

CAN WEALTH BUY HEALTH? A MODEL OF PECUNIARY AND NON-PECUNIARY INVESTMENTS IN HEALTH

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Abstract

In this paper, we develop a life cycle model that features pecuniary and non-pecuniary investments in health in order to rationalize the socioeconomic gradients in health and life expectancy in the United States. Agents accumulate health capital, which affects labor productivity, utility, the distribution of medical spending shocks, and life expectancy. We find that unequal health insurance coverage plays a negligible role in generating the observed gaps in health and longevity. Universal health insurance increases preventive medical spending but not time spent in health promoting activities, as individuals are no longer worried about avoiding high curative medical expenditure shocks due to increased health insurance coverage. Our findings suggest that differences in lifetime income, preferences, and health shocks are the main determinants of inequality in life expectancy. (JEL: E21, D31, D15, I14, I31)

1. Introduction

The gap in life expectancy at age 25 between college graduates and high school graduates in the U.S. is 5.5 years for men. In this paper, we study the underlying sources of this striking inequality and the implications thereof for government policies

The editor in charge of this paper was Nicola Pavoni.

Acknowledgments: We thank Gianluca Violante, Pete Klenow, John Friedman, Francesco Caselli, and Hamish Low for helpful comments. We also thank conference and seminar participants at SSE, University of Groningen, Bank of Portugal, Concordia University, GSMG, University of St. Andrews, Uppsala University, ESSIM 2021, Paris School of Economics, Oxford University, Birkbeck University of London, Aarhus University, University of Le Mans, University of Milan Bicocca, Goethe University Frankfurt, University of Vienna, ETLA, Copenhagen Business School, Umeå University, University of Connecticut, Arizona State University, and Princeton University. Wallenius gratefully acknowledges financial support from the Knut and Alice Wallenberg Foundation (grant # 2014.0228). The computations were enabled by resources provided by Compute Canada.

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Journal of the European Economic Association 2024 22(3):1097–1138

<https://doi.org/10.1093/jeea/jvad044>

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aimed at improving access to healthcare, such as a Medicare-for-all type policy. To do so, we estimate a heterogeneous agent, life cycle model where individuals make both pecuniary and non-pecuniary investments in health.

Using data from the Medical Expenditure Panel Survey (MEPS), we document that, on average, individuals across the educational gradient exhibit similar life cycle profiles of healthcare spending. In other words, despite being in better health, college educated individuals spend on average as much as their high school educated counterparts on their health. However, they exhibit different spending patterns. High school graduates are less likely to use screening and other preventive medical services than college graduates, for every level of health.

Furthermore, we document substantial variation in health insurance coverage across the different levels of educational attainment. College graduates are more likely to be employed in occupations that offer group health insurance (GHI) plans, which offer lower premiums, better coinsurance rates and are non-discriminatory with respect to pre-existing conditions, and less likely to be uninsured. Hence, highly educated individuals not only have more pecuniary resources to invest in their health, but also face a lower effective price.

However, differences in access to resources and health insurance coverage alone cannot fully account for the socioeconomic gradient in life expectancy. Mokdad et al. (2004) document that nearly 50% of all deaths in the U.S. are attributed to modifiable behavioral factors. This is evidenced by the existence and persistence of the life expectancy gradient even in countries with equal (and in some cases free) access to healthcare.¹ These behaviors can be positive (e.g. healthy diet, exercise, and wearing a seatbelt) or negative (e.g. smoking or heavy drinking). Here, we focus on the positive, and specifically on the time investment in health promoting activities, as in the seminal paper of Grossman (1972). We use data from the American Time Use Survey (ATUS) to estimate non-pecuniary investments in health across the different educational levels. Consistent with previous studies, we find that highly educated individuals are more likely to spend time on health promoting activities, such as time spent on doctor's visits for preventive and screening services, sports and exercise, and self-care and personal care compared to low educated individuals.² Some of these health behaviors are indeed influenced by pecuniary resources and health insurance coverage. However, Cutler and Lleras-Muney (2010) show that income and effective price differences account for at most 30% of the educational gradient in health behaviors. Even if medical care is free, the gradient in preventive healthcare utilization still persists (Newhouse 1993).

We develop a life cycle model to account for these salient features regarding the socioeconomic gradients in health and life expectancy. In the model, health is a stock that depreciates stochastically over age. Agents can invest in health through preventive medical spending and time spent in health promoting activities. Health

1. For example, Bueren et al. (2018) document a very similar life expectancy gap for 50 year old males in the U.S. and the U.K., despite the U.K. having universal health insurance coverage which is mostly free at the point of service.

2. Throughout the paper, we refer to individuals with at most a high school degree as high school graduates and individuals with at least some years of college as college graduates.

affects life expectancy, labor productivity, utility, and the distribution of exogenous curative medical spending shocks. Agents are ex-ante heterogeneous with respect to their educational attainment, which determines their labor productivity, the probability of being offered GHI, and their initial level of health. We also allow the preference for leisure to vary over education.

We calibrate the model to the U.S. economy prior to the full implementation of the Affordable Care Act (ACA), and incorporate key features of the U.S. health insurance market and means-tested welfare programs. Agents are offered GHI with a probability conditional on their level of education, and individuals who are not offered GHI can decide whether or not to purchase private health insurance (PHI). Agents are enrolled in Medicaid if their income is below the Medicaid threshold or the medical spending shock is larger than their disposable income. In addition, the government guarantees a minimum level of consumption. Medicare enrollment starts at age 65.

The model matches the salient patterns for health investments, health, and longevity over age and education. Highly educated individuals spend more pecuniary and non-pecuniary resources on health, and are on average healthier and live longer than their less educated counterparts. There are five key drivers of this in our model. First, highly educated individuals have on average higher income and better health insurance options. Second, since agents are risk averse, it is optimal for high income individuals to sacrifice a larger share of current consumption in order to increase their level of utility and enjoy more periods of future consumption. Third, more educated individuals experience lower disutility from engaging in health promoting activities. Fourth, college graduates enter the economy with better health compared to high school graduates, which reflects the socioeconomic gradient in childhood health, and has persistent effects in our model. Finally, high school graduates experience larger health shocks, which proxy for bad habits and differences in cognitive ability.

In the Medicare-for-all policy reform that we consider, the government extends public health insurance coverage to all agents and offers a uniform coinsurance rate that covers the same fraction of total medical spending for everyone. We consider two funding scenarios, lump sum taxes levied on workers and increased progressivity of the labor income tax function. We find that extending Medicare coverage to all ages has a negligible effect on the longevity gap. This is due to the fact that, while agents increase pecuniary investments in health, they do not increase non-pecuniary investments. The incentive to increase non-pecuniary investments is dampened by the fact that agents are less concerned about avoiding curative medical spending shocks, since a larger share is covered by insurance. Our result is consistent with the empirical work of Baicker et al. (2013) on the Oregon Medicaid expansion, which finds an increase in healthcare utilization but no positive health effects from the improved access to healthcare. Our framework offers a mechanism that can shed light on this finding. According to our results, differences in lifetime income, preferences and shocks to health are the main drivers of the longevity gap.³

3. We assume a Cobb–Douglas production function for health, and thus a unitary elasticity of substitution between pecuniary and non-pecuniary investments. To try and gauge the role this rather high degree

There is a sizeable literature that studies medical spending either as an exogenous process that affects savings (e.g. Hubbard, Skinner, and Zeldes 1995; De Nardi, French, and Jones 2010; Kopecky and Koreshkova 2014), labor supply (Rust and Phelan 1997; French 2005; French and Jones 2011), or health insurance decisions (Zhao 2017 and Jeske and Kitao 2009) or as a choice variable that affects life expectancy and quality of life (Hall and Jones 2007 and Zhao 2014) or labor income (Prados 2018 and Halliday et al. 2019). With the exception of Ozkan (2017), the literature rarely treats medical spending as partly endogenous and partly exogenous. We decompose medical spending into both a choice variable in the form of preventive healthcare spending and a curative medical spending shock with an endogenous distribution conditional on the health of the individual.

To the best of our knowledge, we are among the first to study healthcare reform in a quantitative life cycle model with both pecuniary and non-pecuniary investments in health. Health behaviors and non-pecuniary investment in health across the educational gradient have been studied in the empirical literature (e.g. Cutler and Lleras-Muney 2010; Morrill et al. 2016; Bijwaard, van Kippersluis, and Veenman 2015) and have been found to explain a substantial fraction of the observed inequality in health and life expectancy.

The rest of the paper is organized as follows. Section 2 describes the stylized facts of medical spending, health insurance, and non-pecuniary investment in health. Section 3 introduces the model. Section 4 describes the parameterization of the model, while Section 5 discusses the fit of the model to the data. Section 6 presents the results from the quantitative analysis, and Section 7 concludes.

2. Stylized Facts

In this section, we present stylized facts with respect to health, survival, medical spending, health insurance, and time use for different socioeconomic groups of males in the United States before the full implementation of the ACA. In particular, we focus on differences over education and age. These salient patterns motivate many of our modeling choices in order to rationalize the gradients in health and life expectancy, and are instrumental in assessing policy reforms. We refer the reader to the Appendix for details on sample selection and the construction of data moments.

2.1. Data and Methodology

We use data on medical spending, preventive care utilization, medical conditions, and health insurance from the MEPS, time use data from the ATUS, labor income and labor

of substitutability plays for our results, in Section 6.1, we consider a constant elasticity of substitution production function with lower elasticities. To get a decent fit to the data, we need to recalibrate the model when we vary the elasticity. This, unfortunately, means that we are unable to isolate the effect of simply lowering the elasticity of substitution. Conditional on this caveat, our results hold for varying degrees of substitutability.

force participation data from the Panel Study of Income Dynamics (PSID), disability benefits data from the American Community Service (ACS), and mortality data from the Center of Disease Control and Prevention (CDC). We define two education categories, low and high educated. Low educated includes high school dropouts and high school graduates and high educated includes those with some college, college graduates, or more. We group individuals into 6 age intervals: 25–34, 35–44, ..., 65–74 and 75, and older.

We estimate the mortality hazard using data from the CDC, which provides detailed data on mortality by age, education and cause of death, and population estimates from the ACS. The mortality hazard is estimated as the ratio of the total number of deaths over the total population by age and education. We consider only health-related mortality, excluding homicides and accidents from our death estimates, since we want to focus on the effect of the gradient in health on the life expectancy gap.

We construct measures for real medical spending by age and education using total healthcare expenditure adjusted for inflation in medical services using the Medical Price Index. This includes both out-of-pocket payments and payments from public and private institutions. Preventive care utilization by education and age is estimated using MEPS and ATUS data.

Non-pecuniary investment is defined as time spent in health promoting activities, as reported in the ATUS. We focus on three categories of health-related activities: (i) sports and exercise, (ii) utilizing medical services, and (iii) personal care. Physical exercise is well established as an important health factor (Haskell et al. 2007). An increasingly sedentary lifestyle is associated with the rise in the prevalence of obesity, which has adverse effects on life expectancy and health (Griffith, Lluberas, and Lührmann 2016). In our time use measure, we also include the time spent utilizing, traveling, and waiting for medical services. Finally, from the personal care category, we include time spent on personal healthcare, personal health emergencies, and general self-care, but exclude sleeping.

Throughout the paper, we use the so-called frailty index as our measure of health. The frailty index is the accumulated sum of adverse health events or deficits that an individual has incurred. The advantages of the frailty index are that it is an objective measure of health, it is comparable across datasets, and it can be treated as a continuous variable due to its fine scale (see Hosseini, Kopecky, and Zhao 2022).

2.2. Life Expectancy and Health

The striking life expectancy gap is the result of a persistent gradient in health and the probability of survival throughout the life cycle.⁴ Figure 1a shows that, even excluding mortality by homicides and accidents, which is a substantial mortality risk for young

4. It is important to note that the gradients in health and the conditional probability of survival tend to be underestimated due to survival bias. The gradient in the mortality risk puts higher pressure on unhealthy individuals and, on average, healthier individuals survive to older ages. Survival bias is more evident in measures of average health, where we observe an improvement for older high school graduates.

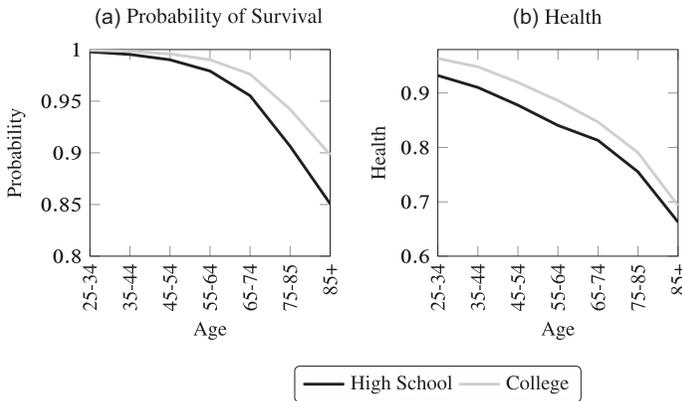


FIGURE 1. Health and conditional probability of survival by education and age. Figure (a) shows the conditional probability of survival by education and age, excluding homicides and accidents. Figure (b) shows average health by age and education, where health is measured by 1-frailty index and 1 corresponds to the best health and 0 to the worst (death). Source: MEPS, CDC and ACS, 2000–2013.

men, the probability of survival is lower for young high school graduates compared to college graduates. The differences in the probability of survival stem from differences in the average level of health (1b), as measured by the frailty index, which has been shown to be a good predictor of mortality (Hosseini et al. 2022). Health is reported as one minus the frailty index, which in turn is measured on a scale of 0–1, where a larger number corresponds to more health deficits and thus a greater degree of frailty.

Differences in health in young adults, adolescents and even fetuses can have persistent effects on health later in life (Almond and Currie 2011). Already at age 25, high school graduates exhibit lower levels of health, and this gap persists throughout the life cycle. Two potential explanations that we discuss in the next sections are the difference in pecuniary and non-pecuniary health investments across high school and college graduates.

2.3. Pecuniary Investment

Figure 2 shows the evolution of healthcare spending over the life cycle for the two education groups. Two patterns emerge: (i) healthcare spending rises steeply over the life cycle, and (ii) there are no consistent differences over education in the slope or the level of medical spending over the life cycle.

Thus, despite being in better health, college educated individuals spend on average as much as their high school educated counterparts on their health.

Highly educated individuals are more likely to make use of preventive medical services than their less educated counterparts. Table 1 shows the share of individuals across education categories who made use of common preventive medical services,

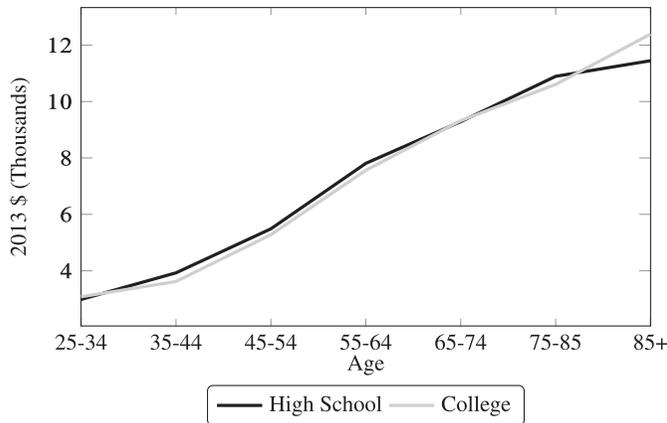


FIGURE 2. Total healthcare spending by education and age. Total healthcare spending includes aggregate healthcare spending taking into account out-of-pocket medical spending, payments by private and public insurance and other sources, excluding over the counter drugs and indirect payments not related to specific medical events. Source: MEPS, 2000–2013.

TABLE 1. Preventive service utilization over education (in last 2 years).

Activity	Routine check	Blood pressure	Flu shot	Dentist
High school	69.77%	82.06%	38.22%	49.75%
College	79.10%	90.07%	51.73%	71.56%

Notes: Percentage of individuals that report utilizing preventive medical services such as routine check, blood pressure check, flu shot, and visiting the dentist within the last two years. Source: MEPS, 2000–2013.

such as routine checks, blood pressure checks, flu shots and visiting the dentist, over the last 2 years.

In this paper, we distinguish between preventive medical spending that improves the level of health and curative medical spending that is increasing with poor health, in order to rationalize the healthcare spending patterns across the education levels. We treat the former as a form of pecuniary investment that the agents choose in order to improve their health and the later as an expenditure shock that depends negatively on health. It is far from trivial to make a clear distinction between preventive and curative medical spending in the data. We proxy preventive medical spending using the subset of individuals with no new medical conditions, above median health and below 75th percentile of spending. Based on this definition of preventive medical expenditure, Figure 3 illustrates that highly educated individuals spend on average more on preventive healthcare measures at all ages than their less educated counterparts.

2.4. Non-Pecuniary Investment

The empirical literature has focused extensively on the positive relationship between socioeconomic status and health (Marmot et al. 1991), and on healthy behaviors

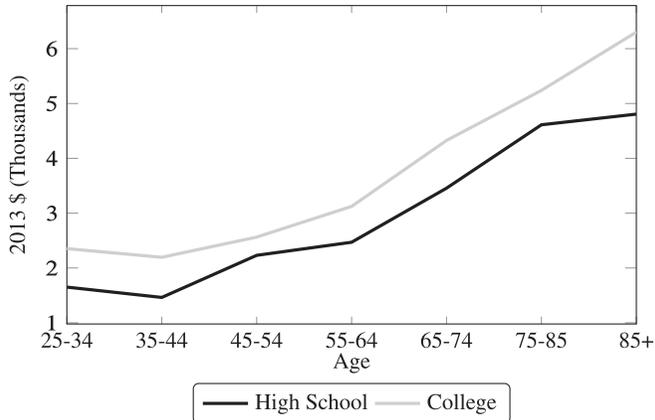


FIGURE 3. Pecuniary investment by education and age. We proxy preventive spending by the medical spending of individuals who face no new medical conditions, and who are above median health and below the 75th percentile of spending. Source: MEPS, 2000–2013.

in particular (Cutler and Lleras-Muney 2010), which are important determinants of health. Nearly half of deaths in the United States are attributed to modifiable behavioral factors such as lack of exercise, smoking, excessive drinking, and obesity (Mokdad et al. 2004). In our model, we focus on a subset of positive health behaviors, which require time investment, such as, sports and exercise, self-care, and time spent in preventive medical services.⁵

We document a strong correlation between education and time spent in health promoting activities. Figure 4 shows the average hours per year spent on health promoting activities by education and age. There is a consistent gradient in non-pecuniary investment throughout the life cycle. Further, college graduates are ten percentage points more likely to participate in sports related activities and three percentage points more likely to engage in self-care activities compared to high school graduates.⁶

Non-pecuniary investment is an important determinant of health, and given the gradient in time spent in health promoting activities between high school and college graduates, plays an important role in our model.

5. We do not explicitly consider negative health behaviors in our model. However, the gradient in negative health behaviors is proxied via three channels. First, agents enter the economy with a level of health that is conditional on their level of education. This captures the adverse effects of negative behaviors on health until age 25. Second, the frailty index explicitly includes smoking. Third, the distribution of health shocks is education-specific, which captures the faster deterioration of health of high school graduates.

6. Despite the seemingly small differences in non-pecuniary investment, even a few minutes of moderate or vigorous exercise can have substantial effects on health outcomes, especially on medical conditions such as cardiovascular disease and type II diabetes, which are leading causes of mortality and morbidity (Gebel et al. 2015).

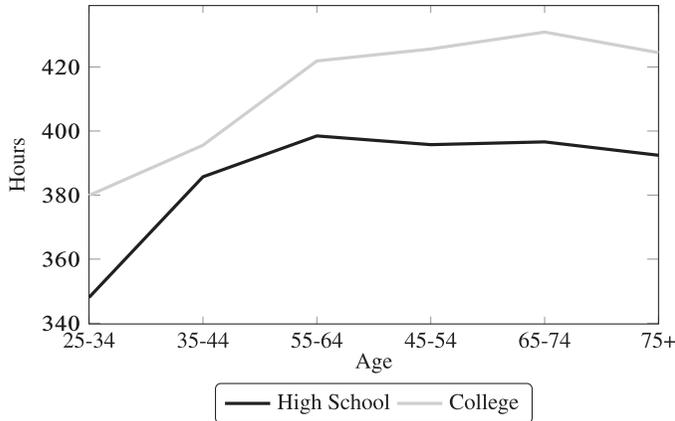


FIGURE 4. Non-pecuniary investment by education and age. Non-pecuniary investment consists of total time spent on: (i) sports and exercise, (ii) visiting doctor, and (iii) selfcare (excluding sleep). Source: ATUS, 2003–2013.

2.5. Health Insurance

Pecuniary and non-pecuniary investments in health are intertwined with access to health insurance, as individuals who are insured find these services more affordable and are more likely to utilize them. College graduates have, on average, better employment opportunities that offer higher labor income and better insurance options compared to high school graduates. Low educated individuals are less likely to receive a GHI offer from their employer. Group health insurance offers better coverage, lower insurance premiums and is non-discriminatory with respect to pre-existing conditions relative to PHI. Figure 5 illustrates the gradient in health insurance access. At ages 25–34, almost a third of high school graduates are uninsured and only a little over half hold any type of PHI. They are also more likely to be covered only by public, means-tested health insurance provisions, a pattern which persists across all age groups with varying intensity. The percentage of uninsured individuals falls over the life cycle, especially for low educated individuals. However, the gap between high school graduates and college graduates is not eliminated until age 65, when all individuals are covered by Medicare.

It should, however, be noted that access to healthcare cannot fully explain the gradients in pecuniary and non-pecuniary investments in health, nor the health and life expectancy gradients. First, Newhouse (1993) and Cutler and Lleras-Muney (2010) find that, even controlling for health insurance status, these services are underutilized by low educated individuals. Second, healthy behaviors are important determinants of health outcomes and life expectancy, and are not always correlated with access to health insurance.

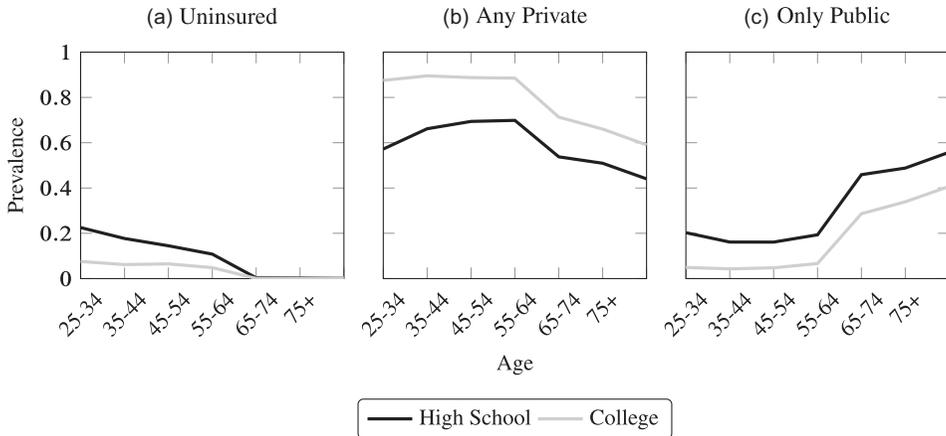


FIGURE 5. Prevalence of insurance coverage by education and age. Figure (a) shows the percentage of uninsured individuals over education. Figure (b) shows the percentage that has any type of private insurance and Figure (c) shows the percentage that is only covered by public insurance programs. Source: MEPS, 2008–2013.

3. Model

In order to rationalize the choices of individuals and the life expectancy gap between different levels of education, we develop a life cycle model where heterogeneous agents make health-related decisions in a realistic institutional environment with both private and public health insurance. Agents are ex-ante heterogeneous over education and face uncertainty with respect to health, survival, curative medical spending, labor productivity, and health insurance status. In the model, agents make decisions with respect to consumption and savings, pecuniary and non-pecuniary investments in health, health insurance, and labor supply (at the extensive margin at retirement).

3.1. Preferences and Demographics

Consider an economy populated by overlapping generations of agents. Each period a continuum of agents, who live for at most J periods, is born. At age $j = 0$, each agent “inherits” a level of education, i , which determines the life cycle profile of productivity, the initial level of health, the probability of being offered employer based health insurance, and the level of social security benefits starting from the age of eligibility J_R . The probability of survival is endogenous and depends on the level of health.

At the beginning of every period, agents observe the idiosyncratic productivity and health shocks, z_j^l and z_j^h respectively, and whether or not they are offered GHI, $GHI_j \in \{0, 1\}$, and then make their health insurance decision. For simplicity, we assume that individuals who are offered GHI are automatically enrolled in it. This assumption reflects the high take-up rate of GHI. Agents who are not offered GHI have the option

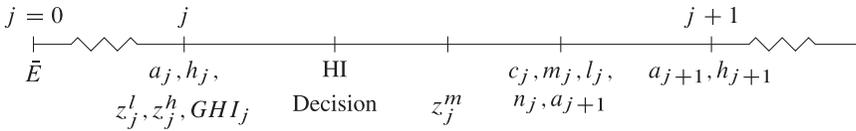


FIGURE 6. Timeline.

of purchasing PHI.⁷ After age J_R , individuals are automatically enrolled in Medicare. Subsequently, the medical spending shock is revealed and agents choose consumption, preventive medical spending, labor supply, time spent in health promoting activities and saving in the risk-free asset. Agents have the option to drop out of the labor market before age 63 and collect disability Insurance Benefits (DIB), if their level of health is below the qualifying threshold. Agents who do not claim disability work until retirement (choice between retiring at age 63 or 65). The timeline of the decision process is outlined in Figure 6.

Agents face the following lifetime utility:

$$U = \sum_{j=1}^J \beta^{j-1} \left[\prod_{k=2}^j P_{k-1}(h_k) \right] [u_j(c_j, l_j, n_j, h_j) + (1 - P_j(h_{j+1}))\theta(\alpha_{j+1})], \tag{1}$$

where β is the subjective discount factor, $P_{k-1}(h_k)$ the endogenous conditional probability of survival from age $k - 1$ to k , and $\theta(\alpha_{j+1})$ the utility derived from accidental bequests. The instantaneous utility $u_j(c_j, l_j, n_j, h_j)$ is

$$u_j(c_j, l_j, n_j, h_j) = \pi_h + v_0 \ln c_j - v_{1,i} \frac{l_j^{1+\frac{1}{\eta}}}{1 + \frac{1}{\eta}} - v_{2,i} \frac{n_j^{1+\frac{1}{\nu}}}{1 + \frac{1}{\nu}} + v_3 \ln h_j, \tag{2}$$

where c_j denotes consumption, l_j labor supply, n_j time spent in health promoting activities, and h_j health. π_h is a constant parameter in the utility function.⁸ We choose this utility function because of its salient properties, allowing us to take into account the effects of health on the quality and quantity of life. Agents derive utility from health directly, and can enjoy more periods of flow utility because of higher probability of survival. Furthermore, this utility function helps shed light on the gradients of pecuniary and non-pecuniary investments. Agents face an intra and intertemporal trade off between consumption and health. Namely, agents need to sacrifice current

7. We condition the PHI premium on the age and education of the individual and the average health of that demographic group. Prior to the implementation of the ACA, insurance firms could charge a premium based on pre-existing conditions for PHI but not GHI.

8. In standard models with exogenous probability of survival, only the marginal utility matters. However, when the probability of survival is endogenous, agents make decisions with respect to medical spending that affect the lifetime utility on the extensive margin. Hence, the constant parameter π_h affects the incentives of the agents to invest in their level of health.

consumption in order to increase: (i) their current level of health, and (ii) their life expectancy. Since consumption is subject to diminishing returns, the willingness to pay for health improvements rises with wealth. Bequests $\theta(a_{j+1})$ are assumed to be a luxury good:

$$\theta(a_{j+1}) = \iota \log(a_{j+1} + \kappa). \quad (3)$$

3.2. Health

As in Grossman (1972), we model health as a stock. Agents can invest pecuniary and non-pecuniary resources in order to increase their level of health, which depreciates stochastically over the life cycle. The law of motion for health is denoted by:

$$h_j = (1 - z_j^h)h_{j-1} + Q_j m_j^{\psi_j} n_j^{1-\psi_j}, \quad (4)$$

where z_j^h is the age-, health-, and education-dependent stochastic depreciation of health, and m_j and n_j are the pecuniary and non-pecuniary investments in health, respectively. We assume a Cobb–Douglas production function for health, where ψ_j is the relative share of preventive spending in the production of health. Q_j determines the productivity of pecuniary and non-pecuniary investments.⁹

3.3. Medical Spending and Health Insurance

Agents face uncertainty with respect to total out-of-pocket medical spending μ_j . Out-of-pocket medical spending consists of the insurance premium, if the agent holds health insurance, and two distinct types of medical spending, preventive medical spending, m_j , which agents choose in order to increase their health, and stochastic curative medical spending, z_j^m , which agents are forced to pay.¹⁰ The distribution of the curative medical spending shocks depends on age, health and education.

The total out-of-pocket medical spending for the insured is denoted by:

$$\mu_j = m_j + z_j^m + pr_j(ins_j) - q(ins_j)(m_j, z_j^m). \quad (5)$$

Conversely, for the uninsured it is:

$$\mu_j = m_j + z_j^m, \quad (6)$$

9. In our specification, the marginal product of health investment is independent of current health. Estimating a health production function where this assumption has been relaxed is an interesting possible extension.

10. If the agent cannot afford to pay the curative medical spending shock, or cannot achieve a minimum level of consumption, the government pays the remainder of the shock. The agent is then enrolled in Medicaid and forced to hold zero assets.

where pr_j denotes the insurance premium, q the coinsurance rate, and ins_j the insurance status. The coinsurance rate is the fraction of total medical spending that is covered by health insurance.¹¹

There are five health insurance states in our model: Medicaid, Medicare, GHI, PHI, and no insurance. Until age 65, agents face uncertainty with respect to their insurance status. Agents face an education and age-specific probability $\zeta(i, j)$ of receiving GHI. A GHI offer translates into automatic enrollment in the GHI scheme for the current period, with a uniform coinsurance rate and health insurance premium. This simplification reflects the high enrollment rate of workers that receive a GHI offer.

If the agent does not receive GHI, the agent can choose to purchase PHI, which offers a lower coinsurance rate and a premium that depends on the age and education of the applicant and the average health status of individuals in that age-education bin. Thus, the health insurance premium is denoted by:

$$pr(PHI) = \omega E\left(z_j^m | j, i, \bar{h}_{i,j}\right), \quad (7)$$

where $E(z_j^m | j, i, \bar{h}_{i,j})$ is the expected curative medical spending of the agent, given age, education and average health.

The government offers two health insurance schemes: (i) means-tested Medicaid that is offered to individuals with income below the Medicaid threshold or who need to pay a curative medical spending shock that does not allow them to achieve a minimum level of consumption guaranteed by the government, and (ii) Medicare for all agents over the age of 65. In a nutshell:

$$ins_j = \begin{cases} Medicare, & \text{if } j \geq J_R \\ Medicaid, & \text{if } c < \bar{c}, \text{ or } y < y_{Medicaid} \\ GHI, & \text{w/prob. } \zeta(i, j) \\ PHI \\ Uninsured \end{cases}, \quad (8)$$

where \bar{c} is the minimum level of consumption guaranteed by the government and $y_{Medicaid}$ is the income threshold for Medicaid eligibility.

The coinsurance rate is uniform across agents that hold PHI, but the insurance premium varies. Agents that hold GHI face a fixed premium. Prior to the implementation of the ACA, only GHI was required by law not to discriminate based on health status, while PHI faced no such restrictions.¹² Consequently, older, less healthy individuals face higher premia.

11. In this model, we consider the effective coinsurance rate, which takes into account both the fraction of out-of-pocket medical spending for healthcare services that are covered and medical spending that the individual pays fully out-of-pocket because they are not covered under the health insurance plan. For example, not all health insurance schemes offer coverage for dental care, which would tend to decrease the effective coinsurance rate.

12. For a detailed discussion regarding the institutional differences between GHI and PHI, see inter alia Jeske and Kitao (2009). In this paper, we do not consider the deductible on the GHI premium nor the pooling effects on the level of the health insurance premium.

Thus, agents face uncertainty with respect to both the magnitude of the curative medical spending shock and their health insurance status before the age of 65, and only the magnitude of the curative medical spending shock after the age of 65.

3.4. Budget Constraints

The agent receives labor income if working, capital income, government transfers if necessary to guarantee a minimum level of consumption, disability insurance benefits if the level of health is below the DIB threshold and the agent is not working, and social security benefits after the eligibility age. The agent allocates resources between general consumption, out-of-pocket medical spending and savings:

$$\tilde{y}_j = (1 + \tau^c)c_j + \mu_j + a_j \quad (9)$$

\tilde{y}_j denotes total net income:

$$\tilde{y}_j = (1 - \tau(y_j) - \tau_{ss})l_j e(h_j, j, i, z_j^l) + ra_{j-1} + ss_j + Tr_j + DIB_j, \quad (10)$$

where $\tau(y_j)$ denotes the progressive tax on labor income, τ_{ss} the proportional social security tax, $e(h_j, j, i, z_j^l)$ the labor productivity as a function of health, age, education, and the labor productivity shock, a_{j-1} the level of assets, Tr_j government transfers, ss_j social security payments, and DIB_j disability insurance benefits.

3.5. Government

The government collects taxes via a progressive income tax, a proportional social security tax and a proportional consumption tax. We use the income tax function as described in Guner, Kaygusuz, and Ventura (2014), which provides a good approximation of the progressivity of the average income tax in the U.S.:

$$\tau(y_j) = 1 - \tau_0 y_j^\varphi. \quad (11)$$

In this specification, τ_0 controls the level of the average income tax and φ the degree of progressivity, with $\varphi = 0$ implying a constant tax over income.

In addition, the government provides means-tested social insurance programs, and social security benefits and Medicare after the eligibility age. In particular, the government provides Medicaid for agents with income below the Medicaid threshold or facing curative medical spending shocks that do not allow the agent to achieve a minimum level of consumption. In addition, the government provides DIB to agents who drop out of the labor market and whose level of health is below the DIB threshold. We assume that the tax revenue which is leftover after funding the social insurance schemes is used for government consumption, which does not affect the marginal utility of private consumption.

3.6. Individual's Problem

Let $V_j(a_j, h_j, z_j^l, z_j^h, z_j^m, GHI_j, i)$ denote the value of an age- j agent with assets a_j , level of health h_j , idiosyncratic productivity, health and medical shocks z_j^l , z_j^h , and z_j^m , respectively, GHI option GHI_j and level of education i and $s_j = (a_j, h_j, z_j^l, z_j^h, z_j^m, GHI_j, i)$ the state vector. We can write the agent's problem recursively as:

$$V_j(s_j) = \max_{c_j, l_j, n_j, m_j, ins_j} \left\{ \begin{array}{l} u_j(c_j, l_j, n_j, h_j) + \beta P(h_j) \int V_{j+1}(s_{j+1}) dF(s_{j+1}) \\ + \beta(1 - P(h_j)\theta(a_{j+1})) \end{array} \right\} \quad (12)$$

subject to the budget constraint (9), out-of-pocket medical spending (5)–(7) and the health production function (4).

4. Parameterization

We follow a two-step procedure for the parameterization of the model. In the first stage, we estimate as many parameters as possible directly from the data, and set some parameters based on commonly adopted values in the literature. In the second stage, we use indirect inference for the vector of remaining parameters, in order to minimize the weighted distance between moments generated from the model simulations and their data counterparts. Here, we provide an overview of the estimations and indirect inference; please see the Appendix for further details.

4.1. Estimated Parameters

The parameters estimated from the data are: (i) the age-specific baseline mortality risk, (ii) the distributions of educational attainment and initial health in the population, (iii) the distribution of health shocks, (iv) the distribution of curative medical spending shocks, (v) the probability of receiving a GHI offer, and (vi) the labor income process.

4.1.1. Demographics. Mortality risk is endogenous, and depends on age and health:

$$p_j^d(h_j, j) = \bar{p}_j^d \exp(\rho_h(h_{\max} - h_j)). \quad (13)$$

Agents across different levels of education face the same, age-specific mortality risk, \bar{p}_j^d , which corresponds to the mortality hazard of an individual in the best health (normalized to 1), and any deviations from this level of health amplify the mortality risk. The baseline mortality risk is estimated using data on the number of deaths by age from the CDC and population estimates by age from the ACS. The sensitivity of the mortality risk to health, ρ_h , is pinned down in the indirect inference to match a life expectancy gap of 5.5 years, given the average level of health over the life cycle for

TABLE 2. Distribution of education and health at age 25.

Education	Share	Bottom health quartile	Median health	Top health quartile
High school	61.0%	0.92	0.98	1.0
College	39.0%	0.95	0.99	1.0

Notes: Descriptive statistics for the distribution of education and health at age 25. Health is measured as 1-frailty index and 1 corresponds to best health and 0 to the worst. Source: MEPS, 2000–2013.

high school and college graduates in the MEPS. We follow Hosseini et al. (2022) and correct for survival bias by assuming a frailty of 1 for those who die.

The distribution of agents over education is computed using data on educational attainment in MEPS. Each agent is also endowed with an initial level of health, which is conditional on education. Again, this is constructed using MEPS data. High school graduates enter the economy with lower health on average, compared to college graduates (see Table 2).

In the model, differences in initial health reflect differences in childhood/early adulthood health, which we do not model, but that can affect health and longevity over the life cycle.

4.1.2. Health Shocks. Recall that, in our model, agents make pecuniary and non-pecuniary investments, which build up the health stock, but face negative shocks which in turn deplete this stock. We estimate the distribution of health shocks using individual level data on medical conditions from the MEPS and the corresponding severity index for each medical condition from the WHO's Global Burden of Disease, similarly to Prados (2018). A health shock is defined as the cumulative severity index for all conditions reported by an individual in a particular wave of the MEPS and not reported in previous waves. The severity index for each condition is between zero (conditions that do not have any effect on the quality or quantity of life) and one (conditions that result in death). Nevertheless, one might worry that the severity index is not constructed in the same units as the frailty index. To address this, we introduce a parameter which scales the health shocks in the model. This scale parameter is estimated in the indirect inference to match the covariance between medical expenditures and health shocks, where the covariance measure is constructed as in (Hosseini, Kopecky, and Zhao 2021) based on the residuals.

Figure 7 shows the 5th, 25th, 50th, 75th, and 95th percentiles of health shocks by age and education. Health shocks become more severe and dispersed with age. Furthermore, the severity of extreme health shocks is larger for high school graduates than for college graduates.

In the context of our model, health shocks are approximated by a discrete, 3-state process, which depends on age and health, similar to De Nardi, Pashchenko, and Porapakarm (2018). First, we construct three health shock groups, below 50th percentile, between 50th and 95th percentile, and above 95th percentile. Individuals are grouped into these bins, conditional on age, education, and health. We then run a

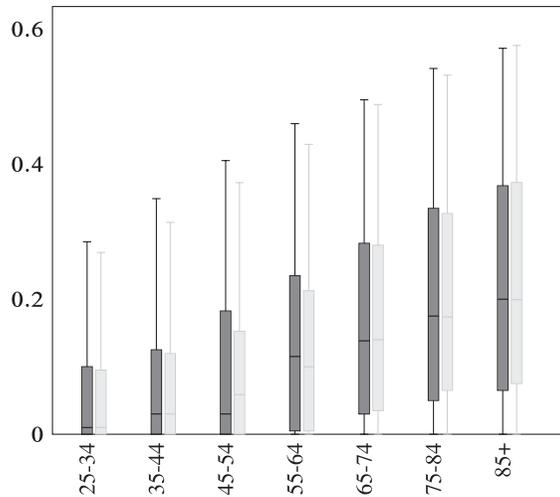


FIGURE 7. Distribution of health shocks by age and education. The graph presents the distribution of health shocks by age and education, as measured by the cumulative health condition severity weights. The line represents the mean, the edges of the box the 25th and 75th percentiles and the whiskers the 5th and 95th percentiles. The dark and light boxplots represent the health shock distributions of high school and college graduates, respectively. Source: MEPS Conditions File (2000–2013) and WHO's Global Burden of Disease (2002).

regression of the level of health shocks on age, age squared, health, and health squared, separately for each bin and level of education.

In the model, agents draw a health shock bin with the corresponding probability, and the severity of the shock is determined by age, health, and education. We use an education-specific distribution of health shocks, which can be thought to capture the differences in negative health behaviors and the differences in the effectiveness of health investments over education, which are not explicitly modeled. In other words, for the same level of health, high school graduates experience higher health shocks on average, which reflects differences in bad habits, such as smoking, and the effectiveness of treatment that could lead to comorbidities and more severe medical conditions in future periods. There is evidence that more educated individuals are more likely to comply with treatments which rely on complex technologies and lifestyle changes such as HIV and diabetes (see Goldman and Smith 2002).

Figure 8 shows an example of the distribution of shocks that an individual faces over the life cycle for different levels of education. The model takes into account that health shocks on average increase with age, and that unhealthy individuals face more severe health shocks.

4.1.3. Curative Medical Spending. Agents face curative medical spending shocks which they cannot default on. We estimate the distribution of these shocks with the same methodology as the distribution of health shocks. We construct three bins for medical expenditures, below 50th, between 50th and 95th and above 95th percentile.

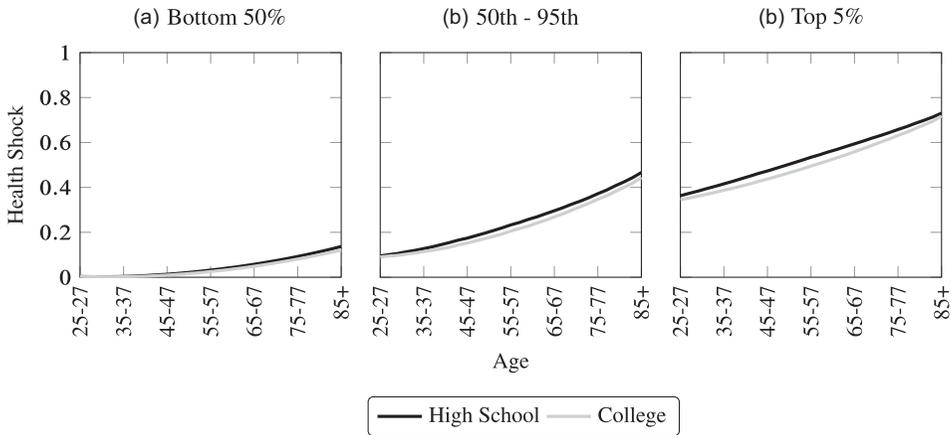


FIGURE 8. Distribution of health shocks by education. We use our parameter estimates to generate the distribution of health shocks over the life cycle for a high school and college graduate with average level of health.

Individuals are then grouped into these bins, conditional on age, education and health. We then regress medical expenditures on age, age squared, health, and health squared.¹³

Figure 9 shows the distribution of curative medical spending shocks over the life cycle for high school and college graduates with average health, respectively. Unsurprisingly, curative medical spending increases with age and is on average higher for high school graduates for all percentiles. This reflects the lower level of health of high school graduates compared to college graduates.

4.1.4. Health Insurance. We estimate the age and education specific probability of receiving a GHI offer by estimating the increase in GHI over the life cycle. The probability of receiving GHI peaks in middle-age, reflecting better employment opportunities.

We estimate the effective coinsurance rates for GHI, PHI, Medicaid, and Medicare from MEPS data, using the share of total medical spending that is paid out-of-pocket (see Table 3). At 90%, Medicaid offers the most generous coinsurance rate. This is hardly surprising, considering that Medicaid is a means-tested program targeted at

13. From the data, we compute the ratio of medical spending of individuals with no health shocks, and who are above median health and below the 75th percentile of spending relative to the rest of the population. This ratio is then used to proxy the fraction of medical spending that is preventive for the population. It should be noted that we do not overestimate total medical spending, since the curative medical spending shocks are scaled down using these shares. In addition, we do not overestimate curative medical spending shocks. Since we capture natural deterioration of health, in our simulation all agents face some health shock, where the magnitude of the shock depends on age, education, and health. In other words, the model does not generate agents who do not face any health shocks and hence zero curative medical spending.

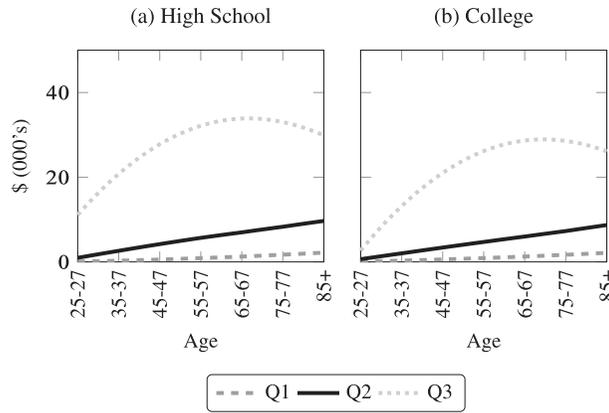


FIGURE 9. Distribution of curative medical shocks by education. We use our parameter estimates to generate the distribution of curative medical spending shocks over the life cycle for high school and college graduates with average health. Q1 is the below 50th percentile, Q2 between 50th and 95th percentile, and Q3 above the 95th percentile.

TABLE 3. Health insurance coinsurance rates and premia.

Type of insurance	Coinsurance rate	Insurance premium
GHI	0.71	895
PHI	0.67	see text
Medicare	0.73	547
Medicaid	0.9	0

Notes: The coinsurance rates are computed as 1-fraction of total medical spending paid out-of-pocket. The GHI premium is estimated using MEPS data and the PHI premium is set endogenously in the model. Source: MEPS, 2000–2013.

individuals with low income or those that face catastrophic healthcare spending which they are not able to pay out-of-pocket. Medicare and GHI offer similar coinsurance rates, while the coinsurance rate offered by PHI is lower.

The health insurance premium for Medicare is estimated using MEPS data. The health insurance premium for GHI is from the Kaiser Foundation (2010). It is the average individual health insurance premium paid by the employee. We find that on average, individuals pay \$895 out-of-pocket annually. The insurance premium for PHI is endogenous in our model, and depends on age, education and average health. It is calibrated such that the fraction of individuals with PHI over education is close to what we observe in the data. We assume that Medicaid has an effective insurance premium equal to zero.

4.1.5. Labor Productivity. The stochastic labor productivity profile is endogenous and depends on age, education, and health. We are interested in estimating the impact of health on earnings, yet earnings may also impact health. Also, both earnings and health are highly persistent. There is also the concern that we only observe earnings

TABLE 4. Demographic parameters.

Parameter	Description	Value
J	Maximum number of periods	38 (101 years old)
J_R	Retirement period	21 (65 years old)
n	Population growth	0.02 (1% annually)

TABLE 5. Preference parameters.

Parameter	Description	Value
β	Discount factor	0.96
η	Frisch elasticity	1
ν	Concavity of disutility from healthy time	1

Notes: Parameters set according to common values in the literature.

TABLE 6. Tax parameters.

Parameter	Description	Value
τ_0	Tax level	0.902
φ	Tax progressivity	0.036
τ^c	Consumption tax	0.05

Source: Guner, Kaygusuz, and Ventura (2014).

TABLE 7. Social security benefit scheme.

Average lifetime earnings	Marginal replacement rate
$y_i \in [0, 0.2\bar{y})$	90%
$y_i \in [0.2, 1.25\bar{y})$	33%
$y_i \in [1.25, 2.46\bar{y})$	15%
$y_i \in [2.46, \infty)$	0%

Notes: \bar{y} is the average labor income in the economy and y_i is the average labor income at each level of education i . Source: Zhao (2017).

for those individuals who work. Thus, we are concerned with simultaneity, dynamic endogeneity, and selection. In light of this, we follow Hosseini et al. (2021) and use a system GMM dynamic panel estimator and a selection correction procedure to estimate the effect of health on productivity. This is done separately for the two education types. This approach is based on Arellano and Bond (1991); please see the Appendix for details. Consistent with Hosseini et al. (2021), we find that health affects the labor income of high school graduates, but not college graduates.

4.2. Exogenous Parameters

Here, we present the parameters that are set exogenously to values that are commonly found in the literature (summarized in Tables 4–7).

4.2.1. Preferences and Demographics. A model period is two years. Agents enter the economy at age of 25 ($j = 1$) and survive until at most age 101 ($j = 38$). Population growth is set to 1% annually.¹⁴

The Frisch elasticity of labor supply, η , and the concavity of the disutility of non-pecuniary investment, ν , are set to 1. The discount factor is set to $\beta = 0.96$ and the interest rate to $r = 0.03$.

4.2.2. Government. We set the consumption tax τ^c to 5%, a common value in the literature, and use the estimates of Guner, Kaygusuz, and Ventura (2014) for the parameters of the income tax function. We follow Ozkan (2017) and set the consumption floor equal to 5,000 USD annually.

The modeled social security and disability benefit systems are stylized representations of the actual US systems, as these are not the focus of the paper. It is not computationally feasible to track the lifetime earnings of agents in order to calculate social security and disability benefits. Instead, we estimate average labor income by education and apply the below social security benefit formula to these averages, as in Zhao (2017). We approximate disability benefits by assigning claimants the average benefit observed in the data for a given age and education. The health threshold for disability benefits is determined endogenously in the model to target the share of disability benefit recipients. For simplicity, we assume that all applicants below the health threshold are granted benefits, if they stop working. In the model, disability benefit claiming is an absorbing state. We abstract from the waiting period, and assume that disability benefit recipients immediately receive Medicaid.¹⁵

4.3. Indirect Inference

The rest of the parameters in the model are jointly estimated using indirect inference. The targeted moments consist of: (i) mean healthcare spending by age and education (12 moments), (ii) mean level of health by age and education (12 moments), (iii) covariance between between health shocks and medical expenditures (1 moment), (iv) life expectancy gap at age 25 (1 moment), (v) share with PHI by education (2 moment), (vi) ratio (college/high school) of time spent in health promoting activities (1 moment), (vii) employment rates at age 63 by education (2 moments), (viii) disability benefit collection rates at age 61 by education (2 moments), and (ix) assets to labor income ratio (1 moment).

The estimated parameters are: (i) the age-specific effectiveness of health investments (Q_j), (ii) the age-specific relative share of preventive spending in the production of health (ψ_j), (iii) the scale parameter for health shocks (h_{scale}),

14. Population growth is necessary to ensure that cohorts have the correct size, in particular for our counterfactual analysis.

15. The average waiting time is a little over a year with only 10% of the applicants exceeding three years (Prenovitz 2021). In our model, every period is two years, which means the decision is finalized within a single period.

(iv) the education-specific disutility from labor supply ($v_{1,i}$), (v) the education-specific disutility from time spent in healthy activities ($v_{2,i}$), (vi) the weights on consumption and health in utility (v_0 and v_3), (vii) the constant in utility (π_h), (viii) the health threshold for receiving disability benefits (h_{DIB}), (ix) the PHI premium parameter (ω), (x) the effect of health on mortality (ρ_h), and (xi) the parameters governing the utility from bequests (ι and κ). In order to reduce the parameter space, we approximate the age-varying parameters with linearly spaced vectors, and estimate the starting and ending points instead of the full vectors.

We choose the parameter vectors to minimize the distance between the model generated variables and their data counterparts for each age bin. We use 10-year intervals (25–34, ..., 65–74, and 75+). Formally:

$$\hat{\theta} = \arg \min[\hat{\psi}^d(\theta) - \hat{\psi}^s(\theta)]' W[\hat{\psi}^d(\theta) - \hat{\psi}^s(\theta)], \quad (14)$$

where $\hat{\theta}$ is the vector of parameters to be estimated, $\hat{\psi}^d$ and $\hat{\psi}^s$ are the vectors of data and simulation moments, respectively, and W is the weighting matrix.¹⁶

There is no one-to-one mapping between a parameter and a particular data moment, rather the parameters are jointly estimated. However, some parameters are more important for matching certain moments. In particular, the education-specific disutilities for work and health promoting activities are largely pinned down by the employment rates and the time spent on healthy activities. The health threshold for disability benefit collection is important for targeting the share of agents collecting said benefits. The PHI premia determine the share that purchase PHI.¹⁷ The weights on consumption and health in utility help match the level of medical spending, while the age-specific effectiveness of health investments and the age-varying relative share of preventive spending in the production of health are important for generating the life cycle profiles for health expenditures and health. Effectiveness must rise with age in order to generate rising health expenditures over age. The age-varying share parameter helps generate a pattern where agents exercise more when young and then increase spending, but not time use, as they age. The covariance between health shocks and medical expenditures is informative for matching the scale parameter for health shocks. The sensitivity of survival to health is pinned down by the longevity gap. The parameters governing the utility from bequests target the assets to labor income ratio. The parameters are summarized in Table 8.

16. We assign a weight of 7 to the longevity gap, a weight of 5 to PHI, disability benefit collection and employment, and a weight of 1 to the other moments. If we weight all data moments equally, the algorithm ends up prioritizing the fit for medical spending and health and sacrificing the fit with respect to the other moments. This is because we are targeting life cycle profiles for medical spending and health, but not for the other moments. Given that the longevity gap is central to our analysis, we feel that it is particularly important to have a good fit along this dimension.

17. The presence of non-pecuniary investment lowers the incentive to purchase PHI, resulting in an ω of less than one in our parameterization. One should also note that in our framework the insurance coverage does not include all curative spending due to implicit insurance from Medicaid. We also abstract from family benefits.

TABLE 8. Estimated parameters.

Parameter	Description	Value
Health production function		
Q_1	Productivity scale age 25	0.89
Q_{38}	Productivity scale age 101	2.34
ψ_1	Share of pecuniary investments age 25	0.01
ψ_{38}	Share of pecuniary investments age 101	0.08
h_{scale}	Health shock scale	1.03
Utility		
π_h	Constant	20.55
u_0	Consumption utility	11.0
$u_{1,1}$	Labor disutility HS	52.2
$u_{1,2}$	Labor disutility C	24.82
$u_{2,1}$	Time invest. disutility HS	1,878.64
$u_{2,2}$	Time invest. disutility C	1,630.76
u_3	Health utility	6.06
ρ	Health in survival probability	3.58
ι	Weight of warm glow	112.72
κ	Elasticity of warm glow	18.35
Insurance		
h_{DIB}	Health threshold for DIB	0.58
ω	PHI premium	0.4

Notes: Model parameters estimated based on indirect inference. For age varying parameters we report the starting and ending values. Source: Indirect inference.

5. Model Fit

The model does quite well in matching the targeted moments. In particular, the model generates better health and longer life expectancy for college graduates relative to high school graduates. High school graduates enter the economy with a lower level of health than their more educated counterparts, and the gap does not narrow later in life. This is driven by two factors: (i) high school graduates invest less pecuniary and non-pecuniary resources in their health, and (ii) a lower level of health implies more severe health shocks in our model. The model does well in matching the life cycle profile of health for college types, but predicts a somewhat sharper decline in health at older ages for high school types than we see in the data (see Figure 10). Importantly, the model matches the life expectancy gap of 5.5 years at age 25.¹⁸

The model does a good job of matching aggregate healthcare spending over age and education, although it slightly over-predicts spending for college types and slightly under-predicts spending for high school types (see Figure 11). The rise in spending

18. The model also does a good job of matching the life expectancy gap later in life, 3.9 years in the model compared with 3.7 years in the data at age 50. The complete untargeted profiles for survival probabilities over age and education are plotted in the Appendix.

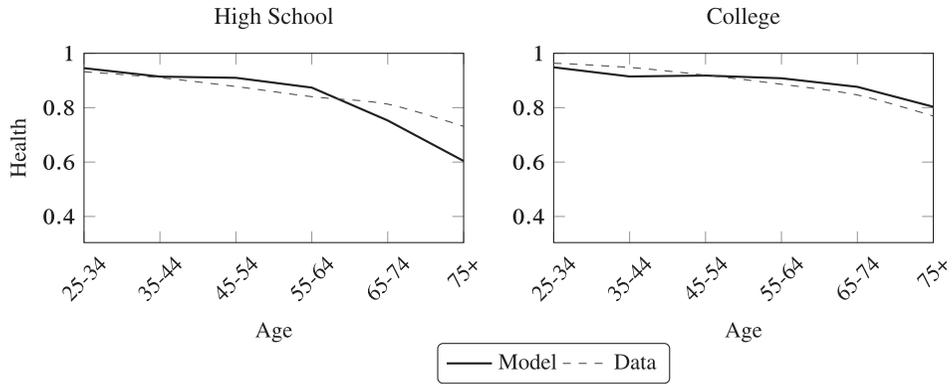


FIGURE 10. Health by education and age, model versus data. Health is measured by 1-frailty index and 1 corresponds to the best health and 0 to the worst (death). Source: MEPS (2000–2013) and simulation results.

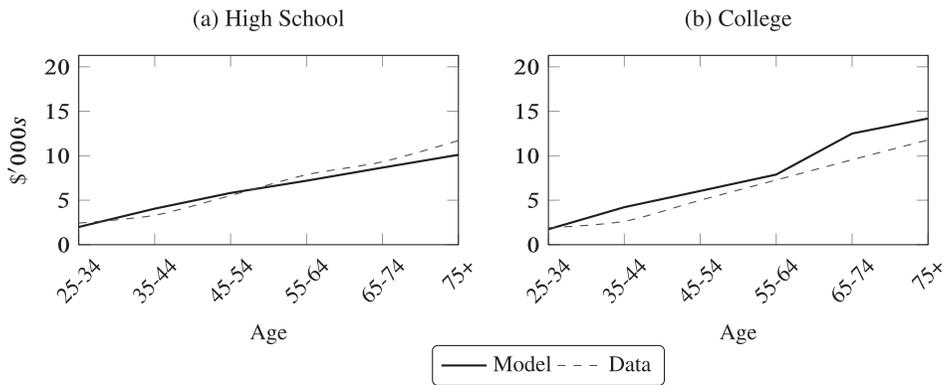


FIGURE 11. Total medical spending by education and age, model versus data. Source: MEPS (2000–2013) and simulation results by education and age.

over the life cycle is consistent with the increase in the magnitude of shocks with age. Recall that we assume that the effectiveness of health investments increases with age. This captures the fact that many preventive procedures are only reasonable after a certain age. The aggregate spending patterns for high school and college are very similar, but high school graduates spend more on curative and less on preventive than college graduates, given their lower health (see Figure 12). The model does well in matching the covariance between health shocks and health investments. The model also matches the age-profiles for the standard deviation of health, which we do not explicitly target (see Figure A.2 in the Appendix).

The model generates an assets to labor income ratio of roughly 2.3, which is somewhat low compared to the data. Introducing both preventive and curative medical expenditures lowers savings motives in our framework.

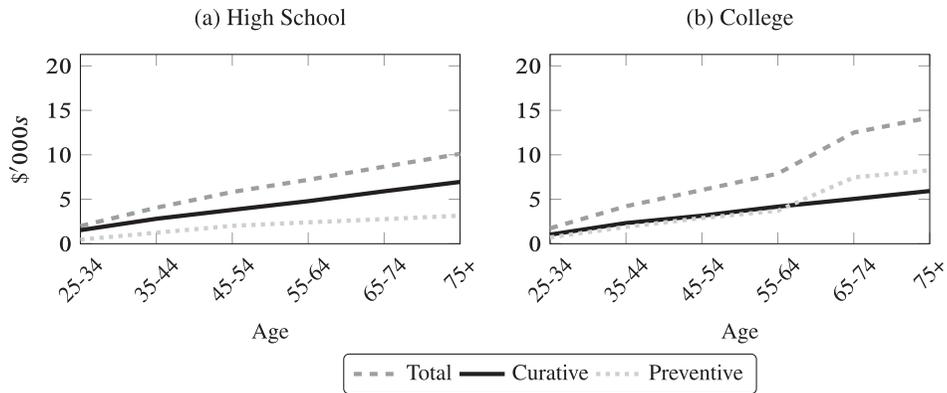


FIGURE 12. Model predicted total, curative and preventive medical spending by education and age. Source: Simulation results.

TABLE 9. Model fit.

	Model	Data
Life expectancy gap	5.51	5.50
Pecuniary ratio	1.03	1.06
PHI (HS)	0.21	0.14
PHI (College)	0.17	0.19
DIB at 61 (HS)	13.64	15.39
DIB at 61 (College)	0.00	7.83
LFP age 63 (HS)	58.83	53.84
LFP age 63 (College)	65.03	68.45
cov(z^h , m)	0.50	0.44

Notes: Data and model predicted moments for: (i) life expectancy gap, (ii) ratio of non-pecuniary investment for college relative to high school graduates, (iii) PHI by education, (iv) disability benefit claiming at age 61 by education, (v) employment at age 63 by education, and (vi) covariance between health shocks and health investments. Source: MEPS (2000–2013), ATUS (2003–2013), PSID (2000–2013), CDC (2000–2013), ACS (2000–2013) and simulation results.

The model does reasonably well in matching the ratio (college/high school) of time spent in health promoting activities, the average of PHI coverage by education, and the employment rates at age 63 over education. The model roughly matches the share of high school graduates claiming disability benefits at age 61, but struggles to generate disability benefit claiming among college graduates. This is summarized in Table 9.

5.1. Validation

Given that the responsiveness of agents to changes in income and the effective price of healthcare are at the heart of our analysis, a key test of the parameterization of the model is its ability to generate reasonable values for the income and price elasticities of healthcare spending. To compute the income elasticity of healthcare spending, we consider an exercise where incomes are increased by 10% across the board. The

income elasticity estimated from the model is 0.83, which is very close to the empirical estimates from the literature (see Acemoglu, Finkelstein, and Notowidigdo 2013). To compute the price elasticity of healthcare spending, we focus on the individuals who receive a GHI offer in a given period. The price elasticity of preventive health spending estimated from the model is -0.27 (recall that curative spending is exogenous although dependent on health), which is very similar to the Ringel et al. (2002) elasticity estimate for preventive care.

Further, we compute the value of statistical life (VSL) at age 50 for high school and college graduates. We estimate the VSL as the inverse of the marginal effect of preventive medical spending on the survival probability.¹⁹ For example, if reducing mortality at age 50 by one percentage point costs \$10,000, then saving a statistical life requires 100 people to make this investment, for a total cost of 1 million USD. Conversely, the monetary value of living an extra year is the VLS divided by life expectancy. Thus, the value of living an extra year for a 50-year old with a life expectancy of 30 years would be \$33,333. In our model, the VSL for high school and college graduates is \$7.42 and \$11.57 million, respectively. Our estimates lie within the range of estimates from the literature (see, e.g. Hall and Jones 2007 and Murphy and Topel 2006). The VSL of college graduates is substantially higher compared to high school graduates. This is driven by the higher pecuniary investments of college graduates, which result in the diminishing returns to health investment being more pronounced for this group.

6. Drivers of Health and Longevity Inequality

To study the determinants of health and longevity inequality and the potential for health insurance reform to mitigate said inequality, we consider a series of decomposition exercises. We focus on the role of five factors: (1) differences in access to healthcare, (2) differences in initial health, (3) differences in income, (4) differences in health shocks, and (5) differences in preferences for healthy time.

6.1. Differences in Health Insurance Coverage

In this sub-section, we study the effects of a Medicare-for-all type policy on health investments, health, life expectancy, and welfare. Our implementation of universal health insurance is one where the government covers a uniform fraction of total healthcare spending (73%, the same coinsurance rate as in the benchmark) and all agents pay the Medicare health insurance premium. The PHI market is eliminated. We assume that the reform is funded through a lump sum tax on workers, but also discuss the implications of a progressive funding mechanism. In the benchmark economy, there

19. Since the probability of survival is a function of health, we make use of the chain rule:

$$VLS = 1 / \frac{\partial P}{\partial h} \frac{\partial h}{\partial m} .$$

is a share of medical expenditures covered by GHI that is not paid by anyone in the model (firms implicitly pay for it). To facilitate a consistent comparison, we assume that firms implicitly continue to pay for the same amount of medical expenditure when we extend Medicare coverage to the whole population. We estimate the employer subsidy as the amount that would make GHI actuarially fair. This means that households do not need to cover the full cost of the Medicare expansion.²⁰

When health insurance becomes more accessible, the effective price of preventive medical spending goes down. Simultaneously, a Medicare-for-all type policy eliminates the uncertainty with respect to health insurance coverage and reduces the effective cost of curative medical spending. Universal health insurance can, therefore, reduce the incentives to invest in health in order to avoid the high curative costs associated with poor health. Furthermore, agents in our model have an additional margin for improving their health, namely non-pecuniary investment. Agents can substitute pecuniary investment for non-pecuniary investment due to the lower effective price of the former, or increase non-pecuniary investment if the expected level of consumption is higher due to lower medical expenditure shocks. *Ex ante*, the overall effects of a Medicare-for-all type policy are ambiguous, and we need a structural model to assess them.

We find that providing universal health insurance has a negligible effect on the longevity gap, with the gap narrowing by 0.26 years. The Medicare-for-all policy induces agents to increase their pecuniary investments in health, but not the time they spend in health promoting activities. Average time spent in health promoting activities is essentially unchanged for high school and slightly lower for college graduates relative to the benchmark (see Table B.1 in the Appendix for details). The low weight on pecuniary investment in the health production function tells us that increasing medical spending alone is not that effective in improving health. That said, clearly there is still an incentive for agents to increase pecuniary investment when it becomes cheaper, since the model predicts a clear increase in spending. So, when health insurance coverage is expanded, pecuniary investment increases. This has a positive effect on health. When health improves and life expectancy increases, the effective discount rate goes up and agents care more about the future. This in turn creates an incentive to also increase the non-pecuniary investment in health (this will be clearly visible in sub-section 6.3 where we consider the role of income differences). However, this effect is offset by the fact that agents worry less about high curative medical spending shocks when a larger share is covered by insurance. As a result, health and life expectancy improve only marginally relative to the benchmark.²¹ This is true for both high school and college. See Figure 13 for details.²²

20. The lump sum tax needed to keep the reform fiscally neutral is \$2,054.

21. Note also that reduced non-pecuniary investments when young are not fully compensated by equally sized investments later in life, since the pecuniary share is increasing over age and any reduction in health early in the life cycle has a compounding effect over time due to health shocks.

22. To gauge the importance of unequal access to healthcare in driving the health and longevity gradients, we could instead equalize the probabilities of getting a GHI offer over education. If we assume that high

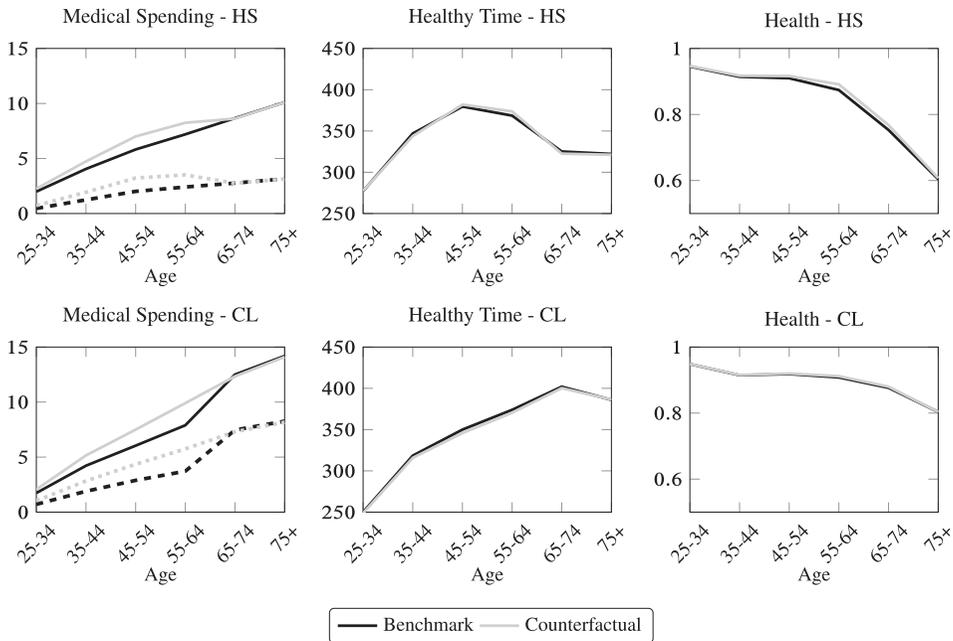


FIGURE 13. Results for Medicare expansion funded by lump sum tax. Benchmark and counterfactual results by age and education for (i) total (solid line) and preventive (dashed line) medical spending (\$'000), (ii) time spent in health promoting activities (hours), and (iii) health (1-frailty index). HS and CL denote high school and college graduates, respectively. Source: Simulation results.

If instead of introducing a lump sum tax on workers, we increase the progressivity of the income tax function to fund the reform, the Medicare expansion has essentially no effect on the longevity gap. Medical spending increases but healthy time declines slightly, leaving health essentially unchanged (see Figure 14).²³

Our results are consistent with the empirical work of Baicker et al. (2013) on the Oregon Medicaid expansion, which finds an increase in healthcare utilization but no positive health effects from the improved access to healthcare. Our framework highlights the importance of distinguishing between preventive and curative medical spending, as well as including non-pecuniary health investments in the model. It also offers a mechanism that can shed light on the findings from the empirical literature. Our results are also consistent with cross-country evidence, which documents comparable life expectancy gaps in countries with universal health insurance coverage, such as the U.K. (Bueren et al. 2018).

school graduates have the same probability of getting GHI as college graduates, the longevity gap narrows by 0.16 years.

23. Please see Appendix for a description of how the tax function is modified in the increased progressivity scenario.

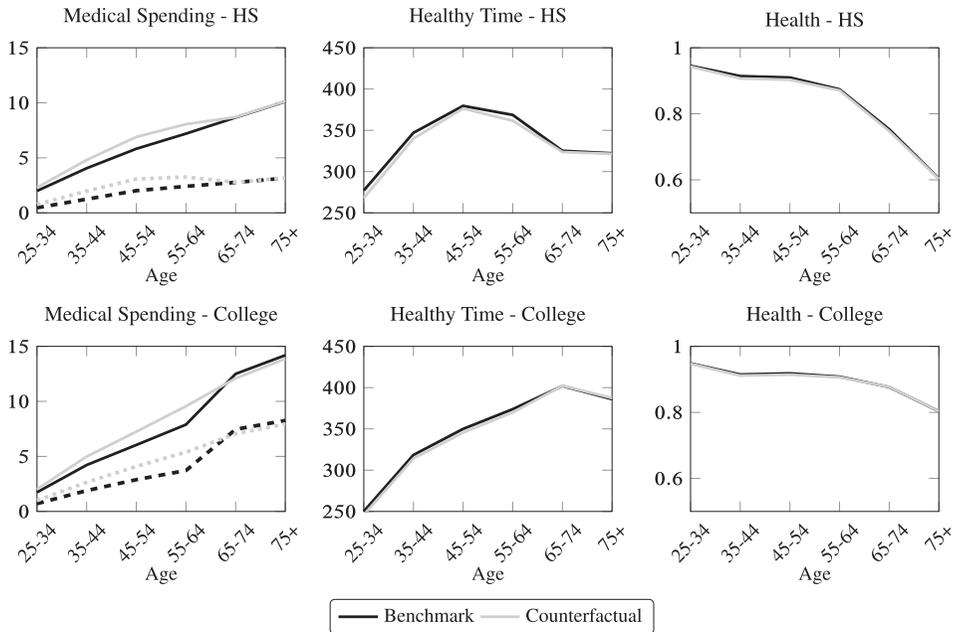


FIGURE 14. Results for Medicare expansion funded by increase in income tax progressivity. Benchmark and counterfactual results by age and education for (i) total (solid line) and preventive (dashed line) medical spending (\$'000), (ii) time spent in health promoting activities (hours), and (iii) health (1-frailty index). HS and CL denote high school and college graduates, respectively. Source: Simulation results.

When the Medicare-for-all policy is funded with the lump sum tax, it is associated with negative welfare gains for both high school and college types, with welfare declining by 3.9% for high school and 2.1% for college graduates. When the reform is funded through an increase in the progressivity of the income tax function, there is a small welfare gain of roughly 0.8% for high school graduates. The welfare of college graduates is reduced by approximately 5.5%. A large fraction of college graduates have GHI in the benchmark, and they face higher taxes under this reform scenario. The results are summarized in Table 10.

Our benchmark specification assumes a Cobb–Douglas production function for health, and thus a unitary elasticity of substitution between pecuniary and non-pecuniary investments. One might worry that our results are driven by this rather high degree of substitutability. We study the sensitivity of our results to lower degrees of substitutability by assuming a constant elasticity of substitution (CES) production function for health with different degrees of substitution. If we change the elasticity of substitution between pecuniary and non-pecuniary investments in the health production function without recalibrating the model, the fit to the data becomes very bad. Most notably, as we lower the elasticity, medical spending and the share purchasing PHI decline. Comparing the policy responses of two economies with vastly different patterns for medical spending and insurance coverage is problematic. We

TABLE 10. Life expectancy and welfare effects of Medicare expansion.

	Life expectancy	CEV
Lump sum tax		
High school	0.39	-3.94%
College	0.13	-2.13%
Tax progressivity		
High school	-0.03	0.76%
College	-0.07	-5.49%

Notes: Change in life expectancy (years) and welfare (%) from Medicare-for-all reform. Welfare measured in terms of compensating variation in consumption. Reform funded through lump sum tax on workers or increase in tax progressivity. Source: Simulation results.

therefore recalibrate the model to lower values of the elasticity parameter. The most notable differences in parameters between the recalibrated lower elasticity economies and the Cobb–Douglas unitary elasticity economy are the higher weight on health in the utility function and the lower effectiveness of health investments in the lower elasticity economies relative to the benchmark economy (please see Appendix for details). This, unfortunately, of course means that we are unable to isolate the effect of simply lowering the elasticity of substitution. Moreover, one should note that even when we recalibrate the model, there is some tension in matching all of the data moments when the elasticity is low. In particular, medical spending is too low relative to the data in the economies where we assume a low elasticity of substitution (please see Appendix for details). That said, we find that the results are robust to lowering the elasticity of substitution from the baseline of 1 to 0.5, or even 0.33. With our benchmark Cobb–Douglas and elasticity of 1, the model predicts a narrowing of the longevity gap of 0.26 years from the Medicare expansion funded by lump sum taxes. The corresponding narrowing of the gap is 0.21 years in the economy with an elasticity of 0.5 and 0.07 years in the economy with an elasticity of 0.33.

When conducting the Medicare-for-all policy exercise, we kept the effectiveness of health investments fixed at the benchmark value. It is conceivable that a drastic improvement in the access to affordable healthcare could improve the effectiveness of individuals' health investments through increased utilization of healthcare services. Disciplining such an effect is challenging and not something that we pursue here. It is also possible that the incentives to invest in education would change in the face of a large-scale reform, which decouples the linkages between employment and health insurance. However, given that the reform essentially does not impact the gaps in health and longevity, this does not appear to be a big concern. Throughout the paper, education is treated as exogenous. Endogenizing education is potentially interesting, but beyond the scope of this paper.

Given that our results suggest that unequal health insurance coverage is not an important factor in accounting for the gradients in health and longevity, it is of interest to ask what is. Next, we explore the role of differences in initial health, labor income, health shocks, and preferences in accounting for the inequality in life expectancy. The results are summarized in Table 11.

TABLE 11. Decomposing life expectancy gap.

	Gap
Initial health	-0.05
Labor income	-2.25
Health shocks	-1.89
Time preference	-2.13

Notes: Change in life expectancy gap between high school and college graduates (years) from counterfactuals.
Source: Simulation results.

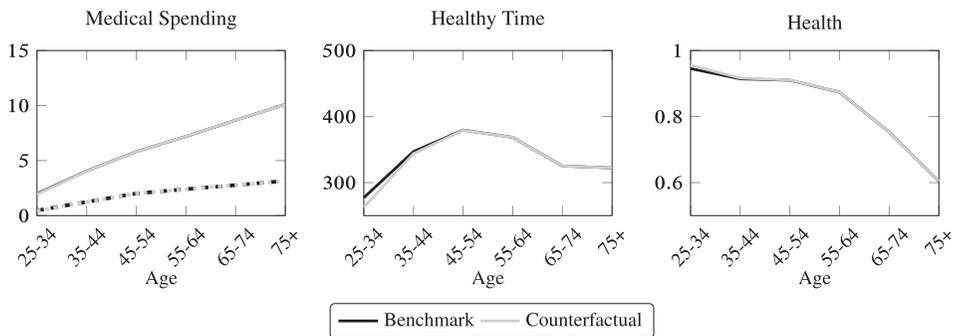


FIGURE 15. Eliminating differences in initial health over education. Total (solid line) and preventive (dashed line) medical spending (\$'000), time spent on health promoting activities (hours), and level of health (1-frailty index) of high school graduates when eliminating education differences in initial health. Source: Simulation results.

6.2. Differences in Initial Health

In the benchmark model, initial health varies with education. Here, we remove these differences by assuming that high school graduates draw their initial health, that is, their health at age 25, from the same distribution as college graduates. We find that this has only a negligible effect in our model, the life expectancy gap narrows by 0.05 years. The differences in health at age 25, as measured by the frailty index, simply are not that large. Moreover, the effect of better initial health is dampened by the fact that young high school graduates spend less time in health promoting activities when they have higher initial health; see Figure 15.

One should bear in mind that in this exercise, we do not claim to be shutting down differences in early life conditions, simply the ones that have been realized by age 25. In our framework, differences in health shocks over education proxy for the effect of early childhood conditions that manifest later. It is also noteworthy that the frailty index understates the differences in initial health relative to a self-assessed measure of health. However, the frailty index has the advantage of being a continuous, objective measure of health, as opposed a discrete, self-reported, subjective measure of health.

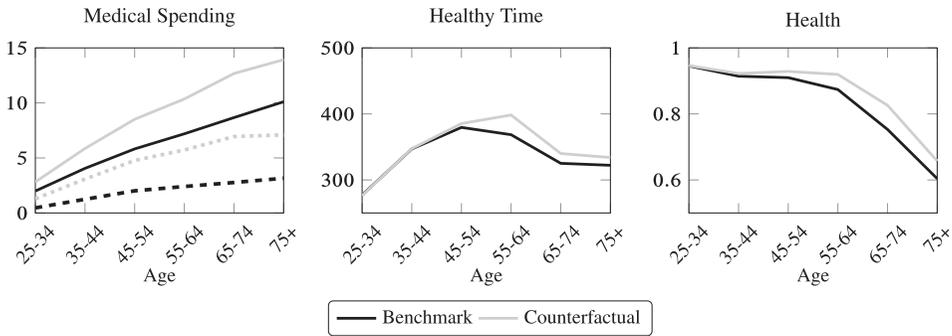


FIGURE 16. Eliminating differences in labor income over education. Total (solid line) and preventive (dashed line) medical spending (\$'000), time spent on health promoting activities (hours), and level of health (1-frailty index) of high school graduates when eliminating education wage premium. Source: Simulation results.

6.3. Differences in Income

High school graduates have substantially lower labor income than college graduates in the benchmark economy. To assess the effect of this differential, we compute the ratio of average lifetime labor income for college relative to high school types and multiply the labor income of high school types by this factor. Note that labor incomes are still not equalized, since health impacts productivity differentially over education. The large increase in income has a positive effect on health investments, which in turn translates into positive effects for health and life expectancy (see Figure 16). Unsurprisingly, agents increase pecuniary investments in health, when they have more resources to do so. Moreover, agents also increase non-pecuniary investments in health. Since life expectancy is endogenous, agents invest in their health in order to increase the number of periods that they derive utility from. As health improves and life expectancy increases, the effective discount rate goes up and agents care more about the future. This in turn creates an incentive to invest in health, re-enforcing the mechanism.²⁴ The effect of labor income on the longevity gap is large, with the gap shrinking by almost 2.3 years in this exercise.

6.4. Differences in Health Shocks

The health shocks in the benchmark model are dependent on age, education, and health. For a given age and health, less educated individuals face larger shocks relative to their more educated counterparts. As noted previously, this can be thought to proxy for differences in negative health behaviors and differences in the effectiveness of health

24. The effect of income on consumption and health investment in models with endogenous life expectancy has been studied extensively in the literature, see, for example, Zhao (2014) and Halliday et al. (2019).

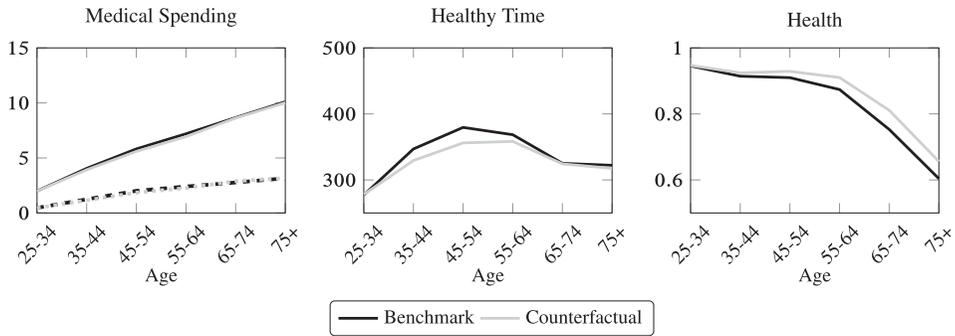


FIGURE 17. Eliminating differences in health shocks over education. Total (solid line) and preventive (dashed line) medical spending (\$'000), time spent on health promoting activities (hours), and level of health (1-frailty index) of high school graduates when eliminating education differences in health shocks. Source: Simulation results.

investments. Here, we eliminate the education difference in health shocks by assuming that, conditional on age and health, high school graduates face the same health shocks as college graduates in the benchmark economy. This has a sizable positive impact on the health and longevity of high school graduates, despite the fact that time spent in health promoting activities declines (preventive and curative medical spending also decline slightly). See Figure 17 for details. The longevity gap shrinks by roughly 1.9 years.

6.5. Differences in Disutility from Time Spent in Health Promoting Activities

In the benchmark parameterization, high school types derive greater disutility from spending time in health promoting activities than their more educated counterparts. Here, we consider the effect of eliminating the differences in disutility from healthy time. Intuitively, lowering the disutility from healthy time leads high school graduates to spend more time on health promoting activities (see Figure 18). This has a large positive effect on health and life expectancy, with the longevity gap shrinking by roughly 2.1 years. Aside from true differences in preferences, this could also be thought to reflect a lesser understanding of the health benefits of these activities.

7. Conclusions

The education gradients in health and life expectancy in the U.S. are striking. In this paper, we study the sources of these inequalities and the potential role for healthcare policy in mitigating them. To rationalize the gradients in health and longevity, we develop a structural life cycle model where heterogeneous agents make decisions with respect to pecuniary and non-pecuniary health investments.

We find that providing universal health insurance coverage has a negligible impact on the longevity gap. This is due to the fact that, although pecuniary investments in

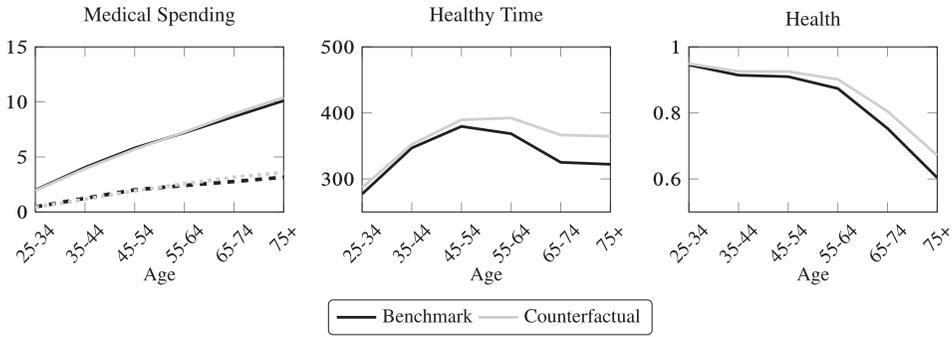


FIGURE 18. Eliminating differences in preferences for healthy time over education. Total (solid line) and preventive (dashed line) medical spending (\$'000), time spent on health promoting activities (hours), and level of health (1-frailty index) of high school graduates when eliminating education differences in preferences for healthy time. Source: Simulation results.

health increase, non-pecuniary investments do not. The underlying intuition is that agents are less worried about high curative medical expenditures, when a larger share of them is covered by insurance. Our results suggest that differences in lifetime income, preferences and shocks to health are the key drivers of the life expectancy gradient.

This paper is an important step in understanding the driving forces behind health and life expectancy inequality and how government policies can affect said inequality. However, there are factors that are not considered in this paper and warrant further research. For example, we do not study the effects of universal public health insurance coverage on the private insurance market and the cost of medical treatment.

Appendix A: Validation

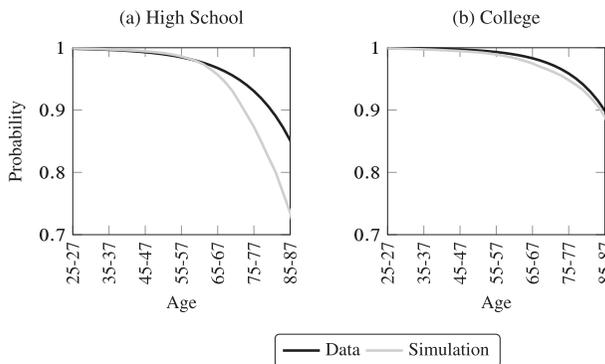


FIGURE A.1. Probability of survival by age and education. Source: Simulation results, CDC, and ACS (2000–2013).

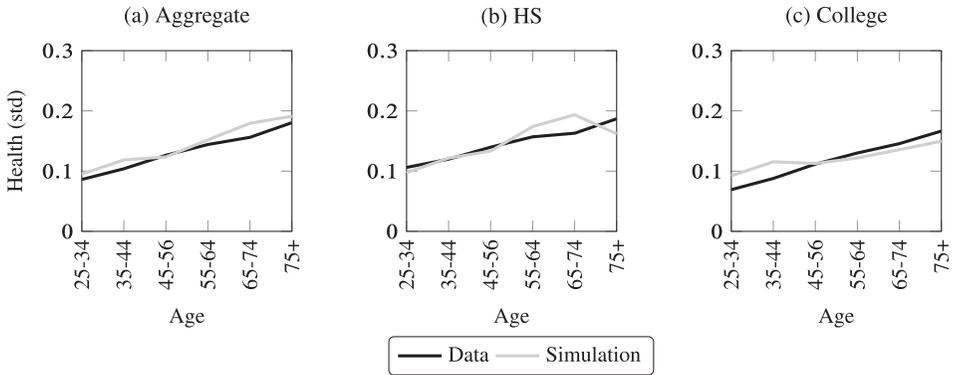


FIGURE A.2. Standard deviation of health by age and education. Source: Simulation results and MEPS (2000–2013).

Appendix B: Policy Analysis

B.1. Progressive Tax Function

Recall that we use the progressive income tax function from Guner, Kaygusuz, and Ventura (2014):

$$\tau(y_j) = 1 - \tau_0 y_j^\varphi, \tag{B.1}$$

where the tax is a function of the agent’s income, expressed in multiples of the agents’ mean income y_j , and τ_0 controls the scale and φ the degree of progressivity of the tax function. We adjust both τ_0 and φ in order to balance the government budget by increasing the progressivity of the tax schedule without reducing the income tax level of low income individuals. Adjusting only φ tilts the tax schedule, resulting in higher tax rates for individuals with above average income and substantially lower ones for

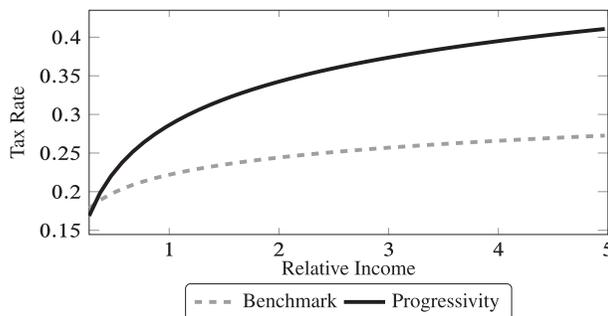


FIGURE B.1. Tax rate adjustment. Income tax schedule when Medicare expansion financed through increase in income tax progressivity. Source: Benchmark tax function from Guner, Kaygusuz, and Ventura (2014), updated tax schedule based on simulation results.

individuals with below average income. This would make our results hard to interpret. To circumvent this issue, we adjust the tax schedule by estimating the ε that balances the government budget in $1 - (\tau_0 + \varepsilon)y_j^{\varphi + \varepsilon}$. The income tax schedule becomes more progressive, yet the reduction in the income tax rate for low income individuals is negligible.

B.2. Time Spent in Health Promoting Activities

TABLE B.1. Healthy time use relative to benchmark.

	High school	College
Lump sum tax	1.02	0.92
Tax progressivity	0.98	0.99
Initial health	1.0	1.00
Preferences	1.06	1.00
Labor income	1.03	1.00
Health shocks	0.97	1.00

Notes: Average healthy time investment by education relative to benchmark across decompositions. Source: Simulation results.

Appendix C: Sensitivity

To study the sensitivity of our main result to the unitary elasticity health production function, we recalibrate the model to a CES health production function with elasticities of 0.5 and 0.33, respectively, and re-run the Medicare-for-all policy exercise.

C.1. CES Elasticity of 0.5

TABLE C.1. Estimated parameters—CES elasticity of 0.5.

Parameter	Description	Value
Health production function		
Q_1	Productivity scale age 25	0.67
Q_{38}	Productivity scale age 101	1.88
ψ_1	Share of pecuniary investments age 25	0.01
ψ_{38}	Share of pecuniary investments age 101	0.07
h_{scale}	Health shock scale	1.03
Utility		
π_h	Constant	24.52
v_0	Consumption utility	11.45
$v_{1,1}$	Labor disutility HS	52.3
$v_{1,2}$	Labor disutility C	24.65
$v_{2,1}$	Time invest. disutility HS	2194.53
$v_{2,2}$	Time invest. disutility C	1895.16

TABLE C.1. Continued

Parameter	Description	Value
v_3	Health utility	25.23
ρ	Health in survival probability	3.68
l	Weight of warm glow	117.28
κ	Elasticity of warm glow	17.88
Insurance		
h_{DIB}	Health threshold for DIB	0.59
ω	PHI premium	0.4

Notes: Model parameters estimated based on indirect inference. For age varying parameters we report the starting and ending values. Source: Indirect inference.

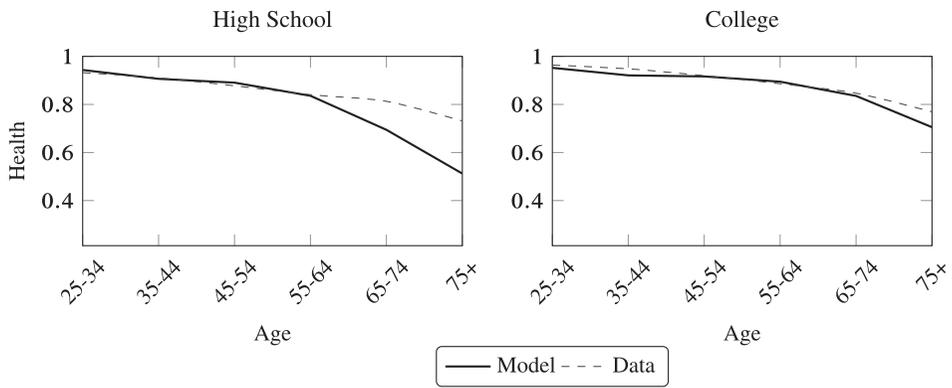


FIGURE C.1. Health by education and age, model versus data—CES elasticity of 0.5. Health is measured by 1-frailty index and 1 corresponds to the best health and 0 to the worst (death). Source: MEPS (2000–2013) and simulation results.

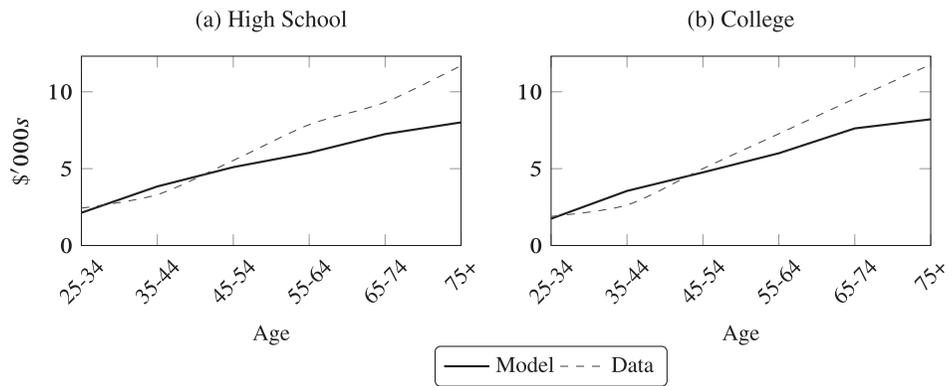


FIGURE C.2. Total medical spending by education and age, model versus data—CES elasticity of 0.5. Source: MEPS (2000–2013) and simulation results.

TABLE C.2. Model fit—CES elasticity of 0.5.

	Model	Data
Life expectancy gap	5.46	5.50
Pecuniary ratio	1.06	1.06
PHI (HS)	0.20	0.14
PHI (College)	0.16	0.19
DIB at 61 (HS)	17.14	15.39
DIB at 61 (College)	0.00	7.83
LFP age 63 (HS)	50.02	53.84
LFP age 63 (College)	62.72	68.45
cov(z^h , m)	0.42	0.44

Notes: Data and model predicted moments for: (i) life expectancy gap, (ii) ratio of non-pecuniary investment for college relative to high school graduates, (iii) PHI by education, (iv) disability benefit claiming at age 61 by education, (v) employment at age 63 by education, and (vi) covariance between health shocks and health investments. Source: MEPS (2000–2013), ATUS (2003–2013), PSID (2000–2013), CDC (2000–2013), ACS (2000–2013) and simulation results.

TABLE C.3. Medicare for all—life expectancy change (CES with elasticity of 0.5).

	High school	College	Gap
Progressivity	−0.09	−0.03	0.06
Lump sum	0.22	0.01	−0.21

Notes: The table reports the change in life expectancy for high school and college graduates relative to the benchmark. Source: Simulation Results

C.2. CES Elasticity of 0.33

TABLE C.4. Estimated parameters—CES elasticity of 0.33.

Parameter	Description	Value
Health production function		
Q_1	Productivity scale age 25	0.58
Q_{38}	Productivity scale age 101	1.56
ψ_1	Share of pecuniary investments age 25	0.01
ψ_{38}	Share of pecuniary investments age 101	0.08
h_{scale}	Health shock scale	1.03
Utility		
π_h	Constant	28.09
ν_0	Consumption utility	11.03
$\nu_{1,1}$	Labor disutility HS	51.49
$\nu_{1,2}$	Labor disutility C	24.02
$\nu_{2,1}$	Time invest. disutility HS	1885.28
$\nu_{2,2}$	Time invest. disutility C	1589.96
ν_3	Health utility	35.81

TABLE C.4. Continued

Parameter	Description	Value
ρ	Health in survival probability	3.62
ι	Weight of warm glow	118.72
κ	Elasticity of warm glow	17.63
Insurance		
h_{DIB}	Health threshold for DIB	0.65
ω	PHI premium	0.4

Notes: Model parameters estimated based on indirect inference. For age varying parameters we report the starting and ending values. Source: Indirect inference.

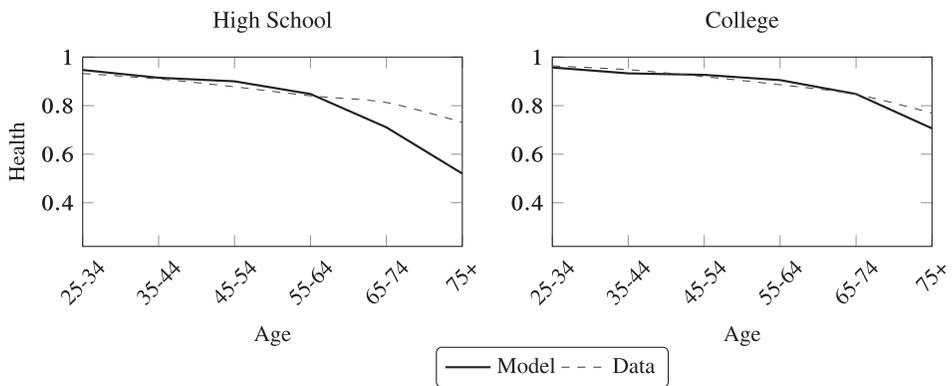


FIGURE C.3. Health by education and age, model versus data—CES elasticity of 0.33. Health is measured by 1-frailty index and 1 corresponds to the best health and 0 to the worst (death). Source: MEPS (2000–2013) and simulation results.

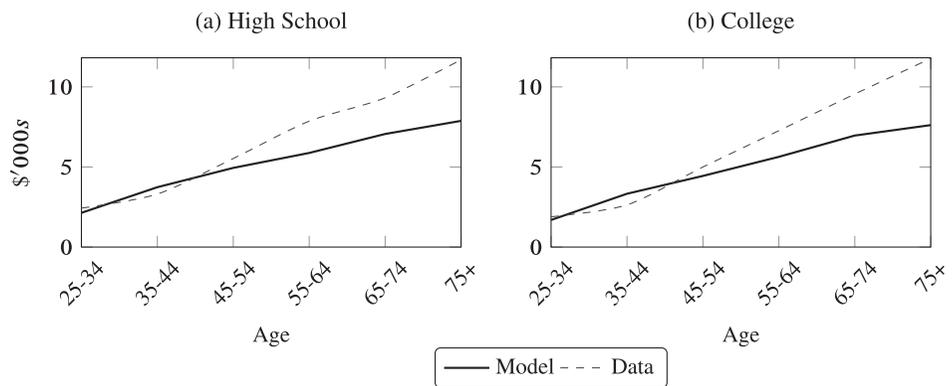


FIGURE C.4. Total medical spending by education and age, model versus data—CES elasticity of 0.33. Source: MEPS (2000–2013) and simulation results.

TABLE C.5. Model fit—CES elasticity of 0.33.

	Model	Data
Life expectancy gap	5.13	5.50
Pecuniary ratio	1.06	1.06
PHI (HS)	0.18	0.14
PHI (College)	0.16	0.19
DIB at 61 (HS)	15.57	15.39
DIB at 61 (College)	0.00	7.83
LFP age 63 (HS)	53.1	53.84
LFP age 63 (College)	63.28	68.45
cov(z^h , m)	0.42	0.44

Notes: Data and model predicted moments for: (i) life expectancy gap, (ii) ratio of non-pecuniary investment for college relative to high school graduates, (iii) PHI by education, (iv) disability benefit claiming at age 61 by education, (v) employment at age 63 by education, and (vi) covariance between health shocks and health investments. Source: MEPS (2000–2013), ATUS (2003–2013), PSID (2000–2013), CDC (2000–2013), ACS (2000–2013) and simulation results.

TABLE C.6. Medicare for all—Life expectancy change (CES with elasticity of 0.33).

	High school	College	Gap
Progressivity	−0.13	−0.05	0.08
Lump sum	0.07	−0.00	−0.07

Notes: The table reports the change in life expectancy for high school and college graduates relative to the benchmark. Source: Simulation results

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Supplementary data

Supplementary data are available at [JEEA](#) online.