Healthy Habits and Inequality*

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February 2023

Abstract

There is an important socio-economic gradient in health outcomes, and this gradient has widened over time. We argue that differences in health behaviors across education groups are key to understanding these two facts. We start by jointly estimating latent lifestyle habit types and health dynamics in both the HRS and the PSID by exploiting data on health behavior and health outcomes. We find that there are large gradients in life expectancy across types (8 years at age 50) and that the higher frequency of health protective lifestyles among the more educated individuals explains 40% of the education gradient in life expectancy. Next, to understand why there is an education gradient in health protective lifestyles, we build a life cycle model with idiosyncratic labor market and health risks. In the model, education and lifestyles are jointly chosen early in life by individuals who are heterogeneous in the cost of adopting protective lifestyles and education. We find that the more educated choose healthier lifestyles partly because of their income advantage (life is more enjoyable with higher consumption possibilities), partly because of their overall better health transitions (a better lifestyle has a larger effect on health transitions for them), and partly due to their better selection in terms of costs of adopting healthier behaviors. Finally, we find that the increase in the college wage premium over the last decades has widened the education gradient in lifestyles, resulting in one-year increase in the education gradient of life expectancy across cohorts born in the 1930s and 1970s. Of this increase, 3/4 is driven by the direct effect of wage changes, while 1/4 is due to changes in selection.

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1 Introduction

In recent decades, Western economies have witnessed an increase in both income and health inequalities, a phenomenon that has attracted considerable attention from economists, demographers and health researchers alike. This trend is underpinned by two fundamental observations: a strong correlation between economic and health outcomes (Kitagawa and Hauser, 1973; Pijoan-Mas and Ríos-Rull, 2014; Chetty et al., 2016) and a widening educational gap in health outcomes (Preston and Elo, 1995; Meara et al., 2008; Case and Deaton, 2015). However, the precise mechanisms linking economic status and health outcomes are not well understood. Our study seeks to address this gap by examining the role of lifestyle factors and health risk behaviors.

Lifestyle habits are important determinants of health outcomes, playing a significant role in shaping health inequalities. Firstly, differences in lifestyle factors and health risk behaviors such as exercise habits, dietary patterns, or smoking have been consistently identified as key drivers of health disparities (Taylor et al., 2002; Li et al., 2018; Zaninotto et al., 2020). Individuals who engage in healthier behaviors are more likely to experience positive health outcomes, while those with unhealthy habits are at greater risk of developing chronic diseases and experiencing premature mortality. Secondly, research has consistently shown that individuals with higher levels of education tend to adopt healthier lifestyles (Lantz et al., 1998; Polvinen et al., 2013). Hence, heterogeneous lifestyle choices may contribute to the educational gradient in health outcomes, wherein individuals with lower levels of education are disproportionately affected by poor health outcomes due to less favorable lifestyle choices.

Our study aims to firstly measure the impact of different lifestyle habits on both health dynamics and economic outcomes. Secondly, we seek to understand the early life joint determination of education and lifestyle habits, particularly exploring why there exists an education gradient in lifestyle choices. Finally, given these ingredients, we aim to assess the extent to which increases in labor earnings inequality across education groups can drive increases in health inequalities.

Using data from the Health and Retirement Study (HRS) and the Panel Study of Income Dynamics (PSID), we exploit a rich array of health behavior indicators. These include preventive tests, substance abuse, and exercise habits, among others. Ideally, we would like to incorporate all this information into a structural model. However, challenges arise due to the noisy nature of observed health behaviors, which are imperfectly correlated across individuals and over time. Additionally, the curse of dimensionality poses a significant obstacle. To address these issues, our study makes a novel contribution by developing a methodology to reduce the dimensionality of the data. This involves identifying permanent patterns in lifestyle behavior, leveraging cross-sectional and panel variation on health behavior and examining the relationship between health behavior and health dynamics.

We find that health behavior can be parsimoniously represented by two distinct lifestyles: protective and detrimental. At age 50, there exists a substantial life expectancy gradient of 8 years between individuals with protective and detrimental lifestyles. Moreover, we observe a strong correlation between lifestyle habits and education, with harmful behaviors being more prevalent among the less educated, which explains approximately 40% of the education gradient in life expectancy. Within education categories, the life expectancy differences across lifestyles types are also large, more so for college graduates than for high-school dropouts. Finally, we find an increasing dispersion in lifestyles across education groups for individuals born in the 1930s and the 1970s.

Then, in order to understand the joint determination of education and health behavior choices, we propose an heterogeneous agents model comprising two distinct stages. In the first stage, individuals make a one-time early-life education and health behavior choice. In this stage, individuals exhibit heterogeneity in both their costs associated with education and their costs associated with engagement in protective health behaviors. In the second stage, during the working/retirement phase, individuals solve a standard life-cycle model with idiosyncratic labor income and health risks, with outcomes conditioned on their specific education and lifestyle choices made in the initial stage.

Our economic model incorporates complementarities between education and lifestyle investments because of two important reasons. First, an extra year of life is more valuable with higher consumption possibilities. This means that the value of a health-protective lifestyle is larger for the mode educated and the value of education is larger for individuals expecting to live more years. Second, as implied by our econometric model, the benefit in health transitions of investing in protective health behavior is also larger for higher-educated individuals. In addition, these two complementarities between health and education investment shape the selection of individuals into different education categories. Specifically, individuals facing lower costs associated with health behavior are more inclined to opt for higher education investments.

We calibrate our model to accurately replicate the joint distribution of education and lifestyle choices for cohorts born in 1930 and 1970, as well as to match the median savings across different education and health behavior categories. In the model, cohorts differ in their education-specific average labor earnings. Notably, our model effectively captures the overall wealth distribution and is able to explain 50% of the observed increase in life-expectancy inequalities across education groups between the 1930 and 1970 cohorts.

Using our model as a laboratory economy, we identify the mechanisms driving the observed disparities in life expectancy and health outcomes across education groups. We find that both the income and health advantage of the more educated are equally important and explain most of the differences in health behavior choices across education groups. Selection on the other hand, plays a quantitatively more modest role. With respect to changes across cohorts, we find worse economic conditions of the high-school dropouts explain 78% of the fall in life-expectancy while 22% is explained by selection. Better economic outcomes for the college educated explain all of the increases in life-expectancy across cohorts.

1.1 Related literature

Our paper is related to a growing literature that employs life cycle models to quantify how heterogeneous health dynamics impact economic outcomes, see for instance De Nardi et al. (2010), French and Jones (2011), De Nardi et al. (2016), Ameriks et al. (2020), Nakajima and Telyukova (2023), or Bueren (2023). Closer to our approach, Braun et al. (2019), Hosseini et al. (2021), and De Nardi et al. (2022) utilize dynamic panel models to characterize health dynamics and estimate significant welfare losses associated with adverse health episodes. The latter paper demonstrates that the impact of health on economic outcomes largely depends on fixed characteristics predetermined earlier in life. Our study provides an econometric framework to leverage information on health behaviors to interpret these fixed types, and it allows for early-life choices of health behavior leading to endogenous health outcomes.

The paper is also related to previous work featuring endogenous monetary health investments, like Fonseca et al. (2021), Ozkan (2023), Hong et al. (2024). These papers struggle to find a strong causal effect of medical spending on health outcomes. The same can be said of quasi-experimental evidence, like Aron-Dine et al. (2013), Finkelstein et al. (2012), and Baicker et al. (2013). This justifies our focus on health behavior choices as a potential driver of the educational gradient of health outcomes.

The paper importantly connects with previous studies that model endogenous health behavior investments (Cole et al., 2019; Mahler and Yum, 2022; Margaris and Wallenius, 2023). These models allow agents to adjust their behavior over the life-cycle while keeping their education choices as given, but assume significant costs associated with changing lifestyles to match the unfrequent switching behavior observed in the data. In contrast, our model capitalizes on the persistence of health behavior, which is often established early in life, to properly estimate its effects on health dynamics. Moreover, these papers assume a uniform non-pecuniary costs of health behaviors across education groups. Our model, instead acknowledges the heterogeneity of these costs. This variation influences selection processes, whereby individuals facing higher costs for protective health behaviors will be more inclined to opt for lower education levels given the complementarity in health and education investments. Through endogenous modeling of both health behavior and education choices, we can precisely assess the extent to which selection drives differences in health inequality across education groups.

Finally, our paper is also related to the *deaths of despair* literature. Case and Deaton (2017) argue that the worsening of labor market opportunities for white males without a high school degree has led to an increase in risky health behavior (in particular, the use of opioids) for this population group. This has damaged the life expectancy of the less educated and widened the education gradient in life expectancy. Our paper broadens the scope of changes in health-related behavior beyond substance abuse and provides a quantitative exercise for this type of argument. However, instead of looking at changes in behavior during the life cycle, it looks at the early life determinants of lifestyle choices, which arguably are more important for comparisons across cohorts.

The remainder of the paper is organized as follows: Section 2 and Section 3 present the econometric model used to identify lifestyles and its results, respectively. Section 4 outlines the economic model, while Section 5 details the calibration strategy. Section 6 presents the quantitative findings, followed by concluding remarks in Section 7.

2 An econometric model of health dynamics with latent types

We combine data from the HRS and the PSID to create an unbalanced panel of individuals $i = 1, \ldots, N$ followed for $t = 0, \ldots, T_i$ periods. For each individual and period we observe standard demographic variables: cohort of birth $c_i \in \{c_{10}, c_{30}, c_{50}, c_{70}, c_{90}\}$ (individuals born around 1910, 1930, 1950, 1970, and 1990), gender $s_i \in \{s_m, s_f\}$ (male, female), education $e_i \in \{\text{HSD}, \text{HSG}, \text{CG}\}$ (high school dropout, high school degree, college degree), and age $a_{it} \in \{25, 26, \ldots, 100\}$, plus a wide array of health-related variables, which we classify into two groups: health outcomes and health behaviour. The health outcome $h_{it} \in H \equiv \{h_g, h_b, h_d\}$ takes three values: good health (h_g), bad health (h_b), or dead (h_d), which is an absorbing state. We build this variable by use of the 5-category self-rated health variable (where the best two categories form the good health state) and the information on survival. The health behavior vector $\mathbf{z}_{it} = \{z_{1,it}, z_{2,it}, \ldots, z_{N_z,it}\}$ contains information on N_z different categorical variables $z_{m,it} \in \{0, 1\}$ describing whether individual i in period t does some particular action. These actions are whether the individual has taken a cancer test (prostrate or mammography), a cholesterol test, or a flu shot in the last year, whether the individual drinks (more than two drinks on the day she drinks), whether the individual smokes, and whether the individual is performs any type of physical activity.[1]

We assume that both the observed health behaviour $\mathbf{z}_{it}$ and health outcomes h_{it} depend on some unobserved time-invariant latent variable $y_i \in Y \equiv \{y_1, y_2, \ldots, y_{N_y}\}$, with $N_y < N_z$. We interpret the latent variable as lifestyle / health habit type —determined before the start of working life— that captures the idea that individuals differ in their propensity to undertake actions that are good for their health. This notion of an unobserved latent variable is important because in the data observed health behaviour is imperfectly correlated across individuals and over time. That it, we want the latent types to also affect health outcomes because we want the classification of individuals based on behavior to be meaningful in terms of health dynamics.

We aim to estimate the parameters of our econometric model by maximizing the probability of observing the joint sequence of health behaviours $\mathbf{z}_i^T$ and health outcomes $\mathbf{h}_i^T$ of each individual i conditional on the demographic variables and initial health. We can write the likelihood of the

[1] Some of the health outcome and health behavior variables for a given individual may be missing for some period t. Indeed, in the PSID we do not observe the variables for health protective behaviour (cancer test, cholesterol test, flu shot). We take missing observations into account under the assumption that they occur completely at random, but we abstract from them in the model description to simplify the exposition.

data as a mixture model:

$$p\left(\mathbf{z}_i^T, \mathbf{h}_i^T | \mathbf{a}_i^T, c_i, s_i, e_i, h_{i0}\right) = \sum_{y \in Y} p\left(\mathbf{z}_i^T | y, h_i^T, \mathbf{a}_i^T, c_i, s_i, e_i\right) p\left(\mathbf{h}_i^T | y, h_{i0}, \mathbf{a}_i^T, s_i, e_i\right) p\left(y | h_{i0}, a_{i0}, c_i, s_i, e_i\right) \quad (1)$$

where the elements in the right hand side, the probability of observing a sequence of health behaviours, the probability of observing a sequence of health outcomes, and the initial distribution of types, are explained in Section 2.1, 2.2, and 2.3 respectively.

2.1 Health behaviour

We assume that the probability of individual i in period t reporting the m^{th} behavior ($h_{m,it} = 1$) depends only the health behaviour type y_i but also on age a_{it}, on health status h_{it}, and on an idiosyncratic shock $\varepsilon_{m,it}$. The idea is that the association of observed behavior such as smoking or cancer tests with types may differ over age and across health states. Instead, conditional on these variables, we impose that health behavior does not depend on cohort c_i, gender s_i, or education e_i. We do so because we want the definition of types to be stable across demographic groups. This makes the types comparable across groups, and it lets the variation in behavior across demographic groups to arise from their different distribution of types.

We assume that, conditional on y_i, a_{it}, and h_{it}, the shock $\varepsilon_{m,it}$ is iid across m, i, and t, and that it follows a standard normal distribution. Then, we can model the probability of individual i in period t reporting the m^{th} behavior ($h_{m,it} = 1$) as a probit model. In particular, let $z^*_{m,it} = z^*_m \left(y_i, a_{it}, h_{it}\right)$ be a latent variable such that $z^*_{m,it} + \varepsilon_{m,it} > 0 \Rightarrow z_{m,it} = 1$.[2] Then, the probability of observing the m^{th} behavior is given by $\Phi\left(z^*_{m,it}\right)$ where $\Phi()$ is the cdf of the standard normal distribution, and the probability of observing a sequence $\mathbf{z}_i^T$ of health behaviour vectors $\mathbf{z}_{it}$ for individual i is given by,

$$p\left(\mathbf{z}_i^T | y_i, h_i^T, a_i^T\right) = \Pi_{t=1}^T \Pi_{m=1}^M \left[\Phi\left(z^*_{m,it}\right)\right]^{z_{m,it}} \left[1 - \Phi\left(z^*_{m,it}\right)\right]^{1 - z_{m,it}} \quad (2)$$

2.2 Health dynamics

We assume that health dynamics for individual i depends on gender s_i, education e_i, health behaviour type y_i, and age a_{it}. The dependence of health dynamics on gender and education is meant to capture differences in health outcomes associated to these variables that are not captured by differences in health behaviour types across these demographic groups. The absence of cohort c_i from the set of conditioning variables is an identification assumption. We do not observe full lifespans for individuals in different cohorts. Rather, we combine information on health dynamics at old ages from individuals born in earlier cohorts with information on health dynamics at young ages from individuals born in later cohorts. This is standard in estimation of models of health dynamics

[2] We model $z^*_m \left(y_i, a_{it}, h_{it}\right)$ as a flexible low order polynomial on age.

with survey data, see for instance Pijoan-Mas and Ríos-Rull (2014). Hence, our assumption is that health dynamics of individuals of given gender and education are, conditional on type, identical across cohorts. However, it is important to note that this allows gender and education health dynamics to differ across cohorts due to the different composition of types.

We assume that conditional on gender s_i, education e_i, health behaviour type y_i, and age a_{it}, the evolution of health outcomes is markovian, that is, only depends on one lag of health outcomes. We model survival and health transition probabilities as a multinomial probit model.

2.3 Distribution of health types

The final element we need is the fraction of individuals of each type, that is, the prior probability of each individual of being of a given health behaviour type before observing the data on health behavior and health outcomes. In particular, we define $p\left(y_i|c_i, s_i, e_i, a_{i0}, h_{i0}\right)$ as the probability that individual i born into cohort c_i, of gender s_i, education e_i, first observed with age a_{i0} and health h_{i0} is of type y_i. One could add this term to the likelihood function and estimate it non-parametrically from the data. However, because the panel is not balanced and the first age of observation of many individuals is quite advanced (a_{i0} is large), there would an identification problem in that observed changes of health behavior $\mathbf{z}_{it}$ with age (for instance, the decline with age of the incidence of smoking) could not be separated into (a) changes over age of health behavior conditional on type $p\left(\mathbf{z}_i^T|y_i, h_i^T, a_i^T\right)$ and (b) changes in the distribution of types with age $p\left(y_i|c_i, s_i, e_i, a_{i0}, h_{i0}\right)$. Therefore, we exploit the model of health dynamics described above to obtain an expression for how the posterior distribution of types conditional on observables evolves with age. This leaves us with the need to only estimate the prior probabilities of each individual of being of each type at the initial age of 25.

In order to do so, note that we can write,

$$p\left(y_i|c_i, s_i, e_i, a_{it}, h_{it}\right) = \frac{p\left(y_i, h_{it}|c_i, s_i, e_i, a_{it}\right)}{\sum_{h \in H} p\left(y_i, h|c_i, s_i, e_i, a_{it}\right)} \tag{3}$$

The joint probability $p\left(y_i, h_{it}|c_i, s_i, e_i, a_{it}\right)$ can be decomposed as,

$$p\left(y_i, h_{it}|c_i, s_i, e_i, a_{it}\right) = \sum_{h_{it-1} \in H} p\left(h_{it}|y_i, h_{it-1}, s_i, e_i, a_{it-1}\right) p\left(y, h_{it-1}|c_i, s_i, e_i, a_{it-1}\right) \tag{4}$$

The first term in the right hand side describes the health dynamics and it has been discussed in Section 2.2. The second term in the right hand side is the same as the left hand side, just one period before. Hence, we can use equation (4) recursively up to age 25, which is our initial age, that is, up to $p\left(y_i, h_{it}|c_i, s_i, e_i, a_{it} = 25\right)$. This term describes the joint probability of an individual in cohort c_i, of gender s_i and education e_i of being of health h_{it} and type y_i at age 25. We decompose this probability in two pieces:

$$p\left(y_i, h_{it}|c_i, s_i, e_i, a_{it} = 25\right) = p(y_i|c_i, s_i, e_i, a_{it} = 25, h_{it})p(h_{it}|c_i, s_i, e_i, a_{it} = 25)$$

The second term in the right hand side describes the share of individuals of age 25 of given cohort c_i, gender s_i, and education e_i that have health h_{it}. This can be measured directly in the PSID for many but not all cohorts. We thus assume that conditional on education and gender, the probability of good and bad health at age 25 does not change across cohorts and we set it equal to the one that we observe in the PSID.[3] The vast majority of observed individuals of age 25 display $h_{it} = h_g$, so we set this probability to one. The first term in the right hand side describes the fraction of individuals of age 25, cohort c_i, gender s_i, education e_i, and health h_{it} that are of type y_i. We model this probability through a multinomial probit. That is, we define thresholds $y^*_{1,i} = y^*_1\left(c_i, s_i, e_i, h\right)$ and $y^*_{2,i} = y^*_2\left(c_i, s_i, e_i, h\right)$ that, given the realization of a shock $\varepsilon_{y,i} \sim N\left[0, 1\right]$, separates individuals into types.

3 Results from the econometric model

We estimate the model using data from the PSID from 1999 to 2019 and the HRS between 1996 and 2018. In case individual's lifestyle y was observed, the evaluation of the likelihood would be simple. However, since it is not the evaluation and maximization of the full likelihood is challenging as there are a large number of parameters to estimate and thousands of latent variables (one by individual). Therefore we resort to Markov Chain Monte Carlo Methods which reduce the full likelihood into smaller simpler blocks. In what follows we describe the results.

3.1 Health behaviour

In our main estimation and in favor of parsimony, we choose $N_y = 2$, that is, we classify individuals into two latent groups. Figure 1 reports the probability of displaying each health behaviour z_{it} as a function of health type y_i and age a_{it} and for $h_{it} = h_g$ (the case $h_{it} = h_b$ is not too different). Individuals in one group have higher likelihood of reporting health protective habits (cancer test, cholesterol test, flu shot, and exercise) and lower probability of reporting health detrimental habits (smoking and drinking). We label this group as *protective* (solid green line). For individuals in the other group, the probability of reporting all the protective habits is lower and their smoking probability is very high. We label this group as detrimental (red dashed line).

[3] The probability of being in good health at age 25 varies between 77% for dropout females to 98% for male college graduates.

3.2 Distribution of health types

Our estimation assigns a different fraction of individuals to each type y depending on cohort c, gender s, and education e. The first column in Table 1 reports these fractions for the 1950 cohort. The main finding is that there is a large educational gradient of health behaviour types: the share of *protective* individuals grows from 42.9% to 91.6% as we move from high school dropout to college graduate. The pattern is similar similar among women, with the difference that among women there are less *harmful* types among the high-school dropouts. These figures are large and reflect a strong correlation between education and lifestyle. In a sense, these numbers are not too surprising: it is well known that the incidence of smoking, drinking, and obesity declines with education, and it is easy to check that —in the HRS— the share of individuals taking cancer tests, cholesterol tests, and flu shots increases with education. It is therefore natural that our classification of individuals into types according to the observed health-related behaviour retains the education gradient of these latter variables. However, we highlight that our classification of individuals into types also uses longitudinal information on health dynamics *conditional on education*. That is, it also uses the fact that within education, *protective* types have better health dynamics than *harmful* types.

A very interesting question is how has the distribution of health types evolved across education groups over time. In Panels (a) to (c) of Figure 2 we report the distribution of types by education group from the 1910 to 1990 cohorts. Within the high school dropouts, the *harmful* types increased monotonically from 40% in the 1930 cohort to 75% in the 1990 cohort. This implies a severe deterioration in the lifestyle of individuals in the least educated group, which reverses a slight improvement in the type distribution between the 1910 and the 1930 cohorts. In contrast, among college educated individuals there is a smaller change, with a slight increase in the share of *protective* and a slight decline of the *harmful*. All in all, this implies that the educational gradient in lifestyles has widened remarkably between the 1930 and the 1990 cohort. As we will see in the next Section, this will generate an increasing life expectancy gap across education groups.

3.3 Putting all together

Combining all previous results, we can compute life expectancies by gender, education, and health behaviour type and quantify the role of each covariate. In particular, in Table 1 we report total life expectancy, healthy life expectancy, and unhealthy life expectancy at age 50. We highlight three main results. First, as it is well known, the education gradient in life expectancy is large: males with a college degree live around 7.8 more years than males without a high school degree, while the gradient is 6.7 years among females. Second, there is a large gradient in life expectancy across health behaviour types *within* each education category: *protective* types live 7.6 more years than *harmful* types among males without a high school degree, 7.2 more years among males with a high school degree, and 8.9 more years among males with a college degree. For females, these numbers are 7.1, 7.2, and 6.7 respectively. And third, the different type composition across education groups explains a big part of the educational gradient of life expectancy but there is still much left. In particular, if males without a high school degree had a distribution of health behaviour types as the males with a college degree, their average life expectancy would rise in 3.7 years (from 24.6 to 28.3 years) and the life expectancy differential with college graduates would fall from 6.8 to 4.3. That is, the different distribution of health behaviour types across education groups among males accounts for 40% of the life expectancy differential between college graduates and high school dropouts. The numbers are of the same order of magnitude among females: the different distribution of health behaviour types across education groups accounts for 33% of the life expectancy differential between college graduates and high school dropouts.

Finally, in Panel (d) of Figure 2 we report the age-50 predicted life expectancy gap between college educated males and high school dropouts over different cohorts. In our estimation, different cohort have different life expectancy because of different composition of latent types as described in Panels (a) to (c) of Figure 2, but health dynamics conditional on type are identical across cohorts. This allows us to infer health dynamics at old ages of younger cohorts, for which most individuals are still alive today. Our finding show a growing education gap in life expectancy: from 6.8 years in the 1930 cohort to 9.1 years in the 1990 cohort, which follows a 0.7 year decline in the gradient between the 1910 and the 1930 cohorts. The increase in the education gradient of life expectancy across cohorts is consistent with the documented increase in the education gradient of period life expectancy across years, but it is a different concept, see for instance Pijoan-Mas and Ríos-Rull (2014).

3.4 Health inequality and economic inequality

Our estimation results classify individuals within two different health behaviour categories based on observed health behaviour and health transitions. We have seen that these types correlate with education. The next question is whether these types also correlate with some economic outcomes. In this Section we show that wealth accumulation is positively linked to health behavior types. To do so, we need to recover the wealth distribution across the unobserved health behavior types. For this purpose, we model the observed wealth distribution as a mixture model. In order to separate the mass point at zero wealth and the distribution of wealth conditional on positive wealth we proceed in two stages. First, we write the distribution of (positive) wealth conditional on observables as:

$$p(w_{i,t}|e_i, a_{it}, z_i^T, h_i^T, w_{i,t} > 0) = \sum_{y \in Y} p(w_{i,t}|y, e_i, a_{it}, z_i^T, h_i^T, w_{i,t} > 0) p(y|e_i, z_i^T, h_i^T),$$

The first term in the right hand side is the conditional probability of observing wealth $w_{i,t}$. We assume that wealth conditional on age a, education e, and type y is lognormally distributed, that is, $\log p(w|y, e, a, w > 0) \sim N(\mu^1(y, e, a), \sigma^1(y, e))$. This implies that we are imposing that given a, e, and y, wealth is independent from h_i^T and z_i^T.

The second term in the right hand side gives the conditional distribution of types, which we have estimated above, see Section 2.3. Hence, we only need to estimate $\mu^1(y, e, a)$ and $\sigma^1(y, e)$ for the sample of male individuals with positive asset holdings.[4]

Second, we can similarly write the probability of reporting zero (or negative) assets conditional on observables as

$$p(w_{it} = 0|e_i, a_{it}, z_i^T, h_i^T) = \sum_{y \in Y} p(w_{it} = 0|y, e_i, a_{it}, z_i^T, h_i^T) p(y|e_i, z_i^T, h_i^T),$$

where the first term on the right hand side is modelled as a probit, that is, it is given by $\Phi\left(w^*\left(y, e_i, a_{it}\right)\right)$, where the threshold $w^*\left(y, e_i, a_{it}\right)$ is modelled as a flexible low order polynomial on age. As above, we assume that this probability does not depends on h_i^T or z_i^T.

We present selected moments of the estimated wealth distribution conditional on age, education and type in scatter plots in Figure 3. As it is well known, wealth accumulation is positively correlated with education. What is interesting of our results is that, within each education category, wealth accumulation is also stronger for better health types. We would like to highlight two results. First, wealth accumulation is stronger for the *protective* type. Second, the difference in wealth accumulation across types is especially apparent within college educated individuals, and much smaller (or null) within the other two education categories.

4 An economic model

Our economic model considers two distinct life stages. The *early life* stage is a static problem where young individuals belonging to a cohort c choose their education $e \in \{\text{HSD}, \text{HSG}, \text{CG}\}$ and their lifestyle or health-related behaviour $y \in \{\text{DET}, \text{PRO}\}$. This problem is a stand-in for choices and investments made by either parents in early childhood or young adults before entering the labor market. The objective is to maximize the expected value of starting working life with a given type (education and lifestyle) minus the (idiosyncratic) costs of choosing each type. This stage serves to account for the observed correlation between education and health types. The *adult life* stage is a dynamic life-cycle consumption-saving problem under uncertainty in both labor market and health outcomes where individuals differ in type (education and lifestyle). This stage serves to link inequality in health and economic outcomes, and provides the value of starting life in each type, which is used in the *early life* stage.

[4] We model $\mu^1(y, e, a)$ as a flexible low-order polynomial on age and $\sigma^1(y, e)$ non-parametrically.

4.1 Stage 1: early life

Let $V_0^{c,e,y}$ be the value of starting working life with a type (e, y) for individuals in cohort c. Before entering the labor market, young individuals choose their type by solving

$$\max_{e,y} \left\{ V_0^{c,e,y} - \tau_e(\epsilon_e) - \tau_y(\epsilon_y) \right\}$$

where $\tau_e()$ and $\tau_y()$ represent the cost of choosing an education and lifestyle, respectively. The education and health behavior costs are heterogeneous in the population, depending on ϵ_e and ϵ_y.[5] This formulation imposes that education and healthy habit choices are taken together at a young age and never change. We want to comment on a few things about this assumption. First, there is empirical evidence on the early-age adoption of health-related habits.[6] Second, there is also evidence of small effects of interventions to change health-related behavior of adults.[7] And third, related to our econometric specification in Section 2 for the identification of behavior types y, we note that a choice of a latent lifestyle type $y \in \{\text{DET}, \text{PRO}\}$ (detrimental and protective) still allows for changes in observed behavior (like smoking, exercise, or preventive tests) over the life-cycle and across health states, see for instance Figure 1.

Going into details, we normalize to 0 the cost of being a high-school dropout, while the cost of graduating from high-school is $\tau_{\text{HSG}}(\epsilon_e) = \mu_{\text{HSG}} + \epsilon_e$ and the cost of graduating from college is $\tau_{\text{CG}}(\epsilon_e) = \mu_{\text{CG}} \times \tau_{\text{HSG}}(\epsilon_e)$. Hence, note there is only one source of heterogeneity in education costs, ϵ_e, which is assumed to follow a normal distribution with mean 0 and variance σ_e^2. The cost of having a detrimental health behavior is normalized to 0, while the cost of protective behavior is $\tau_{\text{PRO}} = \mu_{\text{PRO}} + \epsilon_{\text{PRO}}$. The idiosyncratic shock ϵ_{PRO} is assumed to follow a log-normal distribution, where the $\log(\epsilon_{\text{PRO}})$ follows a normal distribution with mean 0 and variance σ_{PRO}^2.

This framework can generate a correlation between lifestyle and education choices through the complementarity of investments present in $V_0^{c,e,y}$. For instance, let's consider the choice of lifestyle PRO over DET across education categories HSD and CG. If $V_0^{\text{CG,PRO}} - V_0^{\text{CG,DET}} > V_0^{\text{HSD,PRO}} - V_0^{\text{HSD,DET}}$ then more people will choose PRO over DET within the education group CG than within the education group CG. This difference in values is generated by the model of the *adult life* stage.

4.2 Stage 2: adult life

[5] The heterogeneous costs of education ϵ_e may arise due to many different factors, such as differences in family background (Hauser and Featherman, 1976), distance to quality education centers (Card, 1995), or taste (Willis and Rosen, 1979). However, because ϵ_e does not directly affect earnings, we should not think of it as labor market ability in the manner of Keane and Wolpin (1997). Less is known about the heterogeneous costs of healthy habits choices. A recent literature relates brain characteristics of young adolescents with later-in-life health risk behavior (Xiang et al., 2023), which highlights the importance of individual-level variation in ϵ_y.

[6] For instance, Farrell and Fuchs (1982) show that, for a sample of young Americans, the gradient of smoking with education at age 24 is already present at age 17.

[7] See Conner and Norman (2017) and references therein.

4.2.1 Demographics, preferences, and shocks

The model period corresponds to two years. Individuals live for at most T periods but survival is stochastic every period. During the first $R-1$ periods of life people are exposed to health shocks, medical expenditure shocks, and labor income shocks. Individuals retire at age R, when they start receiving a retirement pension instead of stochastic labor income.

Preferences over consumption flows c_t are described by a standard CRRA period utility:

$$u(c_t) = \frac{(c_t/\bar{n}_t)^{1-\sigma}}{1-\sigma} + \bar{b},$$

where σ is the risk-aversion, $\bar{n}_t$ is an age specific household size and $\bar{b}$ is a positive term to ensure that individuals in our model value their life. In the period when they die, individuals also derive utility from leaving a bequest of size k_t:

$$v(k_t) = b_0 \frac{(k_t + b_1)^{1-\sigma}}{1-\sigma}$$

where b_0 drives the strength of the bequest motive and b_1 the extent to which preferences for bequest increase with wealth.

Following the empirical model in Section 2, health h_t can be either good (h_g) or bad (h_b) and it evolves according to the age-dependent Markov chain $\Gamma_t^{e,y}(h)$, which depends on education e and health type behavior y. The survival probability $s_t^{e,y}(h)$ depends on health h, but also (possibly) on education e and health-behavior type y.

Every period of their working life, individuals receive an exogenous income that we model in two components. First, there is an employment shock $\ell_t \in \{0, 1\}$ that determines if the individual has the chance of working in the labor market ($\ell_t = 1$) or not ($\ell_t = 0$). We model $\text{Prob}(\ell_t = 1|e, t, h_t, \ell_{t-1})$ as a Probit model. This component aims to capture the prolonged non-working spells of some individuals in bad health that are at the core of health gradient of labor income. Second, conditional on working individuals receive labor income is given by,

$$\log w_t^{c,e,y}(h_t, \xi_t, \epsilon_t) = \omega_t^{c,e,y}(h_t) + \xi_t + \epsilon_t,$$

where $\omega_t^{c,e,y}(h)$ is a deterministic component depending on cohort, age, education, lifestyle, and health, while ξ_t and ϵ_t are persistent and transitory shocks. The initial value of the persistent component ξ_0 is drawn from a normal distribution with mean zero and variance $\sigma^2_{\xi_0}$. Whenever the worker is attached to the labor force ($\ell_t = \ell_{t-1} = 1$), the stochastic persistent component is assumed to follow a Gaussian AR(1) process with persistence ρ_ξ and variance of the innovations σ^2_ξ. If the worker enters the labor force after a non-working spell ($\ell_t = 1$ and $\ell_{t-1} = 0$) then ξ_t is sampled from the unconditional distribution of ξ_t. The transitory component is i.i.d. and distributed with a Gaussian distribution of variance σ^2_ϵ.

Finally, medical expenses are given by,

$$\log m_t^e(h_t, \zeta_t) = \mu_t^e(h_t) + \zeta_t$$

where $\mu_t^e(h_t)$ is a deterministic component, as a function of age t, education e and health h_t, while ζ_t is an i.i.d gaussian white noise with variance $\sigma_{\zeta,t}^e(h)$.

4.2.2 Taxation and social transfers

We model the tax system as follows. Working households pay payroll taxes, which include the Medicare tax (τ_{MCR}) and the Social Security tax (τ_{ss}). The latter only affects earnings below w_{ss}. There is a progressive labor income tax $T(w)$ which we specify as Heathcote et al. (2020)

$$T(w) = w - a_{\tau 0} w^{1-a_{\tau 1}}$$

We represent several existing mean-tested programs in a stylized way through a public safety-net program. This program guarantees every household a minimum income floor $\underline{x}$. Retirees receive Social Security benefits. In practice, these payments depend on an individual's history of earnings. To capture the existing variation in pension benefits without increasing computational costs, we approximate the benefits using the following approach. First, we divide individuals into groups based on their labor force participation just before retirement, their last draw of the persistent productivity shock and on their education and health behavior type. Then, for each group, we compute average earnings over the 17 model periods (34 years) with the highest earnings. Then we apply the Social Security benefits formula to these average earnings.

4.2.3 The optimization problem

At the beginning of the period, working-age individuals of type (c, e, y) and age t learn their cash in hand x_t, labor force status ℓ_t, persistent component of productivity ξ_t (conditional on participating in the labor force), and health state h_t. All these variables form the state of the individual: x_t is payoff relevant in the current period and the other variables serve to predict next period outcomes. Based on this information, individuals decide on consumption c_t and savings k_{t+1}. At the end of the period, there are new realizations of the shocks for survival, health, labor force participation, productivity (persistent and transitory), and medical expenses. The timing for retired individuals is similar, with the difference that there are no employment or labor earnings shocks.

The optimization problem for working age individuals ($t < R$) can be written in recursive form as:

$$V_t^{c,e,y}(x,h,\ell,\xi) = \max_{c,k'} \left\{ u(c) + \beta s_t^{e,y}(h) \sum_{h'} \Gamma_t^{e,y}(h) \, \mathbb{E}_{\ell,\xi}[V_{t+1}^{c,e,y}(x',h',\ell',\xi')] + \beta \left(1 - s_t^{e,y}(h)\right) v(k') \right\}$$

$$\begin{aligned}
&\text{s.t.}\\
&c + k' = x\\
&x' = \min\left\{ w_{t+1}^{c,e,y}(h',\xi',\epsilon')\ell' - Tax + (1+r)k' - m_{t+1}^{e}(h',\zeta'),\, \underline{x} \right\}\\
&Tax = T\left(w_{t+1}^{c,e,y}(h',\xi',\epsilon')\ell'\right) + \tau_{MCR} w_{t+1}^{c,e,y}(h',\xi',\epsilon')\ell' + \tau_{ss}\min\{w_{t+1}^{e,y}(h',\xi',\epsilon')\ell', w_{ss}\}
\end{aligned}$$

The optimization problem for retired individuals ($t \geq R$) can be written as:

$$V_t^{c,e,y}(x,h,\xi_{R-1}) = \max_{c,k'} \left\{ u(c) + \beta s_t^{e,y}(h) \sum_{h'} \Gamma_t^{e,y}(h) \, \mathbb{E}[V_{t+1}^{c,e,y}(x',h',\xi_{R-1})] + \beta \left(1 - s_t^{e,y}(h)\right) v(k') \right\}$$

$$\begin{aligned}
&\text{s.t.}\\
&c + k' = x\\
&x' = \min\left\{ p^{c,y,e}(\xi_{R-1}) + (1+r)k' - m_{t+1}^{e}(h',\zeta'),\, \underline{x} \right\}\\
&Tax = T\left(p^{c,y,e}(\xi_{R-1})\right)
\end{aligned}$$

where retirement income is constant and determined by the last productivity/labor force shock before retirement ξ_{R-1}.

5 Calibration

The calibration strategy has three distinct parts: the parameters related to the life cycle model of adults (Section 5.1), the parameter $\bar{b}$ driving the value of life, which does not affect the outcomes in the life cycle model (Section 5.2), and the parameters shaping unobserved heterogeneity in the early life stage (Section 5.3).

5.1 Working/retirement phase

We start by calibrating several parameters related to demographics, taxes, and social security outside the model, details in Appendix B. In particular, we estimate the parameters of the income process using data from the PSID. The deterministic component is allowed to change across cohorts, and we calibrate it to match changes in the education wage premium as documented by Autor (2014). Figure 4 illustrates the average wage age profile across education for individuals born in 1930 and 1970. The figure reveals significant increases in the college premium driven by both an increase in college wages and decreases in the wages of high school dropouts. The survival and health process are taken from Section 2.2. We fix the interest rate at 4%, the risk aversion parameter σ at 1, and the discount factor β at 0.98.

Given the parameters from the first step, we estimate the remaining model parameters using the simulated method of moments. We do so by minimizing the sum square difference between median assets by education, age and lifestyle for individuals born in 1930s in the data and in the model. The set of parameters estimated in the second stage are $\{\underline{x}, b_0, b_1\}$.

The third column of Table 2 reports our estimated parameters. The estimated bequest parameters b_0 and b_1 are 3.90 and 103.71, respectively. In a model with risk aversion equal to 1, these values imply that in the period before certain death, the bequest motives becomes active at \$26,000 and the marginal propensity to bequeath is 80 cents out of every additional dollar for bequests. The income floor is estimated at \$17,600 dollar. These parameters fall in the range of parameters estimated by the previous literature.

Figure 5 compares the median wealth from our model (lines) and data (diamonds). Overall, our model is able to generate the fact that higher-educated and health protective individuals accumulate more wealth. It is worth noting that although not specifically targeted, the model is able to match the overall distribution, as indicated by the 25th and 75th quantiles in both the data (squares) and the model (dashed lines).

5.2 Value of a Statistical Life (VSL)

The VSL comes from the estimated wage premium for a given probability of a fatal accident in risky jobs. This literature delivers numbers in the range of \$1 to \$7 million to save one life. We want the model to deliver this same marginal rate of substitution between income and survival probability. Using the value function expressed in Section 4.2.3 we can obtain the total differential:

$$\frac{\partial V_t^{c,e,y}(x,h,\ell,\xi)}{\partial x}dx + \frac{\partial V_t^{c,e,y}(x,h,\ell,\xi)}{\partial s_t^{e,y}(h)}ds_t^{e,y}(h) = 0$$

relating changes in cash-on-hand x and survival probabilities $s_t^{e,y}(h)$ that leave individuals indifferent. Rearranging we obtain,

$$-\frac{dx}{ds_t^{e,y}(h)} = \frac{\partial V_t^{c,e,y}(x,h,\ell,\xi,\zeta)}{\partial s_t^{e,y}(h)}\left[\frac{\partial V_t^{c,e,y}(x,h,\ell,\xi)}{\partial x}\right]^{-1}$$

Hence, for an individual of type (c, e, y) with state variables (x, h, ℓ, ξ) at age t to accept an increase in his survival probability in say 1%, he would require $0.01 \times dx/ds_t^{e,y}(h)$ units of income. Putting 100 identical agents together we would have one death on average in exchange of $dx/ds_t^{e,y}(h)$ units of income. Hence, this expression gives the model equivalent of the VSL. Because the empirical estimates of a VSL typically come from blue-collar jobs, we want the model to deliver a VSL for the average high school dropout of 35 years of age. We target a VSL of 2,000,000 for a high-school graduate aged 40 born in the 1930s. This identifies the parameter $\bar{b}$.

5.3 Early life

In order to calibrate the parameters of the early-in-life model, we require the model to match the joint distribution of education and lifestyles for two different cohorts: 1930s and 1970s. The value functions for each cohort vary differently in terms of education and lifestyle due to the different paths of wages over the life cycle, with the real average wage of high school dropouts being slightly lower for the 1970s cohort, the real average wage of college graduates being larger for the 1970s cohort, and hence the college premium being larger for the 1970s cohort. Taking the parameters from section 5.1 and section 5.2 as given, we solve for the initial value function of individuals born in 1970 where the deterministic component of the wage profile is adjusted to match the increase in the college premium observed in the data.

We have 5 parameters to estimate: $(\mu_{\text{CG}}, \mu_{\text{HSG}}, \mu_{\text{PRO}}, \sigma_e, \sigma_{\text{PRO}})$. Given that we require the model to match the joint distribution of e, y for two different cohorts we have 10 moment conditions ($3 \times 2 - 1$ targets per year). The average cost parameters $(\mu_{\text{CG}}, \mu_{\text{HSG}}, \mu_{\text{PRO}})$ are identified by the average share across cohorts of individuals in each education and life-style group. The parameters driving the dispersion of the idiosyncratic costs $(\sigma_e, \sigma_{\text{PRO}})$ are identified by the changes across cohorts of the share of individuals in each education and lifestyle category as the wage paths of different cohorts change.[8]

Figure 6 shows that the model is able to match well the marginal distributions of education and health behavior as well as their changes across cohorts. Moreover, Figure 7 shows that the model is also able to match the level and changes in the joint distribution of education and lifestyles. First, the model reproduces well the fact that less educated individuals tend to invest less in their health. In the 1930s cohort, the proportion of individuals with detrimental lifestyles among high-school dropouts was 41% in the data and 45% in the model, while for college graduates these figures were 14.6% in the data and 10.5% in the model. This means that the model slightly amplifies the gradient in the data (34.5 vs 26.4 percentage points) and, consequently, the life-expectancy gradient, which is 6.2 in the data and 6.9 in the model. Second, the model reproduces well the fact that the more educated have improved their health-related behavior while the less educated have worsened it. The proportion of individuals with detrimental lifestyles among high-school dropouts has increased by 17.5 percentage points in the data and 11.9 percentage points in the model, while the proportion of individuals with detrimental lifestyles among college graduates has declined by 5.9 percentage points in the data and 1.3 percentage points in the model. This means that the education gradient in lifestyle habits has increased by 23.4 percentage points in the data and 13.2 percentage points in the model. Consequently, the increase in the life-expectancy gradient is estimated at 1.0 years in the model and 1.9 years in the data. Hence, the calibrated model accounts for around 50% of the overall increase in the life-expectancy gradient between college graduates and high-school dropouts between the 1930 to 1750 cohorts.

[8]This extends the identification strategy of Heathcote et al. (2010), whose first stage contains a college education choice but does not consider a lifestyle choice.

6 Results

The model incorporates different mechanisms that can explain why individuals with higher education invest more in their health. Firstly, higher expected income among the more educated encourages healthier behavior as life becomes more valuable. Secondly, as detailed in section 2, the estimated health transitions generate benefits of protective behavior for life expectancy that are greater for those with a college education. Lastly, considering the first two points, individuals facing lower costs of protective behavior (ϵ_{PRO}) are more likely to pursue higher education as the returns on health investments are higher for those who opt for protective measures. This means that low ϵ_{PRO} individuals will be less frequent among the highly-educated.

To gauge the importance of each mechanism, we conduct a series of counterfactual experiments using the model. In these experiments, we keep individuals' education choices fixed and observe how their health investments would differ under various scenarios. In the first scenario, we simulate the behavior of high-school dropouts if they were to have the income prospects of college graduates. Due to the higher consumption possibilities, the increase in expected wages leads to higher values for both y types, which we denote as $\tilde{V}^{c,\text{HSD},\text{PRO}}$ and $\tilde{V}^{c,\text{HSD},\text{DET}}$. However, this gain is higher for $y = \text{PRO}$, as life expectancy is higher for this type and the higher consumption flow is enjoyed for more years. Thus, $\tilde{V}^{c,\text{HSD},\text{PRO}} - \tilde{V}^{c,\text{HSD},\text{DET}} > V^{c,\text{HSD},\text{PRO}} - V^{c,\text{HSD},\text{DET}}$, leading dropout individuals to be more inclined to choose protective behavior despite the associated costs.

The solid blue line in the upper panel of Figure 8 illustrates the distribution of protective behavior costs (τ_{PRO}) for individuals that choose to drop out of high-school in the benchmark model. The vertical solid green line represents $V^{c,\text{HSD},\text{PRO}} - V^{c,\text{HSD},\text{DET}}$. Individuals with $\tau_{\text{PRO}} < V^{c,\text{HSD},\text{PRO}} - V^{c,\text{HSD},\text{DET}}$ opt for protective behavior, while the rest choose detrimental behavior. The integral of the distribution of τ_{PRO} between zero and $V^{c,\text{HSD},\text{PRO}} - V^{c,\text{HSD},\text{DET}}$ represents the fraction of dropouts adopting protective behavior.

As income rises, the threshold value that prompts individuals to adopt protective health behavior shifts to the right. The dashed vertical line in Figure 8 marks the value at $\tilde{V}^{c,\text{HSD},\text{PRO}} - \tilde{V}^{c,\text{HSD},\text{DET}}$. This indicates that income largely influences why high-school dropouts tend to adopt more detrimental behavior. If faced with the same expected income as college graduates, the proportion of high-school dropouts choosing detrimental behavior would decrease from 45.7% to 22.3%, reducing the life-expectancy gap in 1.7 years (from 6.9 to 5.2 years, a 25% reduction).

Another reason why college graduates invest more in health behavior in the model is because the gains in life expectancy due to protective behavior are larger. To analyze this effect, we solve for $V^{c,\text{HSD},y}$ assuming high-school dropouts experience the same health transitions as college graduates. As in the previous counterfactual, the improved health transitions result in higher values for both types, denoted as $\hat{V}^{c,\text{HSD},\text{PRO}}$ and $\hat{V}^{c,\text{HSD},\text{DET}}$ respectively. Our estimation of health transitions in Section 3 deliver higher life expectancy gains of better health behavior for the mode educated, which means that $\hat{V}^{c,\text{HSD},\text{PRO}} - \hat{V}^{c,\text{HSD},\text{DET}} > V^{c,\text{HSD},\text{PRO}} - V^{c,\text{HSD},\text{DET}}$, leading dropout individuals to be more inclined to choose protective behavior despite the associated costs. The vertical dotted line in the middle panel of Figure 8 represents the value $\hat{V}^{c,\text{HSD,PRO}} - \hat{V}^{c,\text{HSD,DET}}$ in this counterfactual scenario. If faced with the same health transitions as college graduates, the proportion of high-school dropouts choosing detrimental behavior would decrease from 45.7% to 22.9%, reducing the life-expectancy gap as much as the income effect.

Lastly, given the complementary nature of health and education investments, individuals facing lower costs of protective behavior (τ_{PRO}) are more likely to pursue higher education. This leads to a sorting effect where the distribution of protective behavior costs for high-school dropouts first-order stochastically dominates the distribution for college graduates. To quantify this effect, we examine the fraction of detrimental types if high-school dropouts had the same cost distribution as college graduates.

The lower panel in Figure 8 displays the distribution of the cost of protective behavior (represented by the dashed line). It shows that the mass of individuals below the $V^{c,\text{HSD,PRO}} - V^{c,\text{HSD,DET}}$ threshold (vertical line) is larger. If faced with the distribution of costs τ_{PRO} of college-educated individuals, the proportion of detrimental behavior would decrease from 45.7% to 40.7%. Therefore, selection would account for approximately 5.4% of the gradient in life expectancy.

6.1 Changes over time

The econometric model estimated in section 3 shows an increase in the life-expectancy gap between college graduates and high-school dropouts of 1.9 years across the 1930s and 1970s cohorts. This increase is driven by lower (higher) health investments among the high-school dropouts (college graduates). As explained in section 5.3, the calibrated model reproduces 50% of the observed increase. To further elucidate the mechanisms driving the expansion of the life-expectancy gap in the model, we delve into identifying these factors. As explained in the previous section, changes in individuals' income prospects influence their educational and health investment decisions. Between the 1930s and 1970s cohorts, there has been a significant rise in the education premium, driven by increases in college wages and slight declines in dropout wages.

Given the complementarity between health and education behaviors in the model, income increases (decreases) for higher (lower) educated individuals lead to greater (lesser) health investments. Moreover, changes in the wage distribution across educational choices also impact the distribution of individuals in terms of the cost of protective behavior across education alternatives. Increases in the wage premium incentivize individuals to pursue educational investments, particularly among those facing lower costs of protective behavior.

To quantify the income effect while controlling for selection, we fix the distribution of health behavior costs faced by individuals in different education categories to the one in 1930. We then analyze how their health investments would have changed solely due to changes in income. In the upper panel of Figure 9, the solid line represents the distribution of the cost of protective behavior faced by individuals in 1930. The vertical solid line indicates the threshold value at which individuals of that cohort decided to switch from a protective to a detrimental lifestyle. The dashed vertical line illustrates that for high-school dropouts, the threshold value decreased across cohorts due to declines in income and consequently, individuals dropping out of high school are less willing to invest in their health. Declines in income account for 78% of the reduction in life expectancy for high-school dropouts between individuals born in the 1930 and 1970.

The dashed line in the upper panel of Figure 9 illustrates the distribution of behavior costs for high-school dropouts in the 1970s. Driven by changes in income across cohorts and education categories, compared to the distribution in 1930, the cost distribution worsened for high school dropouts born in the 1970s. Nevertheless, the effect of selection is modest. We find that if high-school dropouts in 1930 had the same cost distribution than high-school dropouts in 1970, the life-expectancy of the high-school dropout would only have felt 22% of what the original model predicts.

Finally the lower panel of Figure 9 plots the equivalent decompositions for the college graduates. It shows that all increases in life-expectancy for college graduates across cohorts is driven by the better expected income. Selection, on the other hand plays a quantitatively negligible role.

7 Conclusions

In this paper, we propose a latent variable model to characterize how health behavior influences health dynamics across different education groups. Our findings indicate that health behavior can be parsimoniously summarized into two lifestyles: protective and detrimental. We observe that individuals with higher levels of education tend to more frequently choose protective behavior, and differences in lifestyles explain 40% of the variations in life expectancy across education groups. Additionally, conditional on behavior, we find that a protective lifestyle has a greater impact on extending life expectancy for college graduates than for dropouts. Finally, we identify an increasing life-expectancy gradient across education groups between the 1930s and 1970s, driven by worsening lifestyles among the less educated and improved lifestyles among the more educated.

Furthermore, we introduce a heterogeneous agents model comprising two distinct stages. Initially, individuals make a one-time decision regarding education and lifestyle during an early-life health stage. Subsequently, in a working/retirement phase, agents address a consumption savings problem subject to income and health risks, as modeled in the econometric framework.

This model enables us to explain the connection between income and health inequality. Health and education decisions are shown to be complementary due to two key factors. Firstly, higher income increases the value of life, leading to greater returns from investing in health. Secondly, as reflected in our calibration process where we integrate the health dynamics from the econometric model, we observe greater returns to health investment for college-educated individuals. Driven by these complementarities, individuals facing higher costs of maintaining protective health behaviors are more likely to select lower education categories.

We calibrate the model to match savings, education, and lifestyle choices across cohorts, and then we use it to understand why lower-educated individuals tend to choose unhealthier lives. Our analysis reveals that lower income and diminished returns in health outcomes from protective behavior largely account for the disparities observed across education groups.

Finally, the model is able to explain 50% of the increase in health inequality across the 1930s and the 1970s. 80% of the deterioration in life expectancy among the less educated is driven by worsening economic conditions, and 20% is attributed to selection effects. All improvements in lifestyle among college graduates are explained by improvements in economic conditions.

The model cannot fully account for the increase in the life-expectancy gradient observed in the data. Factors such as peer influence, segregation, genetic predispositions, and variations in intergenerational mobility across cohorts are likely significant drivers of health behavior choices made by individuals, which we abstract from in our current analysis. These avenues offer promising directions for future research.

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Appendix A: Estimation details of the health model

In this appendix we explain the details of the estimation of the health model in section 3.

We have an unbalanced panel of individuals $i = 1, \ldots, N$ followed for $t_i = 1, \ldots, T_i$ periods which correspond from age a_1^i to age $a_{T_i}^i$ where $a \in (\underline{a}, \overline{a})$. For each individual, we observe M categorical variables describing habits related to health behaviors which also evolve across time $(z_{1,i,t}, z_{2,i,t}, \ldots, z_{M,i,t})$ provided the individual is alive and interviewed. On top, we observe health status which can be good ($h_{it} = g$) or bad ($h_{it} = b$).

All or some of the health behavior variables for a given individual who is alive can also be missing for some period t_i. Although we take missing observations into account under the assumption that they occur completely at random, we abstract from them in the model description to simplify the exposition.

We assume that there is one source of unobserved heterogeneity in the population: lifestyle (y). Health behavior is assumed to have a finite number possible groups. We assume that individual lifestyle is fixed across time.

Conditioning on age, a, gender, s, and lifestyle, y, the health status of individual i is independent of previous health except for the most recent one (Markov first-order property). Individuals may also die labeled as D.

A.1 Health Dynamics

We model survival and health transition probabilities as a nested probit model. In the first nest, individuals are exposed to a survival/mortality shock. Then, conditional on surviving, individuals suffer a good/bad health shock. In the first nest, an individual i at time t with health status h and education level e will survive ($h_{h,s} = 1$) if $h^*_{h,S} > 0$:

$$h^{\star}_{h,S} = f(a, s, e, y; \boldsymbol{\beta}_{h,S}) + \epsilon_{h,S}, \epsilon_{h,S} \sim N(0, 1)$$

Therefore the probability that an individual survives is given by:

$$\begin{aligned} Pr[h_{i,t+1} = S | a_{it}, s_i, e_i, y_i, h_{i,t} = h] &= Pr[h^{\star}_{h,S} > 0] \\ &= Pr[f(a, s, e, y; \boldsymbol{\beta}_{h,S}) + \epsilon_{h,S} > 0] \\ &= Pr[\epsilon_{h,S} > -f(a, s, e, y; \boldsymbol{\beta}_{h,S})] \end{aligned}$$

We obtain,

$$Pr[h_{i,t+1} = S | a_{it}, s_i, e_i, y_i, h_{i,t} = h] = \Phi(f(a, s, e, y; \boldsymbol{\beta}_{h,S}))$$

Conditional on survival, the transitions an individual can transition into good (G) or bad health (B). An individual will transition to good health ($h_{h,G} = 1$) if $h*_{h,G} > 0$:

$$h^{\star}_{h,G} = f(a, s, e, y; \boldsymbol{\beta}_{h,G}) + \epsilon_{h,G}, \epsilon_{h,G} \sim N(0, 1)$$

We obtain,

$$Pr[h_{i,t+1} = G | a_{it}, s_i, e_i, y_i, h_{i,t} = h, S] = \Phi(f(a, s, e, y; \boldsymbol{\beta}_{h,G}))$$

Moreover, to capture within-health status heterogeneity, transition probabilities can depend on age (a), sex ($s \in \{\text{male}, \text{female}\}$), education ($e \in \{\text{Dropout}, \text{Highschool}, \text{College}\}$), and health behavior through the function $f_{h,h'}(a, s, e, y)$ whose parametric specification is given by

$$\begin{aligned} f(a, s, e, y; \boldsymbol{\beta}_{h,h'}) =& \beta_{1,y,h,h'} + \beta_{3,y,h,h'} \mathbb{1}_{s=\text{female}} + \beta_{4,y,h,h'} \mathbb{1}_{s=\text{female}} \times a + \beta_{5,y,h,h'} \mathbb{1}_{e=\text{Highschool}} + \\ & \beta_{6,y,h,h'} \mathbb{1}_{e=\text{College}} + \beta_{7,y,h,h'} \mathbb{1}_{e=\text{Highschool}} \times a + \beta_{8,y,h,h'} \mathbb{1}_{e=\text{College}} \times a \end{aligned}$$

A.2 Health Behaviors

Given the lifestyle, the probability of having a health habit is allowed to change depending on age and health. An individual will report doing a health habit ($z_m = 1$) if $z^*_m > 0$ following:

$$z^{\star}_m = \gamma_{1,m,y,h} + \gamma_{2,m,y} a + \gamma_{3,m,y} a^2 + \gamma_{4,m,y} \mathbb{1}_{h=B} + \epsilon, \epsilon \sim N(0, 1).$$

Given her behavior, the probability of reporting the m'th habit ($z_{i,m,t} = 1$) is

$$\begin{aligned} \alpha_{m,i,t} =& \alpha_m(a_{i,t}, y_i, h_{i,t}) = \text{Prob}(z^*_m > 0 | a_{i,t}, y_i, h_{i,t}) \\ =& \Phi(\gamma_{1,m,y} + \gamma_{2,m,y} a + \gamma_{3,m,y} a^2 + \gamma_{4,m,y} \mathbb{1}_{h=B}). \end{aligned}$$

Considering independence of habits given type, the probability of observing a sequence of habits for an individual across time, is given by:

$$p(\mathbf{z}_{i,t} | \boldsymbol{\alpha}, y) = \prod_{m=1}^{M} \alpha_{m,i,t}^{z_{m,i,t}} (1 - \alpha_{m,i,t})^{1 - z_{m,i,t}}, \tag{5}$$

A.3 Likelihood function

We can write the likelihood of the data as a mixture model:

$$
\begin{aligned}
p(h^T, z^T|e, s, c, a, h_0, \beta, \gamma, \delta) &= \sum_{y=1}^{K} p(h^T, z^T|\beta, \gamma, e, s, y, a, h_0) p(y|e, s, c, a, \beta, \gamma, \delta, h_0) \\
&= \sum_{y=1}^{K} p(z^T|h^T, \beta, \gamma, y, a) p(h^T|\beta, \gamma, e, s, y, a, h_1) p(y|e, s, c, a, \beta, \gamma, \delta, h_1)
\end{aligned}
$$

where $p(y|e, s, c, a, \beta, \gamma, \delta, h_1)$ are the weights given to each lifestyle and are allowed to change with education, sex, age and initial health status.

We can write the complete data likelihood as:

$$
p(h^T, z^T, \hat{y}|e, s, c, a, h_1, \beta, \gamma, \delta) = \\
\prod_{i=1}^{n} \prod_{y=1}^{K} \Big(p(h^T|\beta, \gamma, y, e, s, a, h_0) p(z^T|h^T, \beta, \gamma, y, a) p(y|e, s, a, \delta, h_1, \beta) \Big)^{\mathbb{1}\{\hat{y}=y\}},
$$

where δ is a vector of parameters driving the ex-ante probability of each lifestyle given education, sex, cohort, and health: $\delta_{e,s,c,a,h} = p(y|h, e, s, c, a = 0)$.

A.4 Gibbs sampler

Appendix B: First step estimation details

B.1 Income process

The labor income process is modeled as the sum of a deterministic and stochastic component:

$$
\begin{aligned}
&\log w_t^{c,e,y}(h_t, \xi_t, \epsilon_t) = \omega_t^{c,e,y}(h_t) + \xi_t + \epsilon \\
&\xi_{t+1} = \rho_\xi \xi_t + \nu_t, \nu_t \sim N(0, \sigma_\nu^2) \\
&\epsilon \sim N(0, \sigma_\epsilon^2) \\
&\xi_0 \sim (0, \sigma_{\xi,0}^2)
\end{aligned}
$$

We propose a Gibbs algorithm to compute the posterior distribution of all parameters using Bayesian methods.

1. Sample from the posterior distribution of y: posterior distribution from the health dynamics mode
2. Sample parameters of the deterministic component: multivariate normal.
3. Sample persistent shocks: Kalman smoother.

4. Sample persistent component parameters : normal posterior for ρ_{xi} and inverse gamma for σ_ν^2.

5. Sample initial distribution of shocks: Metropolis.

6. Sample variance of the transitory component: inverse gamma.

B.2 Medical shocks

To estimate the mean of health cost distribution $\mu_t^e(h_t)$, we run an OLS regression of log out-of-pocket expenditures in the last two years in HRS on a cubic in age, health, health interacted with age and education interacted with age and individual fixed effects. In order to compute the education fixed effects, we regress the residuals of the previous regression on education dummies. In order to estimate $\sigma_{\zeta,t}^e(h)$, we regress the squared residuals from the previous regression on a cubic in age, health, health interacted with age, education, and education interacted with age.

B.3 Tax system

We follow De Nardi et al. (2022) and set the Medicare and Social Security tax rates to 2.9% and 12.4%, respectively. We use the Social Security rules for 2018, and therefore we set the maximum taxable income for Social Security to w_{ss} =\$113,700.

For the progressive tax labor income tax function, we follow Holter et al. (2019) estimates of the tax progressivity for families without children:

$$T(y) = y - 0.873964 \times y^{1-0.108002}$$

List of Figures

Figure 1: Probability of having a health habit by health behavior type as individuals age

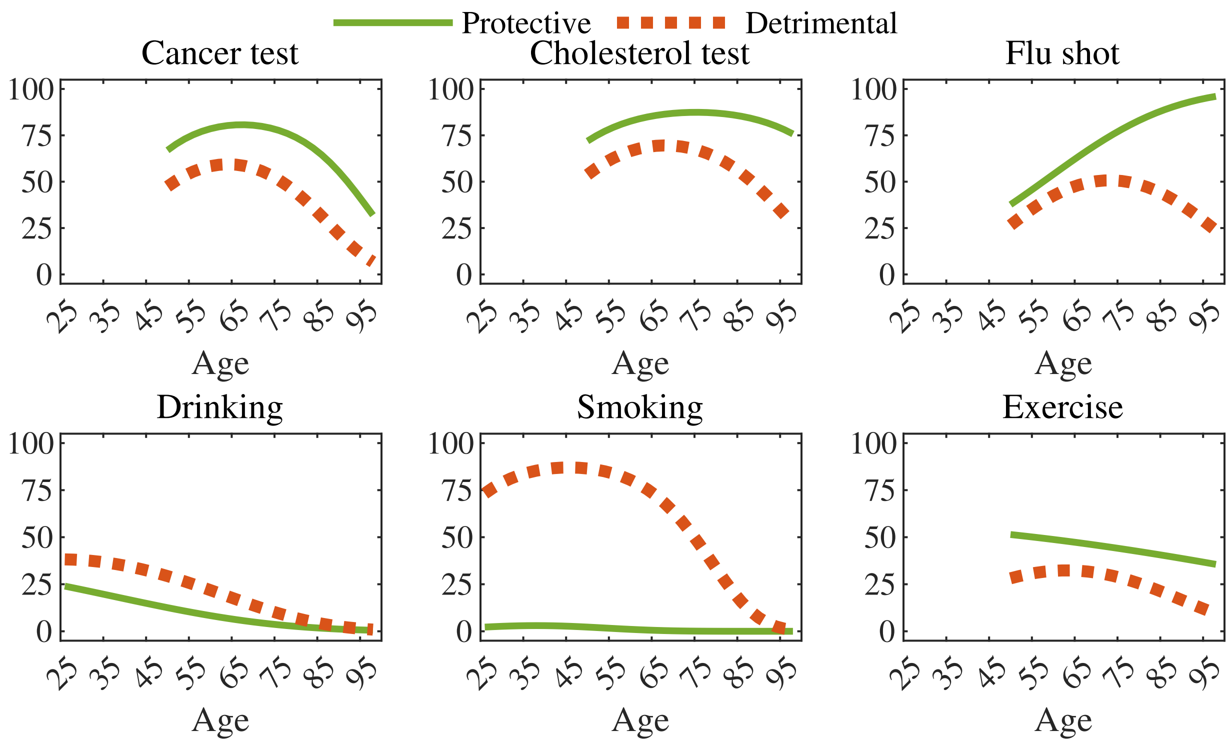


Figure 2: Distribution of types by education and cohort (males)

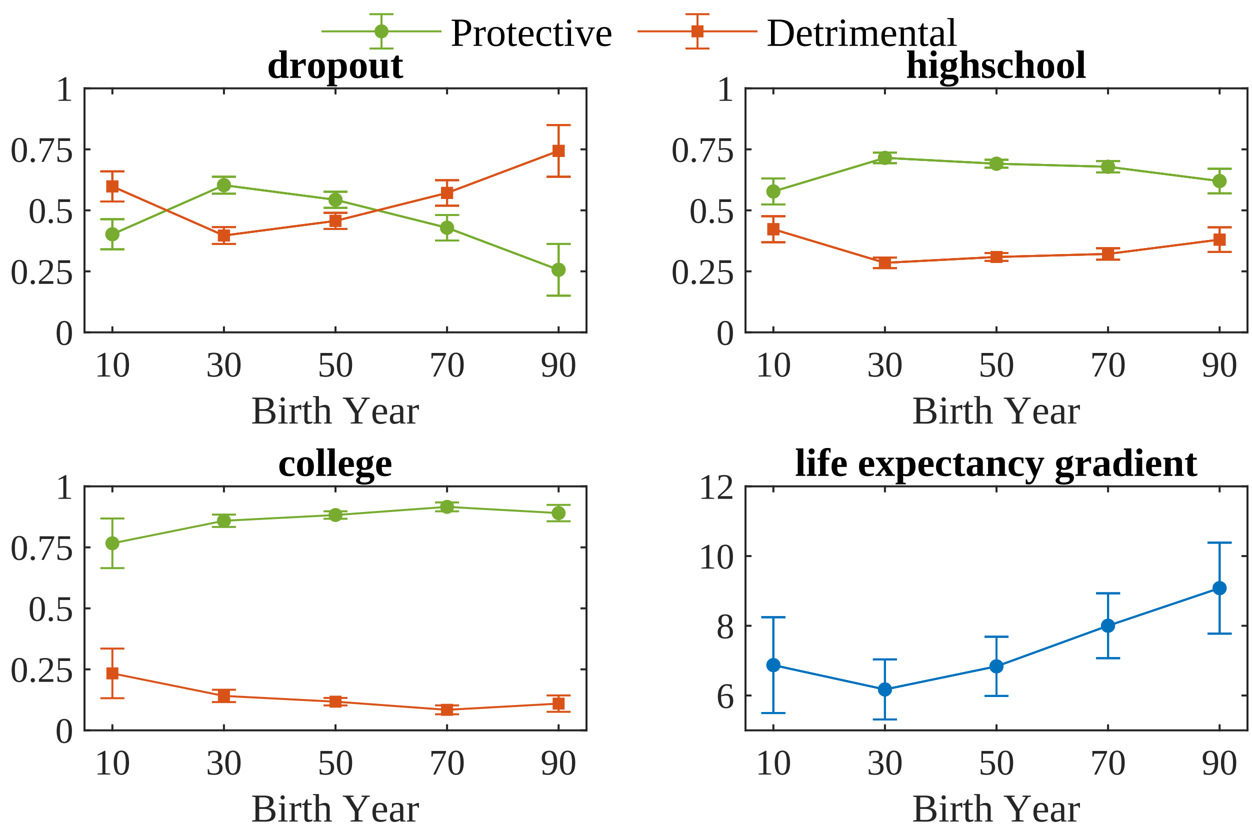


Figure 3: Wealth distribution across lifestyles

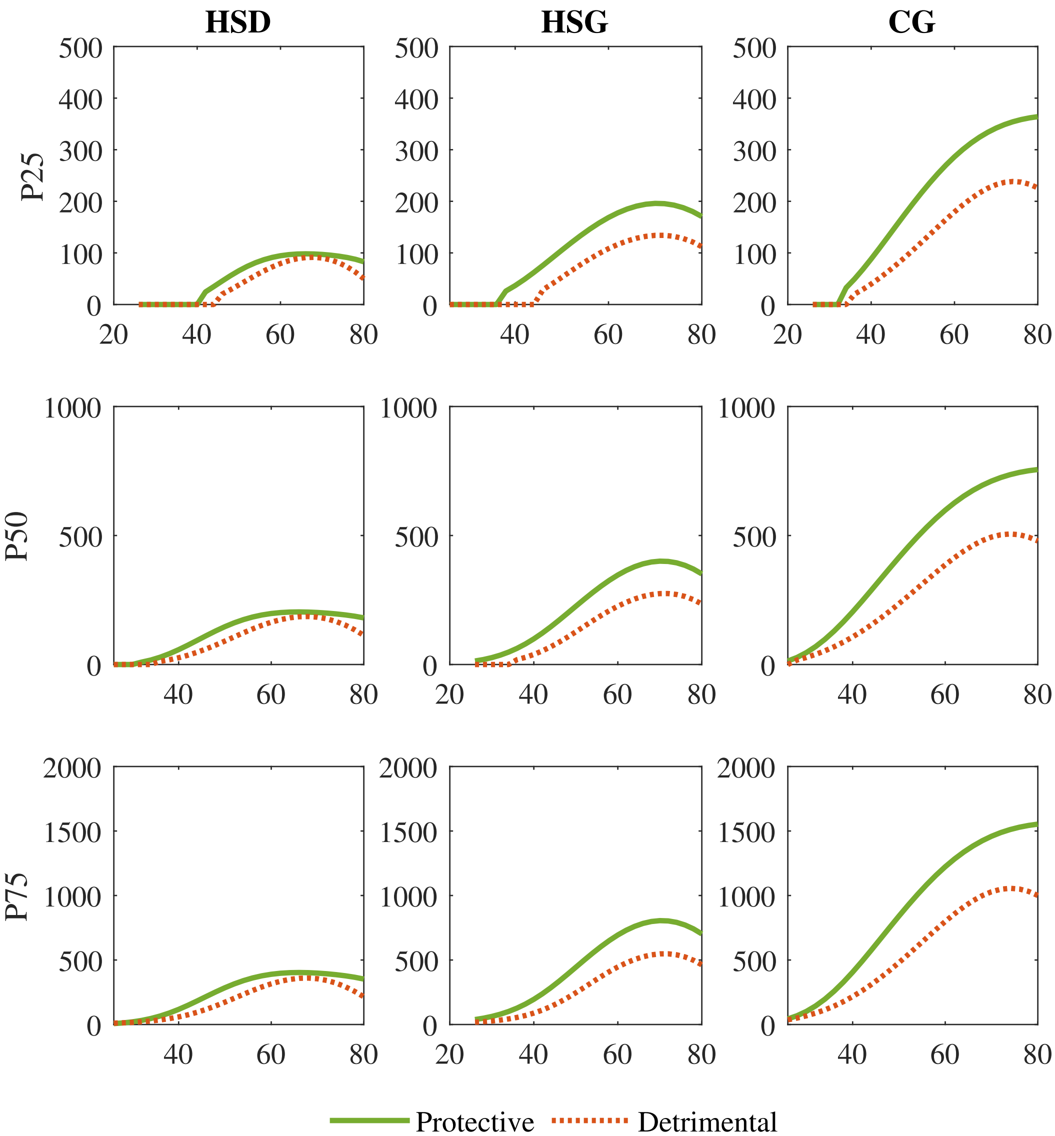


Figure 4: Average income across cohorts and education

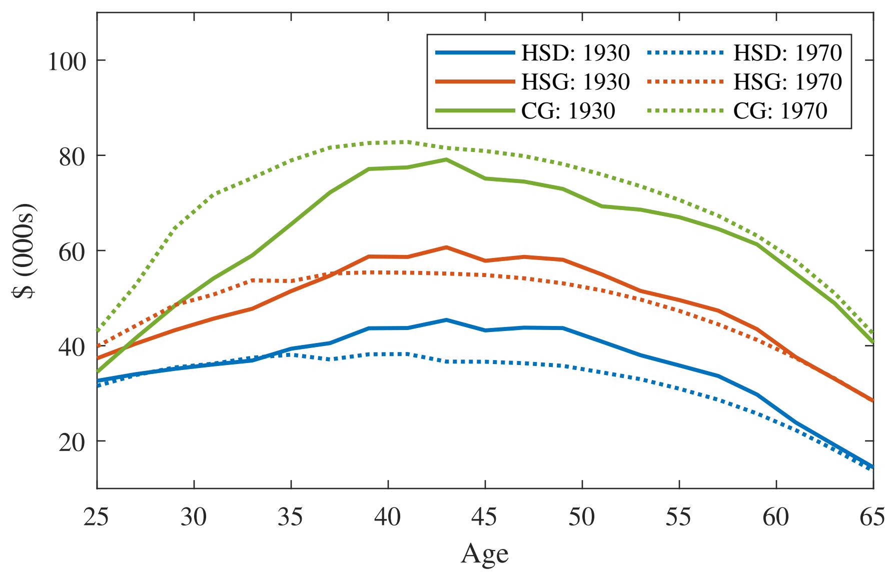


Figure 5: Model fit: wealth distribution model (lines) versus data (scatter)

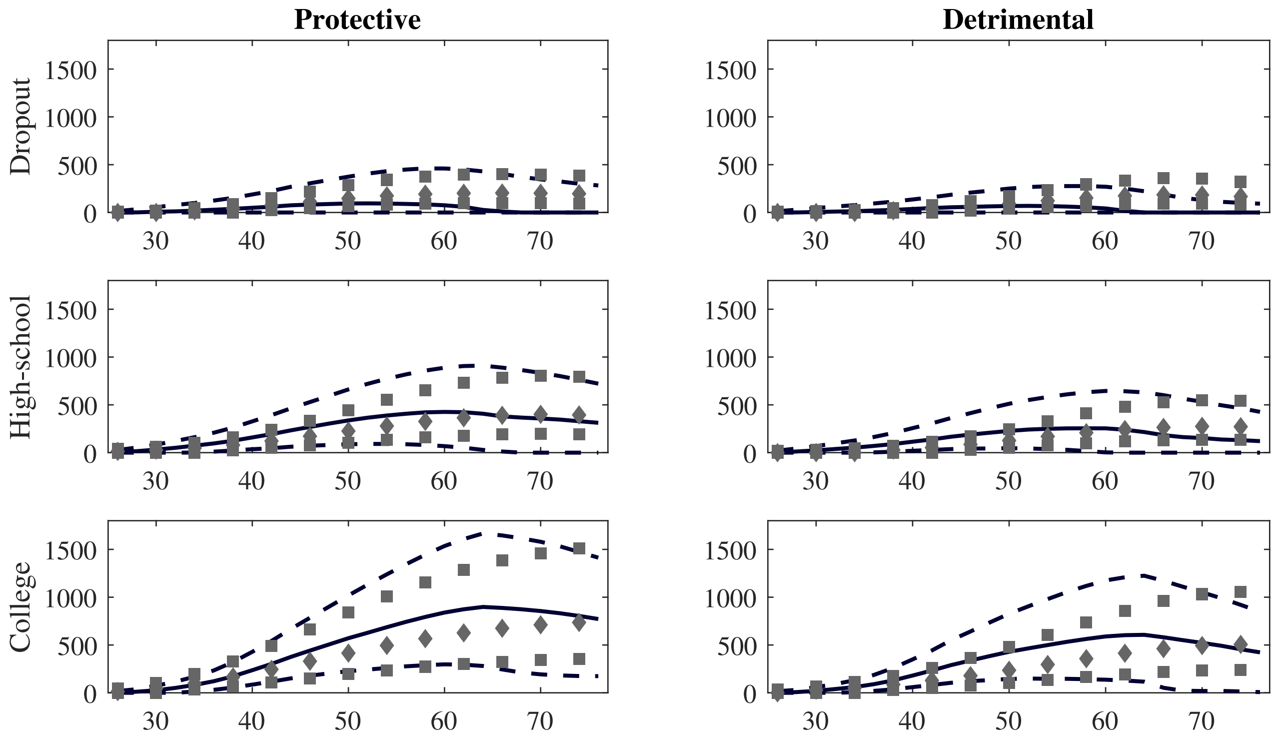


Figure 6: Marginal distributions: Education and Health Behavior

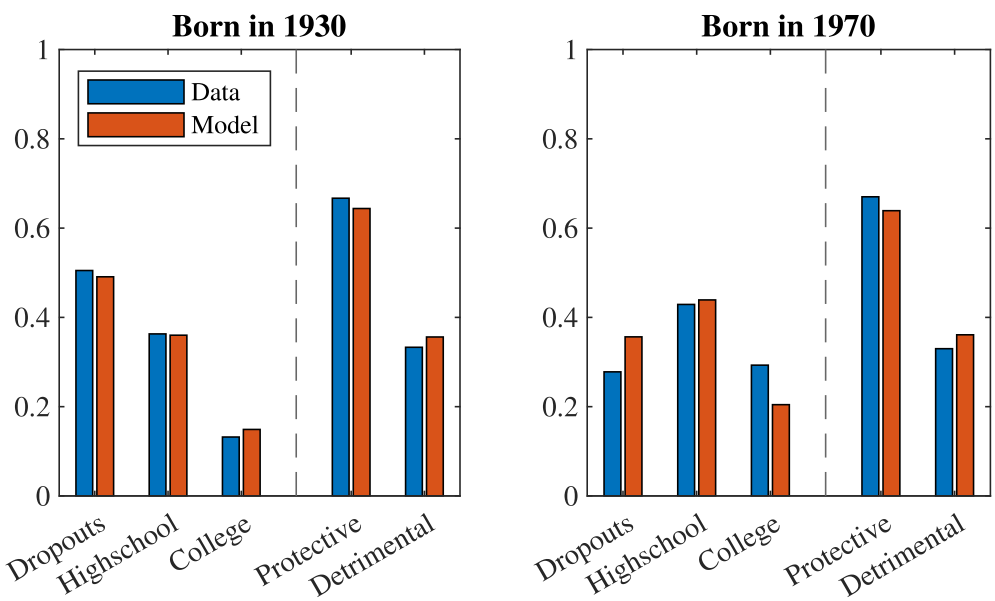


Figure 7: Conditional distribution of Detrimental Behavior by Education

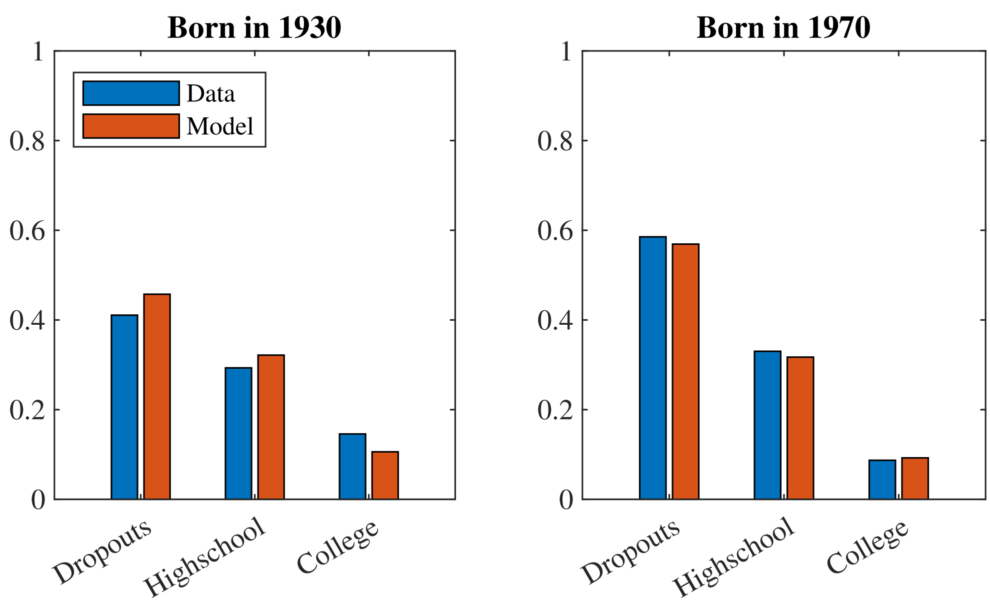


FIGURE 8: Cost of protective lifestyle

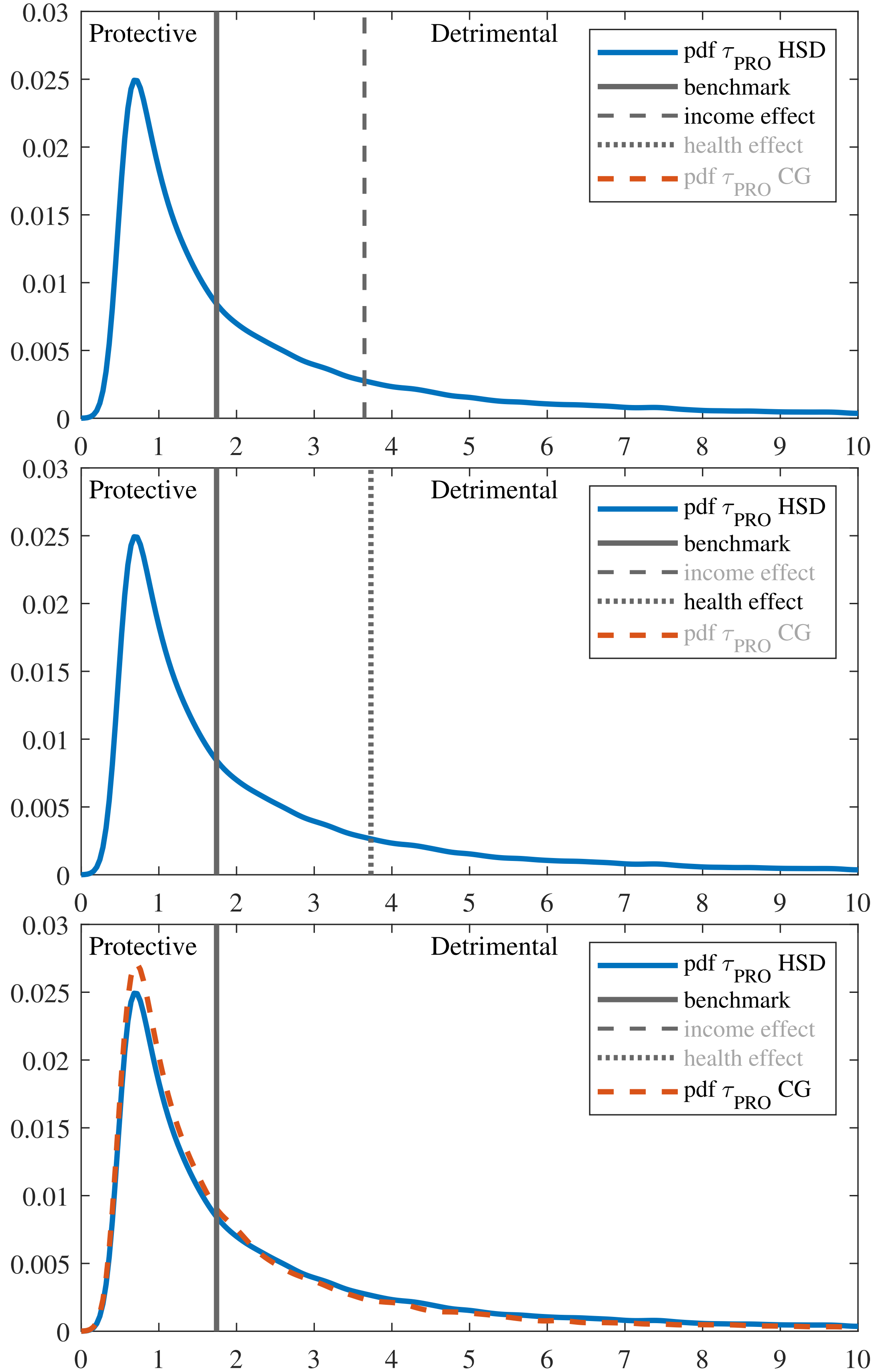
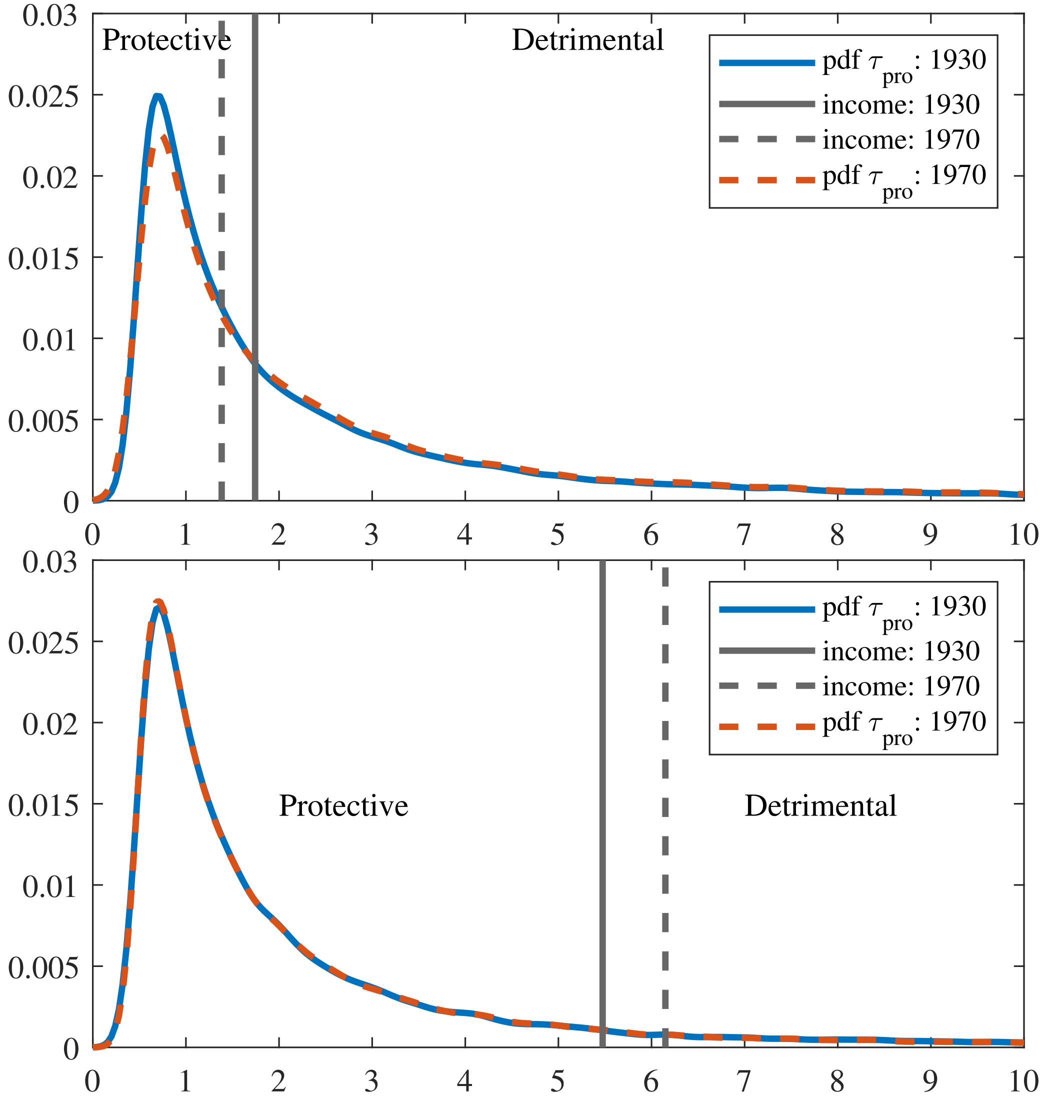


Figure 9: Cost of protective lifestyle across cohorts



List of Tables

Table 1: Expected duration of each health state at age 50 across lifestyle, education, and sex

Health Behavior	Fraction behavior	Life Expectancy	=	Good Health	+	Bad Health
Men: Dropouts						
Protective	42.9	29.0		17.5		11.4
Detrimental	57.1	21.4		11.8		9.6
Δ	-14.3	7.6		5.7		1.8
Average	-	24.6		14.3		10.4
Counterfactual		28.3		17.0		11.3
Men: High-school						
Protective	67.9	30.3		23.9		6.4
Detrimental	32.1	23.0		16.2		6.8
Δ	35.7	7.2		7.7		-0.4
Average	-	27.9		21.4		6.5
Counterfactual		29.7		23.2		6.4
Men: College						
Protective	91.6	33.4		29.6		3.8
Detrimental	8.4	24.5		19.1		5.4
Δ	83.2	8.9		10.5		-1.6
Average	-	32.6		28.7		3.9
Counterfactual		32.6		28.7		3.9
Women: Dropouts						
Protective	55.4	30.3		15.1		15.2
Detrimental	44.6	23.2		9.9		13.3
Δ	10.9	7.1		5.1		2.0
Average	-	27.2		12.8		14.4
Counterfactual		29.8		14.7		15.1
Women: High-school						
Protective	71.8	33.2		25.8		7.4
Detrimental	28.2	26.1		17.6		8.4
Δ	43.6	7.2		8.2		-1.0
Average	-	31.2		23.5		7.7
Counterfactual		32.7		25.2		7.5
Women: College						
Protective	92.7	34.9		30.4		4.5
Detrimental	7.3	28.2		20.8		7.4
Δ	85.4	6.7		9.6		-2.8
Average	-	34.5		29.7		4.7
Counterfactual		34.5		29.7		4.7

Notes: This table reports total life expectancy (3rd column), healthy life expectancy (4th column) and unhealthy life expectancy (5th column) at age 50. This is done within education and behavior type categories. The "Average" row corresponds to the given education category without conditioning on behavior type. The "Counterfactual" row corresponds to the given education category if the distribution of behavior types was the one of college-educated individuals.

Table 2: Internally calibrated parameters

Parameter	Description	Value
$\underline{x}$	income floor	17.60
b_0	bequest motive: marginal utility	3.90
b_1	bequest motive: non-homoteticity	103.71
b	value of life	-0.63

Table 3: Early-life parameters

Parameter	Value	Parameter	Value
μ_e	6.58	σ_e	4.02
μ_{PRO}	8.52	σ_{PRO}	1.45
μ_{CG}	5.26		