < 56	fixed to 0
α_7^π	age effect for women in good health, age: 56-65	estParams.alphaSurv(7)
α_8^π	age effect for women in good health, age: 66-75	estParams.alphaSurv(8)
α_9^π	age effect for women in good health, age: 76-85	estParams.alphaSurv(9)
α_{10}^π	age effect for women in good health, age: 86+	estParams.alphaSurv(10)
α_{11}^π	age effect for men in bad health, age: < 56	estParams.alphaSurv(11)
α_{12}^π	age effect for men in bad health, age: 56-65	estParams.alphaSurv(12)
α_{13}^π	age effect for men in bad health, age: 66-75	estParams.alphaSurv(13)
α_{14}^π	age effect for men in bad health, age: 76-85	estParams.alphaSurv(14)
α_{15}^π	age effect for men in bad health, age: 86+	estParams.alphaSurv(15)
α_{16}^π	age effect for men in good health, age: < 56	fixed to 0
α_{17}^π	age effect for men in good health, age: 56-65	estParams.alphaSurv(17)
α_{18}^π	age effect for men in good health, age: 66-75	estParams.alphaSurv(18)
α_{19}^π	age effect for men in good health, age: 76-85	estParams.alphaSurv(19)
α_{20}^π	age effect for men in good health, age: 86+	estParams.alphaSurv(20)
α_{21}^π	weight effect above age 50, BMI: < 18.5	estParams.alphaSurv(21)
α_{22}^π	constant, reference BMI: $[18.5, 25)$	estParams.alphaSurv(22)
α_{23}^π	weight effect above age 50, BMI: $[25, 30)$	estParams.alphaSurv(23)
α_{24}^π	weight effect above age 50, BMI: $[30, 35)$	estParams.alphaSurv(24)

α^{π}_{25}	weight effect above age 50, BMI: $[35, 40)$	estParams.alphaSurv(25)
α^{π}_{26}	weight effect above age 50, BMI: ≥ 40	estParams.alphaSurv(26)
α^{π}_{27}	black intercept	estParams.alphaSurv(27)
α^{π}_{28}	Hispanic intercept	estParams.alphaSurv(28)

Note: π_{it+1} governs longevity and denotes the probability of surviving to the next period, while $1 - \pi_{it+1}$ denotes the probability of death.

A.2.7 Weight evolution

$$\begin{aligned}\mathcal{W}_{it+1} = \mathcal{W}_{it} \times \exp\big(x_{it}\left[\mathbb{I}^{x}_{it}\alpha^{\mathcal{W}}_{1} + (1-\mathbb{I}^{x}_{it})\alpha^{\mathcal{W}}_{0}\right]\big) \times \tilde{\eta}_{it+1} \\ + \alpha^{\mathcal{W}}_{2} + \alpha^{\mathcal{W}}_{8}K_i + \alpha^{\mathcal{W}}_{9}t_i^{26-40} + \alpha^{\mathcal{W}}_{10}t_i^{41-70} + \alpha^{\mathcal{W}}_{11}t_i^{71+} + \alpha^{\mathcal{W}}_{12}\log(A_{it}+1) \\ + \alpha^{\mathbb{W}}\max\left(\mathbb{W}_i - \mathcal{W}_{it}, 0\right),\end{aligned} \tag{A.7}$$

$$\begin{aligned}\text{with}\quad \mathbb{W}_i &= 25 + \alpha^{\mathcal{W}}_{3}Educ_i + \alpha^{\mathcal{W}}_{4}Fem_i + \alpha^{\mathcal{W}}_{5}Black_i + \alpha^{\mathcal{W}}_{6}Hisp_i + \alpha^{\mathcal{W}}_{7}BT_i, \\ \mathbb{I}^{x}_{it} &\sim Bernoulli(\varrho_x), \\ \tilde{\eta}_{it} &= \exp(\eta_{it} - \sigma^2_{\eta}/2) \quad \text{and} \quad \eta_{it} \sim N(0, \sigma^2_{\eta})\end{aligned}$$

Table A.8: Weight Evolution

Object	Description	MATLAB
$\alpha^{\mathcal{W}}_{0}$	effort effect if not successful	set to -0.005
$\alpha^{\mathcal{W}}_{1}$	effort effect if successful	set to -0.05
ϱ_x	probability of successful effort	estParams.alphaWeight(1)
$\alpha^{\mathcal{W}}_{2}$	constant drift	estParams.alphaWeight(2)
$\alpha^{\mathcal{W}}_{3}$	high education fixed effect	estParams.alphaWeight(3)
$\alpha^{\mathcal{W}}_{4}$	female fixed effect	estParams.alphaWeight(4)
$\alpha^{\mathcal{W}}_{5}$	Black fixed effect	estParams.alphaWeight(5)
$\alpha^{\mathcal{W}}_{6}$	Hispanic fixed effect	estParams.alphaWeight(6)
$\alpha^{\mathcal{W}}_{7}$	high body type fixed effect	estParams.alphaWeight(7)
$\alpha^{\mathcal{W}}_{8}$	late cohort drift	estParams.alphaWeight(8)
$\alpha^{\mathcal{W}}_{9}$	age dependent drift, age: 26-40	estParams.alphaWeight(9)
$\alpha^{\mathcal{W}}_{10}$	age dependent drift, age: 41-70	estParams.alphaWeight(10)
$\alpha^{\mathcal{W}}_{11}$	age dependent drift, age: 71+	estParams.alphaWeight(11)
$\alpha^{\mathcal{W}}_{12}$	wealth dependent drift	estParams.alphaWeight(12)
σ^2_{η}	variance of log-normal weight shock	estParams.alphaWeight(13)
$\alpha^{\mathbb{W}}$	drift toward demographic fixed effects	estParams.alphaWeight(14)

The demographic-specific BMI fixed effect is normalized to 25 and varies with demographics. Regressing BMI on education, gender, race and body type using NHANES yields a regression constant of 24.2, providing empirical justification for this normalization. The parameter $\alpha^{\mathcal{W}}$ governs adjustment toward this (natural) group-specific fixed effect when BMI is below it. For a discussion of the effort effect, please refer to Section A.4.

A.2.8 Self-reported weight

$$\begin{aligned}\widehat{\mathcal{W}}_{it} &= \mathcal{W}_{it} + \xi_{it}(D_i) \\ \text{with} \quad \xi_{it}(D_i) &\sim \mathcal{N}(\alpha_1^{\xi}(1-Fem_i) + \alpha_2^{\xi} Fem_i \,,\, \alpha_3^{\xi}(1-Fem_i) + \alpha_4^{\xi} Fem_i)\end{aligned} \tag{A.8}$$

Table A.9: Self-Reported Weight

Object	Description	MATLAB
α_1^{ξ}	mean self-reporting error, men	estParams.alphaWxi(1)
α_2^{ξ}	mean self-reporting error, women	estParams.alphaWxi(2)
α_3^{ξ}	variance of self-reporting error, men	estParams.alphaWxi(3)
α_4^{ξ}	variance of self-reporting error, women	estParams.alphaWxi(4)

A.2.9 Individual marital matching quality

The individual marital matching quality is first defined in equation A.9 below and then normalized to lie between 0 and 1 using the population density (see below).

$$\begin{aligned}\mu_{it} = {} & \alpha_1^{\mu} + \alpha_2^{\mu} x_{it} + (\alpha_3^{\mu}(1-Fem_i) + \alpha_4^{\mu} Fem_i) \times log(A_{it}/\underline{c} + 1) \\ & + (\alpha_5^{\mu}(1-Fem_i) + \alpha_6^{\mu} Fem_i) \times (\mathcal{W}_{it} - 25) + \alpha_7^{\mu} H_{it} \\ & + \alpha_8^{\mu} Black_i + \alpha_9^{\mu} Hisp_i + \alpha_{10}^{\mu} Educ_i\end{aligned} \tag{A.9}$$

Table A.10: Individual Marital Matching Quality

Object	Description	MATLAB
α_1^{μ}	normalizing constant	set to 0.5
α_2^{μ}	effort effect	estParams.alphaMu(2)
α_3^{μ}	assets effect, male	estParams.alphaMu(3)
α_4^{μ}	assets effect, female	estParams.alphaMu(4)
α_5^{μ}	weight effect, male	estParams.alphaMu(5)
α_6^{μ}	weight effect, female	estParams.alphaMu(6)
α_7^{μ}	health effect	estParams.alphaMu(7)
α_8^{μ}	black intercept	estParams.alphaMu(8)
α_9^{μ}	Hispanic intercept	estParams.alphaMu(9)
α_{10}^{μ}	high education intercept	estParams.alphaMu(10)

The marriage quality of each individual is defined as an index between 0 and 1, analogous to a gender-specific cumulative distribution function (CDF). To ensure that individuals are correctly ranked in the population based on their *raw* marital matching quality, we normalize μ_{it} using the population density over the state space. Specifically, we rank all values of μ_{it} while weighting each grid point by its corresponding population density[1]. Each individual is then assigned the normalized

[1]The population density over the state space is constructed in three steps. First, assets are imputed into NHANES using PSID data by estimating regressions of log real assets on demographics, BMI, health, and age, as well as regressions of log squared residuals on the same set of covariates. Second, each individual's BMI and imputed asset value are assigned to the nearest grid point in the state space used to solve the model. Third, the density of each grid cell is computed using sampling weights and rescaled to sum to one for each age. Since NHANES covers individuals only up to age 85, all ages above 85 are assigned the same population density as age 85. This assumption is innocuous, as marriage transitions beyond age 85 are empirically negligible.

value μ_{it}^*, defined as the CDF evaluated at μ_{it}. By construction, μ_{it}^* represents the individual's relative ranking within their age-gender group. To simplify notation, we omit the asterisk below and use μ_{it} to denote the normalized measure. When simulating counterfactual scenarios, the population density can be replaced by the density implied by the simulated counterfactual economy.

While $\underline{\mu}_{it}$ follows directly from the value functions, the reservation threshold of potential partners, $\widetilde{\underline{\mu}}$, is approximated as a weighted average of reservation marriage qualities across all individuals of the opposite sex with the same marriage quality $\widetilde{\mu}$ across the state space.

Because $\mu_{it} = \mu(D_i, A_{it}, \mathcal{W}_{it}, H_{it}, x_{it})$ summarizes all relevant information (entering the value functions through μ_{it}), bilateral marriage decisions depend only on μ_{it} and $\widetilde{\mu}$. As $\mu(\cdot)$ is not invertible, we cannot recover the exact reservation match of a potential spouse with quality $\widetilde{\mu}$ and specific characteristics. But we can determine the *expected* reservation threshold conditional on $\widetilde{\mu}$, which is sufficient to solve the model. Specifically, we determine μ_{it}, solve for its ranking and approximate $\mathbb{E}(\widetilde{\underline{\mu}}|\widetilde{\mu})$ endogenously on a discrete grid.

A.2.10 One-off utility from marriage

$$z(\tilde{\mu}, t) = \alpha_1^z \tilde{\mu} \times z^\mu(t) \quad \text{with} \quad z^\mu(t) = \sum_{k=1}^{\overline{\text{LExp}}-t} \beta^k \tag{A.10}$$

$$\rho_{it}(t_i) = \alpha_2^z t_i^{16-25} + \alpha_3^z t_i^{26-35} + \alpha_4^z t_i^{36-45} + \alpha_5^z t_i^{46+} \tag{A.11}$$

The scaling factor $z^\mu(t)$ scales the one-off utility from marriage to a discounted residual life expectancy, fixing $\overline{\text{LExp}}$ to a life expectancy of 80 years. This implies that the utility gain from marriage is proportional to its expected discounted duration, capturing in a lighthearted way the "lifelong promise" of marriage, while keeping the model computationally tractable.

Table A.11: One-off Utility from Marriage

Object	Description	MATLAB
α_1^z	utility from marriage quality	estParams.alphaMutility(1)
α_2^z	potential spouse arrival rate, age: 16-25	estParams.alphaMutility(2)
α_3^z	potential spouse arrival rate, age: 26-35	estParams.alphaMutility(3)
α_4^z	potential spouse arrival rate, age: 36-45	estParams.alphaMutility(4)
α_5^z	potential spouse arrival rate, age: 46+	estParams.alphaMutility(5)

A.2.11 Utility function

$$\begin{aligned} u_{it} &= \alpha_1^u + \frac{\mathbb{C}_{it}^{1-\alpha_2^u}}{1-\alpha_2^u} \\ \mathbb{C}_{it} &= \frac{c_{it}}{\alpha_3^u} \times \exp\left[\alpha_8^u x_{it} + \alpha_9^u H_{it} + \alpha_{10}^u E_{it}\right] \\ &\quad \times \exp\left[(\alpha_4^u t_i^{16-35} + \alpha_5^u t_i^{36-60} + \alpha_6^u t_i^{61+} + \alpha_7^u Fem_i) \times (\mathcal{W}_{it} - 25)_+\right], \end{aligned} \tag{A.12}$$

where $(\mathcal{W}_{it} - 25)_+$ is 0 for a BMI below 25, and $\mathcal{W}_{it} - 25$ for a BMI above 25.

Table A.12: Utility Function

Object	Description	MATLAB
α_1^u	constant utility of being alive	estParams.alphaUc(1)
α_2^u	CRRA parameter of consumption	estParams.alphaUc(2)
α_3^u	scale parameter of consumption	set to $\underline{c}$: 5,000
α_4^u	overweight utility at age: 16-35	estParams.alphaUp(4)
α_5^u	overweight utility at age: 36-60	estParams.alphaUp(5)
α_6^u	overweight utility at age: 61+	estParams.alphaUp(6)
α_7^u	overweight utility of women	estParams.alphaUp(7)
α_8^u	constant effort utility	estParams.alphaUp(8)
α_9^u	utility from good health	estParams.alphaUp(9)
α_{10}^u	utility from working	estParams.alphaUp(10)

A.2.12 Bellman equations and dynamics

Let the individual state vector be $\Omega_{it} = \{D_i, A_{it}, \mathcal{W}_{it}, H_{it}, E_{it}\}$, which includes fixed individual characteristics D_i (gender, race, education, ability, cohort, and body type), assets A_{it}, body weight $\mathcal{W}_{it}$, health H_{it}, and employment status E_{it}. Conditional on the current state, individuals choose weight-control effort x_{it} and consumption c_{it}, which equivalently determines next period assets A_{it+1} through the budget constraint. Single individuals additionally decide whether to enter a marriage if a potential partner is encountered.

The value functions depend on both employment and marital status. We therefore distinguish between employed (V) and unemployed (U) individuals, as well as between singles (S) and married individuals (M).

For singles, the Bellman equations are

$$\begin{aligned} V_t^S(\Omega_{it}) = \max_{x_{it}, A_{it+1}} & \; u(c_{it}, x_{it}, \Omega_{it}) \\ & + \beta \pi_{it+1} \lambda_{it+1}^{SV} \mathbb{E} \max[(V_{t+1}^S(\Omega_{it+1}), \mathbb{I}_{it,t+1}^M (V_{t+1}^M(\Omega_{it+1}) + z(\tilde{\mu}, t))] \\ & + \beta \pi_{it+1} (1 - \lambda_{it+1}^{SV}) \mathbb{E} \max[U_{t+1}^S(\Omega_{it+1}), \mathbb{I}_{it,t+1}^M (U_{t+1}^M(\Omega_{it+1}) + z(\tilde{\mu}, t))], \end{aligned} \tag{A.13}$$

$$\begin{aligned} U_t^S(\Omega_{it}) = \max_{x_{it}, A_{it+1}} & \; u(c_{it}, x_{it}, \Omega_{it}) \\ & + \beta \pi_{it+1} \lambda_{it+1}^{SU} \mathbb{E} \max[V_{t+1}^S(\Omega_{it+1}), \mathbb{I}_{it,t+1}^M (V_{t+1}^M(\Omega_{it+1}) + z(\tilde{\mu}, t))] \\ & + \beta \pi_{it+1} (1 - \lambda_{it+1}^{SU}) \mathbb{E} \max[U_{t+1}^S(\Omega_{it+1}), \mathbb{I}_{it,t+1}^M (U_{t+1}^M(\Omega_{it+1}) + z(\tilde{\mu}, t))]. \end{aligned} \tag{A.14}$$

Employed individuals retain their jobs with probability λ_{it+1}^{SV}, while non-employed individuals find jobs with probability λ_{it+1}^{SU}. The expectation operator $\mathbb{E}$ integrates over all sources of uncertainty, including employment, health, weight dynamics, effort success, wage, medical expenditure, and marital matching. Survival occurs with probability π_{it+1}, while β denotes the subjective discount factor. The term $z(\tilde{\mu}, t)$ denotes the one-time utility gain from entering a marriage with match quality $\tilde{\mu}$. Match quality is realized when a potential partner is encountered, and $\mathbb{I}_{it,t+1}^M$ indicates whether a mutually acceptable match occurs.

For married individuals, the Bellman equations are

$$\begin{aligned} V_t^M(\Omega_{it}) = \max_{x_{it}, A_{it+1}} & \; u(c_{it}, x_{it}, \Omega_{it}) \\ & + \beta \pi_{it+1} \lambda_{it+1}^{MV} \mathbb{E}[(1-\delta) V_{t+1}^M(\Omega_{it+1}) + \delta V_{t+1}^S(\Omega_{it+1})] \\ & + \beta \pi_{it+1} (1 - \lambda_{it+1}^{MV}) \mathbb{E}[(1-\delta) U_{t+1}^M(\Omega_{it+1}) + \delta U_{t+1}^S(\Omega_{it+1})], \end{aligned} \tag{A.15}$$

$$\begin{aligned} U_t^M(\Omega_{it}) = \max_{x_{it}, A_{it+1}} & \; u(c_{it}, x_{it}, \Omega_{it}) \\ & + \beta \pi_{it+1} \lambda_{it+1}^{MU} \mathbb{E}[(1-\delta) V_{t+1}^M(\Omega_{it+1}) + \delta V_{t+1}^S(\Omega_{it+1})] \\ & + \beta \pi_{it+1} (1 - \lambda_{it+1}^{MU}) \mathbb{E}[(1-\delta) U_{t+1}^M(\Omega_{it+1}) + \delta U_{t+1}^S(\Omega_{it+1})]. \end{aligned} \tag{A.16}$$

The parameter δ is the (race-specific and exogenously set) probability that a marriage is divorced before the next period (abstracting from partner death), after which the individual becomes single.

A.2.13 Numerical integration over shocks

We approximate the continuous shocks in body weight, wages, and medical expenditures using Gauss-Hermite quadrature, a standard approach for evaluating expectations in numerical dynamic programming. For the log normal BMI shock, we use three nodes, and evaluate the continuation value at the implied next BMI using linear interpolation on the BMI grid. Wage and medical expenditure uncertainty are also modeled as multiplicative log normal shocks and approximated by the product of two three-point rules, generating nine joint nodes with probabilities equal to the product of the marginal weights. At each node, we compute next period assets, linearly interpolate the continuation value on the asset grid, and then integrate over the nine weighted values.

A.3 Moments

This section reports the empirical moments used in estimation and maps them to the structural parameters they primarily discipline. The notation follows the codebook. Age group g refers to the age categories defined above, and BMI group q refers to the BMI categories defined above. In datasets with self reported BMI, we use $\widehat{\mathcal{W}}_{it}$; in NHANES moments based on measured BMI, we use $\mathcal{W}_{it}$. In Appendix B, we describe how we weight simulated life cycles to match the sampling distribution of each dataset, ensuring that moments are based on the same underlying population in both simulated and observed data.

A.3.1 Employment

Table A.13: Employment Moments and Targeted Parameters

Regression	Targeted Parameters
Employment evolution, (MATLAB: Moments.phiLambda)	
mean employment rate by age groups and health if working age (MEPS):	
$E_{it} = \sum_{g=2}^{5} \phi_g^{\bar{E}} \cdot \mathbf{1}\{t_i = g\} + \phi_6^{\bar{E}} H_{it} + \varepsilon_{it}^{\bar{E}}$ if $25 < t_i \leq 63$	$\{\alpha_{8-10}^{\lambda_U}, \alpha_{12}^{\lambda_U}, \alpha_{8-10}^{\lambda_V}, \alpha_{12}^{\lambda_V}, \alpha_{10}^{u}\}$
employment on gender and marital status if working age (MEPS):	
$E_{it} = \phi_1^E + \phi_2^E Fem_i + \phi_3^E M_{it} + \phi_4^E (Fem_i \times M_{it}) + \varepsilon_{it}^E$ if $t_i \leq 63$	$\{\alpha_{1-2}^{\lambda_U}, \alpha_{12}^{\lambda_U}, \alpha_{1-2}^{\lambda_V}, \alpha_{12}^{\lambda_V}\}$
employment on body weight categories, age, gender, and cohort if not employed at $t-1$ and working age (NLSY):	
$E_{it} = \sum_q \phi_q^{E_U} \cdot \mathbf{1}\{\widehat{\mathcal{W}}_{it} = q\} + \phi_1^{E_U} t_i + \phi_2^{E_U} K_i + \phi_3^{E_U} (K_i \times (\widehat{\mathcal{W}}_{it} > 30))$ $+\phi_4^{E_U} Fem_i + \phi_5^{E_U} (Fem_i \times (\widehat{\mathcal{W}}_{it} > 30)) + \varepsilon_{it}^{E_U}$ if $E_{it-1} = 0 \cap t_i \leq 63$	$\{\alpha_6^{\lambda_U}, \alpha_{8-17}^{\lambda_U}\}$
employment on demographics and marital status if not employed at $t-1$ and working age (NLSY):	
$E_{it} = \phi_6^{\star E_U} + \phi_7^{E_U} Fem_i + \phi_8^{E_U} M_{it} + \phi_9^{E_U} Black_i + \phi_{10}^{E_U} Hisp_i + \phi_{11}^{E_U} Educ_i + \phi_{12}^{E_U} Abil_i + \varepsilon_{it}^{E'_U}$ if $E_{it-1} = 0 \cap t_i \leq 63$	$\{\alpha_{1-5}^{\lambda_U}, \alpha_7^{\lambda_U}\}$
employment on body weight categories, age, gender, and cohort if employed at $t-1$ and working age (NLSY):	
$E_{it} = \sum_q \phi_q^{E_V} \cdot \mathbf{1}\{\widehat{\mathcal{W}}_{it} = q\} + \phi_1^{E_V} t_i + \phi_2^{E_V} K_i + \phi_3^{E_V} (K_i \times (\widehat{\mathcal{W}}_{it} > 30))$ $+\phi_4^{E_V} Fem_i + \phi_5^{E_V} (Fem_i \times (\widehat{\mathcal{W}}_{it} > 30)) + \varepsilon_{it}^{E_V}$ if $E_{it-1} = 1 \cap t_i \leq 63$	$\{\alpha_6^{\lambda_V}, \alpha_{8-17}^{\lambda_V}\}$
employment on demographics and marital status if employed at $t-1$ and working age (NLSY):	
$E_{it} = \phi_6^{\star E_V} + \phi_7^{E_V} Fem_i + \phi_8^{E_V} M_{it} + \phi_9^{E_V} Black_i + \phi_{10}^{E_V} Hisp_i + \phi_{11}^{E_V} Educ_i + \phi_{12}^{E_V} Abil_i + \varepsilon_{it}^{E'_V}$ if $E_{it-1} = 1 \cap t_i \leq 63$	$\{\alpha_{1-5}^{\lambda_V}, \alpha_7^{\lambda_V}\}$

within individual employment changes on two-year one point BMI jumps (NLSY):	
$E_{it} - E_{it-2} = \phi_{13}^{E\star} + \phi_{14}^{E}\mathbf{1}\{\widehat{\mathcal{W}}_{it} - \widehat{\mathcal{W}}_{it-2} > 1\} + \varepsilon_{it}^{E^{\Delta}}$ if $\widehat{\mathcal{W}}_{it} > 20 \cap t_i \leq 63$	$\{\alpha_{11}^{\lambda_U}, \alpha_{13-15}^{\lambda_U}, \alpha_{11}^{\lambda_V}, \alpha_{13-15}^{\lambda_V}\}$
within individual employment changes on two-year one point BMI falls (NLSY):	
$E_{it} - E_{it-2} = \phi_{15}^{E\star} + \phi_{16}^{E}\mathbf{1}\{\widehat{\mathcal{W}}_{it} - \widehat{\mathcal{W}}_{it-2} < -1\} + \varepsilon_{it}^{E^{\Delta'}}$ if $\widehat{\mathcal{W}}_{it} > 20 \cap t_i \leq 63$	$\{\alpha_{11}^{\lambda_U}, \alpha_{13-15}^{\lambda_U}, \alpha_{11}^{\lambda_V}, \alpha_{13-15}^{\lambda_V}\}$

We identify the employment age profile from MEPS regressions of employment on age groups, controlling for health. We restrict the sample to individuals older than 25 to abstract from educational investments in early working life, a mechanism outside the model. Using MEPS, we also regress employment on gender, marital status, and their interaction, which disciplines the corresponding parameters in both employment transition equations.

To separately identify hiring and retention, we use the panel structure of the NLSY. We estimate employment regressions conditional on lagged employment status, relating current employment to BMI categories, age, cohort, gender, and interactions of cohort and gender with obesity. Separately by lagged employment status, we also regress employment on demographics including ability. These moments discipline selection into employment by ability, which shapes the composition of the employed population.

Finally, we exploit within individual BMI variation using two-year first difference regressions of employment on indicators for a one point BMI increase or decline. We do not require these BMI changes to be random. They may reflect effort or other behavior correlated with expected returns to work. The model includes such behavioral responses, as well as random BMI shocks. If the empirical moment reflects endogenous BMI changes, the same variation is present in the simulated data. The moment therefore remains informative because it disciplines the joint relationship between BMI dynamics and employment transitions.

A.3.2 Wages

Table A.14: Wage Moments and Targeted Parameters

Regression	Targeted Parameters
Wages, (MATLAB: Moments.phiW)	
mean log hourly wages by age groups, obesity, cohort, gender, and obesity interactions if working age (MEPS):	
$\log(\widetilde{w}_{it}) = \sum_{g=1}^{5} \phi_g^{\bar{w}} \cdot \mathbf{1}\{t_i = g\} + \phi_1^w(\widehat{\mathcal{W}}_{it} > 30) + \phi_2^w K_i + \phi_3^w(K_i \times (\widehat{\mathcal{W}}_{it} > 30))$ $+\phi_4^w Fem_i + \phi_5^w(Fem_i \times (\widehat{\mathcal{W}}_{it} > 30)) + \varepsilon_{it}^{\bar{w}}$ if $t_i \leq 63$	$\{\alpha_1^w, \alpha_{6-10}^w, \alpha_{13}^w, \alpha_{15-18}^w\}$
log hourly wages on body weight categories and health if working age (MEPS):	

$\log(\widetilde{w}_{it}) = \sum_q \phi_q^w \cdot \mathbf{1}\{\widehat{\mathcal{W}}_{it} = q\} + \phi_6^w H_{it} + \varepsilon_{it}^w \quad \text{if } t_i \leq 63$	$\{\alpha_{11-16}^w\}$
variance of log hourly wages if working age (MEPS):	
$(\varepsilon_{it}^w)^2 = \phi_1^{w^2} + \varepsilon_{it}^{w^2} \quad \text{if } t_i \leq 63$	$\{\sigma_w^2\}$
mean hourly wages by age groups if working age (MEPS):	
$\widetilde{w}_{it} = \sum_{g=1}^5 \phi_g^{w,\text{lev}} \cdot \mathbf{1}\{t_i = g\} + \varepsilon_{it}^{w,\text{lev}} \quad \text{if } t_i \leq 63$	$\{\alpha_{7-10}^w, \alpha_{13}^w\}$
log hourly wages on demographics if working age (NLSY):	
$\log(\widetilde{w}_{it}) = \phi_7^{\star w} + \phi_8^w Fem_i + \phi_9^w Black_i + \phi_{10}^w Hisp_i + \phi_{11}^w Educ_i + \phi_{12}^w Abil_i + \varepsilon_{it}^{w'} \quad \text{if } t_i \leq 63$	$\{\alpha_{1-5}^w\}$
within individual log wage changes on two-year one point BMI jumps (NLSY):	
$\log(\widetilde{w}_{it}) - \log(\widetilde{w}_{it-2}) = \phi_{13}^{w\star} + \phi_{14}^w \mathbf{1}\{\widehat{\mathcal{W}}_{it} - \widehat{\mathcal{W}}_{it-2} > 1\} + \varepsilon_{it}^{w^\Delta}$ if $\widehat{\mathcal{W}}_{it} > 20 \cap t_i \leq 63$	$\{\alpha_{12}^w, \alpha_{14-16}^w\}$
within individual log wage changes on two-year one point BMI falls (NLSY):	
$\log(\widetilde{w}_{it}) - \log(\widetilde{w}_{it-2}) = \phi_{15}^{w\star} + \phi_{16}^w \mathbf{1}\{\widehat{\mathcal{W}}_{it} - \widehat{\mathcal{W}}_{it-2} < -1\} + \varepsilon_{it}^{w^{\Delta'}}$ if $\widehat{\mathcal{W}}_{it} > 20 \cap t_i \leq 63$	$\{\alpha_{12}^w, \alpha_{14-16}^w\}$

We identify the wage age profile from MEPS regressions of log hourly wages on age groups, obesity, cohort, gender, and their interactions with obesity. These moments discipline the life cycle wage profile, the average obesity wage gradient, and heterogeneity in this gradient by cohort and gender. The cohort dummy and its interaction with obesity, which enter the wage and employment equations, allow labor market conditions and BMI gradients to differ across cohorts. The same cohort dummy enters body weight evolution, capturing environmental change that contributed to rising obesity. Together, these terms allow the productivity effects of obesity to vary with the content of work, the BMI distribution among workers, and firms' responses, all of which may change over time. The corresponding moments from the regressions identify these cohort-specific changes in labor market conditions.

We also use MEPS regressions of log wages on BMI categories and health. A separate regression of hourly wage levels on age groups disciplines the model in dollar terms.

We identify residual wage uncertainty from the variance of log hourly wages in MEPS, which disciplines the variance of the log normal wage shock. Using the NLSY, we regress log wages on gender, race, education, and ability. These moments identify demographic and ability gradients and allow the model to capture selection into higher wage employment by observed ability and other persistent productivity differences.

Finally, we exploit within individual BMI variation using two-year first difference regressions of log wages on indicators for a one point BMI increase or decline. As for employment, we do not require these BMI changes to be random. By disciplining the joint relationship between BMI dynamics and wage growth, these moments help identify the BMI wage gradient net of persistent heterogeneity.

A.3.3 Health

Table A.15: Health Moments and Targeted Parameters

Regression	Targeted Parameters
Health evolution, (MATLAB: Moments.phiHealth)	
mean health by age groups for women (NHANES):	
$H_{it} = \sum_g \phi_g^{\psi_f} \cdot \mathbf{1}\{t_i = g\} + \varepsilon_{it}^{\psi_f}$ if $Fem_i = 1$	$\{\alpha_{4-7}^{\psi}, \alpha_9^u\}$
mean health by age groups for men (NHANES):	
$H_{it} = \sum_g \phi_g^{\psi_m} \cdot \mathbf{1}\{t_i = g\} + \varepsilon_{it}^{\psi_m}$ if $Fem_i = 0$	$\{\alpha_{8-11}^{\psi}, \alpha_9^u\}$
mean health by body weight categories and age (NHANES):	
$H_{it} = \sum_q \phi_q^{\psi} \cdot \mathbf{1}\{\mathcal{W}_{it} = q\} + \phi_1^{\psi} t_i + \varepsilon_{it}^{\psi}$	$\{\alpha_{12-17}^{\psi}\}$
health on demographics, obesity, body type, and obesity by body type (NHANES):	
$H_{it} = \phi_2^{\psi} + \phi_3^{\psi} Black_i + \phi_4^{\psi} Hisp_i + \phi_5^{\psi} Educ_i + \phi_6^{\psi}(\mathcal{W}_{it} > 30) + \phi_7^{\psi} BT_i$ $+\phi_8^{\psi}((\mathcal{W}_{it} > 30) \times BT_i) + \varepsilon_{it}^{\psi'}$	$\{\alpha_{1-3}^{\psi}, \alpha_{14-19}^{\psi}\}$
health on lagged BMI, lagged health, lagged log assets, age, and demographics (PSID):	
$H_{it} = \sum_q \phi_q^{\psi'} \cdot \mathbf{1}\{\widehat{\mathcal{W}}_{it-2} = q\} + \phi_9^{\psi} H_{it-2} + \phi_{10}^{\psi} \log(A_{it-2} + 1)$ $+\sum_{g=2}^{8} \phi_g^{\psi^*} \cdot \mathbf{1}\{t_i = g\} + \phi_{11}^{\psi} Black_i + \phi_{12}^{\psi} Hisp_i + \phi_{13}^{\psi} Educ_i + \varepsilon_{it}^{\psi''}$	$\{\alpha_{1-21}^{\psi}\}$
within individual health changes on two-year one point BMI jumps (NLSY):	
$H_{it} - H_{it-2} = \phi_{14}^{\psi\star} + \phi_{15}^{\psi} \mathbf{1}\{\widehat{\mathcal{W}}_{it} - \widehat{\mathcal{W}}_{it-2} > 1\} + \varepsilon_{it}^{\psi^{\Delta}}$ if $\widehat{\mathcal{W}}_{it} > 20$	$\{\alpha_{12}^{\psi}, \alpha_{14-17}^{\psi}, \alpha_{19}^{\psi}\}$
within individual health changes on two-year one point BMI falls (NLSY):	
$H_{it} - H_{it-2} = \phi_{16}^{\psi\star} + \phi_{17}^{\psi} \mathbf{1}\{\widehat{\mathcal{W}}_{it} - \widehat{\mathcal{W}}_{it-2} < -1\} + \varepsilon_{it}^{\psi^{\Delta'}}$ if $\widehat{\mathcal{W}}_{it} > 20$	$\{\alpha_{12}^{\psi}, \alpha_{14-17}^{\psi}, \alpha_{19}^{\psi}\}$

We identify the health age profile from NHANES regressions of good health on age groups, separately by gender. These moments discipline the gender specific life cycle decline in health. We also use NHANES regressions of good health on BMI categories and age to identify the health gradient of body weight. A separate NHANES regression on demographics, obesity, body type, and the body type by obesity interaction allows higher BMI to have different health effects for individuals who tend to be heavier because of body morphology.

We use the PSID panel structure to discipline health dynamics. Regressing current health on lagged BMI, lagged health, lagged assets, age, and demographics helps separate the role of past health from other determinants, including body weight. These moments pin down health persistence and discipline the relative

importance of the components in the health transition equation.

Finally, we exploit within individual BMI variation using two-year first difference regressions of health on indicators for a one point BMI increase or decline. As for employment and wages, we do not require these BMI changes to be random. By disciplining the joint relationship between BMI dynamics and health transitions, these moments help identify the BMI health gradient net of persistent heterogeneity.

A.3.4 Medical Expenditures

Table A.16: Medical Expenditure Moments and Targeted Parameters

Regression	Targeted Parameters
Medical expenditures, (MATLAB: Moments.phiMed)	
mean medical expenditures by age groups (MEPS):	
$m_{it} = \sum_{g=1}^{6} \phi_g^{\bar{m}} \cdot \mathbf{1}\{t_i = g\} + \varepsilon_{it}^{\bar{m}}$	$\{\alpha_{1-10}^m\}$
mean log medical expenditures by age groups if health is good (MEPS):	
$\log(m_{it}) = \sum_{g=1}^{6} \phi_g^{\bar{m}^1} \cdot \mathbf{1}\{t_i = g\} + \varepsilon_{it}^{\bar{m}^1}$ if $H_{it} = 1$	$\{\alpha_{1-5}^m\}$
mean log medical expenditures by age groups if health is bad (MEPS):	
$\log(m_{it}) = \sum_{g=1}^{6} \phi_g^{\bar{m}^0} \cdot \mathbf{1}\{t_i = g\} + \varepsilon_{it}^{\bar{m}^0}$ if $H_{it} = 0$	$\{\alpha_{6-10}^m\}$
log medical expenditures on demographics (MEPS):	
$\log(m_{it}) = \phi_1^m + \phi_2^m Fem_i + \phi_3^m Black_i + \phi_4^m Hisp_i + \phi_5^m Educ_i + \varepsilon_{it}^m$	$\{\alpha_{11-14}^m\}$
variance of log medical expenditures if working age (MEPS):	
$(\varepsilon_{it}^m)^2 = \phi_1^{m^2} + \varepsilon_{it}^{m^2}$ if $t_i \leq 63$	$\{\sigma_m^2\}$
log medical expenditures at old ages by health status (HRS):	
$\log(m_{it}) = \phi_6^m H_{it} \mathbf{1}\{t_i = 76\text{–}85\} + \phi_7^m H_{it} \mathbf{1}\{t_i > 85\}$ $+\phi_8^m (1 - H_{it}) \mathbf{1}\{t_i = 76\text{–}85\} + \phi_9^m (1 - H_{it}) \mathbf{1}\{t_i > 85\} + \varepsilon_{it}^{m'}$	$\{\alpha_{4-5}^m, \alpha_{9-10}^m\}$

We identify the age profile of medical expenditures from MEPS regressions of expenditures on age groups. Since the model allows expenditures to differ by health, we also estimate separate log expenditure profiles for individuals in good and bad health. These moments discipline the health specific age profiles in medical spending and capture that poor health raises expenditures differently over the life cycle.

We use MEPS regressions of log medical expenditures on gender, race, and education to identify demographic spending differences. We identify residual medical expenditure uncertainty from the variance of log medical expenditures in MEPS, which disciplines the variance of the log normal medical expenditure shock.

Finally, we use HRS moments on log medical expenditures at older ages by health status. These moments discipline spending at ages where medical costs are high and where MEPS provides less information. Together, the MEPS and HRS moments identify the age, health, demographic, and risk components of medical expenditures over the life cycle.

A.3.5 Longevity

Table A.17: Longevity Moments and Targeted Parameters

Regression	Targeted Parameters
Longevity, (MATLAB: Moments.phiSurv)	
mean two-year survival by age group and lagged health for women (HRS):	
$Alive_{it} = \sum_{g=4}^{8} \phi_g^{\pi_f^0} \cdot \mathbf{1}\{t_i = g\} \times (H_{it-2} = 0)$ $+ \sum_{g=4}^{8} \phi_g^{\pi_f^1} \cdot \mathbf{1}\{t_i = g\} \times (H_{it-2} = 1) + \varepsilon_{it}^{\pi_f}$ if $Alive_{it-2} = 1 \cap Fem_i = 1$	$\{\alpha_{1-10}^{\pi}\}$
mean two-year survival by age group and lagged health for men (HRS):	
$Alive_{it} = \sum_{g=4}^{8} \phi_g^{\pi_m^0} \cdot \mathbf{1}\{t_i = g\} \times (H_{it-2} = 0)$ $+ \sum_{g=4}^{8} \phi_g^{\pi_m^1} \cdot \mathbf{1}\{t_i = g\} \times (H_{it-2} = 1) + \varepsilon_{it}^{\pi_m}$ if $Alive_{it-2} = 1 \cap Fem_i = 0$	$\{\alpha_{11-20}^{\pi}\}$
mean two-year survival by demographics and age (HRS):	
$Alive_{it} = \phi_0^{\star\pi} + \phi_1^{\pi} Fem_i + \phi_2^{\pi} Black_i + \phi_3^{\pi} Hisp_i + \phi_4^{\pi} Educ_i + \phi_5^{\pi} t_i + \varepsilon_{it}^{\pi'}$ if $Alive_{it-2} = 1$	$\{\alpha_{1-20}^{\pi}, \alpha_{27-28}^{\pi}\}$
mean age at death by body weight categories (HRS):	
$t_{it}^{death} = \phi_6^{\star\pi} + \sum_q \phi_q^{\pi} \cdot \mathbf{1}\{\widehat{\mathcal{W}}_{it} = q\} + \varepsilon_{it}^{\pi''}$ if $Alive_{it} = 1$	$\{\alpha_{1-26}^{\pi}\}$
residual life expectancy by race, gender, and age (United States Life Tables, 2010):	
$\overline{LE}_{rfs}^{res} = \mathbb{E}[LE_{it}^{res}(s) \mid Race_i = r, Fem_i = f, t_i = s]$, $r \in \{White, Black, Hispanic\}$, $f \in \{0,1\}$, $s \in \{16, 50, 70, 85\}$	$\{\alpha_{1-28}^{\pi}\}$

We identify longevity parameters from HRS moments on two-year survival probabilities. Regressions by age, gender, and lagged health discipline the

age profile of mortality and the survival difference between good and bad health. Additional HRS moments on gender, race, education, and age discipline demographic mortality gradients. These moments identify mortality risks period by period.

We use age at death by BMI category to discipline the direct BMI component of longevity. This moment is especially important because individuals often lose weight shortly before death, so first difference regressions of survival on BMI changes would not identify the BMI mortality gradient. Instead, we use BMI measured several years before observed deaths in the HRS. This helps separate the direct BMI mortality gradient from late life weight loss and from the indirect channel through health.

Finally, we use residual life expectancy by age, gender, and race from the United States Life Tables, 2010 (Arias, 2014). In the simulation, residual life expectancy is computed as the sum of cumulative products of each individual's model implied mortality probabilities, following the life table definition. We compute this only for the earlier cohort and aggregate individual residual life expectancies by demographic groups, which gives the model equivalent of the life table moments. These moments discipline the cumulative implications of mortality. They are useful because small errors in two-year mortality probabilities can accumulate into large differences in life expectancy over the life cycle.

A.3.6 Body Weight and Effort

Table A.18: Body Weight and Effort Moments and Targeted Parameters

Regression	Targeted Parameters
Weight evolution, (MATLAB: Moments.phiWeight)	
mean body weight by age groups and cohort (NHANES):	
$\mathcal{W}_{it} = \sum_{g=1}^{7} \phi_g^{\bar{\mathcal{W}}} \cdot \mathbf{1}\{t_i = g\} + \phi_8^{\bar{\mathcal{W}}} K_i + \varepsilon_{it}^{\bar{\mathcal{W}}}$	$\{\alpha_2^{\mathcal{W}}, \alpha_{8-11}^{\mathcal{W}}, \alpha_{4-8}^{u}\}$
variance of body weight (NHANES):	
$(\varepsilon_{it}^{\bar{\mathcal{W}}})^2 = \phi_1^{\mathcal{W}^2} + \varepsilon_{it}^{\mathcal{W}^2}$	$\{\alpha_2^{\mathcal{W}}, \varrho_x, \sigma_\eta^2, \alpha^{\mathbb{W}}\}$
mean body weight by demographics (NHANES):	
$\mathcal{W}_{it} = \phi_1^{\bar{\mathcal{W}}} + \phi_2^{\bar{\mathcal{W}}} Fem_i + \phi_3^{\bar{\mathcal{W}}} Black_i + \phi_4^{\bar{\mathcal{W}}} Hisp_i + \phi_5^{\bar{\mathcal{W}}} Educ_i + \phi_6^{\bar{\mathcal{W}}} BT_i + \varepsilon_{it}^{\bar{\mathcal{W}}'}$	$\{\alpha_{2-7}^{\mathcal{W}}\}$
self reported two-year BMI change by age and demographics (PSID):	
$\widehat{\mathcal{W}}_{it} - \widehat{\mathcal{W}}_{it-2} = \sum_{g=1}^{8} \phi_g^{\widehat{\mathcal{W}}} \cdot \mathbf{1}\{t_i = g\} + \phi_9^{\widehat{\mathcal{W}}} Fem_i + \phi_{10}^{\widehat{\mathcal{W}}} Black_i + \phi_{11}^{\widehat{\mathcal{W}}} Hisp_i + \varepsilon_{it}^{\widehat{\mathcal{W}}}$	$\{\alpha_{2-6}^{\mathcal{W}}, \alpha_{8-11}^{\mathcal{W}}, \alpha_1^{\xi}, \alpha_2^{\xi}\}$
variance of self reported two-year BMI change (PSID):	
$(\varepsilon_{it}^{\widehat{\mathcal{W}}})^2 = \phi_1^{\widehat{\mathcal{W}}^2} + \varepsilon_{it}^{\widehat{\mathcal{W}}^2}$	$\{\sigma_\eta^2, \alpha_3^{\xi}, \alpha_4^{\xi}\}$
self reported two-year BMI change on lagged BMI categories (PSID):	

$\widehat{\mathcal{W}}_{it} - \widehat{\mathcal{W}}_{it-2} = \sum_{q=1}^{5} \phi_q^{\widehat{\mathcal{W}}} \cdot \mathbf{1}\{\widehat{\mathcal{W}}_{it-2} = q\} + \varepsilon_{it}^{\widehat{\mathcal{W}}'}$	$\{\alpha^{\mathbb{W}}\}$
self reported two-year BMI change on log assets controlling for age, demographics, and body weight (PSID):	
$\widehat{\mathcal{W}}_{it} - \widehat{\mathcal{W}}_{it-2} = \phi_{12}^{\widehat{\mathcal{W}}} \log(A_{it}+1) + \sum_{g=1}^{8} \phi_g^{\widehat{\mathcal{W}}^*} \cdot \mathbf{1}\{t_i = g\}$ $+\phi_{13}^{\widehat{\mathcal{W}}^*} Fem_i + \phi_{14}^{\widehat{\mathcal{W}}^*} Black_i + \phi_{15}^{\widehat{\mathcal{W}}^*} Hisp_i + \sum_q \phi_q^{\widehat{\mathcal{W}}^*} \cdot \mathbf{1}\{\widehat{\mathcal{W}}_{it} = q\} + \varepsilon_{it}^{\widehat{\mathcal{W}}''}$	$\{\alpha_{12}^{\mathcal{W}}\}$
Effort, (MATLAB: Moments.phiU and Moments.phiWeight)	
mean effort by age groups (NHANES):	
$x_{it-1} = \sum_{g=1}^{7} \phi_g^{\bar{x}} \cdot \mathbf{1}\{t_i = g\} + \varepsilon_{it}^{\bar{x}}$	$\{\alpha_{4-6}^{u}\}$
effort on body weight categories (NHANES):	
$x_{it-1} = \sum_q \phi_q^{\bar{x}} \cdot \mathbf{1}\{\mathcal{W}_{it} = q\} + \varepsilon_{it}^{x}$	$\{\alpha_8^u, \varrho_x, \alpha_7^{\mathcal{W}}\}$
effort on demographics (NHANES):	
$x_{it-1} = \phi_2^{\star x} + \phi_3^x Fem_i + \phi_4^x Black_i + \phi_5^x Hisp_i + \phi_6^x K_i + \phi_7^x Educ_i + \phi_8^x BT_i + \varepsilon_{it}^{x'}$	$\{\alpha_{4-10}^{u}\}$

We identify body weight evolution from moments on both measured BMI levels and self reported BMI changes. NHANES moments on measured BMI by age and cohort discipline the life cycle weight profile and the external cohort shift in body weight. This cohort component captures environmental changes, including rising material abundance and comfort as well as broader shifts in consumption patterns, that have contributed to increasing obesity rates over recent decades. NHANES moments on the variance of measured BMI discipline persistent body type, transitory weight shocks, and the dispersion of body weight in the population. NHANES moments by demographics and body type discipline systematic differences in body weight across gender, race, education, and persistent morphology.

We use the PSID panel structure to discipline BMI dynamics. Regressions of two-year self reported BMI changes on age and demographics identify how weight evolves over the life cycle and across groups. The variance of BMI changes disciplines transitory weight shocks as well as reporting error. Regressions of BMI changes on lagged BMI categories discipline persistence in body weight. Regressions of BMI changes on assets, controlling for age, demographics, and BMI, discipline how economic resources affect weight dynamics.

We identify weight control effort from NHANES moments on observed effort. Since effort is not observed in panel data, identification comes from the joint fit of cross sectional effort rates and panel weight dynamics. If effort were often successful and BMI had large negative consequences, individuals would leave obesity quickly, and few obese individuals would be observed exerting effort. High effort success can therefore be reconciled with high obesity and high effort rates only if average weight drift is sufficiently positive. The PSID weight change moments discipline this drift by age, demographics, and BMI. Conditional on this drift, NHANES effort rates by age, BMI, demographics, cohort, education, and body type discipline the effort success probability and the utility cost of effort through the model structure. Section A.4 discusses how the calibrated size of a successful effort episode is disciplined by external evidence on the causal effect of self administered weight loss efforts.

The model also includes direct utility components from health, work, and weight control effort. Effort reduces effective consumption, which enters utility through a concave function. The utility costs of poor health and work enter the same effective consumption shifter. Since several state variables affect effective consumption jointly, their combined effect has nonlinear implications for utility. These shifters are identified by heterogeneity in effort across the relevant state variables, or empirical proxies for them. For example, if the model predicts too much effort for individuals or demographic groups with a higher incidence of poor health, a larger utility value of good health can reduce the incentive to exert effort in those states. Similarly, work utility is identified residually from how employment and saving behavior vary across states after accounting for wages, assets, health, longevit, and medical expenditures. Thus, the utilities of not working and good health are pinned down residually through behavior, state interactions, and the functional form assumptions of the model.

A.3.7 Self Reported Weight

Table A.19: Self Reported Weight Moments and Targeted Parameters

Regression	Targeted Parameters
Self reported weight, (MATLAB: Moments.phiWxi)	
mean difference between self reported and measured body weight by gender (NHANES):	
$\widehat{\mathcal{W}}_{it} - \mathcal{W}_{it} = \phi_1^\xi + \phi_2^\xi Fem_i + \varepsilon_{it}^\xi$	$\{\alpha_1^\xi, \alpha_2^\xi\}$
variance of difference between self reported and measured body weight by gender (NHANES):	
$(\varepsilon_{it}^\xi)^2 = \phi_3^\xi + \phi_4^\xi Fem_i + \varepsilon_{it}^{\xi^2}$	$\{\alpha_3^\xi, \alpha_4^\xi\}$

We identify reporting error in body weight from NHANES, where both measured and self reported weight are observed for the same individuals. The mean difference between self reported and measured BMI, separately by gender, disciplines systematic reporting bias. The variance of this difference disciplines the dispersion of reporting error and allows this dispersion to differ by gender.

These moments are important because the model uses both measured and self reported BMI moments. NHANES moments discipline the level and dispersion of true body weight, while PSID and NLSY moments rely on self reported BMI. The reporting error process maps true BMI into self reported BMI, allowing the model to use all datasets consistently.

A.3.8 Marriage

Table A.20: Marriage Moments and Targeted Parameters

Regression	Targeted Parameters
Individual marital matching quality and one off utility from marriage, (MATLAB: Moments.phiMu)	
mean marriage status by age and effort at ages 20 to 40 (NHANES):	
$M_{it} = \phi_0^{\bar{\mu}'\star} + \phi_1^{\bar{\mu}'} x_{it-1} + \phi_2^{\bar{\mu}'} t_i + \varepsilon_{it}^{\bar{\mu}'}$ if $20 \leq t_i \leq 40$	$\{\alpha_{1-2}^{\mu}\}$
mean marriage status by age groups (MEPS):	
$M_{it} = \sum_{g=1}^{6} \phi_g^{\bar{\mu}} \cdot \mathbf{1}\{t_i = g\} + \varepsilon_{it}^{\bar{\mu}}$	$\{\alpha_1^{\mu}, \alpha_{1-5}^{z}\}$
mean marriage status by body weight categories, women aged 31 to 40 (MEPS):	
$M_{it} = \sum_q \phi_q^{\bar{\mu}_f} \cdot \mathbf{1}\{\widehat{\mathcal{W}}_{it} = q\} + \varepsilon_{it}^{\bar{\mu}_f}$ if $Fem_i = 1 \cap 30 < t_i \leq 40$	$\{\alpha_6^{\mu}\}$
mean marriage status by body weight categories, men aged 31 to 40 (MEPS):	
$M_{it} = \sum_q \phi_q^{\bar{\mu}_m} \cdot \mathbf{1}\{\widehat{\mathcal{W}}_{it} = q\} + \varepsilon_{it}^{\bar{\mu}_m}$ if $Fem_i = 0 \cap 30 < t_i \leq 40$	$\{\alpha_5^{\mu}\}$
individual having high education on spousal demographics when married (MEPS):	
$Educ_i = \phi_0^{\star\mu} + \phi_1^{\mu} Black_{jt} + \phi_2^{\mu} Hisp_{jt} + \phi_3^{\mu} Educ_{jt} + \varepsilon_{it}^{\mu'}$ if $M_{it} = 1$	$\{\alpha_{8-10}^{\mu}\}$
female spouse log wage on lagged health, assets, and demographics at marriage formation (PSID):	
$\log(\widetilde{w}_{jt}) = \phi_4^{\star\mu} + \phi_5^{\mu} H_{it-2} + \phi_6^{\mu} \log(A_{it-2} + 1) + \phi_7^{\mu} Educ_i + \phi_8^{\mu} Black_i + \phi_9^{\mu} Hisp_i + \varepsilon_{it}^{\mu_w}$ if $M_{it-2} = 0 \cap M_{it} = 1 \cap Fem_i = 0 \cap t_i \leq 45$	$\{\alpha_{3-4}^{\mu}, \alpha_{7-10}^{\mu}\}$
spousal log wage on own log wage (PSID):	
$\log(\widetilde{w}_{jt}) = \phi_{10}^{\mu\star} + \phi_{11}^{\mu} \log(\widetilde{w}_{it}) + \varepsilon_{it}^{\mu_{ww}}$ if $t_i \leq 45$	$\{\alpha_{3-4}^{\mu}\}$
spousal body weight on lagged body weight, assets, health, and demographics at marriage formation (PSID):	
$\mathcal{W}_{jt} = \phi_{12}^{\star\mu} + \phi_{13}^{\mu} \widehat{\mathcal{W}}_{it-2} + \phi_{14}^{\mu} \log(A_{it-2} + 1) + \phi_{15}^{\mu} H_{it-2} + \phi_{16}^{\mu} Educ_i$ $+\phi_{17}^{\mu} Black_i + \phi_{18}^{\mu} Hisp_i + \varepsilon_{it}^{\mu\mathcal{W}}$ if $M_{it-2} = 0 \cap M_{it} = 1 \cap t_i \leq 45$	$\{\alpha_{3-10}^{\mu}\}$
spousal health on lagged health and assets at marriage formation (PSID):	
$H_{jt} = \phi_{19}^{\star\mu} + \phi_{20}^{\mu} H_{it-2} + \phi_{21}^{\mu} \log(A_{it-2} + 1) + \varepsilon_{it}^{\mu_H}$ if $M_{it-2} = 0 \cap M_{it} = 1 \cap t_i \leq 45$	$\{\alpha_{3-4}^{\mu}, \alpha_7^{\mu}\}$

We identify marriage formation and match values from moments on marriage status and spouse characteristics. MEPS moments on marriage status by age discipline the life cycle profile of marriage, spouse arrival rates, and reservation match values. If arrival rates were too high or reservation values too low, individuals would marry quickly and marriage rates would remain close to one throughout the life cycle. NHANES moments on marriage status by age and

effort at ages 20 to 40 discipline the role of effort behavior in marriage incentives. If individuals exert effort mainly to attract potential partners, beyond its effect on weight evolution, effort should fall after marriage and be negatively related to marital status conditional on age.

We use MEPS moments on marriage status by BMI category, separately for women and men aged 31 to 40, to identify the gender specific role of body weight in the marriage market. If individuals with high BMI rank lower and are less acceptable to potential partners, they remain single for longer and have lower marriage rates. These moments discipline how body weight enters individual match value for women and men.

We identify sorting in marriage using spouse characteristics in MEPS and the PSID. For the relevant PSID regressions between spousal characteristics, we focus on marriages formed before age 46. This is the main period in which marriage can also be viewed as an entry point into family formation, which helps justify the potentially large utility gain from marriage. Regressions of own education on spousal race and education discipline the relative importance of fixed demographic factors in matching. Around marriage formation, PSID regressions of female spousal wages on men's lagged health, lagged assets, education, race, and ethnicity discipline the relative importance of health, economic resources, and demographics. The regression of spousal log wages on own log wages further informs assortative matching in labor market productivity. Regressions of spousal BMI on own lagged BMI, assets, health, education, race, and ethnicity discipline the role of body weight and economic resources in matching, while regressions of spousal health on own lagged health and assets discipline sorting by health and resources. Together, these moments identify how individual characteristics map into expected spouse characteristics and the gains from marriage.

A.3.9 Assets, Preferences, and Resources

Table A.21: Asset, Preference, and Resource Moments and Targeted Parameters

Regression	Targeted Parameters
Utility function and resources, (MATLAB: Moments.phiU)	
mean assets by age groups (PSID):	
$A_{it} = \sum_{g=1}^{8} \phi_g^{\bar{A}} \cdot \mathbf{1}t_i = g + \varepsilon_{it}^{\bar{A}}$	$\alpha_2^u, \alpha_{12}^{\lambda_U}, \alpha_{12}^{\lambda_V}, \alpha_{13}^w$
mean assets by gender at ages 50 to 70 (PSID):	
$A_{it} = \phi_1^{A_f} Fem_i + \phi_2^{A_m}(1 - Fem_i) + \varepsilon_{it}^{A^{fm}}$ if $50 \leq t_i \leq 70$	α_2^u
mean assets by demographics and body weight at ages 30 to 60 (PSID):	
$A_{it} = \phi_1^A White_i + \phi_2^A Black_i + \phi_3^A Hisp_i + \phi_4^A Educ_i + \phi_5^A \widehat{\mathcal{W}}_{it} + \varepsilon_{it}^A$ if $30 \leq t_i \leq 60$	α_2^u
first difference of assets by age and demographics (PSID):	
$A_{it} - A_{it-2} = \phi_1^{dA} t_i + \phi_2^{dA} Fem_i + \phi_3^{dA} Black_i + \phi_4^{dA} Hisp_i + \phi_5^{dA} Educ_i + \varepsilon_{it}^{dA}$ if $t_i < 66$	α_2^u
value of statistical life (external target):	

$\text{VSL} = \frac{\partial V/\partial \pi}{\partial V/\partial A}$	α_1^u

Note: Regression coefficients with a star $\phi^\star$ are included in auxiliary regressions but are not used as targeted moments. We do this for selected constants when another dataset already pins down the relevant level or when the constant is not informative for identification. The value of statistical life is disciplined by external estimates from the literature.

We identify assets, preferences, and resources from PSID asset profiles and an external value of statistical life target. Mean assets by age discipline the life cycle saving profile and the model's ability to reproduce asset accumulation before retirement. These moments are informative about consumption smoothing, the value of resources, and the labor market channels that generate earnings over the life cycle.

We use asset levels by gender at ages 50 to 70 and by race, ethnicity, education, and body weight at ages 30 to 60 to discipline heterogeneity in resources. These moments capture differences in asset levels that arise from earnings, employment, income uncertainty, medical expenditures, marriage, longevity, and selection over the life cycle. Including body weight in the demographic asset regression helps discipline how the cumulative economic consequences of BMI are reflected in resources. First differences in assets by age and demographics discipline saving dynamics and help separate asset levels from asset accumulation.

Finally, we use an external value of statistical life target, set to USD 6 million, to discipline the curvature and scale of utility. This target pins down how the model converts longevity gains into willingness to pay in dollar terms. Section A.5.3 describes the corresponding value function calculation. Together, the asset profiles, asset changes, and value of statistical life target discipline the resource side of the model and the marginal value of wealth over the life cycle.

A.4 The effect of weight-loss effort

Identifying the medium-term causal effect of self-administered, broad-spectrum weight-loss efforts requires extrapolating outcomes from structured randomized controlled trials and adjusting for the lack of professional supervision, behavioral support, and maintenance structures inherent in self-guided interventions. Evidence from meta-analyses of structured programs combining dietary restriction, physical activity, and behavioral modification indicates that completers typically maintain weight losses of approximately 3–6% of their initial body weight at four years, with diet-only programs showing declines from about 4.9 kg (∼5%) at six months to 3.0 kg (∼3%) at 48 months (Franz et al., 2007). Similar findings are confirmed in network and umbrella reviews showing that combined diet and exercise interventions outperform either component alone, producing average sustained losses of 3–6 kg at one to four years (Bellicha et al., 2021; Jakicic et al., 2024; Jayedi et al., 2024; Schwingshackl et al., 2014). However, these estimates represent upper bounds achievable under continuous supervision.

Efficacy declines sharply when interventions are self-administered. In the absence of structured maintenance or professional oversight, regain typically begins after 6–12 months at a rate of about 0.03 BMI units per month, implying full regain after approximately 5.5 years (Dansinger et al., 2007). Minimal-structure and advice-only interventions yield negligible long-term loss (Franz et al., 2007; Kirk et al., 2012; Swift et al., 2014), and meta-analytic evidence indicates that even exercise-alone programs generally produce reductions of only 1–3 kg with substantial heterogeneity (Bellicha et al., 2021; Stoner et al., 2016). Thus, self-administered efforts are expected to achieve near-zero maintained loss relative to baseline after five years. Because untreated adults typically gain 1–6 kg over five years (Anderson et al., 2001), even weight stability in the treatment group implies a positive causal effect relative to the counterfactual.

Adjusting for the attenuated durability of self-administered weight-loss efforts places the medium-term causal effect between roughly 0.5% and 5% of initial body weight. Guided by this evidence, we parameterize the effort technology such that successful effort reduces body weight by $\alpha_1^{\mathcal{W}} = -0.05$, while unsuccessful effort still implies a small proportional change of $\alpha_0^{\mathcal{W}} = -0.005$.

In the model, the success of effort is governed by the indicator $\mathbb{I}_{it}^{x} \sim Bernoulli(\varrho_x)$, where ϱ_x denotes the probability that effort is successful. As a consequence, the realized effect of exerting effort varies across periods depending on whether effort succeeds or fails. The average proportional effect of effort is therefore determined endogenously by the estimated success probability ϱ_x and can be substantially smaller than the upper bound of 5% implied by $\alpha_1^{\mathcal{W}}$.

A.5 Utility

This supplementary section motivates the choice of period utility and clarifies how it shapes the willingness to pay (WTP) for weight-loss technologies. It also discusses implications of the utility function for utility costs of effort, health, and working, and derives an expression for the value of statistical life (VSL).

The key design principle is to adopt a period utility specification that is as 'innocent' as possible with respect to the WTP: it should be easy to interpret and avoid imposing strong functional-form restrictions on how WTP varies with wealth, consumption, effort, health, and labor supply. By modeling overweight stigma as a multiplicative shifter of effective consumption, the implied *period* WTP is proportional to consumption and independent of the (dis-)utility from effort, health, and work. As a consequence, heterogeneity in the dynamic WTP is driven primarily by the model's state transitions - in particular, the impact of body weight on future health, longevity, labor-market outcomes, and

marriage prospects - rather than being mechanically generated by curvature assumptions in period utility. Alternative utility formulations (e.g. additively separable stigma with CRRA consumption, or different degrees of curvature across utility components) would instead generate large differences in WTP along the wealth distribution purely from functional-form choices. We therefore adopt the present specification to leave maximal scope for the model dynamics, which are the central object of interest in the paper. Moreover, under plausible assumptions, the utility specification implies that effort and work are more burdensome for obese individuals. This adds realism and ensures that the model can generate a range of plausible behavioral responses in our counterfactual analyses.

The utility function is,

$$u_{it} = \alpha_1^u + \frac{\mathbb{C}_{it}^{1-\alpha_2^u}}{1-\alpha_2^u},$$

with $\mathbb{C}_{it}$ denoting *effective consumption*,

$$\mathbb{C}_{it} = \frac{c_{it}}{\alpha_3^u} \times \exp\left[\alpha_{\mathcal{S}}^u \mathcal{S}(\mathcal{W}_{it}, t_i, D_i) + \alpha_{\mathcal{O}} \mathcal{O}(x_{it}, H_{it}, E_{it})\right],$$

with c_{it} being consumption and $\alpha_{\mathcal{S}}^u \mathcal{S}$ being the utility from having a BMI over 25 – or, simply a linear *overweight stigma* – which is assumed to be negative. Specifically, $\alpha_{\mathcal{S}}^u \mathcal{S}$ is the age- and gender-specific utility from having a BMI above the normal range: $\alpha_{\mathcal{S}}^u \mathcal{S} = (\alpha_4^u t_i^{16-35} + \alpha_5^u t_i^{36-60} + \alpha_6^u t_i^{61+} + \alpha_7^u Fem_i) \times (\mathcal{W}_{it} - 25)_+$ where $(\mathcal{W}_{it} - 25)_+$ is 0 for a BMI below 25, and $\mathcal{W}_{it} - 25$ for a BMI above 25. The last term in effective consumption is the (dis-) utility from effort, health, and working, for simplicity expressed as $\alpha_{\mathcal{O}} \mathcal{O} = \alpha_8^u x_{it} + \alpha_9^u H_{it} + \alpha_{10}^u E_{it}$.

In alternative WTP calculations and counterfactual analyses, we model side effects analogously through a multiplicative shifter of effective consumption. The discussion below of the other effective consumption shifters therefore also applies to side effects.

WTP approximation from period utility

To isolate the role of period utility, we initially abstract from dynamics, which introduce additional considerations discussed in the next subsection. The willingness to pay (WTP) for a technology that reduces body weight W_{it} can then be approximated by the marginal rate of substitution. For the utility function specified above,

$$\text{WTP} \approx \frac{\partial u / \partial W_{it}}{\partial u / \partial c_{it}} \Delta W_{it} = c_{it} \frac{\partial(\alpha_S^u S)}{\partial W_{it}} \Delta W_{it}.$$

The period WTP is zero for $W_{it} < 25$ and positive for a reduction in body weight above this threshold because both $\partial(\alpha_S^u S)/\partial W_{it}$ and ΔW_{it} are negative. It is linear in consumption because overweight stigma enters multiplicatively through effective consumption. This avoids the strong dependence on consumption implied by specifications in which BMI disutility enters utility additively and therefore does not mechanically determine which income groups demand the technology. The stigma parameters can also be interpreted approximately as proportional reductions in effective consumption. Finally, the period WTP is independent of $O(x_{it}, H_{it}, E_{it})$, so the effects of effort, health, and employment on WTP operate through the model dynamics.

A.5.1 WTP in a dynamic framework

The following local approximation summarizes the forces that determine model-implied WTP and thereby guides our decompositions and analyses of WTP heterogeneity. At age t, an individual's

state is $\Omega_{it} = \{D_i, A_{it}, \mathcal{W}_{it}, H_{it}, E_{it}\}$. Let $J_t^s \in \{V_t^S, U_t^S, V_t^M, U_t^M\}$ denote the relevant value function across employment and marital states. For a reduction $\Delta\mathcal{W}_{it} < 0$, define the counterfactual state as $\widetilde{\Omega}_{it} = \{D_i, A_{it} - WTP_{it}^s, \mathcal{W}_{it} + \Delta\mathcal{W}_{it}, H_{it}, E_{it}\}$. The exact WTP is the asset reduction satisfying $J_t^s(\widetilde{\Omega}_{it}) = J_t^s(\Omega_{it})$. A first-order approximation of this indifference condition gives

$$WTP_{it}^{s,\mathrm{FO}} \approx \frac{\partial J_t^s(\Omega_{it})/\partial \mathcal{W}_{it}}{\partial J_t^s(\Omega_{it})/\partial A_{it}}\,\Delta\mathcal{W}_{it}.$$

Using the Bellman equation and the envelope theorem, the marginal value of body weight can be written as

$$\frac{\partial J_t^s(\Omega_{it})}{\partial \mathcal{W}_{it}} = \frac{\partial u_{it}}{\partial \mathcal{W}_{it}} + \beta\,\mathbb{E}\left[\frac{\partial \pi_{it+1}}{\partial \mathcal{W}_{it}} J_{t+1}^{s'}(\Omega_{it+1}) + \pi_{it+1}\frac{\partial J_{t+1}^{s'}(\Omega_{it+1})}{\partial \Omega_{it+1}} \cdot \frac{\partial \Omega_{it+1}}{\partial \mathcal{W}_{it}} \;\middle|\; \Omega_{it}, s\right],$$

where s' denotes next-period marital status. Writing $\Omega_{it+1} = \{D_i, A_{it+1}, \mathcal{W}_{it+1}, H_{it+1}, E_{it+1}\}$, the last term expands as

$$\frac{\partial J_{t+1}^{s'}(\Omega_{it+1})}{\partial \Omega_{it+1}} \cdot \frac{\partial \Omega_{it+1}}{\partial \mathcal{W}_{it}} = \frac{\partial J_{t+1}^{s'}}{\partial A_{it+1}}\frac{\partial A_{it+1}}{\partial \mathcal{W}_{it}} + \frac{\partial J_{t+1}^{s'}}{\partial \mathcal{W}_{it+1}}\frac{\partial \mathcal{W}_{it+1}}{\partial \mathcal{W}_{it}} + \frac{\partial J_{t+1}^{s'}}{\partial H_{it+1}}\frac{\partial H_{it+1}}{\partial \mathcal{W}_{it}} + \frac{\partial J_{t+1}^{s'}}{\partial E_{it+1}}\frac{\partial E_{it+1}}{\partial \mathcal{W}_{it}}.$$

This expression makes explicit that WTP depends on the effect of current body weight on every future state, weighted by the marginal value of that state. Employment and marriage outcomes enter through their transition probabilities and the corresponding max-operators. Derivatives involving these discrete outcomes should therefore be interpreted as shorthand for their effects on expected continuation values.

Combining these expressions yields

$$WTP_{it}^{s,\mathrm{FO}} \approx \frac{\frac{\partial u_{it}}{\partial \mathcal{W}_{it}} + \beta\,\mathbb{E}\left[\frac{\partial \pi_{it+1}}{\partial \mathcal{W}_{it}} J_{t+1}^{s'}(\Omega_{it+1}) + \pi_{it+1}\frac{\partial J_{t+1}^{s'}(\Omega_{it+1})}{\partial \Omega_{it+1}} \cdot \frac{\partial \Omega_{it+1}}{\partial \mathcal{W}_{it}} \;\middle|\; \Omega_{it}, s\right]}{\frac{\partial J_t^s(\Omega_{it})}{\partial A_{it}}}\,\Delta\mathcal{W}_{it}.$$

A.5.2 Interactions among effective consumption shifters

Because utility is concave in effective consumption ($\alpha_2^u > 1$), the utility cost of an adverse shifter is larger when effective consumption is already low. Thus, overweight stigma increases the utility costs of effort, work, and poor health. Side effects, which we include in the main WTP calculations and counterfactual analyses, enter effective consumption in exactly the same way and therefore interact analogously with the other shifters. These interactions also imply that a weight-loss technology may either crowd out effort by substituting for it or crowd in effort by reducing stigma and thereby lowering its utility cost.

A.5.3 The Value of Statistical Life

The value of statistical life (VSL) is the marginal willingness to pay for a small increase in the probability of survival. Differentiating the Bellman equation, $J_t(\Omega_{it}) = u_{it} + \beta\pi_{it+1}\mathbb{E}[J_{t+1}(\Omega_{it+1}) \mid \Omega_{it}]$, with respect to π_{it+1} gives

$$\frac{\partial J_t(\Omega_{it})}{\partial \pi_{it+1}} = \beta\mathbb{E}[J_{t+1}(\Omega_{it+1}) \mid \Omega_{it}]\,.$$

Rearranging the Bellman equation to substitute for the expected continuation value yields

$$\frac{\partial J_t(\Omega_{it})}{\partial \pi_{it+1}} = \frac{J_t(\Omega_{it}) - u_{it}}{\pi_{it+1}}.$$

Applying the envelope theorem to assets gives the envelope condition

$$\frac{\partial J_t(\Omega_{it})}{\partial A_{it}} = \frac{\partial u_{it}}{\partial c_{it}} = \mathbb{C}_{it}^{-\alpha_2^u} \frac{\exp(\alpha_{\mathcal{S}}^u \mathcal{S} + \alpha_{\mathcal{O}} \mathcal{O})}{\alpha_3^u}.$$

Dividing the marginal value of survival by the marginal value of assets therefore gives

$$\text{VSL}_{it} = \frac{\partial J_t(\Omega_{it})/\partial \pi_{it+1}}{\partial J_t(\Omega_{it})/\partial A_{it}} = \frac{J_t(\Omega_{it}) - u_{it}}{\pi_{it+1}} \frac{\mathbb{C}_{it}^{\alpha_2^u} \alpha_3^u}{\exp(\alpha_{\mathcal{S}}^u \mathcal{S} + \alpha_{\mathcal{O}} \mathcal{O})}.$$

References - Appendix A

Anderson, J. W., Konz, E. C., Frederich, R. C., & Wood, C. L. (2001). Long-term weight-loss maintenance: A meta-analysis of us studies. *American Journal of Clinical Nutrition*, *74*(5), 579–584.

Arias, E. (2014). United States Life Tables, 2010, National Center for Health Statistics [Retrieved June 25, 2026, from https://stacks.cdc.gov/view/cdc/231843].

Bellicha, A., van Baak, M. A., Battista, F., Beaulieu, K., Blundell, J. E., Busetto, L., Carraça, E. V., Dicker, D., Encantado, J., Ermolao, A., Farpour-Lambert, N., Pramono, A., Woodward, E., & Oppert, J.-M. (2021). Effect of exercise training on weight loss, body composition changes, and weight maintenance in adults with overweight or obesity: An overview of 12 systematic reviews and 149 studies. *Obesity Reviews*, *22*(S4), e13256.

Dansinger, M. L., Tatsioni, A., Wong, J. B., Chung, M., & Balk, E. M. (2007). Meta-analysis: The effect of dietary counseling for weight loss. *Annals of Internal Medicine*, *147*(1), 41–50.

Franz, M. J., VanWormer, J. J., Crain, A. L., Boucher, J. L., Histon, T., Caplan, W., Bowman, J. D., & Pronk, N. P. (2007). Weight-loss outcomes: A systematic review and meta-analysis of weight-loss clinical trials with a minimum 1-year follow-up. *Journal of the American Dietetic Association*, *107*(10), 1755–1767.

Jakicic, J. M., Rogers, R. J., Donnelly, J. E., Smith, B. K., & Washburn, R. A. (2024). Physical activity and excess body weight and adiposity for adults: A systematic umbrella review. *Medicine and Science in Sports and Exercise*, *56*(5), 935–952.

Jayedi, A., Emadi, A., Khan, T. A., & Shab-Bidar, S. (2024). Aerobic exercise and weight loss in adults: A systematic review and dose–response meta-analysis of randomized controlled trials. *Obesity Reviews*, *25*(8), e13816.

Kirk, S. F., Penney, T. L., & McHugh, T.-L. F. (2012). Effective weight management practice: A review of the lifestyle intervention evidence. *Public Health Nutrition*, *15*(5), 960–967.

Schweizer, V. (2019). Marriage to divorce ratio in the us: Demographic variation, 2018. *National Center for Family and Marriage Research*.

Schwingshackl, L., Dias, S., & Hoffmann, G. (2014). Impact of long-term lifestyle programmes on weight loss and cardiovascular risk factors in overweight/obese participants: A systematic review and network meta-analysis. *Systematic Reviews*, *3*(130).

Social Security Administration. (2010). Social Security Handbook, Section 706: Determining the PIA [Last revised April 19, 2010. Retrieved May 12, 2026]. https://www.ssa.gov/OP_Home/handbook/handbook.07/handbook-0706.html

Stoner, L., Rowlands, D., Morrison, A., Credeur, D., Hamlin, M., Gaffney, K., Lambrick, D., & Matheson, A. (2016). Efficacy of exercise intervention for weight loss in overweight and obese adolescents: Meta-analysis and implications. *Sports Medicine*, *46*(11), 1737–1751.

Swift, D. L., Johannsen, N. M., Lavie, C. J., Earnest, C. P., & Church, T. S. (2014). Exercise and physical activity in weight loss and maintenance. *Progress in Cardiovascular Diseases*, *56*(4), 441–447.

Appendix B

Data

The Life-cycle Consequences of Obesity and the Effects of Weight-Loss Drugs

Jérôme Adda Christian Dustmann Lukas Tohoff

August 2026

B.1 Datasets

NHANES We use the National Health and Nutrition Examination Survey (NHANES) continuous microdata covering 1999 through 2023 (National Center for Health Statistics, 2024), combining interview, examination, and dietary recall files by the respondent identifier. NHANES is a stratified repeated cross-sectional survey representative of the U.S. population that uniquely includes in-person physical exams and laboratory measures in addition to questionnaires on health and health behavior. Following the guidance of the National Center for Health Statistics (NCHS), we treat 2017–March 2020 as the combined pre-pandemic release (2017–2018 merged with 2019–March 2020), and we use the August 2021–August 2023 nationally representative cycle that began after field operations resumed. From NHANES we use the following variables: respondent identifier, survey weights, age, gender, race, education, year of birth, marital status, current BMI, physical activity, dietary recalls, health, effort to control weight (i.e., to lose or not to gain weight). We retain respondents with valid respondent identifier and survey wave information and drop records with missing core demographics needed to construct analysis groups. We set biologically implausible or clearly miscoded values to missing, and recode "refused/don't know" codes to missing. For physical activity and dietary recalls, we follow NHANES practice of averaging Day 1 and Day 2 where available and using single-day totals in early cycles.

Table B.1: Descriptive Statistics NHANES (unweighted)

	Obs.	Mean	Min	Max	Std. dev.
age	68,668	46.56	16.0	85.0	20.47
female (0/1)	68,668	0.52	0.0	1.0	0.50
black (0/1)	68,668	0.24	0.0	1.0	0.43
Hispanic (0/1)	68,668	0.28	0.0	1.0	0.45
highschool degree (0/1)	68,668	0.68	0.0	1.0	0.47
late cohort, born after 1965 (0/1)	68,668	0.49	0.0	1.0	0.50
high body type (0/1)	68,668	0.52	0.0	1.0	0.50
married (0/1)	63,906	0.49	0.0	1.0	0.50
BMI, kg/m^2	62,714	28.80	15.0	50.0	6.73
good health (0/1)	68,668	0.77	0.0	1.0	0.42
weight control effort (0/1)	63,291	0.42	0.0	1.0	0.49

PSID We use the Panel Study of Income Dynamics (PSID) core Family Files from 1999 through 2021 (Panel Study of Income Dynamics Family Files, 2021) and supplement them with the harmonized PSID-SHELF long file (Pfeffer et al., 2023) to backfill historical person-level information and maintain longitudinal consistency across families. PSID is a multigenerational, nationally representative household panel that follows families and their descendants, with biennial interviewing since 1997. From PSID we use the following variables: person identifier, household survey weights, age, gender, race, education, year of birth, marital status, BMI, health, spousal BMI, spousal health, and family net worth (assets including home equity minus debt). We keep individuals who are current members of a PSID family unit in the survey year. We drop records with missing core demographics and recode "don't know/refused" codes to missing. As key information such as BMI is not available for "other" family members and for the remaining records only starting in 1999, we restrict our analysis to heads and spouses/partners and the 1999-2021 waves. We set clearly implausible survey responses on body weight and height to missing before computing BMI. The PSID-SHELF long file only covers PSID waves until 2019. To obtain harmonized variables - family net worth, in particular - also for 2021, we closely follow the replication code of the PSID-SHELF long file, using the 2021 family file. Monetary variables are inflation-adjusted to 2022 USD using the PCEPI by the Federal Reserve Bank of St. Louis.

Table B.2: Descriptive statistics PSID (unweighted)

	Obs.	Mean	Min	Max	Std. dev.
age	132,021	45.23	16.0	100.0	15.60
female (0/1)	132,021	0.53	0.0	1.0	0.50
black (0/1)	132,021	0.31	0.0	1.0	0.46
Hispanic (0/1)	132,021	0.08	0.0	1.0	0.28
highschool degree (0/1)	132,021	0.81	0.0	1.0	0.39
late cohort, born after 1965 (0/1)	132,021	0.47	0.0	1.0	0.50
BMI, kg/m^2	112,627	28.02	15.0	50.0	6.17
good health (0/1)	131,775	0.84	0.0	1.0	0.37
wage rate, 2022 USD	101,823	28.43	0.0	150.0	24.63
hourly wage, spouse, 2022 USD	30,821	26.46	0.0	150.0	20.87
net wealth ('assets'), 2022 USD	132,017	137244.74	0.0	2500000.0	325175.94
married (0/1)	132,012	0.65	0.0	1.0	0.48
age, spouse	42,306	45.13	15.0	94.0	14.11
black spouse (0/1)	42,306	0.20	0.0	1.0	0.40
Hispanic spouse (0/1)	42,306	0.09	0.0	1.0	0.29
good health, spouse (0/1)	42,213	0.86	0.0	1.0	0.34

HRS We use the RAND Health and Retirement Study Longitudinal File from 1992 through 2022, which is a respondent-by-wave panel constructed from the Health and Retirement Study (HRS) core public-use files (Health and Retirement Study Investigators, 2025). The HRS is a nationally representative, biennial survey of U.S. adults aged 50 and older that follows respondents over time. From HRS we use the following variables: respondent identifier, survey weights, age, gender, race, education, year of birth, BMI, health, year of death, and out-of-pocket medical expenditures. We keep person-waves with non-missing core demographics. "Don't know/refused" codes are set to missing and clearly nonsensical records of birth and mortality dates are dropped. We impute the respondent sampling weight for decedents as the person-specific mean to allow approximately representative analyses including the year of death. In some rare cases, sex and education are harmonized within person by taking the modal value across waves, correcting for measurement error. Year of birth, when missing, is inferred

as survey year minus age. Monetary variables are inflation-adjusted to 2022 USD using the PCEPI by the Federal Reserve Bank of St. Louis.

Table B.3: Descriptive statistics HRS (unweighted)

	Obs.	Mean	Min	Max	Std. dev.
age	350,222	70.22	50.0	100.0	12.56
female (0/1)	350,222	0.52	0.0	1.0	0.50
black (0/1)	350,222	0.14	0.0	1.0	0.35
Hispanic (0/1)	350,222	0.11	0.0	1.0	0.32
highschool degree (0/1)	341,934	0.71	0.0	1.0	0.45
late cohort, born after 1965 (0/1)	350,222	0.01	0.0	1.0	0.09
BMI, kg/m^2	154,210	27.92	15.0	50.0	5.51
good health (0/1)	156,444	0.75	0.0	1.0	0.43
age at death	161,779	79.48	50.0	104.0	11.48
out-of-pocket health care expenditure, 2022 USD	182,912	2101.39	0.0	918169.0	6771.13

NLS We use the National Longitudinal Survey of Youth 1979 (NLSY79) and 1997 (NLSY97) cohorts, drawing variables via NLS Investigator extracts created in December 2024 (U.S. Bureau of Labor Statistics, 2024a, 2024b). NLSY79 follows the 1957–64 birth cohorts; NLSY97 follows the 1980–84 cohorts. Both consist of annual early waves and biennial later waves. From both NLS panels we use the following variables: respondent identifier, survey weights, age, gender, race, education, year of birth, BMI, health (in NLSY97, but only at ages 40, 50 and 60 in NLSY79), employment status, hourly wage, and AFQT/ASVAB-based cognitive scores. For our analyses, we pool the two panels. We retain observations with non-missing core demographics and recode "don't know/refused/inapplicable" codes to missing. Age is harmonized from interview-age variables with within-person temporal consistency checks. We set clearly implausible survey responses on body weight and height to missing before computing BMI. Hourly wages are converted to 2022 USD using the PCEPI by the Federal Reserve Bank of St. Louis.

Table B.4: Descriptive Statistics NLS (unweighted)

	Obs.	Mean	Min	Max	Std. dev.
age	476,268	32.04	16.0	63.0	11.68
female (0/1)	476,268	0.49	0.0	1.0	0.50
black (0/1)	476,268	0.28	0.0	1.0	0.45
Hispanic (0/1)	476,268	0.18	0.0	1.0	0.38
highschool degree (0/1)	476,268	0.78	0.0	1.0	0.41
late cohort, born after 1965 (0/1)	476,268	0.34	0.0	1.0	0.47
high ability, above median AFQT (0/1)	421,829	0.50	0.0	1.0	0.50
BMI, kg/m^2	302,430	27.95	15.0	50.0	6.73
good health (0/1)	168,556	0.76	0.0	1.0	0.43
working (0/1)	329,788	0.72	0.0	1.0	0.45
hourly wage, 2022 USD	292,571	19.64	2.1	150.0	15.47

MEPS We use the Medical Expenditure Panel Survey (MEPS) Full-Year Consolidated Files for 1996–2022 (Agency for Healthcare Research and Quality, 2022). MEPS is a nationally representative household survey based on overlapping two-year panels that produce person-year records. From MEPS we use the following variables: respondent identifier, survey weights, age, gender, race, education, year of birth, marital status, spousal race, spousal education, BMI, health, employment status, hourly wage,

total medical expenditures, and self-paid medical expenditures. Adult BMI is suppressed before 2001, in 2019, and in 2021 for confidentiality reasons. We can therefore use data from the respective years only for analyses excluding BMI. We retain person-years with non-missing core demographics and recode "don't know/refused" responses as missing. Nominal monetary amounts (medical expenditures and hourly wages) are converted to 2022 USD using the PCEPI from the Federal Reserve Bank of St. Louis.

Table B.5: Descriptive Statistics MEPS (unweighted)

	Obs.	Mean	Min	Max	Std. dev.
age	493,547	44.95	16.0	89.0	18.50
female (0/1)	493,547	0.54	0.0	1.0	0.50
black (0/1)	493,547	0.18	0.0	1.0	0.38
Hispanic (0/1)	493,547	0.19	0.0	1.0	0.39
highschool degree (0/1)	493,547	0.69	0.0	1.0	0.46
late cohort, born after 1965 (0/1)	493,547	0.51	0.0	1.0	0.50
BMI, kg/m^2	378,245	28.01	15.0	50.0	6.20
good health (0/1)	493,547	0.83	0.0	1.0	0.38
employed (0/1)	489,647	0.58	0.0	1.0	0.49
hourly wage, 2022 USD	249,637	22.58	0.0	150.0	14.92
total health care expenditure, 2022 USD	493,547	6173.30	0.0	2330577.5	18316.09
out-of-pocket health care expenditure, 2022 USD	493,547	835.42	0.0	598396.0	2700.43
married (0/1)	493,275	0.49	0.0	1.0	0.50
age spouse	227,672	49.09	15.0	90.0	15.30
BMI spouse	178,018	28.30	15.0	50.0	5.82
black spouse (0/1)	227,684	0.11	0.0	1.0	0.31
Hispanic spouse (0/1)	227,684	0.17	0.0	1.0	0.37
highschool degree spouse (0/1)	227,684	0.76	0.0	1.0	0.43

For external validation, we additionally use the 2022 and 2023 MEPS prescription drug files to compare predicted and observed GLP-1 agonist adoption patterns across demographic groups. We classify prescriptions as GLP-1-based weight loss drugs using drug names and active ingredients, including semaglutide, tirzepatide, liraglutide, dulaglutide, and GLP-1 receptor agonists. We then restrict the set of drugs to the main brand names observed in the data: Ozempic, Wegovy, Rybelsus, Mounjaro, Zepbound, Saxenda, Victoza, and Trulicity. The measure captures prescription use regardless of treatment indication. Prescription records are collapsed to the person year level. For each user, we compute annual out-of-pocket and total expenditures, convert monetary values to 2022 USD, and annualize expenditures when reported days supplied exceed one year.

Table B.6: Descriptive statistics MEPS 2022-2023 on GLP-1 use (unweighted)

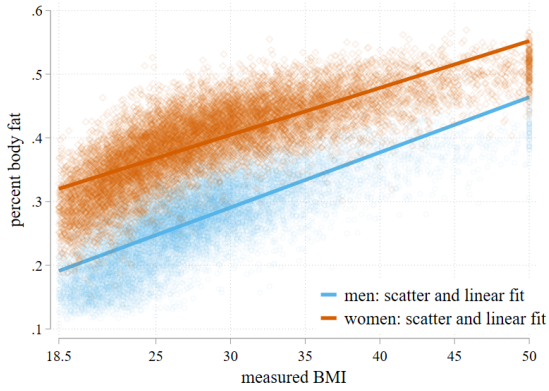
	Obs.	Mean	Min	Max	Std. dev.
any GLP-1 agonist uptake (0/1)	30,628	0.03	0.0	1.0	0.18
out-of-pocket GLP-1 expenditure, 2022 USD	1,005	541.02	0.0	27842.9	1583.65
total GLP-1 expenditure, 2022 USD	1,005	11934.74	30.2	52017.1	4882.29

B.2 Main variables

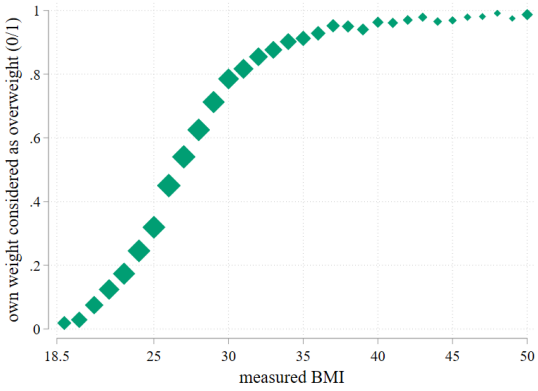
BMI Body Mass Index (BMI) is defined as weight in kilograms divided by height in meters squared. It is reported or can be constructed from weight and height in all five datasets. We winsorize BMI at 15 and 50.

Figure B.1: **BMI as a Measure of Obesity**

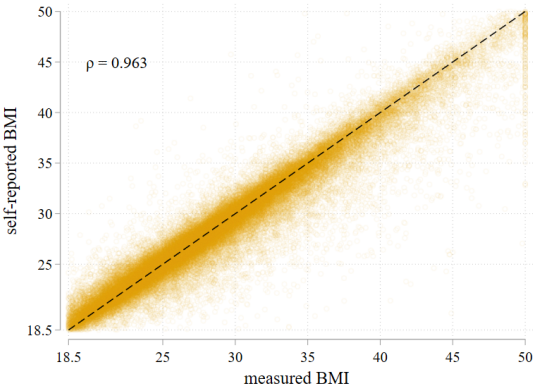
(a) BMI and body fat



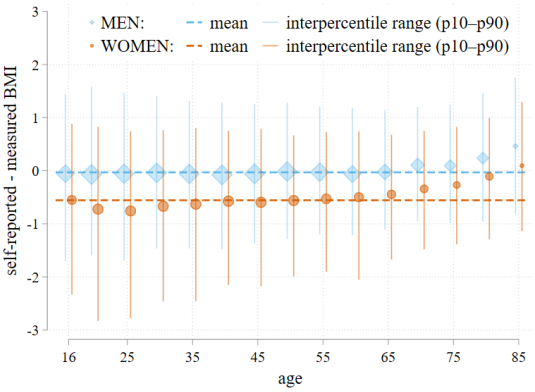
(b) BMI and overweight self-assessment



(c) measured and self-reported BMI



(d) error in self-reported BMI by gender and age



Note: The figure uses NHANES data. Survey weights are applied. Body fat is measured using dual energy X ray absorptiometry and is available only for the 1999 to 2005 and 2011 to 2015 survey waves. Panel (a) plots measured BMI against percent body fat separately by gender, with linear fitted values. Panel (b) plots the share of individuals who classify themselves as overweight by measured BMI bin. Panel (c) plots self-reported BMI against measured BMI; the dashed line is the 45 degree line, and ρ denotes the correlation between the two measures. Panel (d) reports the error in self-reported BMI, defined as self-reported BMI minus measured BMI, by age and gender. Markers report means, and vertical lines report the 10th to 90th percentile range. The size of bin scatter markers is proportional to the survey weighted number of observations in each BMI bin.

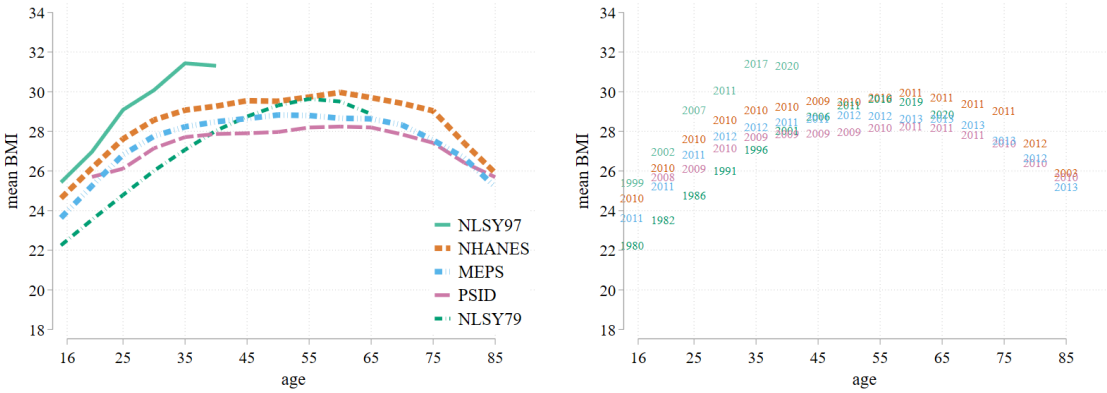
Figure B.1 assesses BMI and reporting error using NHANES. Measured BMI is strongly associated with body fat and self perceived overweight status and is closely aligned with self reported BMI. BMI nevertheless remains an imperfect measure because it does not distinguish fat from lean mass and can reflect demographic differences in body composition. Reporting error is small on average for men and more negative for women, with limited variation across BMI and age. We account for this error by targeting its gender specific mean and variance.

Figure B.2 plots BMI over the life cycle for NHANES, NLSY79, NLSY97, MEPS, and PSID. Overall, the BMI evolution looks very similar across datasets, with most BMI gain happening before the age of 40. Then, BMI is relatively stable until around age 70, and declines thereafter, potentially because of mortality selection.

Figure B.2: **BMI by Age, Dataset, and Survey Year**

(a) BMI by age

(b) mean survey year of data points



Note: The figure reports mean BMI by age. Survey weights are applied. Panel (a) reports age profiles separately for NLSY97, NHANES, MEPS, PSID, and NLSY79. In NHANES, BMI is measured. In NLSY97, NLSY79, MEPS, and PSID, BMI is self-reported. Panel (b) reports mean BMI by age and dataset, with labels indicating the average survey year of the observations in each age bin.

Effort From NHANES we construct the *weight control effort* variable, or in short: effort. It is coded as 1 if a respondent answered the question *During the past 12 months, have you tried to lose weight?* with 'yes', or if the respondent answered the question *During the past 12 months, have you done anything to keep from gaining weight?* with 'yes', or both. If the respondent answered both questions with 'no', effort is coded as 0. When one question is answered with 'no' and the answer to the other question is missing, we also code effort as 0. The first question about effort to lose weight was asked in all survey waves. The second question about effort not to gain weight was only asked in the waves 1999 through 2012. Despite this change in the NHANES questionnaire, 'effort to control weight' is relatively stable across survey waves and ranges approximately between 40 and 50 percent (see Figure B.3b).

Figure B.3a shows that on average 46 percent of respondents have exerted effort in the past year to control their weight. 37 percent have exerted effort to lose weight, 16 percent (22 percent conditional on years when the survey question was asked) exerted effort not to gain weight, and 6 percent did both.

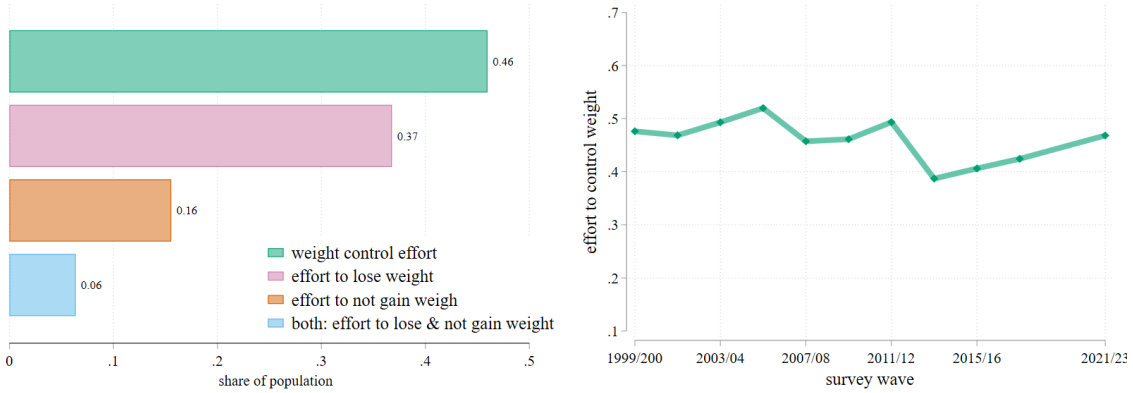
Figure B.4 shows the practices that the respondents applied when they exerted effort to control weight. Figures B.4a and B.4b show that the most common way in which respondents exerted weight control effort consists mainly of healthier eating and exercise. Although the weight control behaviour also includes items such as *started to smoke*, or *had weight-loss surgery*, these items are extremely rare and should not influence any of our results.

Demographics Demographics We classify individuals by six fixed characteristics: gender, race, education, ability, birth cohort, and body type. Gender is coded as reported in the datasets. Race distinguishes non Hispanic White, non Hispanic Black, and Hispanic individuals. We exclude the residual other race category because it is heterogeneous and contains relatively few observations, particularly in early survey waves. High education denotes at least a high school degree, excluding a General Educational Development credential. Individuals born between 1910 and 1964 belong to the early cohort, while those born in 1965 or later belong to the late cohort.

Figure B.3: **Effort to Control Weight**

(a) Weight control by questionnaire items

(b) Weight control effort over survey waves

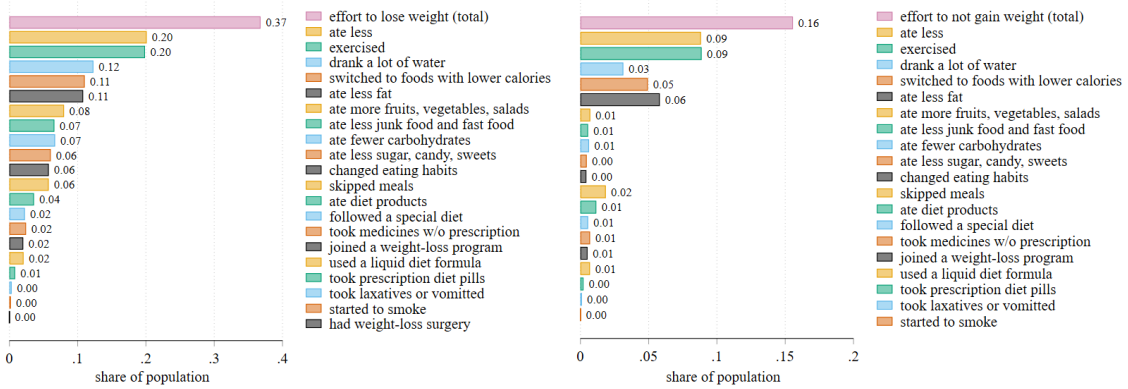


Note: The figure uses NHANES data and applies survey weights. Weight control effort equals one if respondents report trying to lose weight or keep from gaining weight during the previous 12 months. Panel (a) reports the shares reporting any effort, each component of effort, and both components, while panel (b) reports any effort by survey wave. The item on keeping from gaining weight is available only from 1999 through 2012 and is coded as zero thereafter.

Figure B.4: **Weight Control Practices**

(a) Things done to lose weight

(b) Things done to not gain weight

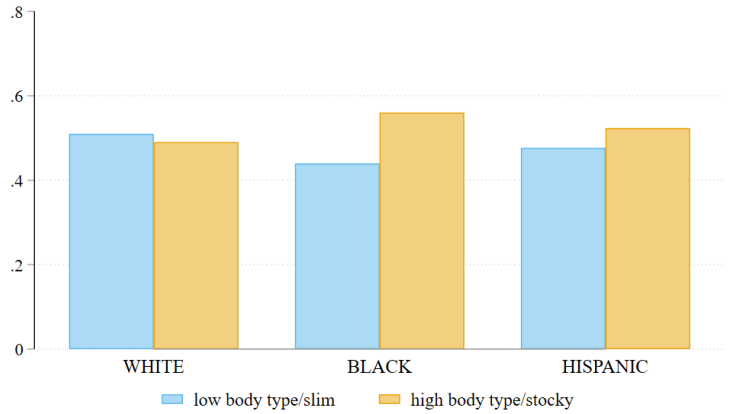


Note: The figure uses NHANES data and applies survey weights. Panel (a) reports practices among individuals who tried to lose weight; these items are unavailable in the 2021 to 2023 wave. Panel (b) reports practices among individuals who tried to keep from gaining weight; these items are available only from 1999 through 2012. Unavailable practice items are coded as zero.

We construct body type using NHANES. Separately by gender, we regress BMI on dietary intake, vitamin consumption, physical activity, height, height squared, age, smoking status, and high school completion. Individuals with a residual above the gender specific median are classified as having a high body type, or stocky, while the remaining individuals are classified as having a low body type, or slender. This measure is intended to capture physiological differences associated with a predisposition toward higher BMI. Figure B.5 reports the resulting distribution by race.

By definition half of men are of the low body type, and half are of the high body type. The same is true for women. However, the distribution of body types is allowed to be uneven across race. Figure B.5 shows that among blacks and Hispanics, the high body type is more prevalent, while among whites

Figure B.5: **Body Type by Race**



Note: The figure uses NHANES data. Survey weights are applied. Body type is constructed from residual variation in BMI after conditioning on diet, vitamin intake, physical activity, height, height squared, age, smoking status, and high school completion. Regressions are estimated separately by gender. Individuals are classified as high body type, or stocky, if their residual is above the gender specific median, and as low body type, or slender, otherwise. Bars report the share of individuals with low and high body type by race.

the low body type occurs slightly more frequently.

Ability is based on the Armed Forces Qualification Test score in NLSY79 and the corresponding mathematics and verbal scores from the Armed Services Vocational Aptitude Battery in NLSY97. Individuals with scores above the median are classified as having high ability. We restrict all samples to individuals aged 16 to 100 and born in 1910 or later.

We measure age in years and exclude all individuals under 16 years of age and over 100 years of age. In addition, we exclude all individuals born before 1910.

Allowing for all interactions between the fixed demographic characteristics results in 96 distinct fixed demographic groups. Multiplying the fixed characteristics by the 85 different age levels, we can distinguish between 8,160 different demographic groups overall. Our model is built to capture this rich demographic heterogeneity.

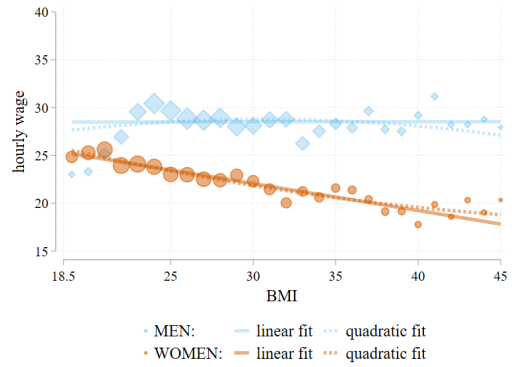
Employment and wages We use data on employment and wages from NLS and MEPS. Figure B.6 shows that the main patterns between employment, wages and BMI look very similar in both datasets. The choice of which dataset we use for these two labor market outcomes is therefore driven by other variables available in the respective datasets (i.e., ability in NLS) and the representativeness of the data for the US population (i.e., NLS is only representative for the birth cohorts 1957-64 and 1980-84, while MEPS is representative for the US population in 1996 through 2022, when applying survey weights).

For both datasets, we condition hourly wages on employment and code zero wages as missing. We inflation-adjust hourly wages to 2022 USD using the PCEPI by the Federal Reserve Bank of St. Louis, and we winsorize real hourly wages at the top at 150 USD. Employment is coded as 1 if a respondent reports working in a job or business, including self-employment, and 0 otherwise.

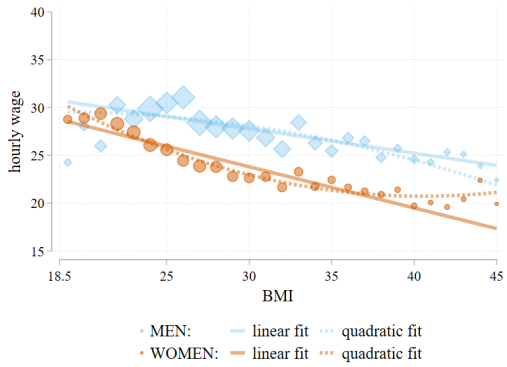
Assets What we refer to as *assets* in both the model and the empirical analysis corresponds more precisely to wealth, defined as the total value of assets, including home equity and real estate, net of debt. We use family-level wealth from the harmonized PSID-SHELF long file (Pfeffer et al., 2023) and construct a consistent and harmonized family wealth variable for 2021 from the PSID core Fam-

Figure B.6: **Labor Market Outcomes by BMI using NLS and MEPS Data at Ages 30 to 40**

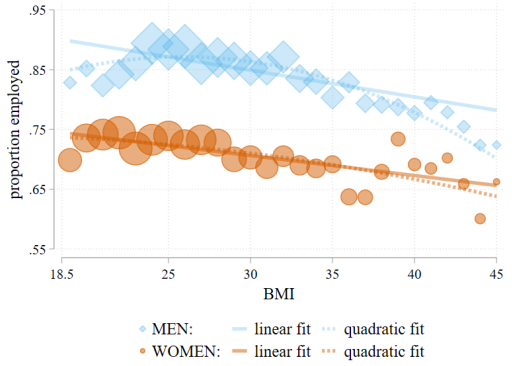
(a) Hourly wage, NLSY79 and NLSY97 pooled



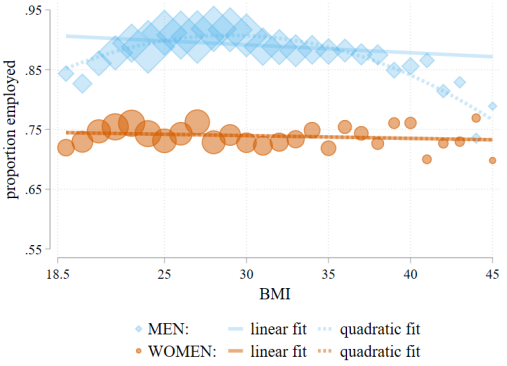
(b) Hourly wage, MEPS



(c) Employment, NLSY79 and NLSY97 pooled



(d) Employment, MEPS



Note: The figure uses MEPS and NLS data. Survey weights are applied. The sample is restricted to individuals aged 30 to 40. The NLS sample combines the NLSY79 cohort, born between 1957 and 1964, and the NLSY97 cohort, born between 1980 and 1984. Hourly wages are expressed in 2022 USD. Panels (a) and (c) use NLS data. Panels (b) and (d) use MEPS data. BMI is self-reported in both datasets. The size of the scatter points is proportional to the number of observations in each BMI bin. Linear and quadratic fitted values are shown separately by gender.

ily Files from 1999 through 2021 (Panel Study of Income Dynamics Family Files, 2021), following the PSID-SHELF long file replication package PSID-SHELF. To construct individual-level wealth from household-level wealth, we apply the OECD equivalence scale (OECD-I). Specifically, for each household we compute the number of adult equivalents as $1 + 0.7 \times$ (if the person is married) $+ 0.5 \times$ (# of children aged 0–18), where the first term represents the reference adult, the second accounts for the spouse, and the third for dependent children. Individual wealth is then calculated as household wealth multiplied by the individual's equivalence weight and divided by the total household equivalence score. This procedure is standard in the literature; see, for example, Altonji et al. (2025). We inflation-adjust *assets* to 2022 USD using the PCEPI by the Federal Reserve Bank of St. Louis (Federal Reserve Bank of St. Louis, 2025). Finally, we winsorize *assets* at the top at 2.5 million USD.

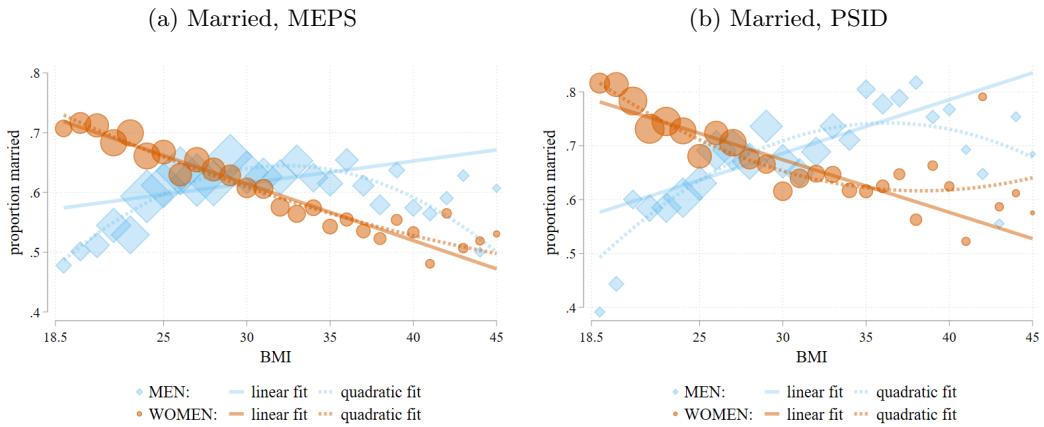
Medical expenditures MEPS reports total and out-of-pocket medical expenditures. Total expenditures include payments by individuals, private insurers, Medicare, Medicaid, and other sources. Out-of-pocket expenditures include payments made directly by the individual or family, including deductibles, coinsurance, copayments, and services not covered by insurance. The structural model

uses out-of-pocket expenditures from MEPS and, at older ages, HRS. For the counterfactual analyses, we impute total expenditures from MEPS using linear regressions on demographics, age categories, BMI categories, out-of-pocket expenditures, and health.

Health We use *self-reported health*, also referred to as *perceived health status*, as our main measure of health. This measure captures individuals' general health status and may reflect both physical and mental health. In all datasets that we use - MEPS, NLS, PSID, NHANES, and HRS - respondents are asked to rate their general health as either *excellent*, *very good*, *good*, *fair*, or *poor*. Following the literature (De Nardi et al., 2025), we create a 'good health' dummy variable that is set to 1 if respondents report having *excellent*, *very good*, or *good* health, and 0 if people report *fair* or *poor* health.

Marriage and spouses We construct the indicator variable *married* using the marital status information available in NHANES, NLS, MEPS, and PSID. Individuals are coded as 1 if reported as currently married, and 0 if reported as never married, divorced, separated, or widowed. Spousal information is drawn from MEPS and from the PSID family files. For spouses, we construct variables for race, education, BMI, wealth, age, and health status, using the same coding conventions as described for the corresponding respondent-level variables above. Figure B.7 shows that the patterns between marital status and BMI are very similar between the MEPS and PSID for individuals aged 30 to 40.

Figure B.7: **Proportion Married by BMI using MEPS and PSID Data at Ages 30 to 40**



Note: The figure uses MEPS and PSID data. Survey weights are applied. The sample is restricted to individuals aged 30 to 40. Panel (a) uses MEPS data, and panel (b) uses PSID data. BMI is self-reported in both datasets. The outcome is an indicator equal to one if the individual is married. The size of the scatter points is proportional to the number of observations in each BMI bin. Linear and quadratic fitted values are shown separately by gender.

Mortality We construct mortality status from the RAND HRS Longitudinal dataset. For each respondent, we observe reported age at death. Using this information, we define the indicator variable *alive*, which equals 1 if the respondent's current age in a given survey wave is strictly less than their reported age at death, and 0 otherwise. Observations with inconsistent or implausible death records (e.g., death dates occurring after the last HRS wave) are excluded. This variable serves as our primary measure of survival across survey waves.

We additionally use residual life expectancy by age, gender, and race from the United States Life Tables, 2010 (Arias, 2014). These life tables provide an external benchmark for cumulative survival

patterns. In the model, we construct the corresponding residual life expectancy moments by summing the cumulative products of individual model-implied survival probabilities and aggregating them by demographic group. Specifically, we define life expectancy as 16 plus the residual life expectancy at age 16.

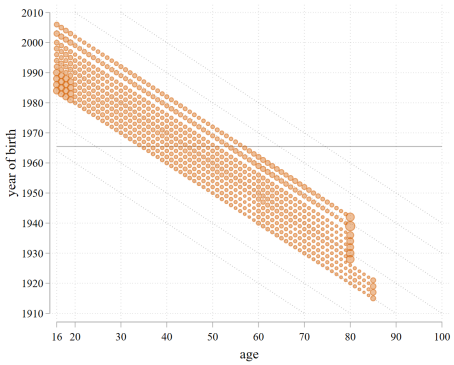
B.3 Sample weights in simulation

When simulating life cycles, we generate all 96 combinations of race, gender, education, ability, cohort, and body type with equal probability and then reweight them to match the empirical population composition. For each data source, we construct survey weighted frequencies by age and demographic profile. Because body type is observed only in NHANES and ability only in the NLSY, we impute these variables in the other datasets using logistic regressions on the demographics available in each source. Each simulated life cycle then receives the weight associated with its age and demographic cell for the relevant dataset.

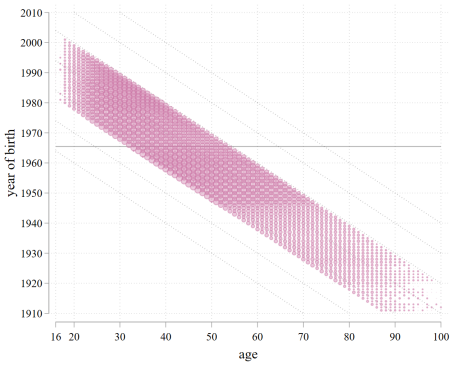
B.4 Coverage by Age and Year of Birth Across Datasets

Figure B.8: **Data availability by age and year of birth**

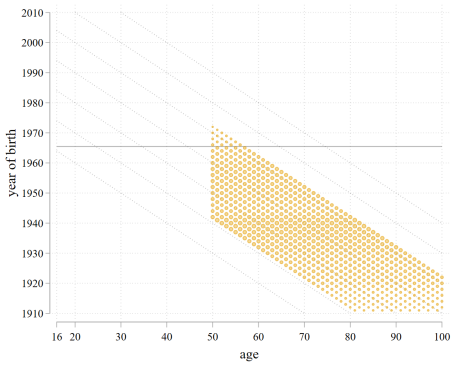
(a) NHANES



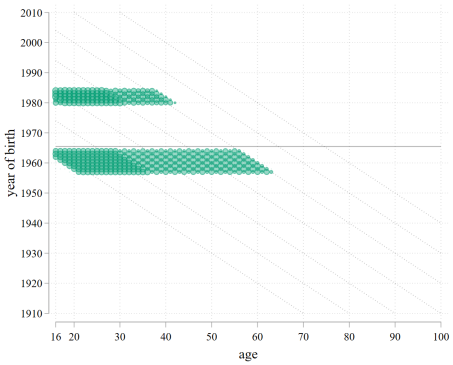
(b) PSID



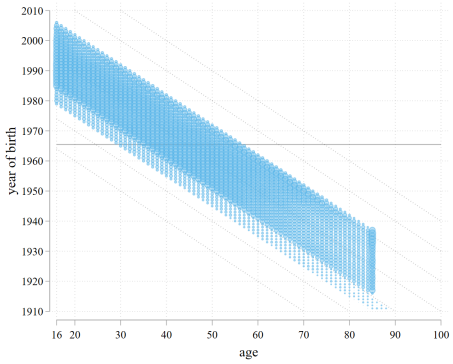
(c) HRS



(d) NLS



(e) MEPS



Note: The figure reports data availability by age and year of birth for NHANES, PSID, HRS, NLS, and MEPS. The sample is restricted to individuals aged 16 to 100 and born in 1910 or later. Each scatter point represents observations in an age by birth cohort cell. The size of the scatter points is proportional to the number of observations in the cell. The solid horizontal line marks the 1965 cohort cutoff used to define early and late cohorts. Dotted 135 degree lines indicate survey years, so that points on the same dotted line are observed in the same survey year.

References - Appendix B

Agency for Healthcare Research and Quality. (2022). Medical Expenditure Panel Survey Full Year Consolidated Data Files, 1996–2022 [Retrieved November 12, 2024, from https://www.meps.ahrq.gov].

Altonji, J. G., Giraldo-Páez, D., Hynsjö, D., & Vidangos, I. (2025). Earnings, marriage, and the variance of family income by age, gender, and cohort. *Journal of Labor Economics*, *43*(S1), S7–S54.

Arias, E. (2014). United States Life Tables, 2010, National Center for Health Statistics [Retrieved June 25, 2026, from https://stacks.cdc.gov/view/cdc/231843].

De Nardi, M., Pashchenko, S., & Porapakkarm, P. (2025). The lifetime costs of bad health. *Review of Economic Studies*, *92*(3), 1987–2026.

Federal Reserve Bank of St. Louis. (2025). Personal Consumption Expenditures: Chain-type Price Index (PCEPI) [Retrieved January 2, 2025, from https://fred.stlouisfed.org/series/PCEPI].

Health and Retirement Study Investigators. (2025). Health and Retirement Study Public Use Dataset, 1992–2022 [Retrieved February 13, 2025, from https://hrsdata.isr.umich.edu/data-products/public-survey-data].

National Center for Health Statistics. (2024). National Health and Nutrition Examination Survey (NHANES), Continuous (1999–present), NHANES I–III, NHES I [Retrieved November 12, 2024, from https://wwwn.cdc.gov/nchs/nhanes/].

Panel Study of Income Dynamics Family Files. (2021). PSID Family Files, 1994–2021 [Retrieved November 18, 2024, from https://simba.isr.umich.edu].

Pfeffer, F., Daumler, D., & Friedman, E. (2023). PSID-SHELF, 1968–2019: The PSID's Social, Health, and Economic Longitudinal File (Beta Release) [Retrieved December 19, 2024]. https://doi.org/10.3886/E194322V1-146484

U.S. Bureau of Labor Statistics. (2024a). National Longitudinal Survey of Youth 1979 [Retrieved December 3, 2024, from https://www.nlsinfo.org/investigator].

U.S. Bureau of Labor Statistics. (2024b). National Longitudinal Survey of Youth 1997 [Retrieved December 13, 2024, from https://www.nlsinfo.org/investigator].

Appendix C

Estimation, Parameter Estimates and Additional Results

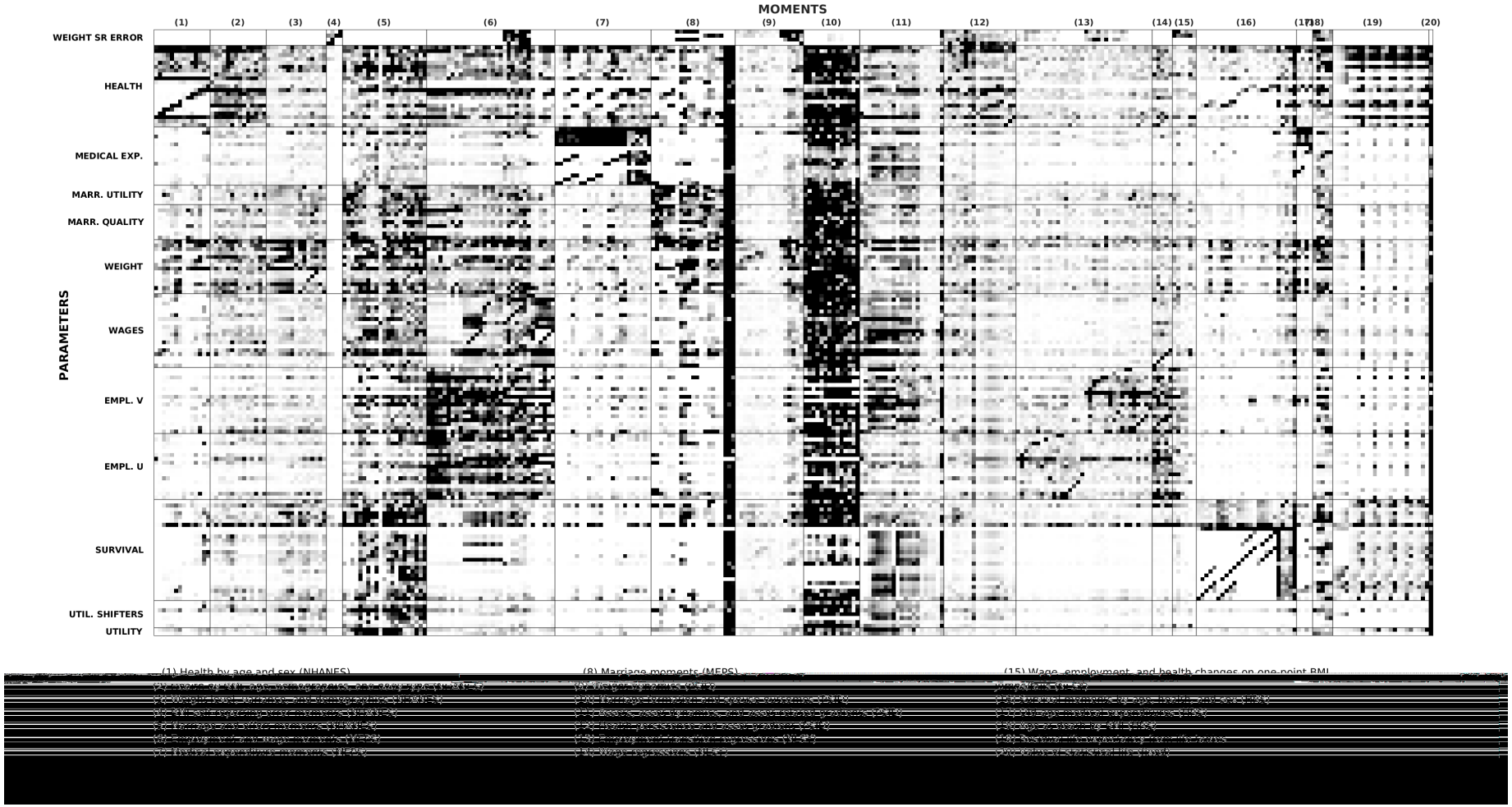
The Life-cycle Consequences of Obesity and the Effects of Weight-Loss Drugs

Jérôme Adda Christian Dustmann Lukas Tohoff

August 2026

C.1 Identification

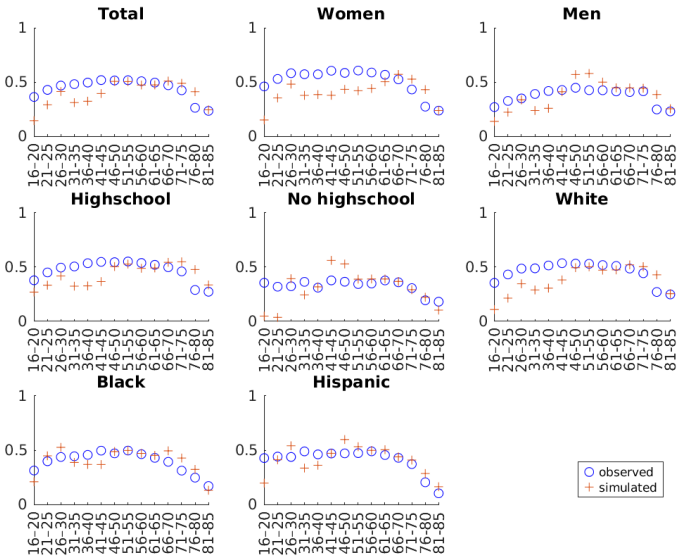
Figure C.1: **Identification: How Moments Map into Parameters**



Note: The figure reports the absolute values of the gradient matrix between estimated parameters and moments. Rows correspond to parameter groups, and columns correspond to moment groups. For illustration, the gradient matrix is normalized in three steps. First, each moment is divided by its observed standard error. Second, each column is divided by its column maximum to indicate which parameters are most responsive to a given moment. Third, the resulting matrix is divided by its 90th percentile and capped at one. Darker cells indicate larger normalized absolute gradients.

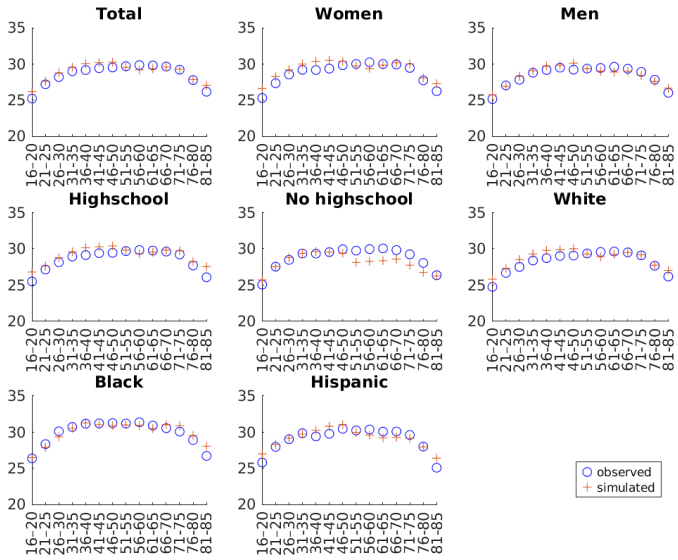
C.2 Goodness of fit

Figure C.2: **Model Fit - Effort**: observed (blue circles) vs. simulated (red crosses) data over the life cycle by selected demographics



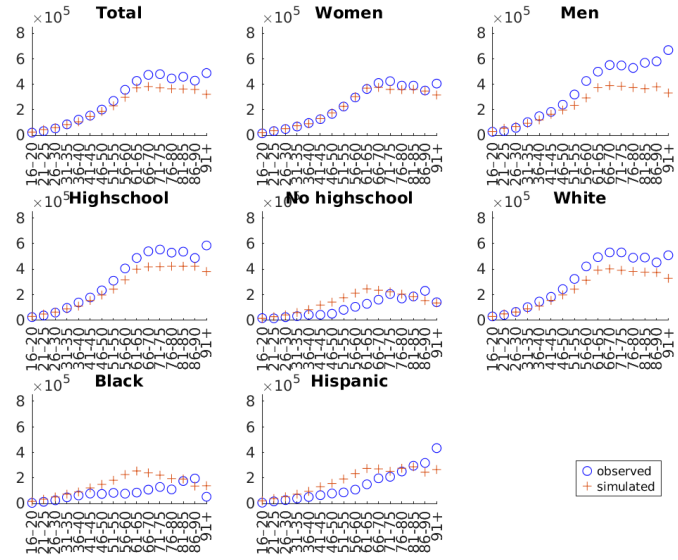
Note: The figure compares empirical and simulated age profiles of weight control effort by selected demographic groups. Empirical moments use NHANES survey weights, and simulated moments are reweighted to match the same target population. Weight control effort is an indicator equal to one if respondents report having tried to lose or maintain weight during the past 12 months.

Figure C.3: **Model Fit - BMI**: observed (blue circles) vs. simulated (red crosses) data over the life cycle by selected demographics



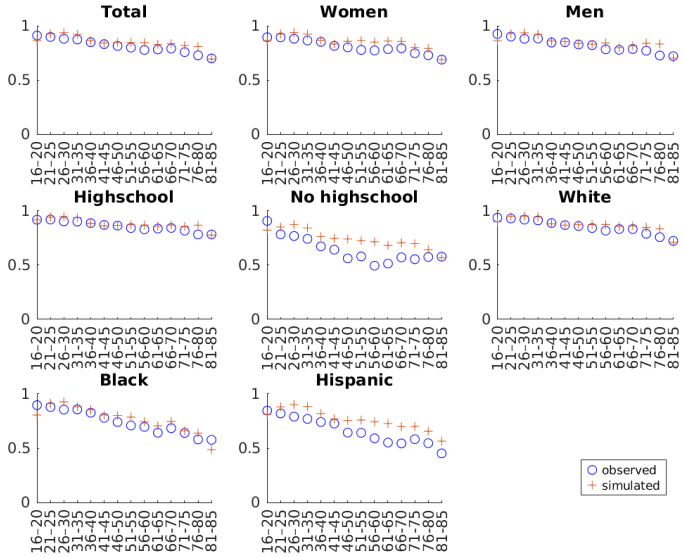
Note: The figure compares empirical and simulated age profiles of BMI by selected demographic groups. Empirical moments use NHANES survey weights, and simulated moments are reweighted to match the same target population. BMI is measured in NHANES.

Figure C.4: **Model Fit - Assets**: observed (blue circles) vs. simulated (red crosses) data over the life cycle by selected demographics



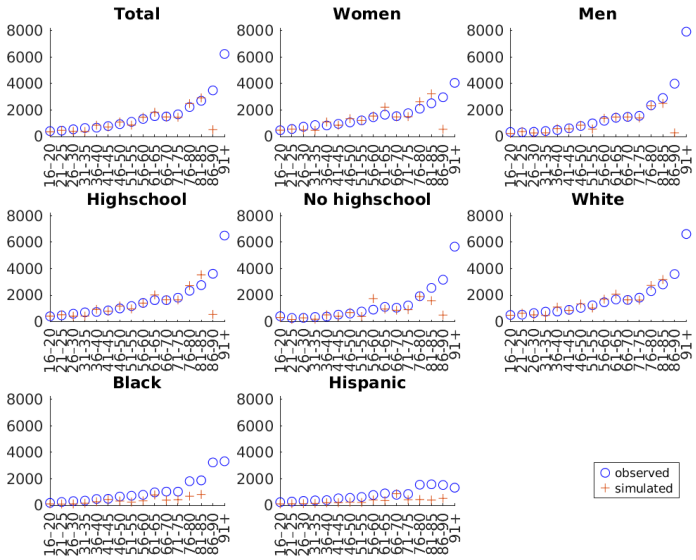
Note: The figure compares empirical and simulated age profiles of assets by selected demographic groups. Empirical moments use PSID survey weights, and simulated moments are reweighted to match the same target population. Assets are measured as individualized family wealth, defined as total assets including home equity and real estate net of debt, adjusted using the OECD equivalence scale. Monetary values are expressed in 2022 USD.

Figure C.5: **Model Fit - Health**: observed (blue circles) vs. simulated (red crosses) data over the life cycle by selected demographics



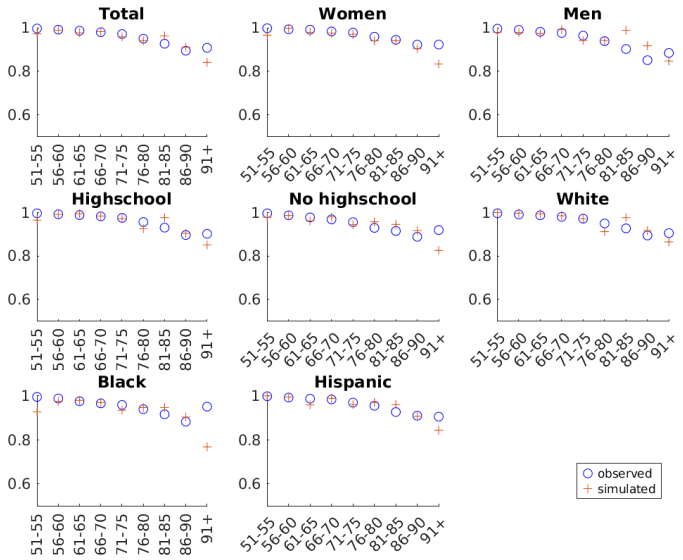
Note: The figure compares empirical and simulated age profiles of good health by selected demographic groups. Empirical moments use NHANES survey weights, and simulated moments are reweighted to match the same target population. Good health is an indicator equal to one if respondents report excellent, very good, or good health, and zero if they report fair or poor health.

Figure C.6: **Model Fit - Medical Expenditures**: observed (blue circles) vs. simulated (red crosses) data over the life cycle by selected demographics



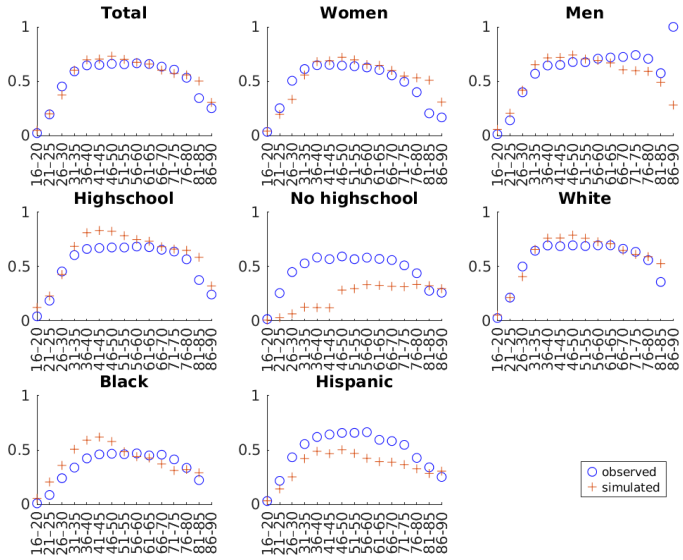
Note: The figure compares empirical and simulated age profiles of out-of-pocket medical expenditures by selected demographic groups. Empirical moments use MEPS and HRS survey weights, and simulated moments are reweighted to match the corresponding target populations. Out-of-pocket medical expenditures are annualized, expressed in 2022 USD, and include payments made directly by individuals or their families that are not reimbursed by other sources.

Figure C.7: **Model Fit - Mortality**: observed (blue circles) vs. simulated (red crosses) data over the life cycle by selected demographics



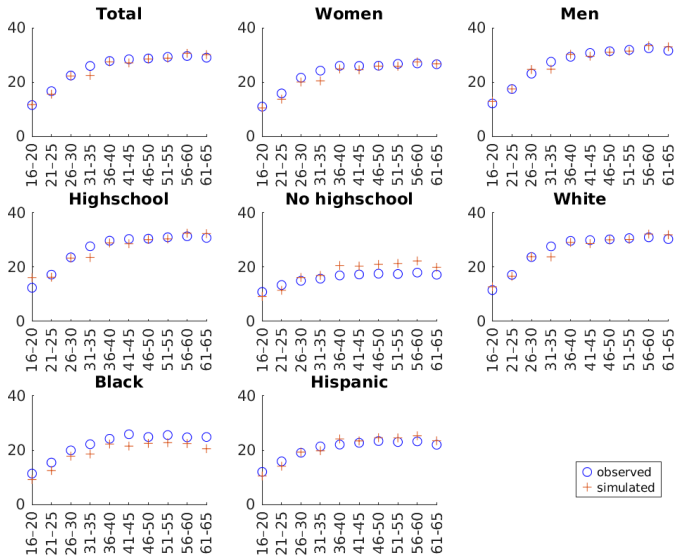
Note: The figure compares empirical and simulated age profiles of mortality by selected demographic groups. Empirical moments use HRS survey weights, and simulated moments are reweighted to match the same target population. Survival (1 minus mortality) is measured as the share of individuals alive at the survey date conditional on being alive in the previous survey observation.

Figure C.8: **Model Fit - Marital Status**: observed (blue circles) vs. simulated (red crosses) data over the life cycle by selected demographics



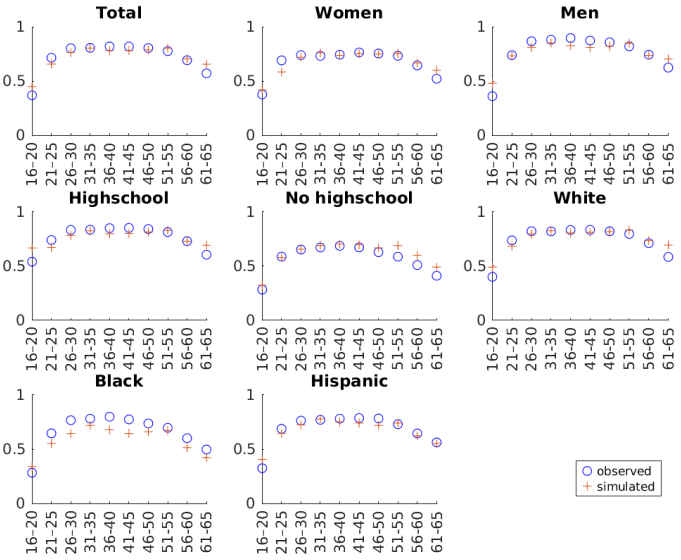
Note: The figure compares empirical and simulated age profiles of marital status by selected demographic groups. Empirical moments use MEPS survey weights, and simulated moments are reweighted to match the same target population. Marital status is measured as an indicator equal to one if the individual is married.

Figure C.9: **Model Fit - Wages**: observed (blue circles) vs. simulated (red crosses) data over the life cycle by selected demographics



Note: The figure compares empirical and simulated age profiles of hourly wages by selected demographic groups. Empirical moments use MEPS survey weights, and simulated moments are reweighted to match the same target population. Wages are measured in 2022 USD and are observed conditional on employment.

Figure C.10: **Model Fit - Employment**: observed (blue circles) vs. simulated (red crosses) data over the life cycle by selected demographics

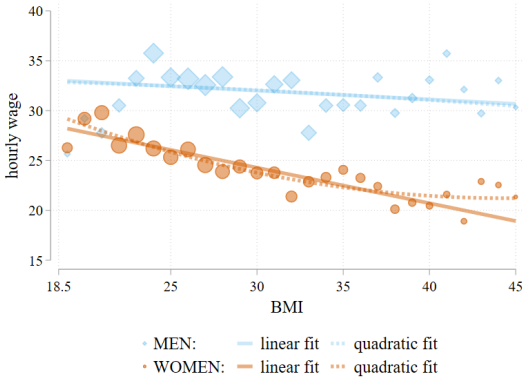


Note: The figure compares empirical and simulated age profiles of employment by selected demographic groups. Empirical moments use MEPS survey weights, and simulated moments are reweighted to match the same target population. Employment is defined as an indicator equal to one if an individual reports working in a job or business, including self-employment.

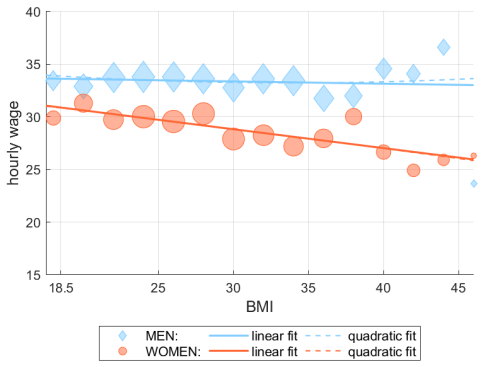
C.3 Replication of descriptive figures with simulated data

Figure C.11: **Hourly Wage, Employment, and Marital Status by BMI: observed vs. simulated data**

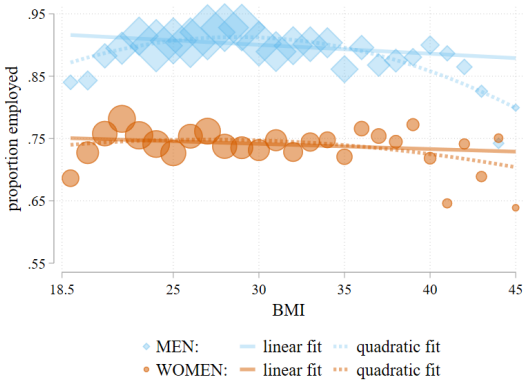
(a) Observed hourly wage, NLS



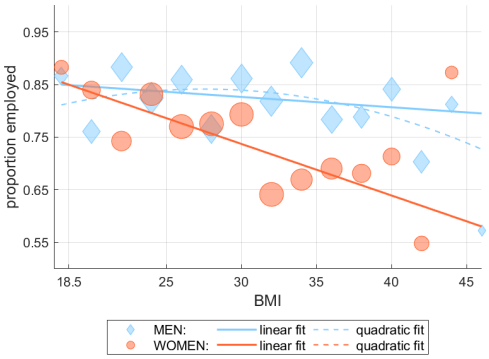
(b) Simulated hourly wage



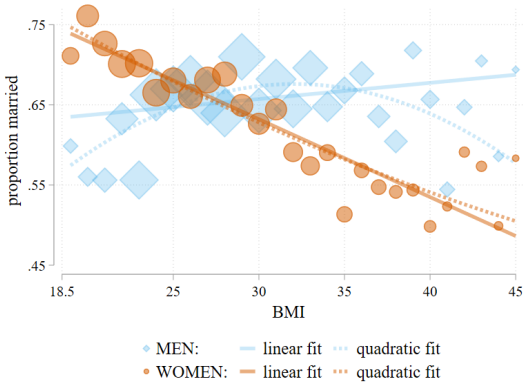
(c) Observed employment rate, MEPS



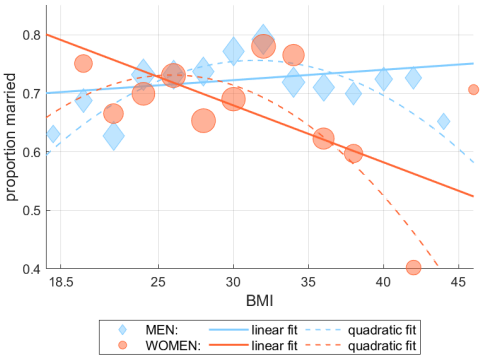
(d) Simulated employment rate



(e) Observed marriage, MEPS



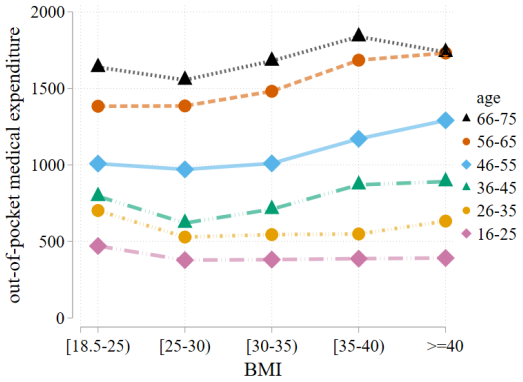
(f) Simulated marriage



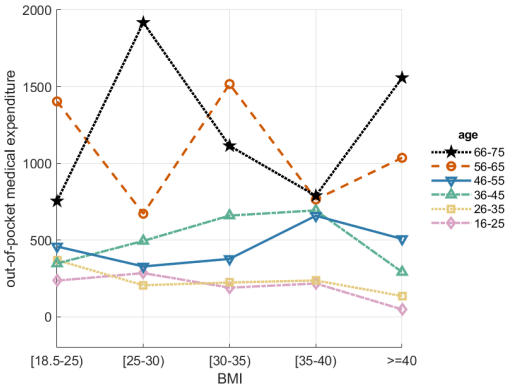
Note: The figure uses weighted MEPS and NLS data for individuals aged 36–40. The MEPS sample includes birth cohorts 1960–1986, while the NLS sample combines the NLSY79 (1957–1964) and NLSY97 (1980–1984) cohorts. Simulated observations are based on 1,920 life cycles and weighted to be representative of the U.S. population. Hourly wages are expressed in 2022 USD. Scatter-point size is proportional to the number of observations in each BMI bin.

Figure C.12: **Medical Expenditures by BMI and Age Group: observed vs. simulated data**

(a) Observed out-of-pocket medical expenditures



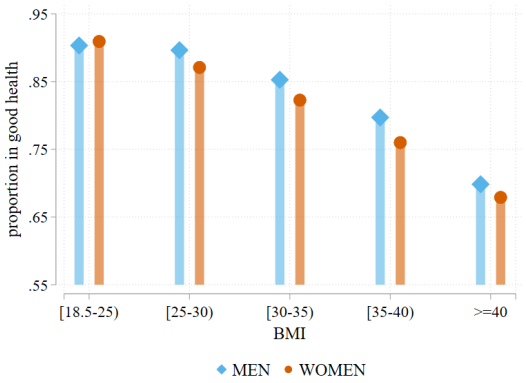
(b) Simulated out-of-pocket medical expenditures



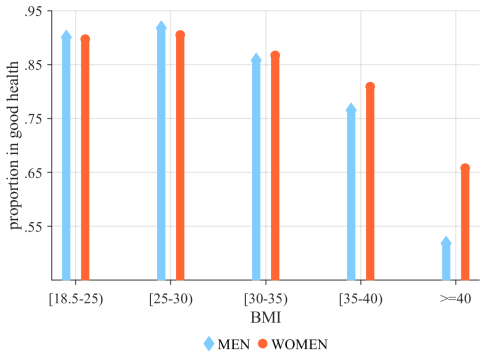
Note: Observed out-of-pocket medical expenditures are computed using weighted MEPS data. Simulated observations are based on 1,920 life cycles and weighted to be representative of the U.S. population. Medical expenditures are annualized and reported in 2022 USD. Out-of-pocket expenditures include unreimbursed payments made directly by individuals or their families, including deductibles, copayments, coinsurance, and spending on uncovered services.

Figure C.13: **Health by BMI and Mortality by Age and BMI: observed vs. simulated data**

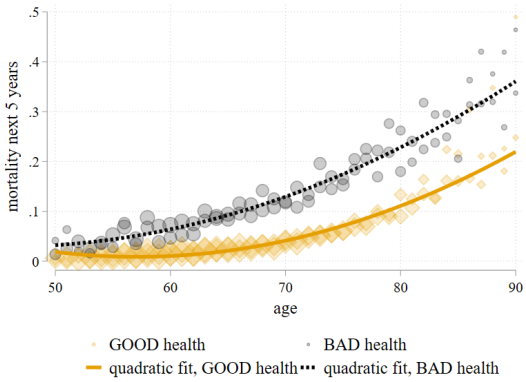
(a) Observed good health, MEPS



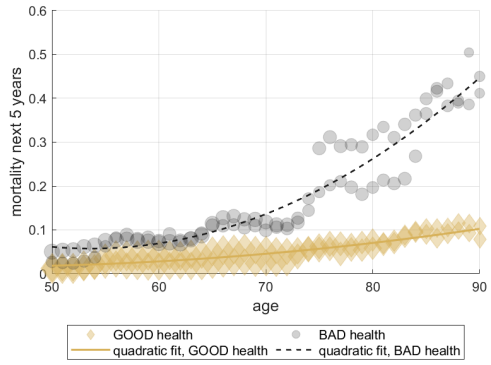
(b) Simulated good health



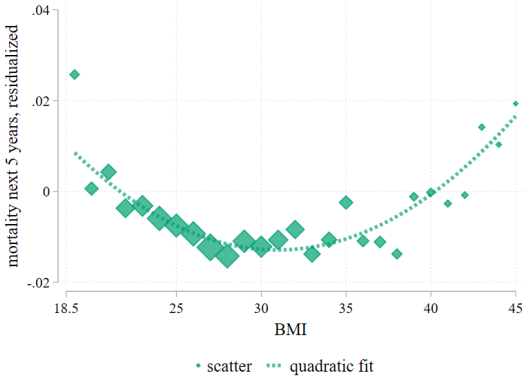
(c) Observed mortality by age and health, HRS



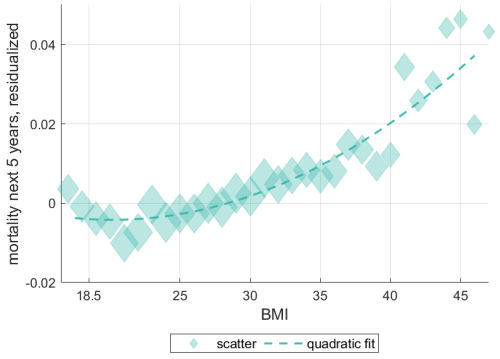
(d) Simulated mortality by age and health



(e) Observed residualized mortality by BMI, HRS



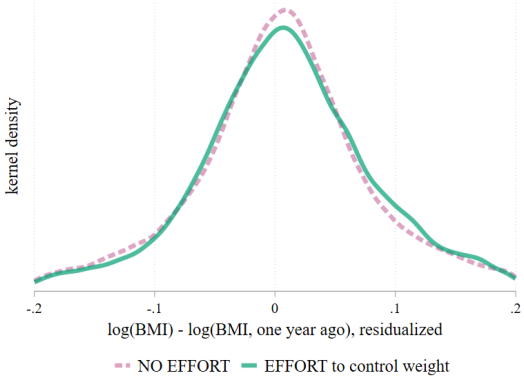
(f) Simulated residualized mortality by BMI



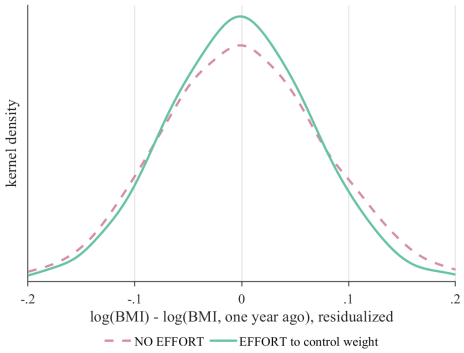
Note: Panel (a) uses weighted MEPS data, while panels (c) and (e) use weighted HRS data. Simulated observations are based on 1,920 life cycles and weighted to be representative of the U.S. population. Good health is an indicator equal to one if respondents report excellent, very good, or good health. Mortality is measured over the subsequent five years among individuals aged 50–90 and equals one if the respondent dies within five years of the survey date. In panel (e) and (f), mortality is residualized with respect to age-group indicators, health status, and gender. Scatter-point size in panels (b) to (f) is proportional to the number of observations in each age or BMI bin.

Figure C.14: **Proportional One-Year BMI Change by Weight-Control Effort: observed vs. simulated data**

(a) Observed BMI change by effort



(b) Simulated BMI change by effort



Note: Panel (a) uses weighted NHANES data, and panel (b) uses 1,920 simulated life cycles weighted to represent the U.S. population. In panel (a), weight control effort equals one if respondents report attempting to lose or maintain weight during the previous 12 months; panel (b) uses the corresponding model choice. The outcome is the one year proportional change in BMI, computed from self-reported BMI one year before the survey and measured BMI at the survey date in panel (a), and from current and one year lagged simulated BMI, including self-reporting error, in panel (b). BMI changes are residualized with respect to age group indicators, lagged BMI group indicators, gender, race, body type, and education. Because effort is likely endogenous to idiosyncratic weight shocks and lagged BMI is self-reported while current BMI is measured, the empirical comparison is descriptive rather than causal. Densities are estimated using Gaussian kernels.

C.4 Parameter estimates

Table C.1: Estimates of Employment Retention Probability

Object	Description	Estimate	(SE)
$\alpha_1^{\lambda_V}$	female effect if single	-0.269	(0.0103)
$\alpha_2^{\lambda_V}$	female effect if married	-0.131	(0.0107)
$\alpha_3^{\lambda_V}$	black intercept	-0.169	(0.0122)
$\alpha_4^{\lambda_V}$	Hispanic intercept	-0.011	(0.0077)
$\alpha_5^{\lambda_V}$	high education effect	0.223	(0.0112)
$\alpha_6^{\lambda_V}$	obesity effect for late cohort	-0.099	(0.0106)
$\alpha_7^{\lambda_V}$	high ability effect	0.057	(0.0090)
$\alpha_8^{\lambda_V}$	age effect, age: 26–55	0.505	(0.0119)
$\alpha_9^{\lambda_V}$	age effect, age: 56+	0.198	(0.0824)
$\alpha_{10}^{\lambda_V}$	good health effect	0.540	(0.0116)
$\alpha_{11}^{\lambda_V}$	body weight effect, BMI: < 18.5	-0.115	(0.0626)
$\alpha_{12}^{\lambda_V}$	constant, reference BMI: $[18.5, 25)$	0.066	(0.0097)
$\alpha_{13}^{\lambda_V}$	body weight effect, BMI: $[25, 30)$	0.015	(0.0070)
$\alpha_{14}^{\lambda_V}$	body weight effect, BMI: $[30, 35)$	-0.017	(0.0219)
$\alpha_{15}^{\lambda_V}$	body weight effect, BMI: ≥ 35	-0.029	(0.0196)
$\alpha_{16}^{\lambda_V}$	late cohort intercept	0.008	(0.0044)
$\alpha_{17}^{\lambda_V}$	female obesity effect	-0.039	(0.0142)

Note: Standard errors are reported in parentheses and are computed using the asymptotic variance formula for the simulated method of moments estimator.

Table C.2: Estimates of Hiring Probability from Non-Employment

Object	Description	Estimate	(SE)
$\alpha_1^{\lambda_U}$	female effect if single	-0.117	(0.0118)
$\alpha_2^{\lambda_U}$	female effect if married	-0.342	(0.0223)
$\alpha_3^{\lambda_U}$	black intercept	-0.421	(0.0163)
$\alpha_4^{\lambda_U}$	Hispanic intercept	-0.032	(0.0151)
$\alpha_5^{\lambda_U}$	high education effect	0.196	(0.0131)
$\alpha_6^{\lambda_U}$	obesity effect for late cohort	0.023	(0.0325)
$\alpha_7^{\lambda_U}$	high ability effect	0.092	(0.0132)
$\alpha_8^{\lambda_U}$	age effect, age: 26–55	0.061	(0.0127)
$\alpha_9^{\lambda_U}$	age effect, age: 56+	-0.282	(0.0823)
$\alpha_{10}^{\lambda_U}$	good health effect	0.584	(0.0307)
$\alpha_{11}^{\lambda_U}$	body weight effect, BMI: < 18.5	-0.013	(0.0231)
$\alpha_{12}^{\lambda_U}$	constant, reference BMI: $[18.5, 25)$	-0.418	(0.0284)
$\alpha_{13}^{\lambda_U}$	body weight effect, BMI: $[25, 30)$	-0.046	(0.0161)
$\alpha_{14}^{\lambda_U}$	body weight effect, BMI: $[30, 35)$	-0.100	(0.0328)
$\alpha_{15}^{\lambda_U}$	body weight effect, BMI: ≥ 35	-0.175	(0.0198)
$\alpha_{16}^{\lambda_U}$	late cohort intercept	-0.009	(0.0127)
$\alpha_{17}^{\lambda_U}$	female obesity effect	-0.048	(0.0217)

Note: Standard errors are reported in parentheses and are computed using the asymptotic variance formula for the simulated method of moments estimator.

Table C.3: Estimates of Wage Parameters

Object	Description	Estimate	(SE)
α_1^w	female intercept	-0.117	(0.0041)
α_2^w	black intercept	-0.051	(0.0075)
α_3^w	Hispanic intercept	-0.028	(0.0058)
α_4^w	high education effect	0.177	(0.0061)
α_5^w	high ability effect	0.204	(0.0065)
α_6^w	obesity effect for late cohort	-0.012	(0.0026)
α_7^w	age effect, age: 26–35	0.289	(0.0059)
α_8^w	age effect, age: 36–45	0.524	(0.0066)
α_9^w	age effect, age: 46–55	0.577	(0.0074)
α_{10}^w	age effect, age: 56+	0.706	(0.0086)
α_{11}^w	health effect	0.048	(0.0048)
α_{12}^w	body weight effect, BMI: < 18.5	-0.118	(0.0302)
α_{13}^w	constant, reference BMI: $[18.5, 25)$	2.671	(0.0070)
α_{14}^w	body weight effect, BMI: $[25, 30)$	-0.009	(0.0023)
α_{15}^w	body weight effect, BMI: $[30, 35)$	-0.025	(0.0042)
α_{16}^w	body weight effect, BMI: ≥ 35	-0.050	(0.0069)
α_{17}^w	late cohort intercept	0.050	(0.0053)
α_{18}^w	female obesity effect	-0.058	(0.0048)
σ_w^2	variance of log wage shock	0.056	(0.0018)

Note: Standard errors are reported in parentheses and are computed using the asymptotic variance formula for the simulated method of moments estimator.

Table C.4: Estimates of Health Parameters

Object	Description	Estimate	(SE)
α_1^ψ	black intercept	-0.106	(0.0130)
α_2^ψ	Hispanic intercept	-0.133	(0.0123)
α_3^ψ	high education effect	0.259	(0.0077)
α_4^ψ	age effect for women, age: 26–35	-0.143	(0.0209)
α_5^ψ	age effect for women, age: 36–55	-0.339	(0.0241)
α_6^ψ	age effect for women, age: 56–75	-0.484	(0.0166)
α_7^ψ	age effect for women, age: 76+	-0.797	(0.0196)
α_8^ψ	age effect for men, age: 26–35	-0.207	(0.0265)
α_9^ψ	age effect for men, age: 36–55	-0.385	(0.0140)
α_{10}^ψ	age effect for men, age: 56–75	-0.505	(0.0221)
α_{11}^ψ	age effect for men, age: 76+	-0.688	(0.0306)
α_{12}^ψ	weight effect, BMI: < 18.5	-0.180	(0.0254)
α_{13}^ψ	constant, reference BMI: $[18.5, 25)$	-0.761	(0.0131)
α_{14}^ψ	weight effect, BMI: $[25, 30)$	-0.023	(0.0028)
α_{15}^ψ	weight effect, BMI: $[30, 35)$	-0.136	(0.0126)
α_{16}^ψ	weight effect, BMI: $[35, 40)$	-0.249	(0.0110)
α_{17}^ψ	weight effect, BMI: ≥ 40	-0.832	(0.0216)
α_{18}^ψ	constant effect of high body type	0.060	(0.0079)
α_{19}^ψ	obesity effect of high body type	-0.083	(0.0088)
α_{20}^ψ	persistence in health	2.484	(0.0141)
α_{21}^ψ	wealth effect	0.031	(0.0012)

Note: Standard errors are reported in parentheses and are computed using the asymptotic variance formula for the simulated method of moments estimator.

Table C.5: Estimates of Medical Expenditure Parameters

Object	Description	Estimate	(SE)
α_1^m	age effect for good health, age: 16–35	5.565	(0.0169)
α_2^m	age effect for good health, age: 36–55	5.968	(0.0177)
α_3^m	age effect for good health, age: 56–75	6.706	(0.0183)
α_4^m	age effect for good health, age: 76–85	7.277	(0.0279)
α_5^m	age effect for good health, age: 86+	7.662	(0.0727)
α_6^m	age effect for bad health, age: 16–35	6.130	(0.0385)
α_7^m	age effect for bad health, age: 36–55	6.981	(0.0251)
α_8^m	age effect for bad health, age: 56–75	7.507	(0.0435)
α_9^m	age effect for bad health, age: 76–85	7.366	(0.0533)
α_{10}^m	age effect for bad health, age: 86+	7.865	(0.1336)
α_{11}^m	female intercept	0.520	(0.0105)
α_{12}^m	black intercept	-1.509	(0.0158)
α_{13}^m	Hispanic intercept	-1.683	(0.0164)
α_{14}^m	high education effect	0.612	(0.0129)
σ_m^2	variance of log medical expenditure shock	3.590	(0.0137)

Note: Standard errors are reported in parentheses and are computed using the asymptotic variance formula for the simulated method of moments estimator.

Table C.6: Estimates of Longevity Parameters

Object	Description	Estimate	(SE)
α_1^π	age effect for women in bad health, age: < 56	0.0020	(0.0013)
α_2^π	age effect for women in bad health, age: 56-65	0.0185	(0.0024)
α_3^π	age effect for women in bad health, age: 66-75	0.0246	(0.0028)
α_4^π	age effect for women in bad health, age: 76-85	0.0838	(0.0044)
α_5^π	age effect for women in bad health, age: 86+	0.1461	(0.0157)
α_6^π	age effect for women in good health, age: < 56	0.0000	(fixed)
α_7^π	age effect for women in good health, age: 56-65	0.0004	(0.0003)
α_8^π	age effect for women in good health, age: 66-75	0.0013	(0.0006)
α_9^π	age effect for women in good health, age: 76-85	0.0042	(0.0014)
α_{10}^π	age effect for women in good health, age: 86+	0.0073	(0.0044)
α_{11}^π	age effect for men in bad health, age: < 56	0.0080	(0.0009)
α_{12}^π	age effect for men in bad health, age: 56-65	0.0130	(0.0016)
α_{13}^π	age effect for men in bad health, age: 66-75	0.0281	(0.0024)
α_{14}^π	age effect for men in bad health, age: 76-85	0.0472	(0.0032)
α_{15}^π	age effect for men in bad health, age: 86+	0.1158	(0.0124)
α_{16}^π	age effect for men in good health, age: < 56	0.0000	(fixed)
α_{17}^π	age effect for men in good health, age: 56-65	0.0059	(0.0004)
α_{18}^π	age effect for men in good health, age: 66-75	0.0078	(0.0005)
α_{19}^π	age effect for men in good health, age: 76-85	0.0090	(0.0012)
α_{20}^π	age effect for men in good health, age: 86+	0.0098	(0.0040)
α_{21}^π	weight effect above age 50, BMI: < 18.5	0.0031	(0.0055)
α_{22}^π	constant, reference BMI: $[18.5, 25)$	0.0005	(0.0001)
α_{23}^π	weight effect above age 50, BMI: $[25, 30)$	0.0011	(0.0001)
α_{24}^π	weight effect above age 50, BMI: $[30, 35)$	0.0022	(0.0002)
α_{25}^π	weight effect above age 50, BMI: $[35, 40)$	0.0039	(0.0002)
α_{26}^π	weight effect above age 50, BMI: ≥ 40	0.0076	(0.0006)
α_{27}^π	black intercept	0.0031	(0.0004)
α_{28}^π	Hispanic intercept	-0.0010	(0.0005)

Note: Standard errors are reported in parentheses and are computed using the asymptotic variance formula for the simulated method of moments estimator.

Table C.7: Estimates of Weight Parameters

Object	Description	Estimate	(SE)
$\alpha_0^{\mathcal{W}}$	effort effect if not successful	-0.005	(fixed)
$\alpha_1^{\mathcal{W}}$	effort effect if successful	-0.050	(fixed)
ϱ_x	probability of successful effort	0.045	(0.0011)
$\alpha_2^{\mathcal{W}}$	constant drift	0.006	(0.0010)
$\alpha_3^{\mathcal{W}}$	high education fixed effect	1.669	(0.0775)
$\alpha_4^{\mathcal{W}}$	female fixed effect	1.071	(0.0637)
$\alpha_5^{\mathcal{W}}$	Black fixed effect	1.543	(0.1227)
$\alpha_6^{\mathcal{W}}$	Hispanic fixed effect	0.626	(0.0884)
$\alpha_7^{\mathcal{W}}$	high body type fixed effect	12.354	(0.1006)
$\alpha_8^{\mathcal{W}}$	late cohort drift	0.098	(0.0033)
$\alpha_9^{\mathcal{W}}$	age dependent drift, age: 26-40	0.069	(0.0046)
$\alpha_{10}^{\mathcal{W}}$	age dependent drift, age: 41-70	0.078	(0.0032)
$\alpha_{11}^{\mathcal{W}}$	age dependent drift, age: 71+	-0.135	(0.0084)
$\alpha_{12}^{\mathcal{W}}$	wealth dependent drift	-0.016	(0.0002)
σ_η^2	variance of log-normal weight shock	0.003	(0.0000)
$\alpha^{\mathbb{W}}$	drift toward demographic fixed effects	0.048	(0.0008)

Note: Standard errors are reported in parentheses and are computed using the asymptotic variance formula for the simulated method of moments estimator.

Table C.8: Estimates of Self-Reported Weight Parameters

Object	Description	Estimate	(SE)
α_1^{ξ}	mean self-reporting error, men	-0.007	(0.0084)
α_2^{ξ}	mean self-reporting error, women	-0.498	(0.0087)
α_3^{ξ}	variance of self-reporting error, men	1.914	(0.0444)
α_4^{ξ}	variance of self-reporting error, women	2.580	(0.0458)

Note: Standard errors are reported in parentheses and are computed using the asymptotic variance formula for the simulated method of moments estimator.

Table C.9: Estimates of Marital Matching Quality Parameters

Object	Description	Estimate	(SE)
α_1^μ	normalizing constant	0.5	(fixed)
α_2^μ	effort effect	0.032	(0.0007)
α_3^μ	assets effect, male	0.007	(0.0004)
α_4^μ	assets effect, female	0.003	(0.0002)
α_5^μ	weight effect, male	-0.002	(0.0001)
α_6^μ	weight effect, female	-0.003	(0.0001)
α_7^μ	health effect	0.086	(0.0048)
α_8^μ	black intercept	-0.014	(0.0006)
α_9^μ	Hispanic intercept	-0.017	(0.0005)
α_{10}^μ	high education intercept	0.115	(0.0048)

Note: Standard errors are reported in parentheses and are computed using the asymptotic variance formula for the simulated method of moments estimator.

Table C.10: Estimates of One-Off Utility from Marriage Parameters

Object	Description	Estimate	(SE)
α_1^z	utility from marriage quality	0.245	(0.0149)
α_2^z	potential spouse arrival rate, age: 16–25	0.091	(0.0031)
α_3^z	potential spouse arrival rate, age: 26–35	0.350	(0.0034)
α_4^z	potential spouse arrival rate, age: 36–45	0.217	(0.0076)
α_5^z	potential spouse arrival rate, age: 46+	0.022	(0.0007)

Note: Standard errors are reported in parentheses and are computed using the asymptotic variance formula for the simulated method of moments estimator.

Table C.11: Estimates of Utility Parameters

Object	Description	Estimate	(SE)
α_1^u	constant utility of being alive	0.566	(0.0384)
α_2^u	CRRA parameter of consumption	2.805	(0.0185)
α_3^u	scale parameter of consumption	5000.0	(fixed)
α_4^u	overweight utility at age: 16-35	-0.021	(0.0026)
α_5^u	overweight utility at age: 36-60	-0.002	(0.0014)
α_6^u	overweight utility at age: 61+	-0.001	(0.0016)
α_7^u	overweight utility of women	-0.008	(0.0019)
α_8^u	constant effort utility	-0.262	(0.0078)
α_9^u	utility from good health	0.017	(0.0056)
α_{10}^u	utility from working	-0.022	(0.0079)

Note: Standard errors are reported in parentheses and are computed using the asymptotic variance formula for the simulated method of moments estimator.

C.5 Additional tables and figures

Table C.12: Indirect BMI Gradients Operating Through Health

	Baseline	Change relative to normal BMI		
	Normal BMI 22.5	Overweight BMI 27.5	Obese BMI 32.5	Severely obese BMI 42.5
Panel A. BMI gradient in health				
Average	87.99	-0.22	-1.80	-12.31
Panel B. Indirect BMI gradients operating through health				
(i) Life expectancy, in years				
Average	86.03	-0.06	-0.51	-3.17
(ii) Hourly wage, in 2022 USD				
Average	30.52	-0.00	-0.03	-0.18
Women	28.67	-0.00	-0.02	-0.17
Men	32.38	-0.00	-0.03	-0.20
(iii) Employment retention probability, in percent				
Average	81.63	-0.04	-0.29	-1.95
Women	79.18	-0.04	-0.30	-2.04
Men	84.09	-0.03	-0.28	-1.86
(iv) Hiring probability from non employment, in percent				
Average	53.16	-0.05	-0.39	-2.70
Women	48.85	-0.05	-0.37	-2.60
Men	57.49	-0.05	-0.41	-2.81
(v) Marriage quality ranking, in percentiles				
Women	65.74	-0.09	-0.79	-5.58
Men	57.45	-0.09	-0.78	-5.19

Note: Simulated observations are weighted to be representative of the U.S. population. Column 1 reports average predicted outcomes at normal BMI, evaluated at BMI 22.5, while columns 2 to 4 report changes relative to normal BMI, evaluated at BMI 27.5, 32.5, and 42.5. Panel A reports the BMI gradient in the predicted probability of good health. Panel B reports the resulting indirect gradients in life expectancy, hourly wages, employment retention, hiring from non-employment, and marriage market ranking. For each individual, the BMI induced change in the probability of good health is multiplied by the individual specific effect of good health on each outcome, evaluated at normal BMI with all other state variables held fixed, and the table reports the weighted average of these products. Health, employment probabilities, and marriage market ranking are reported in percentage points; life expectancy, defined as 16 plus residual life expectancy at age 16, is reported in years; and wages are reported in 2022 USD per hour.

Table C.13: Education Gradients

	(1) baseline	(2) equalized education	(3) difference	(4) *percent*
A: Overall sample				
BMI	28.81	28.59	-0.22	*-0.77%*
Probability of good health, in percent	86.52	89.05	+2.53	*+2.92%*
Hourly wage, in 2022 USD	28.13	29.06	+0.93	*+3.30%*
Probability to be employed, in percent	72.32	74.53	+2.21	*+3.05%*
Life expectancy, in years	84.75	85.68	+0.93	*+1.10%*
Assets, in thousands of 2022 USD	174.87	186.30	+11.43	*+6.53%*
B: Low education sample				
BMI	27.36	27.09	-0.27	*-1.00%*
Probability of good health, in percent	77.29	87.71	+10.42	*+13.49%*
Hourly wage, in 2022 USD	20.95	25.24	+4.29	*+20.48%*
Probability to be employed, in percent	54.64	64.69	+10.05	*+18.40%*
Life expectancy at age 16, in years	81.97	85.79	+3.81	*+4.65%*
Assets, in thousands of 2022 USD	106.71	151.76	+45.04	*+42.21%*

Note: The table reports a counterfactual that removes education differences in employment, wages, health, medical expenditures, and marriage quality by assigning individuals with low education the corresponding processes of individuals with high education. The model is solved and simulated under the counterfactual parameters, with the marriage market population distribution updated iteratively, and simulated observations are weighted to represent the U.S. population. Panel A reports outcomes for the full population, while Panel B reports outcomes for individuals with low education. Columns 1 and 2 report baseline and counterfactual outcomes, while columns 3 and 4 report absolute and percentage changes relative to the baseline, respectively. Hourly wages and employment are computed for individuals below retirement age. Assets are reported in thousands of 2022 USD.

Table C.14: Marriage Market Ranking Effects

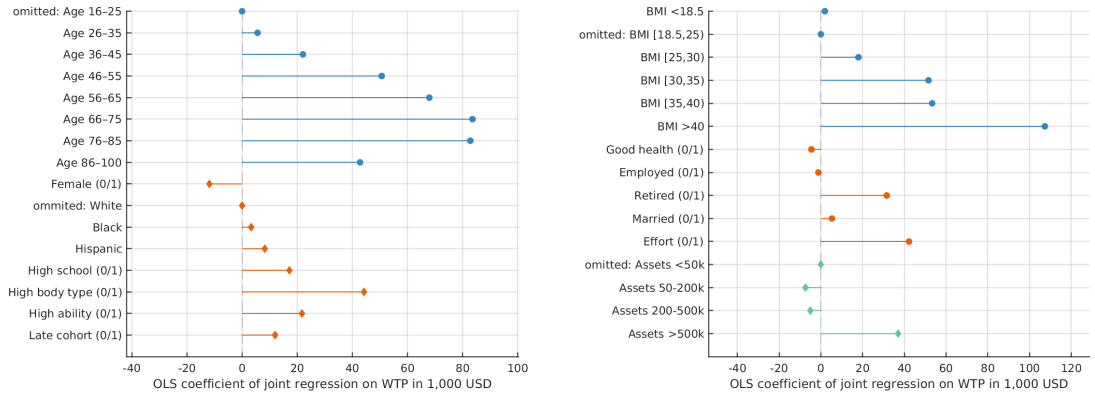
	Marriage market rank effect		
	All	Women	Men
Panel A. Individual characteristics			
High education vs low education	+44.62	+43.89	+45.36
Good health vs poor health	+33.60	+33.60	+33.60
Effort vs no effort	+29.80	+27.42	+32.18
Black vs white	-14.11	-13.15	-15.07
Hispanic vs white	-16.86	-15.86	-17.86
Panel B. Assets, relative to USD 20,000			
Baseline rank at USD 20,000	40.54	45.30	35.75
Assets 0 vs USD 20,000	-6.19	-4.01	-8.39
Assets 100,000 vs USD 20,000	+7.23	+3.89	+10.59
Assets 500,000 vs USD 20,000	+15.49	+8.30	+22.72

Note: The table reports model-implied effects on marriage market ranking. Simulated observations are weighted to be representative of the U.S. population. Effects are computed by changing one characteristic at a time while holding all other state variables fixed. The resulting marriage quality index is ranked relative to the baseline population within age and gender cells. Panel A reports the effects of education, health, effort, and race. Panel B reports asset effects relative to USD 20,000. All entries are reported in percentile points.

Figure C.15: **WTP by Demographics and State Variables with Side Effects**

(a) WTP by fixed demographics and age

(b) WTP by current state variables

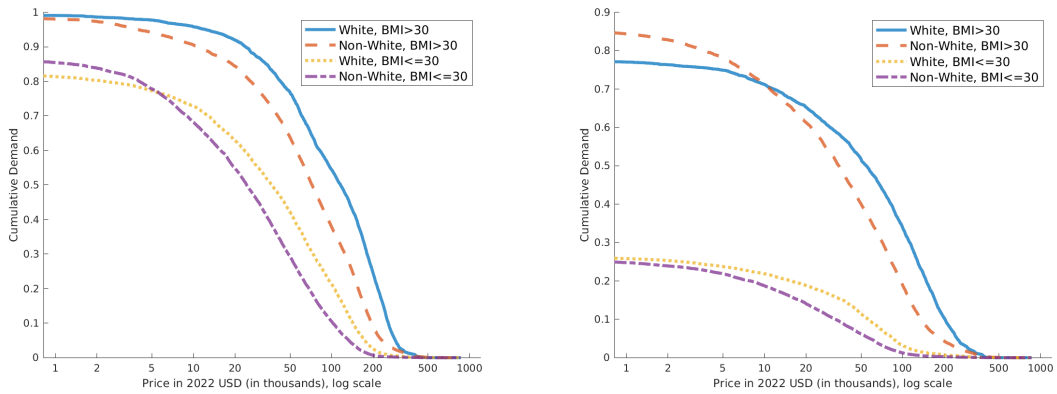


Note: The figure reports OLS coefficients from separate regressions of model-implied willingness to pay for a technology that reduces body weight by 10 percent and includes side effects. Simulated observations are weighted to represent the U.S. population. Willingness to pay is defined as the compensating reduction in current assets that makes an individual indifferent between the baseline state and a counterfactual state with 10 percent lower body weight and a 10 percent reduction in effective consumption. The reduction in effective consumption captures appetite suppression and the associated loss in the utility value of consumption. Panel (a) includes fixed demographic characteristics and age group indicators, while panel (b) includes current state variables. The figure reports coefficients from two OLS regressions, one for each panel. Within each regression, all covariates shown in the panel are included jointly. The regression constant is omitted. Dollar values are expressed in 2022 USD.

Figure C.16: **Model-Implied Demand Curve for a 10 Percent Weight Reduction by Race and BMI with and without Side Effects**

(a) Baseline

(b) With side effects



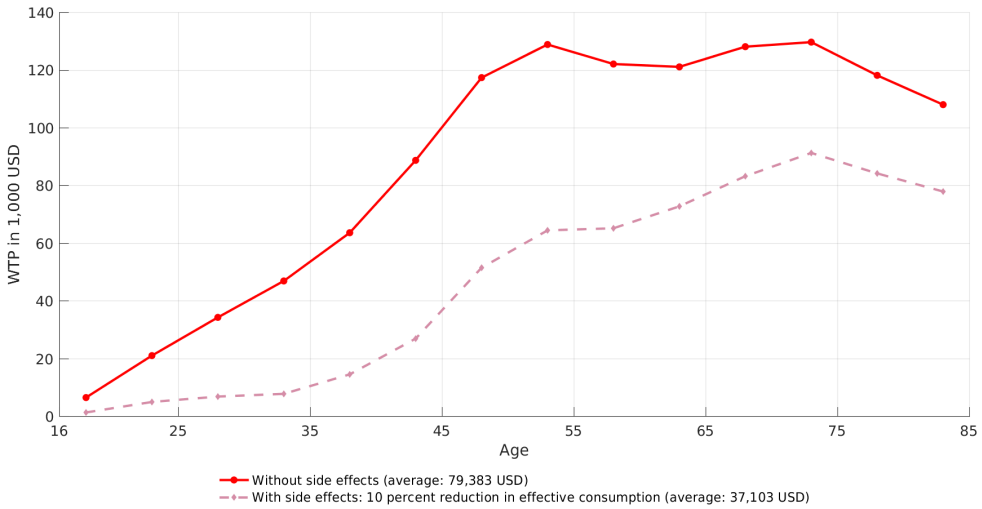
Note: The figure reports model-implied demand curves for a technology that permanently reduces body weight by 10 percent, by race and obesity status. Simulated observations are weighted to represent the U.S. population. Obesity is defined as BMI above 30. Willingness to pay is computed as the compensating reduction in current assets that makes an individual indifferent between the baseline state and a counterfactual state with lower body weight. In the baseline counterfactual, body weight is reduced by 10 percent. In the side effects counterfactual, the 10 percent reduction in body weight is combined with a 10 percent reduction in effective consumption, capturing appetite suppression and the associated loss in the utility value of consumption. At each price, demand is the share of simulated individuals whose willingness to pay is at least that price. Panel (a) reports baseline demand, and panel (b) reports demand with side effects. Dollar values are expressed in 2022 USD.

Table C.15: **Decomposing the Drivers of Willingness to Pay and Other Outcomes with Bootstrapped Standard Errors**

	(1) WTP	(2) BMI	(3) good health	(4) effort	(5) life exp.	(6) assets
baseline, in levels	79.383	28.807	0.865	0.382	84.753	174.87
	(2.51)	(0.03)	(0)	(0.01)	(0.24)	(2.94)
A: Single-Channel Exclusions, in difference to baseline:						
Health	-14.354	0.348	0.047	-0.12	1.497	-9.222
	(1)	(0.03)	(0)	(0.01)	(0.11)	(1.58)
Longevity	-16.425	0.33	-0.006	-0.117	1.209	11.547
	(1.97)	(0.02)	(0)	(0.01)	(0.09)	(3.57)
Wages	1.545	-0.002	0.001	-0.003	0.06	4.052
	(0.42)	(0.01)	(0)	(0)	(0.02)	(0.97)
Employment	0.001	0.004	0.002	-0.002	0.043	-0.518
	(0.32)	(0.01)	(0)	(0)	(0.02)	(0.72)
Marriage	-1.354	0.085	-0.002	-0.01	-0.069	0.214
	(0.22)	(0.01)	(0)	(0)	(0.02)	(0.8)
Body weight disutility	0.406	-0.046	0.002	0.004	0.104	5.595
	(0.39)	(0.01)	(0)	(0)	(0.02)	(1.13)
B: Cumulative Channel Exclusions, in difference to baseline:						
Health & longevity	-63.726	0.81	0.047	-0.273	3.337	-4.768
	(2.07)	(0.02)	(0)	(0.01)	(0.14)	(2.16)
Health, long. & wages	-66.625	0.8	0.046	-0.273	3.357	2.222
	(2.01)	(0.02)	(0)	(0.01)	(0.14)	(2.17)
Health, long., wages & empl.	-67.889	0.802	0.046	-0.273	3.362	3.084
	(2.02)	(0.02)	(0)	(0.01)	(0.14)	(2.3)
Health, long., wages, empl. & marr.	-71.181	0.938	0.047	-0.295	3.355	3.709
	(2.1)	(0.02)	(0)	(0.01)	(0.14)	(2.41)
All BMI-related channels	-79.383	0.926	0.047	-0.295	3.373	8.327
	(2.02)	(0.02)	(0)	(0.01)	(0.14)	(2.26)
C: Effort Disutility Exclusion, in difference to baseline:						
Effort disutility	-9.42	-1.367	0.012	0.464	0.649	3.347
	(1.9)	(0.05)	(0)	(0.03)	(0.1)	(1.29)

Note: The table reports average outcomes in the baseline simulated economy and in counterfactual economies that remove selected channels linking BMI to outcomes. Simulated observations are weighted to be representative of the U.S. population. Willingness to pay (WTP) is defined as the compensating reduction in current assets that leaves an individual indifferent between the baseline state and a counterfactual state with 10 percent lower body weight. To remove a BMI-related channel, overweight and obese individuals are assigned the effects associated with the normal BMI range (18.5–25), while parameters for BMI below 18.5 are left unchanged. WTP and assets are reported in thousands of 2022 USD. Good health and effort are indicator variables, and life expectancy (16 plus the residual life expectancy at age 16) is reported in years. Effort remains positive when all channels are removed in Panel B because it also affects outcomes through the marriage market, independently of its effect on body weight. Bootstrapped standard errors are reported in parentheses and are based on 100 parameter draws from the asymptotic distribution implied by the simulated method of moments estimator. The bootstrapped standard errors refer to the baseline levels and the difference between counterfactual and baseline, respectively.

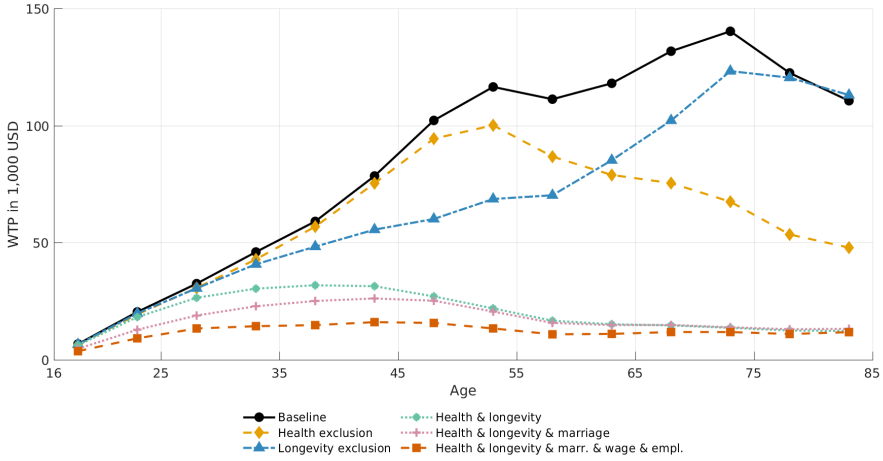
Figure C.17: **WTP over the Life Cycle with and without Side Effects**



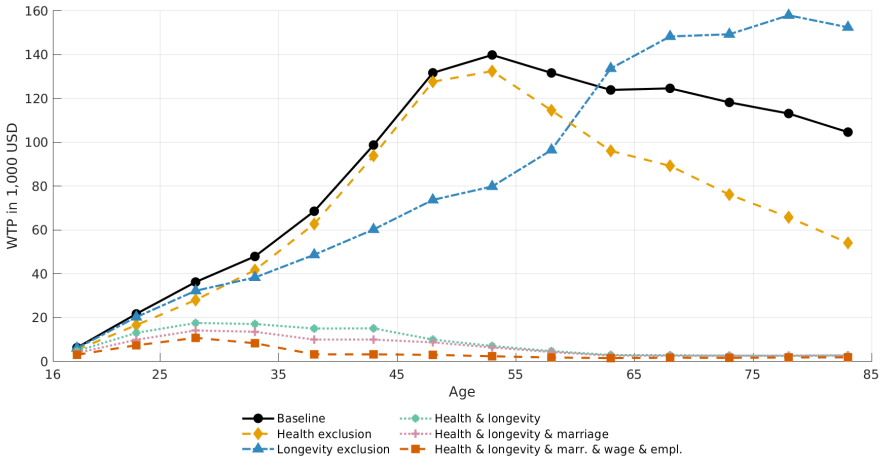
Note: The figure reports age specific averages of model-implied willingness to pay for a technology that permanently reduces body weight by 10 percent, with and without side effects. Simulated observations are weighted to represent the U.S. population. Willingness to pay is computed as the compensating reduction in current assets that makes an individual indifferent between the baseline state and a counterfactual state with lower body weight. In the baseline counterfactual, body weight is reduced by 10 percent. In the side effects counterfactual, the 10 percent reduction in body weight is combined with a 10 percent reduction in effective consumption, capturing appetite suppression and the associated loss in the utility value of consumption. The legend reports average WTP in 2022 USD for each counterfactual. Age specific WTP is expressed in thousands of 2022 USD.

Figure C.18: **WTP Decomposition over the Life Cycle by Gender**

(a) Women



(b) Men



Note: The figure reports, plotted separately by gender, age specific averages of model-implied willingness to pay for a technology that permanently reduces body weight by 10 percent. Simulated observations are weighted to represent the U.S. population. Willingness to pay is computed as the compensating reduction in current assets that makes an individual indifferent between the baseline state and a counterfactual state with 10 percent lower body weight. The baseline series uses the estimated model. The remaining series use counterfactual models in which selected channels linking BMI to outcomes are removed. Channels are removed by assigning overweight and obese individuals the effects associated with the normal BMI range, 18.5 to 25, while leaving the underweight category unchanged. Residual WTP is driven by body weight disutility. WTP is expressed in thousands of 2022 USD.

Table C.16: **Price Counterfactual with Bootstrapped Standard Errors**

		difference to baseline (bootstrapped SE) *change relative to baseline*	
	(1)	(2)	
annual WLT price, in USD		600	
	baseline	50/month	
Panel A: Uptake and uptaker characteristics (in levels)			
WLT uptake	0	0.823	(0.006)
Fraction uptakers below retirement age		0.834	(0.005)
Mean BMI of uptakers		27.44	(0.047)
Panel B: Outcomes in differences to baseline			
BMI	28.81	-2.179	(0.021)
		-7.6%	
Effort	0.382	-0.066	(0.011)
		-17.3%	
Good health	0.865	0.02	(0.001)
		2.3%	
Out-of-pocket medical exp., in USD	956.8	-14.26	(3.774)
		-1.5%	
Total med. exp., in USD (imp.)	4424	-288.7	(14.71)
		-6.5%	
Life expectancy	84.75	1.204	(0.079)
		1.4%	
Hourly wages, in USD	22.28	0.358	(0.028)
		1.6%	
Employment	0.6	0.006	(0.001)
		0.9%	
Consumption, in 1,000 USD	40	0.281	(0.06)
		0.7%	
Assets, in 1,000 USD	174.9	-2.292	(2.608)
		-1.3%	
Flow utility, normalized	100	0.469	(0.047)
		0.5%	
Utility (value function), norm.	100	1.321	(0.093)
		1.3%	
Gini of assets	0.477	-0.006	(0.003)
		-1.3%	
Gini of utility (VF), at age 40	0.033	-0.002	(0.001)
		-6.5%	
Gini of life exp.	0.036	-0.002	(0)
		-6.1%	
White-Black gap in life exp.	9.883	-0.015	(0.074)
		-0.2%	

Note: The table reports average outcomes in the baseline simulated economy and in a counterfactual economy with market-based access to a weight-loss technology. Simulated observations are weighted to be representative of the U.S. population. The technology reduces BMI by 10 percent while in use, leaves the latent BMI process unchanged, and requires continued use to maintain the reduction. In column 2, individuals may purchase the technology at an annual price of USD 600. Medical expenditures exclude payments for the weight-loss technology. Total medical expenditures are imputed from MEPS and include payments by individuals, private insurers, Medicare, Medicaid, and other payers. Self-paid medical expenditures include unreimbursed payments made directly by individuals or their families. Rows in italics report percentage changes relative to the baseline. Dollar values are expressed in 2022 USD. The Gini coefficient of life expectancy uses 16 plus the residual life expectancy at age 16, and the Gini coefficient of lifetime utility is evaluated at age 40. Flow utility and lifetime utility are normalized to 100 in the baseline. Bootstrapped standard errors are reported in parentheses and are based on 100 parameter draws from the asymptotic distribution implied by the simulated method of moments estimator. The bootstrapped standard errors refer to the difference between counterfactual and baseline.

Table C.17: **Policy Counterfactuals with Bootstrapped Standard Errors**

	baseline (in levels)	difference to baseline (bootstrapped SE) *change relative to baseline*			
	(1)	(2)		(3)	
policy	baseline	Obesity Plus $BMI \geq 30$ & poor health		Obesity Only $BMI \geq 30$	
Panel A: Uptake and uptaker characteristics (in levels)					
WLT uptake		0.249	(0.011)	0.58	(0.014)
Fraction uptakers below retirement age		0.733	(0.009)	0.806	(0.006)
Mean BMI of uptakers		30.10	(0.219)	29.35	(0.176)
Panel B: Outcomes in differences to baseline					
BMI	28.81	-0.713	(0.03)	-1.653	(0.036)
		-2.5%		*-5.7%*	
Effort	0.382	-0.013	(0.003)	-0.037	(0.006)
		-3.3%		*-9.7%*	
Good health	0.865	0.015	(0.001)	0.02	(0.001)
		1.8%		*2.3%*	
Out-of-pocket medical exp., in USD	956.8	-6.88	(2.811)	-13.81	(3.804)
		-0.7%		*-1.4%*	
Total med. exp., in USD (imp.)	4424	-175	(10.08)	-293.3	(11.68)
		-4.0%		*-6.6%*	
Life expectancy	84.75	0.843	(0.049)	1.189	(0.057)
		1.0%		*1.4%*	
Hourly wages, in USD	22.28	0.154	(0.016)	0.36	(0.024)
		0.7%		*1.6%*	
Employment	0.6	0.002	(0.001)	0.006	(0.001)
		0.4%		*1.0%*	
Consumption, in 1,000 USD	40	0.354	(0.026)	0.763	(0.056)
		0.9%		*1.9%*	
Assets, in 1,000 USD	174.9	1.678	(0.625)	-0.455	(1.802)
		1.0%		*-0.3%*	
Flow utility, normalized	100	0.214	(0.028)	0.576	(0.071)
		0.2%		*0.6%*	
Utility (value function), norm.	100	1.536	(0.092)	1.51	(0.099)
		1.5%		*1.5%*	
Gini of assets	0.477	-0.002	(0.001)	-0.007	(0.002)
		-0.5%		*-1.4%*	
Gini of utility (VF), at age 40	0.033	-0.004	(0)	-0.003	(0)
		-10.7%		*-8.2%*	
Gini of life exp.	0.036	-0.002	(0)	-0.002	(0)
		-6.5%		*-6.3%*	
White-Black gap in life exp.	9.883	-0.062	(0.059)	-0.055	(0.08)
		-0.6%		*-0.6%*	

Note: The table reports average outcomes in the baseline simulated economy and in two counterfactual economies with prescription-based access to a weight-loss technology. Simulated observations are weighted to be representative of the U.S. population. The technology reduces BMI by 10 percent while in use, leaves the latent BMI process unchanged, and requires continued use to maintain the reduction. In columns 2 and 3, eligible individuals receive access at zero cost and decide whether to adopt. Eligibility is restricted to individuals with BMI above 30 and poor health in column 2 and to all individuals with BMI above 30 in column 3. Medical expenditures exclude payments for the weight-loss technology. Total medical expenditures are imputed from MEPS and include payments by individuals, private insurers, Medicare, Medicaid, and other payers. Self-paid medical expenditures include unreimbursed payments made directly by individuals or their families. Rows in italics report percentage changes relative to the baseline. Dollar values are expressed in 2022 USD. The Gini coefficient of life expectancy uses 16 plus the residual life expectancy at age 16, and the Gini coefficient of lifetime utility is evaluated at age 40. Flow utility and lifetime utility are normalized to 100 in the baseline. Bootstrapped standard errors are reported in parentheses and are based on 100 parameter draws from the asymptotic distribution implied by the simulated method of moments estimator. The bootstrapped standard errors refer to the difference between counterfactuals and baseline.

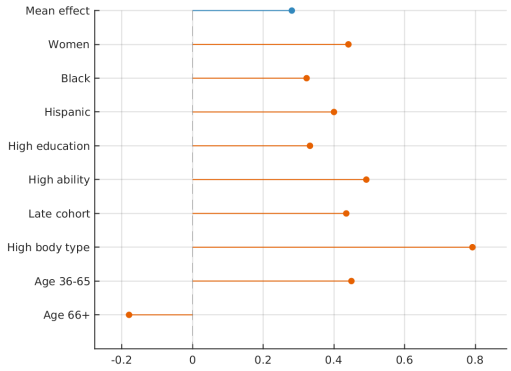
Table C.18: **Effects of Weight-Loss Technologies under Alternative Access Regimes with Side Effects**

		average outcomes *change relative to baseline*		
	(1)	(2)	(3)	(4)
allocation rule	baseline	Market-based USD 600/year	Obesity Plus $BMI \geq 30$ + poor health	Obesity Only $BMI \geq 30$
WLT uptake		0.529	0.18	0.448
Fraction uptakers below retirement age		0.767	0.712	0.778
Mean BMI of uptakers		29.58	31.23	30.81
BMI	28.807	27.47	28.324	27.591
		-4.6%	*-1.7%*	*-4.2%*
Effort	0.382	0.283	0.353	0.317
		-25.9%	*-7.4%*	*-16.9%*
Good health	0.865	0.881	0.878	0.883
		1.9%	*1.5%*	*2.1%*
Out-of-pocket medical exp., in USD	956.75	945.38	951.71	944.07
		-1.2%	*-0.5%*	*-1.3%*
Total med. exp., in USD (imp.)	4424.2	4188.4	4283.2	4166.3
		-5.3%	*-3.2%*	*-5.8%*
Life expectancy	84.753	85.827	85.456	85.823
		1.3%	*0.8%*	*1.3%*
Hourly wages, in USD	22.28	22.579	22.395	22.59
		1.3%	*0.5%*	*1.4%*
Employment	0.6	0.605	0.601	0.605
		0.8%	*0.2%*	*0.9%*
Consumption, in 1,000 USD	40.002	40.376	40.297	40.731
		0.9%	*0.7%*	*1.8%*
Assets, in 1,000 USD	174.87	174.12	176.27	173.64
		-0.4%	*0.8%*	*-0.7%*
Flow utility, normalized	100	99.959	100.03	100.11
		-0.0%	*0.0%*	*0.1%*
Utility (value function), norm.	100	100.75	100.95	100.89
		0.8%	*0.9%*	*0.9%*
Gini of assets	0.477	0.472	0.475	0.471
		-1.0%	*-0.3%*	*-1.2%*
Gini of utility (VF), at age 40	0.033	0.031	0.03	0.031
		-5.9%	*-9.0%*	*-7.3%*
Gini of life exp.	0.036	0.034	0.034	0.034
		-5.3%	*-6.0%*	*-5.5%*
White-Black gap in life exp.	9.883	9.999	9.92	9.986
		1.2%	*0.4%*	*1.0%*

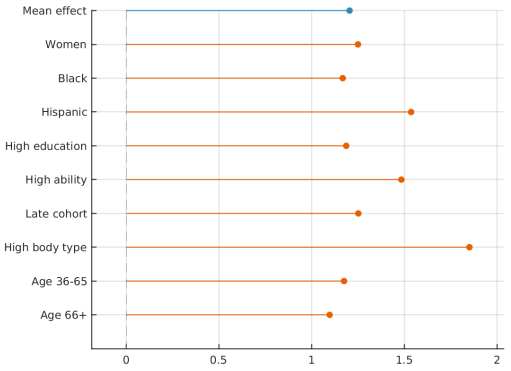
Note: The table reports average outcomes in the baseline simulated economy and in three counterfactual economies with access to a weight-loss technology with side effects. Simulated observations are weighted to represent the U.S. population. The technology reduces BMI by 10 percent while in use, leaves the latent BMI process unchanged, and requires continued use to maintain the reduction. Side effects are modeled as a 10 percent reduction in effective consumption while using the technology, capturing appetite suppression and the associated loss in the utility value of consumption. In column 2, individuals may purchase the technology at an annual price of USD 600. In columns 3 and 4, eligible individuals receive access at zero cost and decide whether to adopt. Eligibility is restricted to individuals with BMI above 30 and poor health in column 3 and to all individuals with BMI above 30 in column 4. Medical expenditures exclude payments for the weight-loss technology. Total medical expenditures are imputed from MEPS and include payments by individuals, private insurers, Medicare, Medicaid, and other payers. Self paid medical expenditures include unreimbursed payments made directly by individuals or their families. Rows in italics report percentage changes relative to the baseline. Dollar values are expressed in 2022 USD. The Gini coefficient of life expectancy uses 16 plus the residual life expectancy at age 16, and the Gini coefficient of lifetime utility is evaluated at age 40. Flow utility and lifetime utility are normalized to 100 in the baseline.

Figure C.19: **Additional Effects of Market-Based Access to a Weight-Loss Technology**

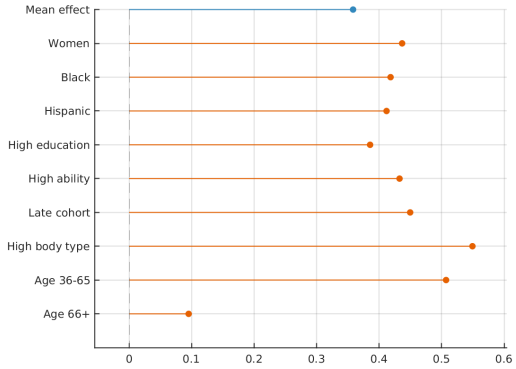
(a) Consumption, in 1,000 USD



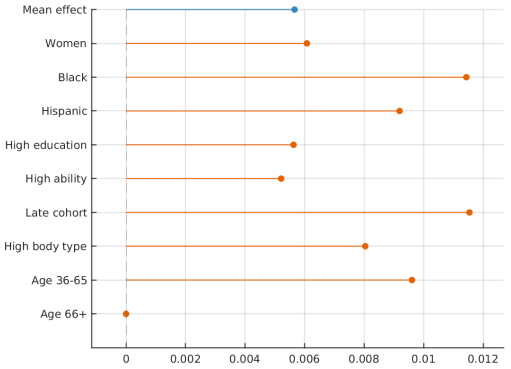
(b) Life expectancy



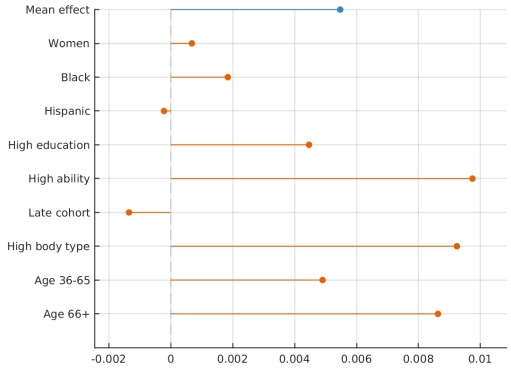
(c) Hourly (potential) wage, in USD



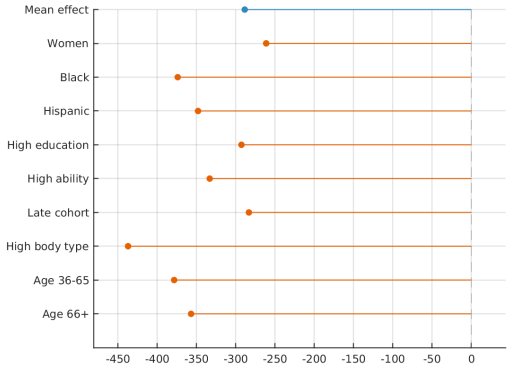
(d) Employment



(e) Married



(f) Total Med. Exp., in USD (imp.)



Note: The figure reports heterogeneity in the effects of a counterfactual in which a weight-loss technology is available at an annual price of USD 600. Simulated observations are weighted to be representative of the U.S. population. The technology reduces BMI by 10 percent while in use, leaves the latent BMI process unchanged, and requires continued use to maintain the reduction. Effects are measured relative to the baseline simulated economy. The blue marker reports the average effect in the population, while orange markers report unconditional subgroup averages for the demographic groups shown on the vertical axis. Total medical expenditures exclude payments for the weight-loss technology and are imputed from MEPS; they include payments by individuals, private insurers, Medicare, Medicaid, and other payers. Dollar values are expressed in 2022 USD.