Lifestyle Behaviors and Wealth-Health Gaps in Germany*

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Abstract

We document significant gaps in wealth across health status over the life cycle in Germany—a country with a universal healthcare system and negligible out-of-pocket medical expenses. To investigate the underlying sources of these wealth-health gaps, we build a heterogeneous-agent life-cycle model in which health and wealth evolve endogenously. In the model, agents exert efforts to lead a healthy lifestyle, which helps maintain good health status in the future. Effort choices, or lifestyle behaviors, are subject to adjustment costs to capture their habitual nature in the data. We find that our estimated model generates the great majority of the empirical wealth gaps by health and quantify the role of earnings and savings channels through which health affects these gaps. We show that variations in individual health efforts account for around a quarter of the model-generated wealth gaps by health, illustrating their role as an amplification mechanism behind the gaps.

Keywords: Health Inequality, Wealth Inequality, Healthy Lifestyle, Germany

JEL codes: E2, D3, I1

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1. Introduction

A large body of literature across economics, sociology, and public health demonstrates strong positive associations between financial and health status at the individual level. For example, De Nardi et al. (2023) document substantial differences in wealth over the life cycle in the United States between men with a high school degree who report being in good health and those in poor health. In this paper, we show that large gaps in wealth by health exist in Germany as well. These gaps appear not only within the nationally representative sample but also within education groups. The gaps begin to open up at around the age of 25 and grow over the life cycle before stabilizing after retirement. For example, median wealth among *healthy* 60-64-year-olds (100,000 EUR) amounts to more than three times that of *unhealthy* individuals in the same age group (31,000 EUR).

What explains such large gaps in a country like Germany, characterized by universal health insurance, low out-of-pocket medical expenses, and generous sickness benefits (OECD, 2019)? Existing studies on the positive relationship between health and wealth have tended to focus on the U.S., highlighting the role of large out-of-pocket medical expenditures and unequal access to health insurance (e.g. De Nardi et al. (2010)), or the unilateral effect of health on labor supply and productivity coupled with the availability of disability insurance (Hosseini et al., 2021).[1] In this paper, we employ a structural framework in which individuals' wealth and health evolve endogenously over the life cycle to investigate lifestyle behaviors as potential drivers of these observed wealth-health gaps.

Our model explicitly allows the possibility of individuals influencing their health evolution through their health-related lifestyle behaviors (Cawley and Ruhm, 2011; Cole et al., 2019) in an otherwise standard heterogeneous-agent life-cycle framework. We include these endogenous health behaviors given that in Germany, as in most developed countries, morbidity and mortality are predominantly attributed to individuals' behavioral risk factors, including dietary risks, smoking, and physical inactivity (Darden et al., 2018; Kvasnicka et al., 2018; OECD, 2019). Furthermore, behavioral health risks tend to be more common among people of low socio-economic status, with evidence suggesting that divergences in health behaviors have accelerated in recent years (Lampert et al., 2018). It has thus become ever more important to understand the consequences of healthy lifestyles not only for health inequality, but also for wealth inequality. Our quantitative theoretical framework allows to shed greater light on these empirical observations on health and wealth inequality.

[1] For a comprehensive review of the potential mechanisms underlying the positive relationship between health and socio-economic status more generally, see, for example, Cutler et al. (2011).

In the model, individual health efforts increase the probability of being healthy in the future. Good health, in turn, raises survival probability, affects labor income through productivity and the disutility of working, and complements utility from consumption. These channels influence economic resources through labor supply choices and affect savings decisions, both of which shape wealth and health inequality. As a higher fraction of individuals maintain the same lifestyle behaviors over time in the data, in our model health effort adjustment is subject to stochastic adjustment costs. This allows us to capture healthy (e.g., physical exercise) and unhealthy (e.g., smoking) lifestyle habits. Agents differ along several fixed dimensions including education, discount factor, productivity type, and health type. We include such ex-ante heterogeneity to account for additional forces driving the life cycle evolution of health and wealth.

We estimate our model using the method of simulated moments and information from the German Socio-Economic Panel. Our estimated model is consistent with a number of salient features in the data. For example, the model-generated data align with the observed joint evolution of labor supply and earnings by health and education over age, and match the empirical age pattern of average health effort choices by education. Furthermore, the model replicates the degree of wealth accumulation as well as wealth and income inequality seen in Germany. It also reproduces more detailed aspects of effort choices, such as its dispersion, persistence over time and the share of individuals making large positive and negative adjustments or no adjustments.

We find that the estimated model accounts for between 75% to 100% of the observed wealth-health gaps in the data, depending at which point of the distribution and which age this is measured. In contrast, an estimated model with comparable richness in heterogeneity but without lifestyle behaviors and thus purely exogenous health transitions explains less than two thirds of the empirical gaps, highlighting our baseline model's ability to rationalize observed wealth-health gaps. We then investigate two channels behind the wealth-health gaps that work primarily from health to wealth. On the one hand, good health outcomes are associated with higher labor earnings, as a result of both higher labor supply and higher productivity. This translates into larger wealth. On the other hand, good health outcomes also affect the incentives to accumulate wealth because of higher expected longevity and improved quality of life in the future. Having illustrated these channels using a conceptual, simple two-period model, we conduct counterfactual exercises using our estimated life-cycle model to quantify their relative importance. We find that the second channel working through savings contributes quantitatively most to the wealth-health relationship, accounting for, on average around 50% of the gap. The other channel that works through earnings is particularly relevant for the young and asset-poor agents for whom earnings provide the main basis for wealth accumulation.

Finally, motivated by our empirical evidence suggesting the potential role of lifestyle behaviors as a dynamic amplification vehicle which fuels the wealth-health gaps, we run another counterfactual experiment that quantifies the extent to which heterogeneity in lifestyle behaviors accounts for the wealth-health gaps. We find that eliminating variations in individual lifestyle behaviors reduces the wealth-health gaps by between 12% and 29%, as compared to the baseline model economy. This significant effect demonstrates the role of lifestyle behaviors that operate in the direction from wealth to health: wealthier individuals engage in more health-promoting efforts, which dynamically feeds back into better health in the presence of the earnings and savings channels. We further demonstrate, both theoretically and quantitatively, that the anticipation of future utility resulting for example from exogenous changes in wealth could prompt agents to modify current lifestyle behaviors, thereby influencing the health distribution and the wealth-health gaps.

Our paper primarily intersects with a growing literature that augments structural life-cycle models with idiosyncratic health risk to study the aggregate and distributional economic effects of health and health-related policies. Much early research in this direction has focused on the influence of health and mortality risk on the labor supply and savings of people around retirement age (French, 2005; French and Jones, 2011; De Nardi et al., 2010; Kopecky and Koreshkova, 2014). More recent studies analyze rising health care expenditures and explore specific questions regarding the implementation and economic consequences of health care programs in the U.S.[2] Capatina (2015) and De Nardi et al. (2023) endeavor to quantify the accumulated, life-time consequences of health, and calibrate their models to U.S. data. While Capatina (2015) highlights the importance of the productivity and time endowment channels that influence labor supply and precautionary savings, De Nardi et al. (2023) find that a substantial degree of ex-ante heterogeneity and a rich health process are required to be able to match the observed wealth-health gradient in the U.S. Building on their work, we empirically document and study inequality in health and wealth in the case of Germany. Notably, while De Nardi et al. (2023) study the interaction between wealth and health in an exogenous health framework, we study

[2] See e.g., Hall and Jones (2007); Attanasio et al. (2010); Kitao (2014); Zhao (2014); Jung and Tran (2016); Pashchenko and Porapakkarm (2017); Jang (2023). Much work has also been devoted to understanding the dynamics of the insurance incentive trade-offs associated with health or disability insurance, again with a focus on the U.S., see e.g. Low and Pistaferri (2015); Cole et al. (2019).

this in a model with endogenous health.

In this regard, our paper is closely related to several studies that endogenize health through some form of individuals' effort choices in a structural framework. We build, for example, on Cole et al. (2019), who similarly construct a model with endogenous effort choices but focus on a very different research question; namely, the interaction between labor market and health insurance policies. In addition to this work, a number of recent studies, including Capatina et al. (2020), Hai and Heckman (2022), and Margaris and Wallenius (2023), highlight the interaction between health and human capital accumulation and the role of the latter in explaining observed socio-economic gradients in health. We follow these insights by including two education groups in our analysis. We focus, however on the relation between health and wealth, rather than earnings, as wealth provides a more comprehensive assessment of the accumulated costs of poor health.

The aforementioned literature tends to look at the U.S., and often finds that health insurance is a crucial mechanism that amplifies the two-way relationship between health and earnings along the income distribution. For example, several studies, including Prados (2018), Chen et al. (2022), and Ozkan (2017), use structural models for policy counterfactual experiments and conclude that a switch to more universal health care coverage could substantially lower health-related income inequality.

Given this, Germany offers a particularly interesting case for studying the wealth-health relationship. Most notably, it is compulsory by law for all citizens and residents to have health insurance in Germany.[3] The country moreover mandates health insurance providers to cover a relatively generous package of benefits compared to international standards. In general, Germany reports low levels of self-reported unmet medical needs and low out-of-pocket medical expenses relative to its European neighbors (OECD, 2019).[4] Despite these, we document that gaps in health-related outcomes between members of low and higher socio-economic groups are sizeable in Germany. In examining a novel mechanism—lifestyle behaviors—our study thus offers complementary findings to a literature that has largely focused on mechanisms such as health insurance and medical expenses to explain wealth-health gaps.

Finally, our paper also relates to the voluminous empirical literature studying the relationship between socio-economic status and health. A survey and summary of the main empirical findings of this literature is provided in Cutler et al. (2011). We contribute to this body of work by providing an update on the state of health-related inequalities in Germany. In doing so, we complement other studies using this same

[3]See Appendix A.1 for a detailed discussion of the German healthcare system.

[4]The German healthcare system is also characterized by the highest per capita spending among EU countries and some of the highest rates of available beds, doctors, and nurses per population.

data set, such as Lampert et al. (2018), who employ the latter to compare the socioeconomic-health gradient in Germany to other countries and across time.

The remainder of the paper is organized as follows. Section 2 sets forth a number of empirical observations related to wealth, health, and lifestyle behaviors that guide the development of our structural model. We then present the model economy in Section 3 and describe its estimation in Section 4. Section 5 provides and discusses the main quantitative results. Section 6 concludes.

2. Empirical Observations on Health, Lifestyle Behaviors, and Wealth in Germany

Throughout this paper, we rely on data from the German Socio-Economic Panel (SOEP). The SOEP is an annual representative longitudinal panel study of private households, conducted by the German Institute for Economic Research, DIW Berlin. We use information from the 2004-2018 survey waves. We convert nominal variables into 2015 Euros using a CPI index for inflation adjustment.

2.1. Health and Lifestyle Behaviors

Health Status

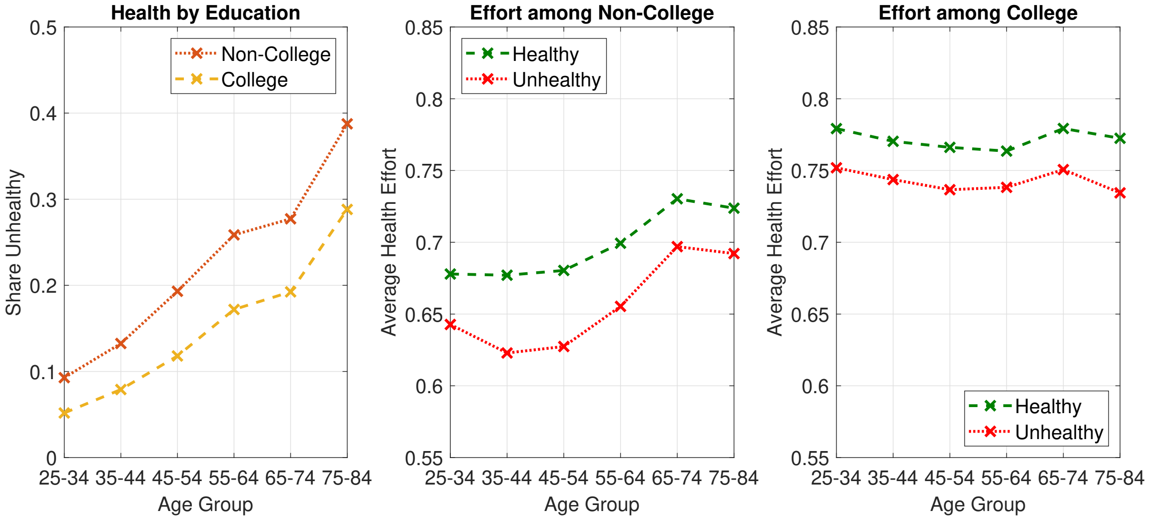
We measure individual health using information on self-rated health status in the SOEP.[5] In every survey wave, respondents are asked "How would you rank your current health?" to which respondents can answer *Very good, good, satisfactory, less well, or poor*. Consistent with much of the literature (De Nardi et al., 2023; French, 2005), we combine the first three categories into one *healthy* category and the last two into one *unhealthy* category.[6]

The left panel of Figure 1 shows the average share of unhealthy individuals by 10-year age groups, starting at ages 25-34 and ending with ages 75-84. We also

[5]In select survey waves, the SOEP also contains more objective health measures, such as a series of concrete diagnoses. We use this information to construct an index of *frailty*, similar to that in Hosseini et al. (2022), by adding one to the index each time an individual is diagnosed with a specific health condition. Moreover, since 2002, the SOEP includes questions that allow to construct generic indicators of perceived physical and mental health, called Physical and Mental Component Summary scores (PCS and MCS, respectively). In Appendix A.2, we check the correlation of our benchmark binary health measure and these two alternatives. We focus on the self-reported health status measure because this maximizes the amount of data available for our empirical analysis, given that most of the more detailed questions about health deficits only started to be asked in 2011.

[6]This procedure could mitigate potential issues related to measurement errors and also reduces computational burden when we estimate our quantitative model presented in Section 3.

Figure 1: Average Health and Health Effort over the Life Cycle by Education



Notes: Left: Share of unhealthy people in the SOEP over 10-year age groups, distinguishing between the non-college-education and college-education groups. Center and Right: Average health effort by 10-year age groups for non-college (center) and college-educated (right) individuals in the SOEP, distinguished between unhealthy status and healthy status.

distinguish between individuals according to their education level, where those in the college group have obtained a college degree, and those in the non-college group have not. Already at ages 25-34, members of the non-college education group are around 2 percentage points more likely to be unhealthy than the college-educated. This gap grows over the life course. At ages 75 and older, around 40% of non-college educated individuals are in poor health compared to around 30% of the college-educated.

Lifestyle Behaviors

We measure *lifestyle behaviors* by individual *health efforts*—a composite measure of three individual behaviors for which we have information. These behaviors include: (i) the frequency of sport or physical exercise; (ii) health-conscious nutrition; and (iii) the daily number of cigarettes smoked. In Germany, as in most developed countries, physical inactivity, smoking, and poor diet are recognized as the most important contributors to individual health risk (OECD, 2019). We first standardize each component so that they have mean zero and standard deviation one (Kling et al., 2007). We then construct health effort as a weighted sum of these, which we normalize to be in the unit interval.[7] Overall, individual health effort observations have a mean of around 0.71 and a standard deviation of 0.16. Moreover, we observe

[7]The weights are taken from the relative loadings of each behavior on the first principal component of all behaviors, after stripping them of variation coming from observable characteristics. Details are explained in Appendix A.3.

substantial path dependence in health efforts. For example, the autocorrelation of health efforts in a two-year interval is high at 0.76.

Figure 1 compares the average health effort levels for the non-college (central panel) and the college-educated (right panel), separately for unhealthy and healthy individuals. Three patterns are worth noting. First, the life-cycle patterns for each group are relatively flat.[8] Second, there are large and persistent differences in average health effort across education groups. College-educated individuals are characterized by health efforts that are, on average, around half a standard deviation higher than those non-college-educated individuals. Third, conditional on education, unhealthy individuals consistently exert less health effort on average, than healthy ones. Unhealthy individuals could experience physical and mental difficulties exerting efforts (contributing to a higher health gap). At the same time, they could also have a greater incentive to exert more efforts to recover health (Verdun, 2022). These two countervailing forces could explain the relatively small yet still significant observed differences across health status (around 1/4 of a standard deviation).

2.2. The Relationship between Health and Wealth

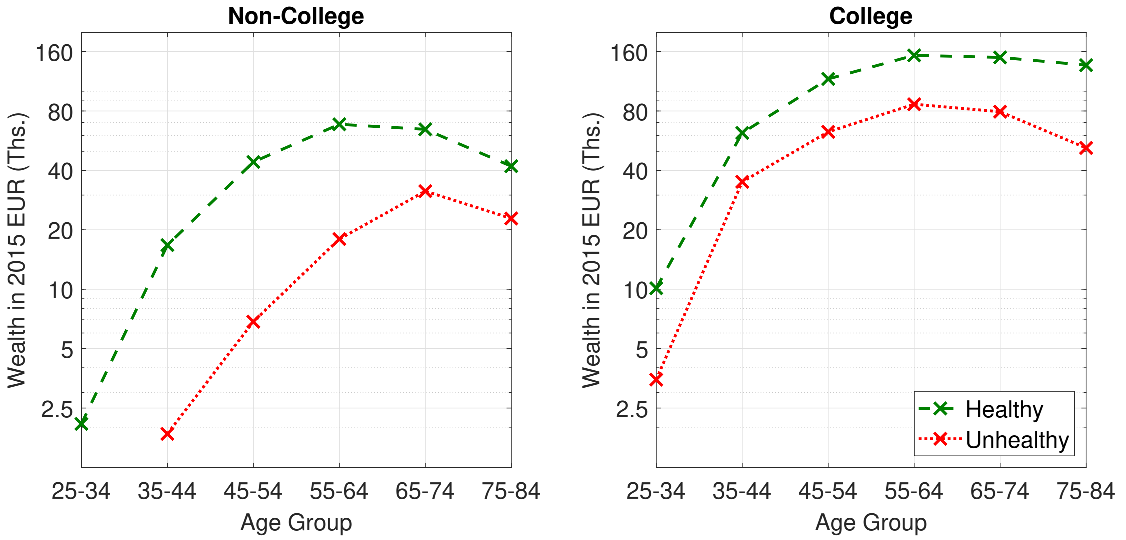
Germany is no different from many countries in the strong association we observe between financial well-being and health-related well-being. To illustrate, Figure 2 shows the evolution of median wealth over the life cycle, separately for healthy and unhealthy individuals in each education group (non-college and college). Wealth is measured as net worth, as is standard in the literature. It includes information on owner-occupied housing and other properties (net of mortgage debt), financial and business assets, tangible assets, private pensions (including life insurance) and consumer credits (Frick et al., 2007).[9] Wealth levels are plotted on a log/ratio scale, such that equal spaced points go up by a factor of 2.

For both education groups, the wealth levels of the healthy are consistently higher than those of the unhealthy. This *wealth-health gap* is already present early on in life. The percentage gap is generally higher among non-college educated individuals than among college educated ones. In both groups, the percentage gap is relative

[8]This does not preclude significant age-trends in lifestyle behaviors. For instance, while sport and exercise frequencies seem to decrease over age, healthy nutrition and abstention from smoking increase (see Figure A.3).

[9]It does not include information on pension entitlements through both company pensions and the statutory German social pension fund as well as the pension entitlements for civil servants. Contrary to widely used surveys in other countries such as the Panel Study of Income Dynamics, the SOEP provides information on wealth at the individual level. This is achieved by asking the respondents for their personal share of ownership regarding each of the above components of wealth. In our analysis, we use an average of individual wealth across different imputation techniques.

Figure 2: Median Wealth Profiles of Healthy and Unhealthy Individuals by Education



Notes: Median wealth by 10-year age-groups and health status for non-college-educated (left panel) and college-educated (right panel) individuals in the SOEP, plotted on a log/ratio scale.

constant throughout the working years. It decreases slightly after retirement among the non-college educated whereas it increases slightly among the college educated. The existence of these significant wealth-health gaps in both education groups indicates that the association between wealth and health cannot be explained solely by education. Similar exercises can, in fact, be carried out using different dimensions of socioeconomic status. For instance, occupations could, through their potentially different toll on health, contribute to the wealth-health gap (see Figure A.6). Yet, in all cases, an independent correlation between wealth and health seems to persist, suggesting the existence of other channels driving this relationship.

Perhaps the most natural channel of this type consists of the detrimental effect of poor health on an individual's ability to productively participate in the labor market. Indeed, a large empirical literature documents that health deficits significantly contribute to employment decline (Blundell et al., 2023b). Moreover, even when they are working, individuals in worse health tend to reduce their hours and are less productive, as reflected in their lower wages relative to healthy workers. Together, these factors contribute to the significantly lower labor incomes observed for unhealthy individuals.[10] Worse health thus leads to lower available resources to accumulate

[10]Relatedly, Hosseini et al. (2021) decompose the channels through which worse health leads to reduced labor income in the U.S. They find that the most important driver behind declines in earnings is exit from employment. In Appendix A.4, we investigate the effect of health on labor income in the SOEP data using an instrumental variables approach. Our results indicate that being healthy increases the probability of being employed by an estimated 10.8%, even conditional on employment in the past two periods. Moreover, when working, good health increases labor income

wealth over the life cycle.

Yet, as pointed out by Poterba et al. (2017) and De Nardi et al. (2023), a simple accumulation of lost labor income due to poor health over the lifetime does not explain the majority of the association between health and wealth.[11] In light of these results, we explore the importance of individual health behaviors as an additional mechanism underlying the wealth-health relationship.[12]

Health Efforts and the Wealth-Health Relationship

Given that an individual's health outcomes benefit from better health behaviors (Darden et al., 2018; Kvasnicka et al., 2018), variations in that latter could in part explain the considerable wealth-health gap observed in the data. Moreover, economic theory suggests that, in a world where survival is endogenous and can be influenced by healthy lifestyles or investments into health, the return to such efforts should increase in wealth, as richer people gain relatively more from prolonging their life.[13]

In line with this, Figure 3 illustrates that, indeed, healthy behaviors increase with wealth in the SOEP data. The figure displays the average level of our constructed health effort measure across wealth quartiles, conditional on education and age group. Health effort consistently rises in wealth. The increase is especially pronounced for non-college-educated 45-64-year-olds, where average effort increases by almost one standard deviation when going from the bottom to the top wealth quartile.

These effort differences by wealth might be driven by the fact that richer people can simply afford more or higher quality health investments thanks to their greater financial resources. We argue, however, that this is not the case here since our health effort measure contains variables that are mostly behaviorally driven. Moreover,

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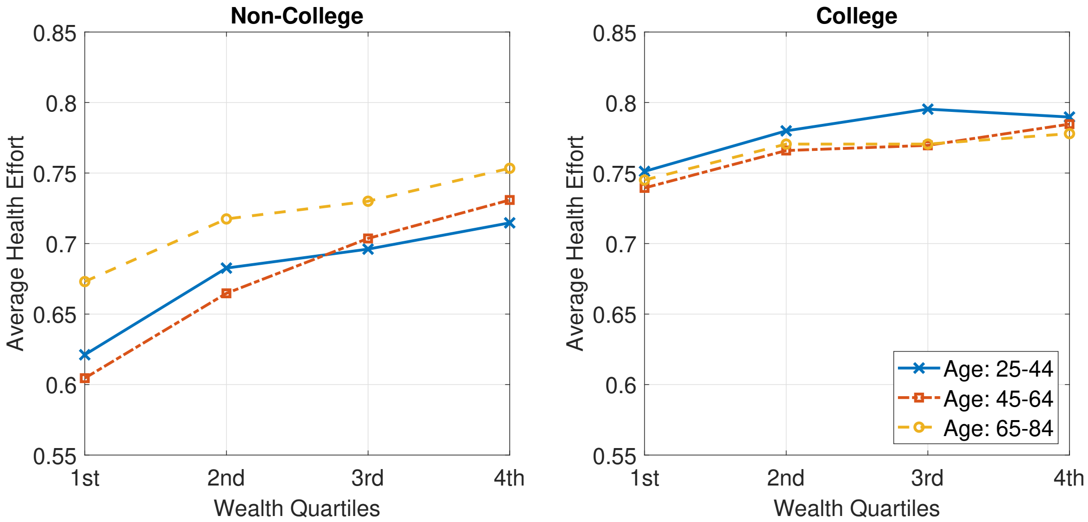
by around 10%. The majority of this increase is due to longer working hours, which increase by over 6%, while the rest is explained by higher wages.

[11] In their findings for the U.S., Poterba et al. (2017) argue that between 20 and 40% of the asset costs of poor health are attributable to lower income and annuity income. We find similar effects in our quantitative results. De Nardi et al. (2023) estimate that even adding out-of-pocket medical expenses does not close the wealth-health gap.

[12] A number of other influences of wealth on health have been investigated in the literature, including the direct effects of material resources on health, such as living conditions, the affordability of better health care, or certain psychological effects that can translate into better physical health. These studies draw mixed conclusions, see for example Cesarini et al. (2016); Schwandt (2018), and a survey in O'Donnell et al. (2015).

[13] We illustrate this argument in a very simple model even without monetary investments in Section 5.2. The idea is that, when survival is endogenous, what matters for inter-temporal decisions is not just the marginal utility of consumption, but the *levels* of utility, which increase in wealth. Similar theories that typically include monetary investments into health (i.e. where health can be "bought") have been set forth in several seminal papers, such as Rosen (1988), Becker (2007), and Hall and Jones (2007), where they serve as the main explanation for the rising share in healthcare spending in the U.S.

Figure 3: Mean Health Effort by Wealth Quartiles



Notes: Average health effort by age group and wealth quartiles for non-college-educated (left panel) and college-educated (right panel) individuals in the SOEP data.

in the case of abstention from smoking, higher health effort actually requires lower financial expenditure.

To further investigate the role of health-related behaviors in influencing the wealth-health relationship net of potentially confounding factors, we estimate the following equation:[14]

$$Health_{i,t+k} = \beta_1 Wealth_{i,t} + (\beta_2 Effort_{i,t}) + \gamma \mathbf{X_{i,t}} + u_{i,t}, \tag{1}$$

where $\mathbf{X_{i,t}}$ includes a constant, age, age^2, years of schooling, labor income, hours worked, lagged health, gender, marital status, labor force status, type of health insurance (private or public), year dummies, number of children in the households, as well as a measure of individual patience.[15] Row (1) in Table 1 reports the estimated coefficients $\hat{\beta}_1$ of wealth on health in the current year t and in a future year $t+k$ for $k = 1, 2, 3$. The coefficients confirm a persistent positive correlation between wealth

[14]We note that we do not intend to estimate causal effects of wealth on health from this regression. Instead, the purpose of this exercise is to illustrate how dynamic correlations between current wealth and future health are affected by the presence of health efforts, which can play a role of a mediating force behind such dynamic relationships. In fact, it is the difficulty of estimating causal effects of wealth on health in a reduced-form way that, amongst other things, motivates our structural analysis in the following sections.

[15]We include patience in an attempt to control for unobserved discount factor heterogeneity that could be correlated with individual health evolution and health behaviors but also wealth. Due to the fact that detailed wealth information is only available every 5 years in the SOEP, we cannot directly estimate a version of (1) that includes individual fixed effects. Section 4 details how we measure patience from the data, as our quantitative model also features discount factor heterogeneity.

Table 1: Effect of Wealth on Current and Future Health, with and without Effort

		Effect on $Health_{i,t+k}$			
		(i)	(ii)	(iii)	(iv)
		$k=0$	$k=1$	$k=2$	$k=3$
(1)	$Wealth_{i,t}$	0.106	0.111	0.134	0.139
		(0.035)	(0.031)	(0.043)	(0.048)
(2)	$Wealth_{i,t}$	0.100	0.103	0.124	0.128
		(0.033)	(0.036)	(0.039)	(0.044)
	$Effort_{i,t}$	0.103	0.148	0.170	0.192
		(0.015)	(0.015)	(0.016)	(0.017)
(1) R^2		0.299	0.253	0.234	0.215
(2) R^2		0.301	0.256	0.238	0.219

Notes: Estimated coefficient $\hat{\beta}_1$ from equation (1) in row (1), and $\hat{\beta}_1$ and $\hat{\beta}_2$ in row (2). Columns (i) - (iv) correspond to separate regressions for $k = 0, 1, 2, 3$. Numbers in parentheses are heteroskedasticity-robust standard errors. The estimated coefficients and standard errors of wealth are multiplied by 10^7. $N = 24,928$.

and current and future health, net of other confounding influences.

Row (2) reports the estimated coefficients on wealth, while *including current health effort* as an additional regressor. The estimated coefficients on wealth, $\hat{\beta}_1$, decrease by 6-8% across all horizons of health. That is, a non-negligible share of the estimated effect of wealth on current and future health can be explained by variations in health effort. This suggests that health effort can mediate the positive relationship between wealth and health. At the same time, the estimated coefficients on health effort, $\hat{\beta}_2$ are all positive and increase with the horizon of health, indicating that our measure of health effort captures aspects of lifestyle behaviors that positively affect the probability of being healthy, and that these effects take time to materialize.

The empirical observations presented in this section paint a clear picture. There exists a strong association between individual health and financial resources in Germany. These wealth-health gaps grow substantially in absolute terms over the working career and persist even after controlling for obvious potential confounding factors, such as education and occupation. We provide suggestive evidence that variations in individual lifestyle behaviors play an important role in explaining these gaps. Over time, positive wealth gradients in efforts could translate into better health outcomes, which in turn are associated with higher earnings.

The dynamic nature and mutual dependencies of these effects make empirically assessing the relative importance of the different mechanisms underlying the wealth-health relationship particularly challenging without a structural framework. In the following sections, we therefore construct and estimate a model around the joint evolution of wealth and health of heterogeneous agents over the life cycle that allows us to disentangle the contribution of the different channels.

3. Model

3.1. Demographics

Agents enter the model at the beginning of their working career at age $j = 1$ and live at most for J periods. A period corresponds to two years. They decide how much to work for every period until age j_R, when they retire and consume out of their savings and pension benefits.

Agents are ex-ante heterogeneous along several dimensions. First, education status e can either be high ($e = 1$), corresponding to college education, or low ($e = 0$), corresponding to no college education. Second, agents also differ in their fixed discount factor β. Moreover, we allow agents to be different in their productivity type θ, which affects life-cycle wage offers (Storesletten et al., 2004). Finally, agents differ in their fixed health type η, which influences the health transition over the life cycle. We think of these health types as primarily capturing heterogeneity in health evolution that stems from factors that occur before agents enter the model (such as child and adolescent health and lifestyles or family environment and upbringing) or innate and genetic heterogeneity.[16]

3.2. Health and Lifestyle Behaviors

At every age j, agents can be either healthy ($h_j = 1$) or unhealthy ($h_j = 0$). Being unhealthy affects economic outcomes in several ways. First, it decreases the survival probability from age j to $j + 1$, denoted by $S_j(h_j, e)$, which also depends on age and education. Second, it results in productivity loss when working, which manifests in a constant education-specific productivity penalty. Third, poor health affects the disutility incurred from working and the marginal utility derived from consumption. Finally, it also affects the utility costs associated with maintaining a healthy lifestyle.

We view lifestyles as being the result of health effort choices $f_j \in [0, 1]$. Analogous to the definition in Section 2, we think of this level as a compound measure of

[16] In their analysis of the joint wealth and health distribution in the U.S., De Nardi et al. (2023) find that inherent differences in time preferences across fixed health types are a substantial driving force of the observed wealth-health gradient. As detailed in Section 4.2, we also allow the initial conditions to be correlated with each other, in line with the data.

all the efforts an individual makes to lead a healthy lifestyle. Agents enter every period j with a health effort level f_{j-1}, chosen in the past period. They then decide whether to change their health effort level from f_{j-1} or not. This decision is subject to a stochastic adjustment cost drawn from an age-dependent uniform distribution $\chi_j \in \mathcal{U}[0, B_j] \equiv H_j(\chi)$, which has to be paid if the agent decides to change her effort level relative to her previous level f_{j-1}.[17] The inclusion of such a cost is motivated by the fact that a relatively high number of people in the data do not adjust their health efforts over time. Intuitively, this captures the idea of habits in health-related lifestyle behaviors.

Aside from a discrete decision on adjustment, we maintain the assumption that exerting health effort f_j comes at a direct contemporaneous utility cost, as in Cole et al. (2019). This utility cost $\varphi_j(f_j; h_j, e)$ is allowed to differ by age, health status and education. The dependence on education could capture any advantages more educated people have when exerting efforts, such as better neighborhoods or social networks, which could mitigate disutility of exerting healthy behaviors (Cutler and Lleras-Muney, 2010).

The benefit of leading a healthy lifestyle is that the latter increases the probability of being healthy in $j+1$, denoted by $\pi(h_{j+1} = 1 | h_j, f_j, f_{j-1}, e, \eta)$. This probability firstly depends on the fixed health type η. Moreover, it depends not only on health efforts undertaken in period j, but also on those in the previous period. This assumption at least partially accommodates the fact that healthy lifestyles take time to materialize and may have health benefits that persist into the future (Cutler et al., 2011). Through its effect on health, higher health effort is then also associated with better survival prospects, given that survival probability increases in health. Finally, we let this probability be education-specific to allow for potential advantages in good health outcomes stemming from higher education net of its effect on efforts, for example through better living conditions.[18]

3.3. Preferences

Agents derive utility from consumption c and disutility from hours worked n. We assume that n can take a value from $\{0, n_p, n_f\}$, allowing for adjustments along both extensive and intensive margins. Working in age j implies a utility cost $\phi_j(n_j; h_j, e)$

[17] Stochastic adjustment costs are widely used in different contexts such as firm investment and price adjustment in order to generate behaviors that often feature inaction. See Khan and Thomas (2008) for an overview.

[18] Moreover, this dependence on education allows us also to capture effects that cannot be picked up by our health effort measure, because of the way we construct it. For example, these could be more regular preventive doctor visits of the better educated because of better knowledge or access to information that would not show up in our data.

that decreases in current health and is age- and education-dependent. This captures the fact that continuing to work when unhealthy may be more inconvenient.

Moreover, we assume that health affects the utility of consumption, where the effect is governed by $\kappa(h_j)$. This takes a value of one if healthy and $\tilde{\kappa}$, which is less than one if unhealthy. We include this complementarity between health and consumption utility as, for the great majority of goods and services, there is evidence that individuals enjoy their consumption more when healthy.[19]

Under these assumptions, per-period utility then takes the following form:

$$u(c_j, n_j, f_j; h_j, e) = \kappa(h_j)\left(\frac{c_j^{1-\sigma}}{1-\sigma} + b\right) - \phi_j(n_j; h_j, e) - \varphi_j(f_j; h_j, e), \qquad (2)$$

where σ denotes the inverse of the elasticity of intertemporal substitution and b is a utility constant that is added to ensure that the value of being alive is always greater than the value of being dead (Hall and Jones, 2007). We let this utility constant be also dependent on health through $\kappa(h_j)$. Without this, the utility level would shift up for the unhealthy with an empirically reasonable value of $\sigma > 1$, which could result in higher utility of life for the unhealthy relative to the healthy.

The addition of this constant b has implications for the levels of future utility. Since survival is endogenous and can be influenced by health effort, the future utility levels play a role in shifting individual effort choices. This is in contrast to standard dynamic problems, where agents only care about marginal utility in each given period of life. The dependence on future utility levels through endogenous survival therefore incentivizes richer individuals (who can expect to have higher future utility levels through a longer life length) to increase their health efforts (Becker, 2007). This is because the return to health effort, namely the ability to enjoy a longer and healthier life, increases with wealth—one of the reasons why we expect our model to generate a wealth gradient in health efforts, as in the data. We explore this mechanism both theoretically and quantitatively in Section 5.2.

3.4. Earnings, Taxes and Transfers

When working in age j, agents receive gross labor income equal to $w_j(h_j, e, \theta, z_j)n_j$. The wage offer $w_j(h_j, e, \theta, z_j)$ consists of a deterministic component $\lambda_j(h_j, e)$ that depends on health h_j and education e as well as the fixed productivity type θ and

[19]For example, Finkelstein et al. (2013), using data from the U.S. Health and Retirement Survey, observe a decline in marginal utility of consumption when health deteriorates; medical goods and services, such as nursing care, being the exception. Similarly, Blundell et al. (2023a) find that the resulting consumption drop of non-durable goods after an adverse health shock comes mainly from a change in the utility of consuming them rather than from the effect of health on resources.

persistent idiosyncratic productivity risk z_j:

$$w_j(h_j, e, \theta, z_j) = exp(\lambda_j(h_j, e) + \theta + z_j) \tag{3}$$

We include the fixed effects θ to allow for the possibility that factors beyond education, age, and health can shift wage profiles (Low and Pistaferri, 2015).

We incorporate progressive labor income taxation captured by $\mathcal{T}(y_j, \bar{y})$ (Heathcote et al., 2017), where y_j denotes gross labor income and $\bar{y}$ refers to its average in the economy. In addition, agents are provided with transfers $T(c_j, h_j, n_j)$ that incorporate two types of welfare programs. First, a minimum consumption $\tilde{c}$ is guaranteed by the government to every individual, so that $T(c_j, h_j, n_j)$ includes $\tilde{c} - c_j$ if $c_j < \tilde{c}$. This could capture various means-tested social safety programs in Germany that are especially relevant to those with zero labor income, in particular Germany's basic social security provisions. We also incorporate a state-contingent transfer to capture sickness benefits, which would provide insurance against adverse health shocks. Specifically, $T(c_j, h_j, n_j)$ includes $\widetilde{T} > 0$ if an agent is unhealthy ($h_j = 0$) and does not work ($n_j = 0$).[20] Finally, the government provides pension benefits $P(e)$, which are paid out in retirement periods.

3.5. Individual Optimization Problems

We first describe the individual optimization problem of a *working-age agent* ($j < j_R$). At the beginning of each period j, the agent learns about her current health realization h_j and productivity draw z_j. At this point, the state variables are composed of a vector given by $\mathbf{s}_j = (e, \beta, \theta, \eta, a_j, h_j, z_j)$. Given $(\mathbf{s}_j, f_{j-1})$, the value function at the beginning of age j is then given by:

$$V_j(\mathbf{s}_j, f_{j-1}) = \mathbb{E}_{\chi_j} M_j(\mathbf{s}_j, f_{j-1}, \chi_j), \tag{4}$$

where M_j denotes the interim value after the stochastic effort adjustment cost draw χ_j is realized. This is given by:

$$M_j(\mathbf{s}_j, f_{j-1}, \chi_j) = \max \left\{ \underbrace{W_j^{adj}(\mathbf{s}_j, f_{j-1}, \chi_j)}_{\text{value of } \textit{adjusting effort}}, \underbrace{W_j^{not}(\mathbf{s}_j, f_{j-1})}_{\text{value of } \textit{not adjusting effort}} \right\}. \tag{5}$$

[20] In Germany, an integral part of the health insurance system consists of sickness benefits provisions that are paid to insured people in case they become incapable of working due to sickness (disability).

Here, W_j^{adj} is the value of adjusting health effort relative to its level in the previous period, which is given by:

$$W_j^{adj}(\mathbf{s}_j, f_{j-1}, \chi_j) = \max_{\substack{c_j, a_{j+1} \geq 0 \\ f_j \in [0,1], n_j \in \{0, n_p, n_f\}}} \left\{ \begin{array}{c} u(c_j, n_j, f_j; h_j, e) - \chi_j \\ +\beta S_j(h_j, e) \mathbb{E}_{h_{j+1}, z_{j+1} | \Omega_j} V_{j+1}(\mathbf{s}_{j+1}, f_j) \end{array} \right\}, \tag{6}$$

subject to

$$\begin{aligned} c_j + a_{j+1} &\leq a_j(1+r) + T(c_j, h_j, n_j) + w_j(h_j, e, \theta, z_j)n_j - \mathcal{T}(w_j(h_j, e, \theta, z_j)n_j, \bar{y}) \\ h_{j+1} &= 1 \quad \text{with prob. } \pi_j(h_{j+1} = 1 | h_j, f_j, f_{j-1}, e, \eta) \\ &= 0 \quad \text{with prob. } 1 - \pi_j(h_{j+1} = 1 | h_j, f_j, f_{j-1}, e, \eta). \end{aligned}$$

That is, the adjustment cost χ_j must only be paid when an agent decides to change her health effort relative to her previous level. Ω_j refers to the relevant subset of the state variables in period j used for taking conditional expectations.

Finally, W_j^{not} is the value of not adjusting health effort:

$$W_j^{not}(\mathbf{s}_j, f_{j-1}) = \max_{\substack{c_j, a_{j+1} \geq \underline{a}_j \\ n_j \in \{0, n_p, n_f\}}} \left\{ \begin{array}{c} u(c_j, n_j, f_{j-1}; h_j, e) \\ +\beta S_j(h_j, e) \mathbb{E}_{h_{j+1}, z_{j+1} | \Omega_j} V_{j+1}(\mathbf{s}_{j+1}, f_{j-1}) \end{array} \right\}, \tag{7}$$

subject to

$$\begin{aligned} c_j + a_{j+1} &\leq a_j(1+r) + T(c_j, h_j, n_j) + w_j(h_j, e, \theta, z_j)n_j - \mathcal{T}(w_j(h_j, e, \theta, z_j)n_j, \bar{y}) \\ h_{j+1} &= 1 \quad \text{with prob. } \pi_j(h_{j+1} = 1 | h_j, f_{j-1}, f_{j-1}, e, \eta) \\ &= 0 \quad \text{with prob. } 1 - \pi_j(h_{j+1} = 1 | h_j, f_{j-1}, f_{j-1}, e, \eta). \end{aligned}$$

During retirement periods ($j \geq j_R$), the optimization problem reduces to a standard consumption-savings problem in combination with choosing whether or not to adjust health effort and, in the affirmative, to which level. Thus, the interim value function (5) becomes:

$$M_j(\mathbf{s}_j, f_{j-1}, \chi_j) = \max \Bigg\{ \underbrace{R_j^{adj}(\mathbf{s}_j, f_{j-1}, \chi_j)}_{\text{value of } \textit{adjusting}}, \; \underbrace{R_j^{not}(\mathbf{s}_j, f_{j-1})}_{\text{value of } \textit{not adjusting}} \Bigg\} \tag{8}$$

where the values of adjusting effort, R_j^{adj}, and not adjusting effort, R_j^{not}, during retirement are now defined as

$$R_j^{adj}(\mathbf{s}_j, f_{j-1}, \chi_j) = \max_{\substack{c_j, a_{j+1} \geq 0 \\ f_j \in [0,1]}} \left\{ \begin{array}{c} u(c_j, 0, f_j; h_j, e) - \chi_j \\ +\beta S_j(h_j) \mathbb{E}_{h_{j+1}|\Omega_j} V_{j+1}(\mathbf{s}_{j+1}, f_j) \end{array} \right\}, \tag{9}$$

$$R_j^{not}(\mathbf{s}_j, f_{j-1}) = \max_{c_j, a_{j+1} \geq 0} \left\{ \begin{array}{c} u(c_j, 0, f_{j-1}; h_j, e) \\ +\beta S_j(h_j) \mathbb{E}_{h_{j+1}|\Omega_j} V_{j+1}(\mathbf{s}_{j+1}, f_{j-1}) \end{array} \right\}, \tag{10}$$

subject to the constraints

$$\begin{aligned} c_j + a_{j+1} &\leq a_j(1+r) + P(e) \\ h_{j+1} &= 1 \quad \text{with prob. } \pi_j(h_{j+1} = 1 | h_j, f_j, f_{j-1}, e, \eta) \\ &= 0 \quad \text{with prob. } 1 - \pi_j(h_{j+1} = 1 | h_j, f_j, f_{j-1}, e, \eta) \end{aligned}$$

Thus, during retirement, expectations are only made over future health realizations.

4. Estimation

4.1. Estimation Strategy

For the estimation of our model, we adopt a two-step strategy. In the first step, a set of parameters are set or estimated externally without using our model. Some of these, in particular the survival probabilities and the parameters governing the health transition probabilities are estimated directly from the SOEP data (waves 2004–2018). For the others, we set their values in line with the literature.

In the second step, we estimate the remaining set comprising 42 parameters using a moment matching estimator that minimizes the distance between model-implied moments and the corresponding empirical moments, taking as given the parameter values determined in the first step. Most importantly, we require the model to match the joint distribution of earnings and labor supply by age, health and education as well as the joint distribution of health efforts by age, health and education.[21] This results in 64 target empirical moments that are estimated from the data or taken from other sources, and summarized together with the parameters in Table 2.[22]

Formally, let Θ_0 be a vector of the 42 parameters to be estimated and $\hat{\Delta}$ be a vector

[21]We do not explicitly target the joint distribution of wealth and health over age. This is because one of our key quantitative exercises is to investigate how much of the observed positive wealth-health association can be generated through the forces present in our model.

[22]Table A.5 in the Appendix provides the full list of target statistics.

of the 64 empirical moments that we want to match. Our structural model provides a mapping from a set of parameters Θ to the model-implied moments, denoted by a function $h(\Theta)$. The method of simulated moments estimator of Θ_0 is then given by

$$\hat{\Theta} = \arg\min_{\Theta}(\hat{\Delta} - h(\Theta))' W(\hat{\Delta} - h(\Theta)), \tag{11}$$

where W is a 64-by-64 weighting matrix. The standard errors of each individual component of $\hat{\Delta}$ (i.e., $\hat{\delta}_1, ..., \hat{\delta}_{64}$) are estimable in our case, although the full variance-covariance matrix of $\hat{\Delta}$ is unknown. For that reason, we follow the algorithm proposed by Cocci and Plagborg-Møller (2021) to estimate the standard errors of our estimates $\hat{\Theta}$. Their strategy first obtains the *worst-case* standard errors by assuming that all elements of $\hat{\Delta}$ are perfectly correlated with each other, which bounds the variance of any linear combination of its elements and therefore the variance of the estimator $\hat{\Theta}$. They then show that one can use an efficient selection of moments for every parameter that minimizes the worst-case estimator variance when the model is over-identified. We describe the algorithm to compute the standard errors and justify its use in detail in Appendix A.5. The resulting estimates and standard errors are reported in the second and third columns of Table 2.

4.2. Model Parameters

As is well known for the application of the method of simulated moments, some moments are more informative for particular parameters although there is no one-to-one mapping between them. We now explain these links intuitively along with the description of the parameters belonging to the first step.

Demographics

We estimate the model at a biannual frequency so as to align with the frequency of health effort variables in our micro data. The first model period ($j = 1$) corresponds to age 25, so that agents enter the model after having obtained an education level. We assume that agents live at most until age 99, so that $J = 38$ with a model period of two years. Retirement age is set at 65 ($j_R = 21$).

Preference: Consumption/Saving and Labor Supply

We set the inverse of the elasticity of intertemporal substitution to $\sigma = 2$, a commonly-used value in the literature. The effect of poor health on the marginal utility of consumption, $\tilde{\kappa}$, is estimated internally to match the consumption differences between healthy and unhealthy 25-64 year-olds in the data (1.16). Note that in the model, a certain degree of consumption differences across health types is also endogenously generated. We estimate $\tilde{\kappa} = 0.872$, which implies a 13% loss for the unhealthy.

Next, we specify the disutility of working $\phi_j(n_j; h_j, e)$ as a combination of an age-, education-, and health-dependent shifter and a standard constant-Frisch-elasticity function:

$$\phi_j(n_j; h_j, e) = \nu_j^{h_j} \exp(\nu_e \mathbb{I}\{e = 0\}) \frac{n_j^{1+1/\gamma}}{1 + 1/\gamma}. \tag{12}$$

Thus, the labor supply disutility shifter is a combination of age- and health-specific coefficients—$\nu_j^{h_j}$—and ν_e, which determines extra disutility for those with a lower education level. Several labor supply patterns in the data motivate our parametric assumptions. As shown in the left panel of Figure 5, employment rates over age are hump-shaped with substantial gaps across health status. Moreover, there is a robust gap in employment rates between the education groups, as shown in the right panel of Figure 5. We estimate the above parameters internally to match two sets of moments that capture these patterns. These are the average employment shares among the healthy and unhealthy, by the age groups 25-34, 35-44, 45-54, and 55-64 and the average ratio of the employment rate of the college-educated to that of non-college educated (1.24). Given these nine target moments, we estimate nine parameters—ν_j^h for $j \in \{1, 8, 13, 20\}$ and $h \in \{0, 1\}$ as well as ν_e—while interpolating ν_j^h using piece-wise cubic splines for each h to obtain its value for all j.

The parameter γ is the Frisch elasticity of both intensive and extensive labor supply and is set to $\gamma = 1$, as is standard in the literature. We set $n_p = 0.5$, $n_f = 1$, and $\bar{n} = 3$ so that full-time work is one third of the total time endowment.

Preference: Lifestyle Behaviors

Health effort is a key and novel endogenous variable in our model. Its dynamics at the individual level are influenced by two kinds of utility costs in the model. Our aim is to parameterize such costs parsimoniously while being empirically consistent with the effort evolution across agents and over age.

We first specify the contemporaneous disutility incurring from exerting health effort level f_j as a combination of age-, education-, and health-dependent effort cost shifters, and a power function that increases with efforts, with the curvature parameter ψ shaping the degree of responsiveness in efforts:

$$\varphi_j(f_j; h_j, e) = \iota_j^{h_j, e} \frac{f_j^{1+1/\psi}}{1 + 1/\psi}. \tag{13}$$

To reproduce the education and health gradients in efforts presented in Figure 1 in Section 2.1, we adopt age-specific coefficients $\iota_j^{h_j,e}$ for each health status h_j and education e. These empirical patterns are well summarized in the target moments, which consist of the mean health effort observed in the data by the age groups 25-34, 35-44, 45-54, 55-64, 65-74 and 75-84, separately for each health status and education. To match these 24 moments, we estimate 16 parameters—$\iota_j^{h_j,e}$ for $j \in \{1, 12, 20, 31\}$, $h \in \{0, 1\}$ and $e \in \{0, 1\}$—while interpolating $\iota_j^{h_j,e}$ using piece-wise cubic splines for each h and e. Next, we internally estimate the curvature parameter $\psi = 1.115$ to match the empirical dispersion of efforts (standard deviation of 0.16).

The other kind of the utility cost concerns the distribution of the stochastic effort adjustment costs. This dynamic adjustment cost is crucial in governing the proportion of agents who choose not to adjust their efforts. In the data, this share increases with age, as reported in Table 2. To replicate this pattern, we parameterize the age-dependent upper bound of $\mathcal{U}[0, B_j]$ as

$$B_j = \varsigma_0 \exp(\varsigma_1(j-1)). \tag{14}$$

and estimate the two parameters—ς_0 and ς_1—to match the share of individuals not adjusting efforts for three age groups: 25-44, 45-64, and 65-84.

Next, we internally estimate the utility constant to $b = 13.1$, such that the model-implied value of a statistical life year (VSLY) is equal to 8.49 times average annual per capita consumption. The VSLY describes the average utility-equivalent value that individuals in our model would attach to one extra year of life. In quantitative models with endogenous survival, the VSLY can be defined by equalizing the average flow utility of a life year across individuals with average consumption, multiplied by average marginal utility of consumption so as to transform this into utility units, as in Glover et al. (2023):[23]

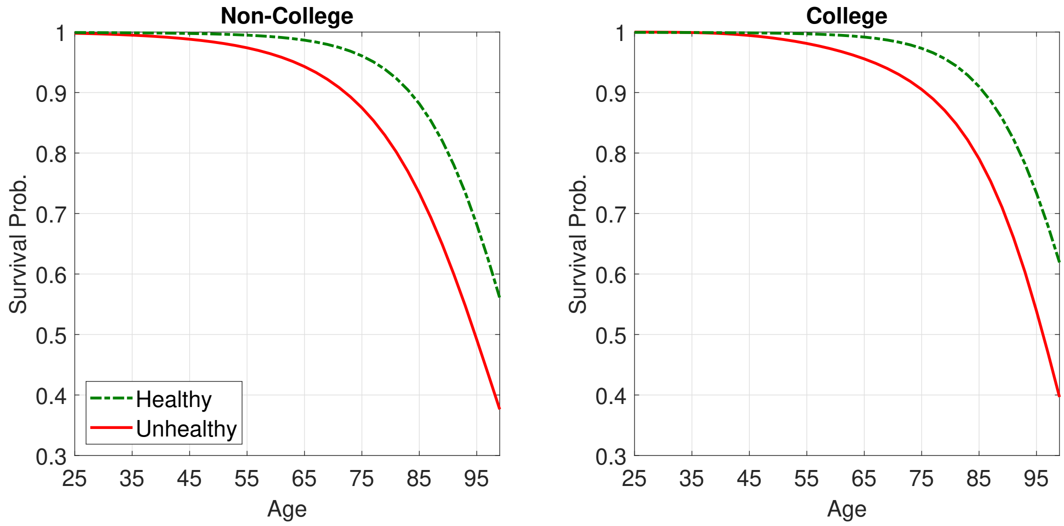
$$\bar{u}(c_j, n_j, f_j; h_j, e) + b = \frac{\bar{\partial u}}{\partial c} \times \underbrace{8.49\bar{c}}_{\text{VSLY}}. \tag{15}$$

We take the empirical target for the VSLY from a meta-analysis of value of a statistical life estimates in OECD (2012), who report a value of around 4.7 million 2005-USD among a sample of EU countries.[24] We transform this value into a VSLY

[23]Since our model frequency is two life years, we are technically comparing the value of two extra life years to average consumption over two years when estimating b. Thus, we can still use the ratio of 8.49 as our target statistic.

[24]The estimates are obtained from surveys, where participants are asked about their willingness to pay for small reduction in mortality risks. The results are in Table 6.1 in OECD (2012). In comparison to other estimates in the literature (such as Glover et al. (2023)), this is a rather

Figure 4: Estimated Conditional Survival Probabilities by Education and Health



Notes: Probability of survival for two years conditional on being alive at a given age, coming from a probit model of survival on a cubic polynomial in age estimated on SOEP data. Survival probabilities are estimated separately for non-college and college individuals and by health status.

of around 140 thousand 2018-EUR using the average age (44.4 years) and average life expectancy at that age (34.8 years) in Germany in 2018 and under the assumption of a 3% annual discount factor (Glover et al., 2023).

Survival Probability

We estimate the two-year survival rates $S_j(h_j, e)$ directly from the data using information on deaths of survey respondents contained in the SOEP. Specifically, we fit a probit model of survival up to age $j+1$ on a cubic polynomial in age by health status at age j and education. The resulting estimated conditional two-year survival probabilities are plotted in Figure 4.[25] Conditional on being alive at a given age, healthy people are more likely to survive the next two years than unhealthy people. This difference increases with age. Moreover, at all ages, higher educated people have higher chances of survival than lower educated people although the differences driven by education are relatively small (Pijoan-Mas and Ríos-Rull, 2014).

Health Evolution and Fixed Health Types

The probability of being healthy in the next period is a function of an individual's age, education, current health, and past and present health efforts. On top of that,

conservative estimate.

[25]To check that the estimated survival rates are reasonable and do not suffer from a lack of tracking the reasons respondents exited the SOEP survey, we compare the results in Figure 4 with the German Statistical Office's mortality risk tables. Doing so largely confirms our estimates.

we allow the health evolution to depend on unobserved fixed type, which we consider arising primarily from different initial conditions before the age of 25 when agents enter the model. As such, they can originate from inherent genetic predispositions but also from differences in family environments and lifestyles during childhood and adolescence. Given the inclusion of the unobserved heterogeneity, we employ a two-step group fixed effects estimator (Bonhomme et al., 2022) to estimate the health evolution process.

The first step in the estimation involves classifying individuals into a small number of discrete fixed health types η, based on the *kmeans* clustering algorithm. The goal is to group individuals together that are most similar in terms of a latent type which influences their health evolution net of observable characteristics. To that end we define a vector of individual-specific moments that are likely informative about an underlying latent health type. These moments include the number of doctor visits, self-rated health status (5-point scale), inpatient nights in a hospital, both physical and mental health summary scores (PCS and MCS) and the body mass index. Details on these moments, as well as the clustering procedure are given in Appendix A.6. We run the classification repeatedly while increasing the number of clusters and randomizing the initial group centers. We then compare the total within-cluster sum of squares of each cluster solution to find a suitable number of clusters. We end up with two fixed health types $\eta \in \{0, 1\}$, where around 2/3 of individuals in our data are of the high health type $\eta = 1$ and the rest are of the low health type $\eta = 0$.[26]

In the second step, we estimate the probability of being healthy in the next period conditional on current and past health effort, education, current health and these fixed health type groups, $\pi_j(h_{j+1} = 1|h_j, f_j, f_{j-1}, e, \eta)$, directly from the data with the following logistic model:

$$\begin{aligned} &\pi_j(h_{i,j+1} = 1|h_{i,j}, f_{i,j}, f_{i,j-1}, e_i, \eta_i) = \\ &\Big(1 + \exp\left(-(\pi^0_{i,j} + \lambda_1 f_{i,j} + \lambda_2 f_{i,j-1} + \delta h_{i,j} + \gamma_1 e_i + \gamma_2 \eta_i + \gamma_3 \mathbf{A}_i)\right)\Big)^{-1}, \end{aligned} \tag{16}$$

where $h_{i,j}$ is a dummy variable that equals 1 if person i is healthy at age j, $f_{i,j}$ is our compound health effort measure, e_i is a dummy variable equal to 1 if person i has college education, η_i is a dummy variable that equals 1 when individual i's health type is high, and $\mathbf{A}_i$ is a vector of dummies that are equal to 1 when individual i is

[26]When comparing the total within-cluster sum of squares as a measure for cluster homogeneity, a kink appears most noticeably at two and three clusters. We opted for two health type groups, which offers a compromise between maintaining computational feasibility and accounting for a sufficient degree of heterogeneity.

a member of a 10-year age group.

We present the exact logistic estimates from (16) that we use in the model in Table A.6 along with detailed discussions in Appendix A.7. Notably, the estimated effects of current and past health effort are positive and quantitatively meaningful. The estimates imply that, for example, a 75-year-old college-educated individual of the high health type can increase her probability of being healthy by almost 2% if she is currently healthy and increases just her contemporaneous health effort by one standard deviation above the average. If she is currently unhealthy this effort improvement will raise her probability of being healthy next period by over 7%. Moreover, by increasing effort for two consecutive periods to one standard deviation above the mean, the probability will be increased by 15% if she is currently unhealthy and over 3% if she is currently unhealthy. Generally speaking, past health effort is, on average, slightly more productive in increasing the healthy probability, which underlines the importance of considering the dependence of good health outcomes on a longer history of healthy lifestyles.

We gauge the empirical realism of our health transition parameter estimates in detail in Appendix A.7 and discuss their implications for disease prevalence and mortality in comparison to existing estimates in the medical literature. Relative to the latter, we conclude that our estimated effectiveness of past and present health effort in improving health outcomes is rather conservative.

Wage and Fixed Productivity Types

For estimation, we augment the wage equations (3) with the specification of the idiosyncratic risk z_j and statistical error terms:

$$\begin{aligned} \ln w_j &= \lambda_j(h_j, e) + \theta + z_j + \varepsilon_j \\ z_j &= \rho z_{j-1} + \upsilon_j, \end{aligned} \tag{17}$$

where $\theta \sim \mathcal{N}(0, \sigma_\theta^2)$, $\varepsilon_j \sim \mathcal{N}(0, \sigma_\varepsilon^2)$, and $\upsilon_j \sim \mathcal{N}(0, \sigma_\upsilon^2)$. Thus, log wages are a combination of an observed, deterministic component $\lambda_j(h_j, e)$ that is dependent on education and health, as well as an idiosyncratic component that consists of unobserved fixed productivity heterogeneity θ and persistent shocks z_j.[27]

We estimate the deterministic component $\lambda_j(h_j, e)$ internally within our structural model to address selection bias that might arise due to the well-known issue that we

[27]Although the wage equations (3) in the model do not include transitory shocks ε_j, the empirical equations do so in order to identify fixed productivity types θ (Storesletten et al., 2004). We abstract from correlations of fixed productivity or idiosyncratic shocks with observables, in particular health and education, as is common in the literature (e.g., Low and Pistaferri (2015)).

do not observe wages for non-working individuals and it is likely that individuals select into employment based on their observable characteristics, including their health status (Low and Pistaferri, 2015). Specifically, we parameterize it such that for each education group e,

$$\lambda_j(h_j, e) = \zeta_0^e \exp(\zeta_1^e(j-1) + \zeta_2^e(j-1)^2) \times (1 - w_p^e \mathbb{I}\{h_j = 0\}). \tag{18}$$

The coefficients ζ_0^e allow the two education groups to have a different intercept in their deterministic wage profile. The exponential term captures different trajectories of productivity over age by education group. The last term is a constant productivity penalty w_p^e that captures productivity losses due to poor health. In line with the literature (Hosseini et al., 2021), we allow these contemporaneous effects of poor health to differ by education, which might capture, for example, the fact that non-college workers are more likely to work in physically demanding jobs, where poor health might be more consequential in terms of productivity losses. We then estimate these eight parameters—ζ_0^e, ζ_1^e, ζ_2^e, and w_p^e for $e \in \{0, 1\}$—internally so that the model matches the mean (two-year) earnings by education and health status for the age groups 25-34, 35-44, 45-54, and 55-64 (16 moments in total) in the data.

Next, we estimate the distribution of fixed productivity types and the persistence of idiosyncratic shocks directly using individual-level wage data in the SOEP, using a standard procedure in the literature (De Nardi et al., 2023; French, 2005), as detailed in Appendix A.6. This yields an estimated persistence of idiosyncratic productivity shocks of $\rho = 0.975$ and provides a distribution of empirical individual-specific productivity fixed effects estimates $\hat{\theta}_i$. To recover the fixed productivity types used in our model, we classify this distribution of $\hat{\theta}_i$ into two discrete types, similar to Low and Pistaferri (2015), corresponding to low productivity θ_l (the bottom 50%), and high productivity types θ_h (the top 50%).[28] We then set $\theta_l = -0.29$ and $\theta_h = 0.29$ symmetrically, such that the variance of the discrete types corresponds to the estimated variance $\sigma_\theta^2 = 0.084$. Given the estimates of the persistence of idiosyncratic shocks and the fixed productivity type distribution, the variance of the idiosyncratic productivity component σ_v^2 is estimated internally such that the model matches the observed variance of log earnings (0.59) in the data.

[28] We also experimented with three discrete productivity types as in Low and Pistaferri (2015), which did not alter the results significantly. As in Low and Pistaferri (2015), we classify the individuals who never work in our sample and, hence, do not have an estimated productivity fixed effect into belonging to the low productivity type.

Initial Distribution

We construct the initial distribution of agents over the state space upon entry into the model directly from the data. We first describe the distribution over the fixed types. As before, education distinguishes college (31%) and non-college education (69%). As detailed above, the fixed productivity types are discretized into two equal-sized masses, and the fixed health types are estimated using the *kmeans* clustering algorithm, leading to 63% of the high health type ($\eta = 1$) and 37% of the low health type ($\eta = 0$). The remaining source of ex-ante heterogeneity in our model comes from differences in the discount factor β. We discretize the distribution of β into two equal-sized masses, β_l and β_h, using information about time preferences coming from an incentivized experiment conducted in the 2006-wave of the SOEP.[29] Since this information does not inform the levels of the discount factors in the model directly, we assume that $\beta_l = \mu_\beta - \delta_\beta$, and $\beta_h = \mu_\beta + \delta_\beta$, and estimate μ_β and δ_β internally, such that our simulated data matches the following seven relevant moments in the data: the median wealth for the age groups 25-34, 35-44, 45-54, 55-64, 65-74, and 75-84 (as shown in the left panel of Figure 8) and the Gini-index of wealth (0.746).

We require the joint distribution over education, unobserved health types, productivity types and discount factor types upon entry into the model to be the same as in the working-age population in the data.[30] This is important since the observed positive wealth-health association can be at least partly explained by the joint density of discount factor and other fixed types, in particular unobserved health types, as highlighted by De Nardi et al. (2023). In our sample, patience and fixed health types are indeed positively correlated (with the correlation being 0.1). Moreover, the health type is slightly positively correlated with the productivity type.

We also require the initial distribution to reflect differences in initial health and healthy lifestyles. Accounting for these initial differences is potentially important given the habitual nature of healthy lifestyles and path-dependence of health evolution, reflected in our estimated health technology (16). To that end, we use the conditional means of health and health effort at ages 25 to 30 as the initial states, where we condition on education and fixed health type. We report the resulting exogenous

[29] Details on the experiment are given in Richter and Schupp (2014). The experiment consisted of the individual's decision whether to obtain money now or at a later point in time with increasing interest rates. From the implied interest rate each individual requires to be indifferent between the two options, we can extract information about their patience.

[30] In the data there remain small differences in the distributions over age, despite age typically being a control variable in the construction of the types. The only source that influences the distribution of fixed types over age in the model is endogenous survival. This may in particular be a concern, if agents of the low health type are more likely to exit the model due to death. However, given that exogenous survival rates during the working ages are very high (see Figure 4), we see this issue as negligible.

distribution across states including average health and health effort at the beginning of our model in Table A.14. Finally, we assume that agents enter the model with zero wealth and set the real interest rate to $r = 0.082$, which corresponds to an annual rate of 4%.[31]

Taxes and Transfers

We specify the progressive labor tax system using a commonly used parametric function (Heathcote et al., 2017):

$$\mathcal{T}(y_j, \bar{y}) = y_j - (1 - \tau_s) y_j^{1-\tau_p} \bar{y}^{\tau_p}. \tag{19}$$

In this formulation, τ_s captures the scale and τ_p captures the degree of progressivity of the tax system. $\bar{y}$ is the average income. In accordance with the estimates in Kindermann et al. (2020) for Germany, we set to $\tau_s = 0.321$ and $\tau_p = 0.128$.

In terms of pension benefits $P(e)$, we follow a similar approach as in Kindermann et al. (2020). We initially set these as equal to the earnings agents would have earned in the period prior to retirement if they had worked full-time with a median productivity shock value. We then scale them by a constant ω, which we estimate internally to match the average pension replacement rate of 47.7% in our data.

Finally, $\tilde{c}$ is the consumption floor given by the government to all agents, which is particularly relevant for those who do not work. We set this to 10% of average income.[32] Sickness benefits, captured by $\widetilde{T}$, paid to non-workers who are unhealthy are set to 11.5% of average income. Sickness benefits in Germany are, as a rule, based on 70% of the gross labor income and paid for a maximum duration of 78 weeks over three years for the same disease.[33] In the data, the average duration of payments due to sickness that are covered by the benefits ranges from 5 to 120 days per year, depending on the disease (Knieps and Pfaff, 2019). We choose an average duration of 60 days per year, which results in our chosen value for $\widetilde{T}$.

[31] In our data, we do not have sufficient information about wealth at age 25 and younger to justify a different assumption about initial wealth when entering the model.

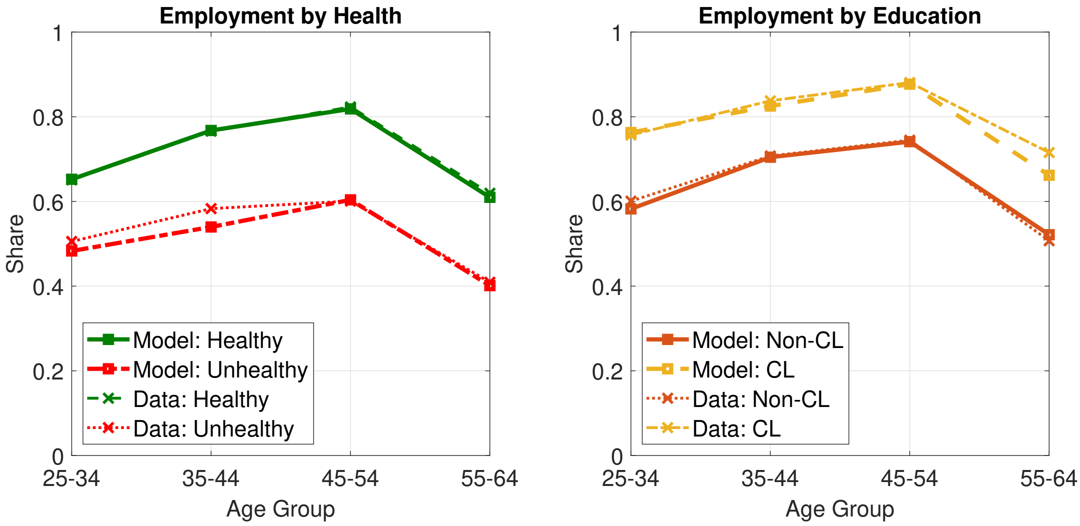
[32] In 2018, the calculated government transfer that is guaranteed as part of basic social security to secure the subsistence level was around 400 Euros per month for a single household (BAMS, 2018). This amounts to around 10% of average labor income in the same year.

[33] For the first up to 6 weeks after sickness, labor income is paid fully by their employer. After that, the health insurance company is mandated to pay. Eligibility of these sickness benefits depend on having worked for at least 4 weeks prior to sickness.

Table 2: Internally Estimated Parameters

Param -meter	Estimate	S.E.	Description	Target Statistics Model	Data	Description
Labor Supply and Wages						
$\nu_1^{h=1}$	2.634	0.399	Disutility of work	Figure 5		Age-Employment
$\nu_8^{h=1}$	1.666	0.081	parameters	(Left Panel)		Profiles by
$\nu_{13}^{h=1}$	1.278	0.027	(healthy)			Health
$\nu_{20}^{h=1}$	1.714	0.207				
$\nu_1^{h=0}$	2.412	0.445	Disutility of work			
$\nu_8^{h=0}$	1.813	0.126	parameters			
$\nu_{13}^{h=0}$	1.391	0.090	(unhealthy)			
$\nu_{20}^{h=0}$	2.415	0.377				
ν_e	0.807	0.005	Work Disutility for Non-CL	Figure 5 (Right Panel)		Employment by Education
$\zeta_0^{e=0}$	0.899	0.009	Deterministic wage	Figure 6		Age-Earnings
$\zeta_1^{e=0}$	0.0616	0.004	profiles			Profiles by Education
$\zeta_2^{e=0}$	-0.0025	0.0003	(non-college)			and Health
$\zeta_0^{e=1}$	1.165	0.026	Deterministic wage			
$\zeta_1^{e=1}$	0.0874	0.004	profiles			
$\zeta_2^{e=1}$	-0.0029	0.0002	(college)			
$w_p^{e=0}$	0.178	0.026	Wage loss for the unhealthy: Non-College			
$w_p^{e=1}$	0.145	0.051	Wage loss for the unhealthy: College			
Health Effort						
$\iota_1^{h=1,e=0}$	0.146	0.042	Disutility of effort	Figure 7		Age-Effort
$\iota_{12}^{h=1,e=0}$	0.560	0.066	parameters			Profiles by
$\iota_{20}^{h=1,e=0}$	1.048	0.086	(healthy +			Health and
$\iota_{31}^{h=1,e=0}$	1.603	0.081	non-college)			Education
$\iota_1^{h=0,e=0}$	0.628	0.186	Disutility of effort			
$\iota_{12}^{h=0,e=0}$	1.366	0.155	parameters			
$\iota_{20}^{h=0,e=0}$	1.650	0.129	(unhealthy +			
$\iota_{31}^{h=0,e=0}$	0.735	0.070	non-college)			
$\iota_1^{h=1,e=1}$	0.0913	0.024	Disutility of effort			
$\iota_{12}^{h=1,e=1}$	0.302	0.042	parameters			
$\iota_{20}^{h=1,e=1}$	0.740	0.065	(healthy +			
$\iota_{31}^{h=1,e=1}$	1.366	0.088	college)			
$\iota_1^{h=0,e=1}$	0.469	0.151	Disutility of effort			
$\iota_{12}^{h=0,e=1}$	0.997	0.143	parameters			
$\iota_{20}^{h=0,e=1}$	1.654	0.136	(unhealthy +			
$\iota_{31}^{h=0,e=1}$	1.089	0.084	college)			
ψ	1.115	0.067	f cost elasticity	0.163	0.161	Std.Dev.(f)
ς^0	0.00012	0.0001	Adjustment costs	0.256	0.267	Share of
ς^1	0.145	0.015		0.355	0.328	Non-Adjusters
				0.389	0.404	by Age Group
Remaining Parameters						
$\tilde{\kappa}$	0.872	0.038	Cons. Util. shifter	1.146	1.163	Cons. Ratio by Health
μ_β	0.943	0.003	Mean of β	Figure 8		Median Wealth Profiles
δ_β	0.0284	0.005	Dispersion of β	0.718	0.746	Wealth Gini
σ_x	0.0289	0.001	Produc. shock dispersion	0.585	0.595	Var(log income)
ω	0.359	0.011	Pension scale	0.473	0.477	Replacement rate
b	13.11	0.296	Utility constant	8.83	8.49	VSLY/$\bar{c}$

Figure 5: Model Fit of Employment by Health and by Education



Notes: Two-year employment rate by health status (left) and by education (right) over 10-year age groups in the model and data.

4.3. Estimation Results

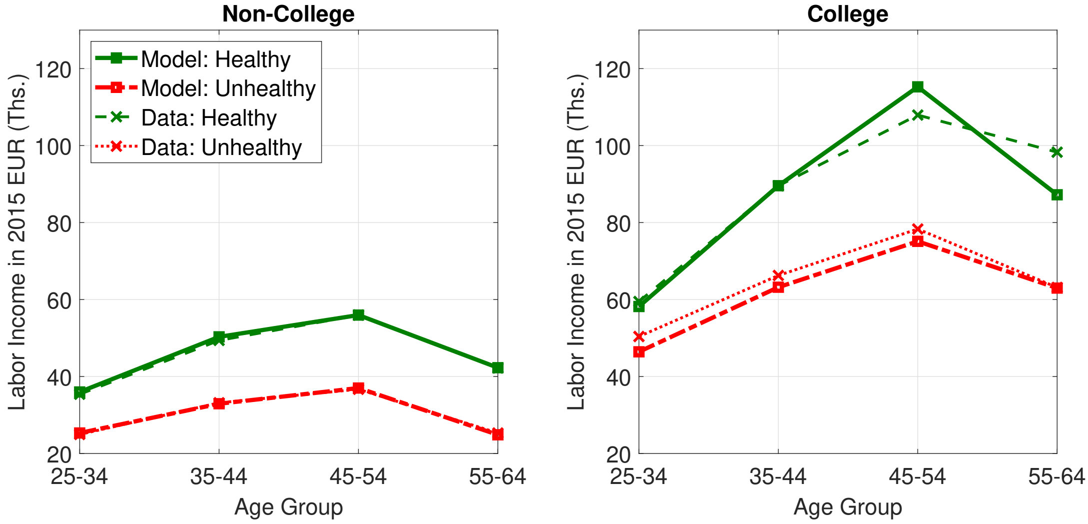
Table 2 summarizes the internally estimated parameters (both point estimates and their standard errors), their target statistics, as well as the match between the empirical and model-implied data moments. We now discuss the fit of the model in greater detail along the dimensions relevant for the quantitative exercises in the following section.

The left panel of Figure 5 displays the employment rate by health status over 10-year age groups, comparing our model results with their data counterparts. The right panel shows employment by education.[34] Similarly to what we observe in the data, the model generates a gap in the working population fraction by health. For example, at ages 25-34, the employment rate among healthy individuals is around 72%, whereas it is only 53% among the unhealthy. This gap in employment remains relatively constant over the working career. Similarly, our model replicates well the employment patterns by education, where non-college individuals work less than college individuals over all age groups. Notably, a constant additional work disutility for non-college workers suffices to generate the age pattern despite only targeting the average difference by education.

Figure 6 compares the life-cycle profiles of average labor income from our model-generated data with the SOEP data. We distinguish between the non-college (left

[34] In the data, we define two-year employment to be 1, if an individual is recorded as employed part- or full-time, or has labor income larger than 5,400 EUR in two consecutive years. If she is only recorded as employed for one year, we set 2-year employment to 0.5 and set it to 0 otherwise.

Figure 6: Model Fit of Labor Income by Health and Education



Notes: Average two-year labor income by 10-year age groups, distinguishing between healthy individuals (green) and unhealthy ones (red) in the data and the model. Left panel: Non-college educated individuals. Right panel: College educated individuals.

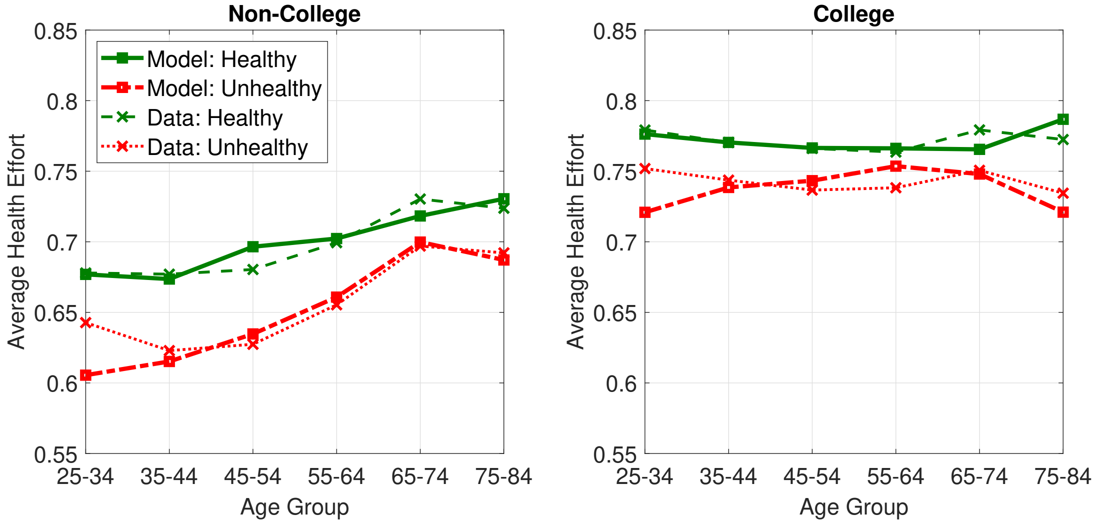
panel) and college-educated (right) and plot the average earnings for healthy (green) and unhealthy (red) individuals. For both education groups, healthy individuals earn substantially more compared to unhealthy ones. Our model captures this difference conditional on education well. The productivity loss when working due to poor health is estimated to be 18% for non-college workers and 14% for college workers.

Figure 7 displays the evolution of average health effort over the life cycle by health status, again separating between the two education states. In the data, average health effort increases slightly for the non-college educated individuals over age and tends to be relatively stable, albeit at a higher level, for the college-educated cones. Healthy individuals always exert more health effort compared to unhealthy ones. Our estimated model produces a similarly consistent difference between health groups, conditional on education.

Our estimation strategy is designed to discipline effort dynamics to be empirically reasonable along various dimensions. One such feature is the sizeable share of individuals who do not adjust their efforts, which in fact increases with age. Specifically, around 24% of young individuals (age 25-44) do not adjust their efforts, compared to a much higher share of 39% among the retired. Due to the adjustment costs that become more sizeable with age, our model replicates this pattern quite successfully.

Finally, the left panel of Figure 8 shows median wealth profiles over age in the model and data, as before on a log/ratio scale. While we match the peak wealth in age group 55-64, the model produces slightly lower wealth levels at younger and older age groups. This is not surprising as in our model all agents start out with zero

Figure 7: Model Fit of Health Effort



Notes: Average health effort by 10-year age groups, distinguishing between individuals being healthy (green) and unhealthy (red) in the model and data. Left panel: Non-college educated individuals. Right panel: College educated individuals.

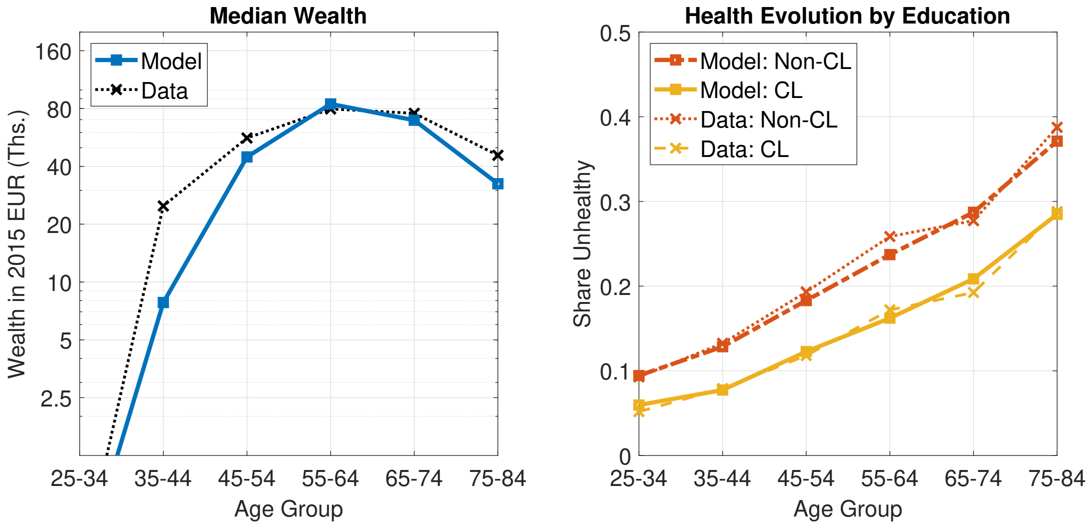
initial wealth and there are no bequests motives that would prompt individuals to maintain high wealth levels well into retirement. We estimate average β generating these profiles to be 0.943. Moreover, the differences in discount factors across β types is estimated to be 0.0284, which together with other forces in the model generates a Gini coefficient of wealth of around 0.72, slightly below its empirical counterpart.

4.4. Non-targeted Moments

We now turn to several relevant non-targeted moments generated by the model, as a validation check of our estimated model. First, our model successfully captures the evolution of health status in the data that we discussed in Section 2.1, as shown in the right panel of Figure 8.

In addition to the health-, and education-specific age profiles of health effort behavior, which we target in our estimation procedure, we also investigate how well our model captures the non-targeted adjustment patterns in individual lifestyle behaviors. To this end, the model produces an autocorrelation coefficient of health effort choices of 0.81, which is close to its data counterpart, 0.76. In light of the non-convex adjustment costs to health efforts, we further compare the model-generated shares of individuals that change their health effort levels by more than 10% or 20% to their empirical counterparts. Table 3 displays theses shares, separately for increases (positive changes) and decreases (negative changes) in health effort, by three different age groups.

Figure 8: Model Fit of Wealth Evolution and Average Health



Notes: Left panel: Median wealth by 10-year age group in the model and data. Right panel: Average share of unhealthy individuals by education in the model and data.

We find that our model is successful in reproducing these micro-level adjustment distributions observed in the data. Overall, the model generates relatively large adjustments of around 20%, and their shares align quantitatively well with the data. Moreover, the model successfully generates asymmetry: for the same size changes, there is a higher fraction of agents making a positive adjustment compared to a negative adjustment for the young and prime-age groups. This is a salient feature in the data, which our model captures despite the fact that the estimation does not directly target these moments.

Table 3: Health Effort Adjustment at the Individual Level in Model and Data

Age Group	Shares with positive changes				Shares with negative changes			
	10%		20%		10%		20%	
	Model	Data	Model	Data	Model	Data	Model	Data
24-44	0.18	0.29	0.09	0.14	0.18	0.22	0.04	0.08
45-64	0.20	0.27	0.08	0.12	0.13	0.21	0.04	0.07
65-84	0.22	0.25	0.10	0.10	0.16	0.22	0.11	0.06

Notes: Average shares of individuals adjusting health effort in the model and data by age groups. Positive (Negative) Change: $\frac{f_j - f_{j-1}}{f_{j-1}} > (<)10\%$ or 20%.

Finally, in line with the empirical observations outlined in Section 2.2, our model features a pronounced wealth gradient of lifestyle behaviors. To quantify this, we compute a wealth elasticity of health effort defined as the estimated coefficient on the logarithm of average wealth per age-group specific wealth quartiles from a linear regression of the logarithm of health effort on a constant, age group dummies and logarithm of average wealth per age-group specific wealth quartiles. We find that our model features a wealth elasticity of health effort of 2.4, which is very close to the one we obtain in the data at 2.5.

5. Quantitative Results

5.1. Wealth-Health Gaps and Channels

In this section, we use our estimated model to investigate the joint evolution of wealth and health and its underlying drivers. We begin by presenting how much of the wealth-health gaps are generated endogenously by our baseline model. The life cycle profiles of median wealth of healthy and unhealthy people are plotted in the left panel of Figure 9, as before on a log/ratio scale.[35]

We see that the relative gap in median wealth between the healthy (dashed green line) and the unhealthy (dotted red line) in the data is already present at young ages and persists throughout the life cycle. Our estimated model is able to endogenously generate a wealth-health gap that amounts to around three quarters of that observed in the data at younger ages, and that is as large as the one in the data for individuals between 65 and 74 years-old.[36] Given that our model agents differ in various characteristics, including rich ex-ante heterogeneity, one might wonder whether we should be surprised by this quantitative success.

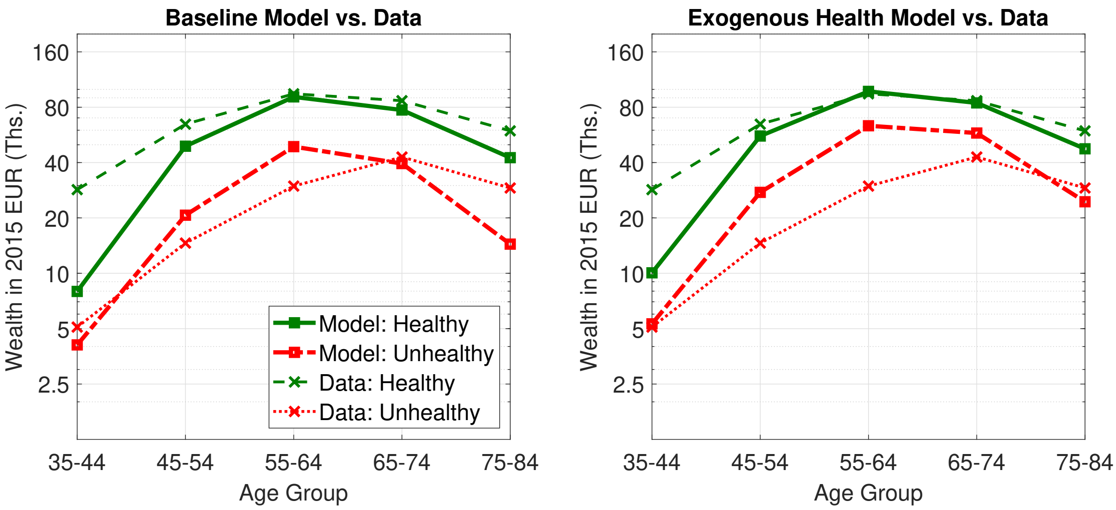
For that reason, we consider a variant of our model, where health transitions are no longer affected by health efforts, removing the need for the individual agents to decide on optimal health efforts. We estimate this *exogenous health model*, which still maintains the same rich ex-ante heterogeneity as in our baseline model, using a parallel estimation strategy and find that the model fits the target moments equally well.[37] However, as shown in the right panel of Figure 9, this exogenous health model

[35]Since wealth levels are (almost) zero in the youngest age group (25-34 year-olds) both in the data and in the model, we plot the gaps from age group 35-44. We report the age profiles of wealth by health status at different points of the wealth distribution (25th percentile, 50th percentile, and 75th percentile) in Appendix Figure A.7. At all wealth quartiles, the model generates sizable wealth-health gaps, which grow over age and are comparable in size as those in the data among prime-age groups. We also report the wealth-health gaps for each education group in Figure A.8, confirming that our model generates sizable wealth-health gaps even conditional on education.

[36]It is not surprising that the model-generated gaps tend to open up later than in the data, given that all our model agents start with zero initial wealth.

[37]Concretely, we re-estimate the health transition probabilities in (16) without current and past health efforts but keeping all other covariates (see Table A.6). Naturally, the estimated parameters exclude those shaping health effort disutility and adjustment in (13)-(14) and the target moments exclude those concerning health efforts.

Figure 9: Median Wealth Profiles by Health: Model vs. Data



Notes: The left panel displays median wealth by 10-year age groups, distinguishing between healthy individuals (green) and unhealthy ones (red) in the baseline model relative to the data. A log scale is used for the vertical axis. The right panel plots the counterparts from the re-estimated exogenous health model that abstracts from health efforts.

can only account for less than two thirds of the non-targeted wealth-health gaps observed in the data, performing considerably worse than our endogenous health model. This result indicates that individual lifestyle behaviors contain valuable information for rationalizing the observed wealth-health gaps.

We now investigate and quantify channels behind these wealth-health gaps using a series of counterfactual experiments. To develop an intuition behind the logic of these experiments, we begin by presenting a greatly simplified version of our full model that nevertheless contains the key forces that are chiefly responsible for the wealth-health gaps. To that end, consider an individual who maximizes utility solving the following two-period problem (using the same notation as before):

$$\begin{aligned} &\max_{c_0,c_1,f,n} \quad u_0(c_0) - \varphi(f) - \phi(n,h_0) + \beta S(h_1) u_1(c_1,h_1) \\ &\text{subject to} \quad c_0 + c_1 = w(h_0)n \\ &\qquad\qquad\qquad h_1 = \pi(f), \end{aligned} \tag{20}$$

where choice variables include current consumption (c_0), future consumption (c_1), lifestyle behaviors (f), and labor supply (n).[38] The key assumptions, as in our quantitative model, are that (i) better health improves the survival probability ($S'(h) > 0$); (ii) better health improves productivity or the wage offer ($w'(h) > 0$);

[38]In this simple model, we abstract from several mechanisms that are present in our quantitative model to focus on illustrating the key mechanisms we highlight below. See Appendix A.9 for details.

(iii) health status affects the disutility of labor supply ($\phi(n,h)$); (iv) better lifestyle behaviors improve health ($\pi'(f) > 0$); and (v) the marginal utility from future consumption is higher with better health ($\partial^2 u_1(c,h)/(\partial c \partial h) > 0$).

Using this simple model, we first illustrate two broad channels through which the health status affects wealth accumulation. The first is an *earnings channel*, which can drive the wealth-health relationship as unhealthy individuals mechanically earn less even when supplying the same hours (as they are less productive), but also because labor supply itself is affected by health status. To see how, we can combine the first order conditions of consumption and labor supply resulting from (20) (given by equations (A.4) and (A.5) in Appendix A.9), which yields the labor-leisure condition:

$$\frac{\partial \phi(n,h_0)}{\partial n} = u_0'(c_0)w(h_0). \tag{21}$$

The left-hand side shows the marginal cost of labor supply, which is expected to be larger for the unhealthy. Hence, this force would induce the unhealthy to work less keeping wages constant. The right-hand side shows the marginal benefit of labor supply, which primarily consists of the wage. Since this is lower for the unhealthy, the first-order effect could potentially reduce the incentives to work.[39]

The second broad channel is a *savings channel*, which results from unhealthy individuals having different incentives to accumulate wealth compared to healthy individuals. The Euler equation resulting from (20) is given by:

$$u_0'(c_0) = \beta S(h_1) \frac{\partial u_1(c_1,h_1)}{\partial c_1} \tag{22}$$

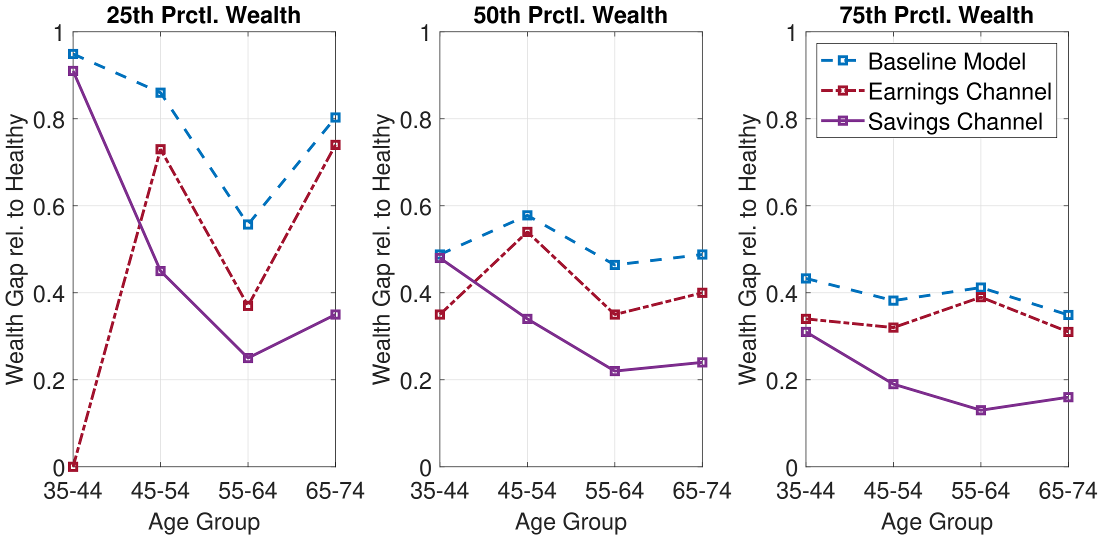
The right-hand side shows that savings can be higher with better health for two reasons; if one expects to live longer (i.e., a higher survival probability $S(h)$) or if one expects to have a higher quality of life (i.e., a higher marginal utility from consumption $\partial u(c_1,h)/\partial c_1$). We therefore expect this channel to contribute to the wealth-health gaps endogenously generated in the model.[40]

To quantify how important these channels working mostly from health to wealth are in our full quantitative life-cycle model, we perform two counterfactual experiments. First, to quantify the earnings channel, we assume that both the disutility from work and labor productivity are no longer affected by health status (i.e., the disutility of labor supply is as if one was healthy for everyone and $w_p^e = 0$ for both education

[39]In practice, this effect depends on whether the substitution effect dominates the income effect as well as whether a health shock is permanent or not. See Appendix A.9 for further discussions.

[40]Note that our simplified model intentionally assumed that today's utility is independent of health to illustrate the savings channel clearly. Having the health-dependence in u_0 would affect the result, as discussed in Appendix A.9.

Figure 10: Effects of the Earnings and Savings Channels on Wealth-Health Gaps



Notes: Differences in the wealth levels of those being healthy and unhealthy at the 25th (left), 50th (middle), and 75th (right) percentile of the wealth distribution in the baseline model (blue), and in the counterfactual scenarios without differences in labor supply disutility and labor productivity by health (red), and with average savings choices across health status (purple) across 10-year age groups. The counterfactual experiments are calculated using the baseline distribution of health.

groups). This effectively shrinks the differences in labor incomes across health status. Second, to quantify the savings channel, we assume that the survival probability is as if one was healthy for everyone (i.e., $S_j(h_j = 1, e)\ \forall j, e$), and that the consumption utility and value of life is no longer diminished from being unhealthy (i.e., $\tilde{\kappa} = 1$). This reduces differences in the incentives to accumulate wealth between the healthy and unhealthy, conditional on other states. In both exercises above, we let agents behave optimally in terms of their labor supply, savings, and health effort choices. However, to isolate the effects going from health to wealth, we keep the baseline distribution of health when we simulate the counterfactual economy.[41]

Figure 10 summarizes the effects of these experiments on the wealth gap between healthy and unhealthy agents at the 25th percentile (left), the median (center) and the 75th percentile (right) and over age, expressed relative to the wealth of the healthy.[42] Both the red dash-dotted line, illustrating the experiment of closing the earnings channel, and the purple solid line, which depicts the gaps after removing the

[41] That is, unbeknownst to the agents in the model, their health outcomes at the beginning of each period are set to be exactly the same as in the baseline economy. This also implies that survival realizations are the same as in the baseline.

[42] For the counterfactual exercises hereafter, we present wealth-health gaps in relative terms to ease interpretation. They are constructed as the difference between wealth owned by healthy and unhealthy individuals in a given age groups, divided by wealth of the healthy. Thus, a number of 0.6, for example, means that going from healthy to unhealthy amounts to a 60% drop in wealth or that unhealthy individuals own 40% of the wealth of healthy ones at that point in the distribution.

savings channel as defined above, are below the baseline blue dotted line throughout the life cycle. This suggests that both channels contribute to the wealth-health gaps. Yet, their relative importance differs across age groups and wealth positions. The earnings channel is quantitatively more important for the younger, and particularly asset-poor agents, for whom wealth levels are relatively small such that differences in savings across health status are of little consequence. In contrast, differences in earnings across health status play a major role, as they provide almost the sole basis for wealth accumulation. In fact, at the 25th wealth percentile, minimizing such differences effectively closes the entire model-generated wealth-health gap in age group 35-44. At median wealth levels, the gaps between those being healthy and unhealthy are reduced by over 10 percentage points in that age group.

For all other age groups however, the effect of turning off the savings channel has quantitatively larger implications for the wealth-health gaps. The effect is particularly strong for asset-rich individuals, where the gaps are approximately halved, on average, and even reduced by almost 70% at age group 55-64. With the exception of the youngest age groups, the relative importance of the savings channel for driving the wealth-health gaps is quite constant across age. In sum, these results suggest that different savings incentives originating from differences in the length and quality of life across health status are an important reason why relative wealth-health gaps are persistent over the life-cycle.

Against the backdrop of the illustration in the simple model above, we use our model to further decompose the contributions of the earnings channel into effects that work through health-dependent labor productivity and disutility from work separately. As shown in Table A.12, we find that the former is quantitatively much more important and that these two sub-channels are complementary to each other in generating the total effects of the earnings channel. Similarly, we further decompose the contributions of the savings channel into effects that come from the quality of life (i.e. through differences in κ) and effects that work through the length of life (survival rates) across healthy and unhealthy agents. We find that the survival channel is quantitatively more relevant in delivering the total effects of the savings channel, especially for the relatively older individuals, as shown in Table A.12.

5.2. Heterogeneity in Lifestyle Behaviors and Wealth-Health Gaps

In Section 2.2, we presented suggestive evidence that lifestyle behaviors could contribute to the positive association between wealth and health observed in the data. In contrast to the channels investigated in Section 5.1 that run from health to economic outcomes, endogenous lifestyle choices have the potential to capture effects running in the other direction. By doing so, they can potentially *amplify* the wealth-health relationship over the life-cycle if good economic outcomes and higher wealth lead to higher effort choices, which in turn improve the probability of good health outcomes, feeding back into the channels in Section 5.1.[43] We investigate these effects in our model in two ways: First, we quantify the extent to which differing lifestyle behaviors across individuals explain the large wealth-health gaps in the model. Second, we illustrate how wealth impacts lifestyle choices, net of other factors.

Regarding the first way, we perform a counterfactual experiment, in which we force all agents to choose the age-specific average health effort level at the baseline model.[44] The rest of the model remains unchanged and we let the agents optimize given this constraint. In particular, the earnings and savings channels of health we investigated in Section 5.1 are operative in generating wealth-health gaps.

Figure 11 summarizes the wealth-health gaps in the data, the baseline model and the counterfactual model with equalized health effort choices at three different points along the wealth distribution. Equalizing health efforts throughout the life span reduces the wealth-health gaps across the wealth distribution relative to the baseline economy. For example, the maximum percentage difference in median wealth of the unhealthy relative to the healthy is reduced to around 33% from around 46% in the baseline at ages 55-64. Across the life cycle, equalizing health efforts reduces the relative wealth-health gap on average by 12% at the 25th percentile, by 23% at the median, and by 29% at the 75th percentile relative to the baseline model. These findings obtained in the presence of the earnings and savings channels yet in the absence of effort heterogeneity suggest that individual health behaviors are an important amplification mechanism for wealth-health gaps.[45]

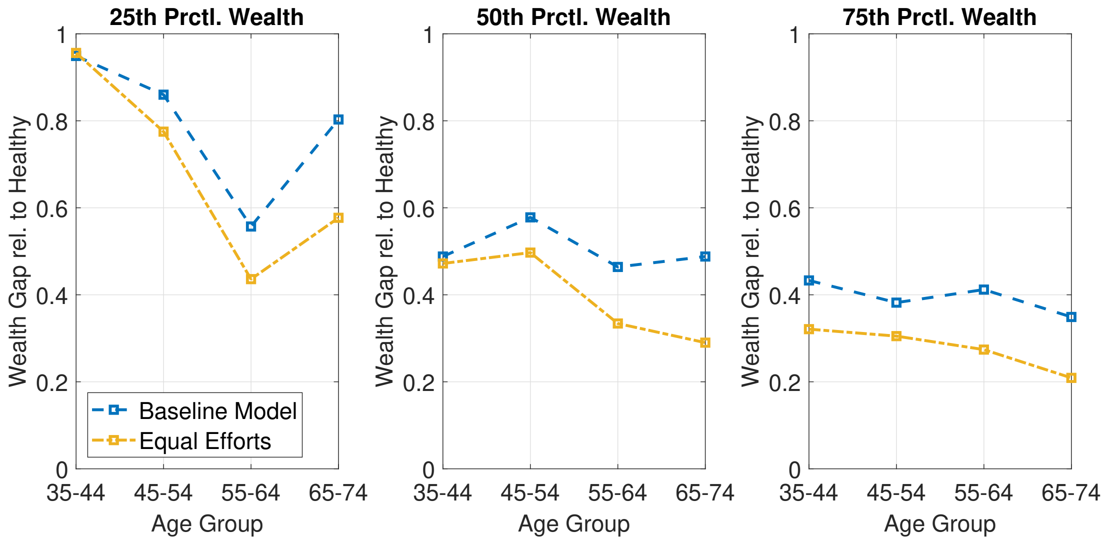
When we force everyone to choose the same average lifestyles, we remove heterogeneity in health outcomes that arises solely from differences in lifestyle behaviors. Since our model features a realistic positive wealth gradient of health efforts, this on average reduces the share of good health outcomes among rich individuals and

[43] Such an amplification mechanism could therefore be especially powerful if the wealth-gradient in health efforts observed in both model and data is driven by higher wealth itself, on top of third factors such as education.

[44] In this exercise, we therefore maintain the estimated effects of other characteristics such as education on health transitions when removing effort heterogeneity, whereas the re-estimated exogenous health model does not (as can be seen in Table A.6). Moreover, the current exercise allows us to flexibly explore the role of differences in lifestyle behaviors at different points in the life cycle.

[45] If we close both savings channel and earnings channel in the model, there are no incentives left to exert health efforts as being healthy has no benefits. Yet, some of the wealth-health gaps remain, as shown in Figure A.4. This is because there remain other factors in the model that drive the evolution of both health and wealth. In particular, education affects the probability of being healthy even without any efforts, while at the same time generating higher wages.

Figure 11: Effect of Equalizing Health Efforts on Wealth-Health Gaps



Notes: Differences in the wealth levels of those being healthy and unhealthy at the 25th (left), 50th (middle), and 75th (right) percentile of the wealth distribution in the baseline model (blue) and in the counterfactual scenario with constant health effort choices (yellow). Differences are expressed relative to the wealth levels of the healthy.

increases the share of good health outcomes among poorer individuals, keeping the distribution of wealth fixed, which decreases the wealth-health gap.[46] At the same time, the counterfactual of equalizing efforts could in principle also affect other choices that drive the gap, even without its effect on health.[47] In Appendix A.10, we quantify these two effects and find that total effects of equalizing efforts works primarily through its direct effect on the health distribution.

In addition, given the habitual character of lifestyle behaviors both in the data and in the model, it is conceivable that behavior differences at younger ages matter relatively more for the whole life cycle than those at older ages. In Figure A.5 in Appendix A.10, we investigate the extent to which the wealth-health gaps are differently affected according to the timing of equalizing health behaviors. The results suggest that eliminating effort variation during earlier life years, especially in prime ages, has prominent lasting effects in terms of reducing the wealth-health gaps in later years.

The second important question is then what drives heterogeneity in lifestyle

[46]Therefore, by construction, *averages* of key variables such as life expectancy, health, earnings and health barely change.

[47]For example, an agent choosing lower health efforts relative to the baseline may find it optimal to also save less in anticipation of worse health outcomes in the future, which will make consumption less enjoyable. For the same reason, however, she might also save more to insure against the risk of not being able to work because of poor health outcomes. Overall, these indirect effects of the effort equalization counterfactual on the relationship between wealth and health are therefore ambiguous.

behaviors, in particular, along the wealth dimension. Although the wealth-gradient in lifestyles is likely in part driven by ex-ante heterogeneity, more wealth raises the incentive to exert better lifestyle behaviors even conditional on these fixed types. To see this, we resort again to the simple model (20), this time considering the optimality condition for efforts derived in Section A.9:

$$\varphi'(f) = \beta S'(\pi(f))\pi'(f)u_1(c_1, \pi(f)). \tag{23}$$

The right-hand side determines the benefit of exerting more efforts. It shows that improvement in the survival probability driven by better health is multiplied by the *level of utility*, a feature that is common to models with endogenous survival. Since utility levels are increasing in (future) wealth, richer individuals, or those expecting to be rich in the future should, all things equal, thus have a stronger incentive to exert health efforts. This also means that the (anticipation of) redistribution of future consumption has the potential to reduce current disparities in lifestyle behaviors. This, in turn, could reduce inequalities in future health outcomes and consequently narrow wealth-health gaps.

We illustrate the importance of these dynamic effects working through endogenous lifestyle behaviors using the following experiment in our quantitative model. We solve for optimal effort choices in a counterfactual economy where all agents think that when entering retirement, all assets and pensions will be taxed at 100% and everyone instead receives transfers that equal exactly the average retirement wealth in the baseline economy. In the simulation of the distribution, however, we maintain the savings and labor supply levels of the baseline model for every agent. Thus, only effort choices and their consequences for the health distribution are changed.

We report the results of this experiment in Table 4. Panel A shows the percentage changes in average health effort, conditional on wealth quartiles and age groups. For almost every age group and wealth quartile, agents increase their efforts relative to the baseline case.[48] This rise in healthy behaviors is accelerated with age. Moreover, there is a clear negative trend in the change in efforts going from the first wealth quartile to the fourth one at every age group. This is precisely because for rich individuals, this counterfactual scenario does not lead to significantly different expectations in wealth levels during retirement. For that reason, they do not need to change their lifestyles (which were already at a high level). Poor individuals, on the other hand, have much stronger incentives to survive and be healthy in later years, anticipating increased wealth that will allow them to enjoy a larger utility from consumption.

[48]This is sensible given that the size of the average uniform transfers is quite generous for a large fraction of agents given the skewed wealth distribution.

The adjustments in health efforts translate into changes in health outcomes, as shown in changes in the share of individuals in bad health in Panel B of Table 4. As expected the share drops in particular among poorer individuals. Mirroring the lifestyle changes, the improvements in average health again become stronger with age, but are already visible even before retirement. Taken together, the disparities in health outcomes of poor and rich individuals therefore become smaller, which eventually narrows the wealth-health gap (as presented in Panel C of Table 4), even in the absence of the earnings and savings channels defined in Section 5.1.

These results also indicate that changes in economic conditions during the life course can lead to meaningful changes in the distribution of health outcomes. A natural question is then to ask how much of inequality in health outcomes is predetermined at the initial period (age 25). Using a decomposition exercise following Huggett et al. (2011) (as discussed in details in Appendix A.8), our model shows that although initial conditions at age 25 play a substantial role in shaping the variation in economic outcomes, such as lifetime earnings, they are less important for explaining lifetime inequality in health-related outcomes. For example, approximately one-third of the variation in the share of healthy life years is predetermined by the conditions at age 25, in contrast to nearly 80% for lifetime earnings. In sum, these results add support to the idea that lifestyle behaviors, which allow individuals to react to changing economic circumstances, can act as an amplification mechanism between economic outcomes and health over the life cycle.[49]

6. Conclusion

We document a strong association between individual wealth and health over the life cycle in Germany. We then build a structural life-cycle model of endogenous wealth and health evolution as individual lifestyle behaviors shape future health outcomes. These, in turn, affect wealth accumulation through differences in earnings and savings behaviors across health status. Our estimated model accounts for the great majority of the empirical wealth-health gaps, rationalizing that large and persistent wealth-health gaps can occur even in countries where the healthcare

[49]The fact that health efforts react to changes driven by future wealth leaves untouched other reasons that drive effort choices that also work through the utility level channel, and could potentially also affect the wealth-health relationship. For example, the return to efforts is higher when the future is expected to be more enjoyable, which is the case not only when one is rich but also healthy. Moreover, during working years, the return to effort includes an effect coming through higher expected future wages. Interestingly, this last motive can be decreasing in wealth, as we show in Appendix A.9. Generally, the direction in which such forces could affect the wealth-health relationship is often not clear, and a quantitative exploration goes beyond the scope of this paper.

Table 4: Results of Equalizing Wealth during Retirement Periods

Unit: %	Panel A				Panel B				Panel C		
	Average Effort by Wealth Quartile				**Share Bad Health** by Wealth Quartile				**Wealth-Health Gaps** at Percentile		
Age Group	1st	2nd	3rd	4th	1st	2nd	3rd	4th	25th	50th	75th
35-44	0.4	0.7	0.1	-0.3	0.0	-0.8	-1.2	0.0	0.0	0.0	-1.1
45-54	2.0	1.4	0.7	0.0	-1.5	-0.7	0.0	0.0	-0.1	-0.8	-0.7
55-64	7.7	4.0	1.8	0.1	-4.1	-2.3	-1.1	0.0	-4.3	-5.5	-5.6
64-75	11.2	10.2	4.8	1.1	-8.9	-7.4	-4.3	-1.1	-7.0	-16.4	-17.6

Notes: Reported numbers are percentage changes relative to the benchmark case without the counterfactual experiment. The counterfactual experiment assumes that effort choices are based on the belief of a uniform 100% tax on wealth and retirement benefits during retirement years along with transfers equal to the average retirement wealth in the baseline economy.

system does not frequently entail large out-of-pocket expenses. Through a series of decomposition exercises, we find that, quantitatively, while the earnings channel is important for the young and asset poor, the savings channel drives the wealth-health gaps at most ages, and especially for asset-rich individuals. We demonstrate that lifestyle behaviors can act as an amplification mechanism behind the dynamic relationship between wealth and health since good economic outcomes lead to higher health effort choices in our model.

While our model is relatively rich, we abstract from several potentially relevant mechanisms, in particular those through which money itself could influence future health. These include private medical expenditures, preventive monetary investments in health, and higher-quality but costly private insurance options. While we believe that these channels are likely less important in the German context, as we discuss in Appendix A.1, they could nonetheless help the model to match the wealth-health gaps more closely. Moreover, these channels are crucial to consider when analyzing other countries where out-of-pocket medical expenses are more prevalent and private insurance frequently consists of better healthcare relative to the public option.

Our results imply that policies aimed at improving individual health behaviors (e.g., conditional cash transfers when joining a gym Charness and Gneezy, 2009), can result not only in lasting benefits in terms of improving health inequality over the life course but may also extend into dimensions of economic inequality. Conversely, our findings also suggest that rising wealth inequality may, by exacerbating heterogeneity in lifestyles, contribute to consolidating the pronounced positive association between economic- and health-related well-being, and could underlie the increasing divergence in health-related behaviors observed in recent years (Lampert et al., 2018). We leave this interesting empirical question for future work.

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A. Online Appendix

A.1. Medical Spending in Germany

The healthcare system in Germany is characterized by the co-existence of two insurance systems. Almost 90% of the population are covered by statutory health insurance (SHI), while the remaining share is covered by a substitutive private health insurance (PHI). Only individuals with an annual income above a certain opt-out threshold (currently around 64,000 EUR annually in 2022), the self-employed, or civil servants can choose to be covered by a PHI. A detailed discussion of the differences between the two insurance types and their funding and reimbursement schemes can be found in Karlsson et al. (2016). Notably, SHI coverage, as mandated by law, includes a very generous package of benefits, including all medically necessary treatments, prescription drugs, and, importantly for our purpose, preventive, and rehabilitation care. The PHI benefit packages are more heterogeneous but typically oriented towards the public package. They may include additional features, such as preferential treatment in hospitals, or dental and eye care. Given that PHI enrollees are generally wealthier, as they tend to be better educated and earn higher incomes (Karlsson et al., 2016), if these features materially improve individual health, they may be an important explanatory factor for the wealth-health relationship.

On top of that, there are numerous "individual health services", including non-standard screenings and therapies that are increasingly offered by physicians but are typically paid for directly by the patients and not covered by health insurance. Similarly, other potentially health-promoting expenses on nutritional supplements, physical treatments or even private psychological counselling could theoretically strengthen the wealth-health relationship if these are normal goods and significantly improve an individual's future health prospects.

However, the use of many of these health services is at least scientifically unclear, and they often comprise medically unnecessary cosmetic and luxury treatments or use methods whose benefits have not been sufficiently certified (Schnell-Inderst et al., 2011).[50] Moreover, using data on household consumption spending from the 2010 survey wave of the SOEP, we do not see a significant statistical correlation between spending on health-related goods and services and labor income (or wealth) after controlling for individual characteristics (that are also present in our model). Table A.1 shows the results of a linear regression of annual consumption of health-

[50]This is not to say that in given circumstance, such services may be very sensible. However, consumer protection authorities frequently warn against using unsolicited health services without extensive information.

Table A.1: Effect of Earnings and Wealth on Spending on Health Goods

	Cons. of Health Goods and Services$_i$	
Good Health$_i$	-108.7***	-107.9**
	(53.1)	(59.2)
Age$_i$	8.1***	6.7***
	(1.0)	(1.3)
College$_i$	104.3***	92.7***
	(32.7)	(28.3)
Earnings$_i$	0.7	
	(0.5)	
Wealth$_i$		0.07
		(0.05)
N	16,193	11,314
R^2	0.007	0.006

Notes: The dependent variable is annual household consumption spending on health goods and services. Coefficients and standard errors (in parentheses) of earnings and wealth are multiplied by 1,000. Stars denote statistical significance at the 10%, 5%, and 1% level.

related goods and services on a dummy for good health, age, college education, and labor income or wealth, respectively. In line with our expectations, the estimated coefficients indicate that individuals in good health spend significantly less on health-related consumption, while older and higher educated individuals tend to spend more.[51] Labor income or wealth, in contrast, are not statistically significantly associated with higher health-related consumption.

Notwithstanding this suggestive evidence, there can be alternative possibilities through which larger financial resources could affect health that go beyond direct medical goods and services. These include, for instance, access to better housing in less polluted, quieter neighborhoods, the possibilities of more frequent or costly recreational activities or vacations, and potential effects of wealth on psychological stress, which can also translate to physical health conditions (Schwandt, 2018). However, such effects are hard to detect statistically as they likely take a long time horizon to realize and are dependent on individual circumstances. Perhaps unsurprisingly, the literature that tries to establish a causal link from resources to health among adults in developed countries remains debatable (Cutler et al., 2011).

In sum, the arguments provided in this discussion lead us to believe that a "money can buy health" channel is less relevant in Germany than it might be in other countries, such as the U.S. Thus, our paper focuses on another margin

[51] Karlsson et al. (2016) investigate individual medical spending using data from a private health insurer and find that medical spending increases over age and is particularly concentrated in the last three years before death.

that is frequently pondered as an important mechanism behind the wealth-health relationship: lifestyle behaviors (Cutler et al., 2011; Cawley and Ruhm, 2011).

A.2. Comparison of Different Health Measures

We compare our binary health measure to two alternative measures of health. First, beginning in 2002, the SOEP includes a series of questions on the health-related conditions of the respondents, which are repeated every second year. These are designed to mirror the second version of the 12-item Short Form Health Survey (SF-12 v2) questionnaire. The purpose of these questions is to provide generic indicators of perceived physical and mental health, called Physical and Mental Component Summary scores (PCS and MCS, respectively). For example, they ask about difficulty getting dressed, climbing stairs, or feeling alone. The scores are transformed into a 0-100 range and standardized to have a mean of 50 and standard deviation of 10. Figure A.1 displays box plots of the evolution of these indicators by 10-year age group.

Second, we construct a *frailty* index of individuals' health history as in Hosseini et al. (2022). Beginning in 2011, the SOEP added questions regarding the diagnosis of specific health conditions by doctors, ranging from diabetes and asthma to depression and anxiety. We construct the index by adding a 1 whenever an individual has been diagnosed with one of these illnesses. Thus, the higher the frailty, the worse the health. The resulting average frailty by 10-year age groups is depicted in Figure A.2.

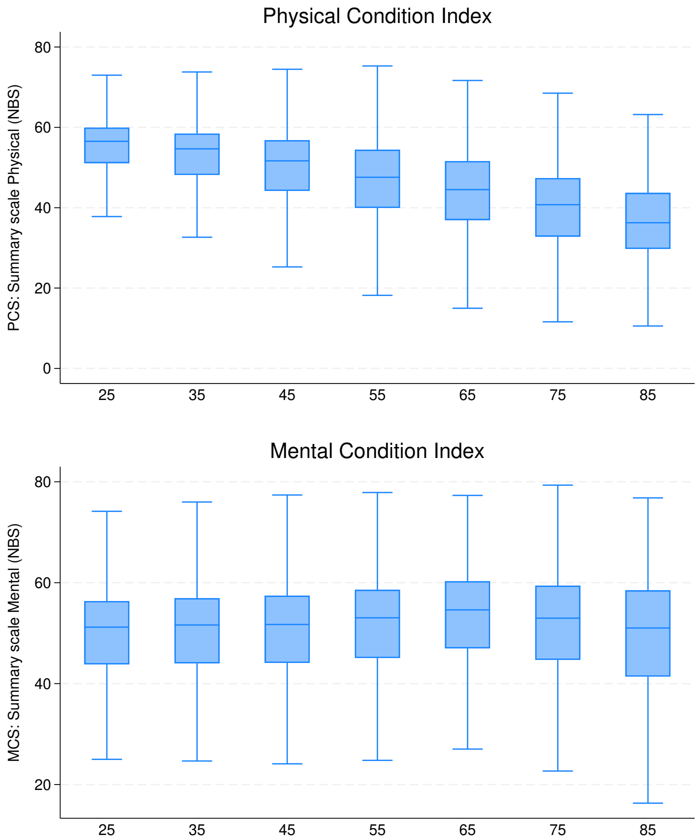
Table A.2 summarizes the correlation between our preferred binary health measure and these alternative, possibly more objective, health measures, as well as with the original 5-point self-reported health scale.[52] As expected, binary health is negatively correlated with frailty and positively correlated with the physical and mental health summary score (though the correlation with the mental health score is rather weak). Moreover, the correlations of the original 5-point self-reported health scale with these measures are only slightly higher than with the aggregated binary health measure, which suggests that we do not lose much variation by focusing on the latter.

A.3. Construction of Health Effort

We use information on three individual health-related behaviors in constructing our health effort measure, following Cole et al. (2019). First, the frequency of practicing a sport or exercising is given by never or almost never, several times a year, at least

[52] All measures have been standardized. Note that PCS and MCS scores are orthogonal to each other by construction.

Figure A.1: Physical and Mental Health Summary Scores over the Life Cycle



Notes: The scores are calculated based on the SF-12 v2 series of questions on health-related quality of life. They are normalized to a mean of 50 and a standard deviation of 10 for 2004. A higher score indicates better health.

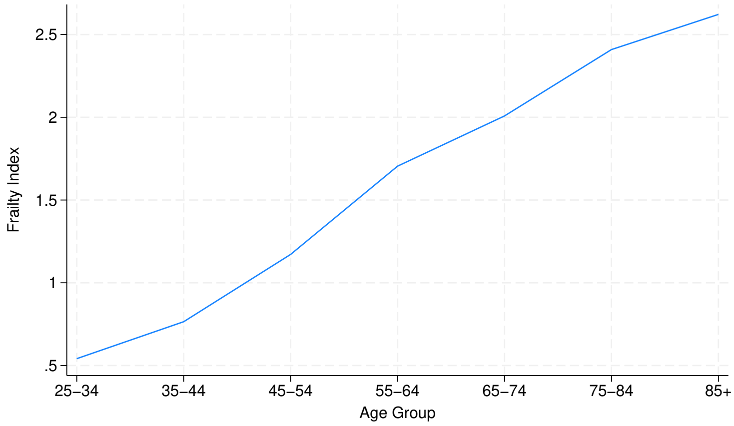
Table A.2: Correlations across Different Health Measures

	Binary Health	5-point SRHS	Frailty	PCS	MCS
Binary Health	1	0.77	-0.41	0.62	0.26
5-point SRHS		1	-0.50	0.76	0.29
Frailty			1	-0.55	-0.16
PCS				1	-0.02
MCS					1

once a month, and at least once a week. Second, survey respondents are asked how strongly they take health considerations into account in their nutrition. The answers range from very strongly to not at all.[53] Third, we use information on the number of cigarettes smoked in a day, which we cap at 50 as in Cole et al. (2019). We

[53]Information about amounts and frequencies of alcohol consumption are only infrequently included in our data, which is why we rely on more general health-conscious nutrition.

Figure A.2: Evolution of Frailty over the Life Cycle



Notes: The frailty index is calculated by adding a 1 each time an individual is diagnosed with a specific health condition (Hosseini et al., 2022).

standardize each measure to have mean zero and standard deviation one (Kling et al., 2007) and use the negative of cigarettes smoked as a measure of healthy behaviors. The correlation of the three behaviors is reported in Table A.3.

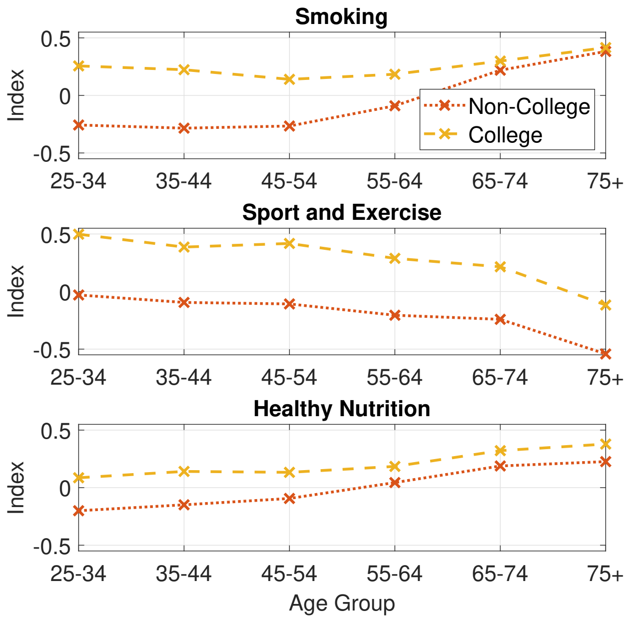
Table A.3: Health Effort Components and Weights

Health Behavior	Physical Exercise	Healthy Nutrition	Abstention from Smoking	Loading
Physical Exercise	1	0.17	0.15	0.5918
Healthy Nutrition		1	0.21	0.5865
Abstention from Smoking			1	0.5530

All of these behaviors are likely also correlated with other observable characteristics. For example, Figure A.3 shows the average evolution over age of the three components of health effort, separately for the college and non-college educated. While smoking becomes less frequent with age, and nutrition becomes healthier, physical exercise declines. For each component, a clear positive educational gradient is observed. Similarly, each behavior, in particular the frequency of sports and exercises, is positively correlated with wealth. Given that the weight on each behavior should reflect its relative importance in explaining lifestyle variations net of potentially confounding factors, we purge each behavior from variation coming from such factors by regressing them on age, age squared, years of schooling, marital status, work status, insurance type, labor income, and wealth.

Using the residualized effort measures, we perform a principal component analysis, where we take as the first principal component the measure that most closely resembles the notion of individual lifestyle behaviors. The first principal component

Figure A.3: Evolution of Standardized Healthy Lifestyle Behaviors



Notes: Average of the standardized components of health effort by 10-year age group: Abstention from smoking, sport of exercise, and health-conscious nutrition.

explains around 45% of all variance in the residualized physical exercise, nutrition, and abstention from smoking. We then calculate the weights as the relative loadings of each behavior, which are relatively equal as summarized in the last column of Table A.3. Finally, we normalize the aggregated effort variable to be in the unit interval.

A.4. The Effects of Health on Employment and Labor Income

In our baseline model in the main text, we introduce a productivity (wage) penalty and differences in disutility of work for unhealthy individuals. In this subsection, we provide empirical evidence that supports our modeling approach. Specifically, we estimate how contemporaneous health affects the probability of working, as well as labor income and hours worked conditional on working, using the SOEP data and the following model:

$$y_{i,t} = \alpha_h Health_{i,t} + \delta_1 y_{i,t-1} + \delta_2 y_{i,t-2} + \gamma \mathbf{X_{i,t}} + \gamma_i + u_{i,t}, \tag{A.1}$$

where $y_{i,t}$ denotes either a dummy that equals 1 if individual i is working at time t and 0 otherwise, log labor income conditional on employment, or log hours worked conditional on employment. $\mathbf{X_{i,t}}$ includes a constant, age, age^2, marital status, type of health insurance (private or public), survey year, the number of children in

Table A.4: Effect of Health on Work Status, Labor Income, and Hours Worked

	(i) $work_{i,t}$	(ii) $\log(income_{i,t} \mid work_{i,t}=1)$	(iii) $\log(hours_{i,t} \mid work_{i,t}=1)$
$Health_{i,t}$	0.152	0.072	0.068
	(0.016)	(0.017)	(0.017)
N	104,085	61,185	61,185

Notes: Estimated coefficient $\hat{\alpha}_h$ from equation (A.1). $Health_{i,t}$ is instrumented by number of doctors visits and nights spent in the hospital in t. Column (i) reports results from the estimation on the whole sample of 25-64 year-olds, column (ii) and (iii) only on the sample of employed individuals. First-stage tests confirm relevance assumption of these instruments.

the household, and dummies for the occupation in case of work. We also include individual fixed effects γ_i. We are interested in α_h, the contemporaneous effect of health on wage or hours worked.[54] In estimating such an effect, one concern might be simultaneity bias, which arises if labor income or hours worked themselves affect health status. We consequently instrument health status in year t by the number of doctor visits and the nights spent in the hospital in that same year. Given generous health insurance coverage benefits and sick-day regulations in Germany, the effect of the number of doctor visits or nights spent in the hospital on earnings and hours should work largely through health.

The results of estimating (A.1) using GMM are reported in Table A.4. Column (i) gives the estimated effect of health in year t on the probability that individual i works in the same year, estimated across the whole population. Going from being unhealthy to healthy increases this probability by an estimated 15.2%, even conditional on employment in the past two periods. We find a similar role of health in affecting labor supply along the extensive margin as that observed in other countries.

Columns (ii) and (iii) report the effect of being healthy on income and hours worked, restricting the sample to those working in t. Good health increases labor income conditional on working by around 7%. The majority of this increase is due to longer working hours, which increase by over 6%. This suggests that, even conditional on working, healthy individuals increase their labor supply, possibly through switching from part-time to full-time work. The results furthermore indicate that good health could be accompanied by an increase in productivity that manifests in higher wages per hour, and thus larger labor income gains from being healthy.

[54]It would also be reasonable to assume that health has only lagged effects on labor income and supply. Moreover, we could also highlight heterogeneous effects of health on particular demographic subgroups, as in Hosseini et al. (2021). However, our goal here is simply to quantify the contemporaneous effects of health on labor market outcomes, net of other confounding effects.

A.5. Details on the Estimation of Standard Errors

We estimate 42 parameters Θ_0 to match 64 empirical moments $\hat{\Delta}$ using the method of simulated moments. To conduct standard inference on our estimates using this estimator, we would need know a consistent estimate of the full variance-covariance matrix of the empirical moments $\hat{V}$. Alternatively, a bootstrap method can be used to construct standard error estimates. In our case both of these options are infeasible. While most of our empirical moments are computed from the SOEP data, they often use specific subsets of the data. In particular, wealth information is only available every 5 years. On top of that, the estimate for the values of a statistical life year (VSL) are taken from a meta-analysis of VSL estimates in OECD countries (OECD, 2012), which prevents us from computing the correlation between the elements of $\hat{\Delta}$. Moreover, the application of a bootstrap method would be computationally expensive given that our parameter and moment space is relatively large.

For that reason, we use the strategy of Cocci and Plagborg-Møller (2021), who show that the standard errors of the method of moment estimates $\hat{\Theta}$ can be bounded when assuming that the elements of $\hat{\Delta}$ are perfectly correlated with each other. They are computed as the weighted sum of the standard errors of individual empirical moments. They show that these worst-case standard errors can further be minimized for over-identified models by selecting only those moments which are most-informative about the parameter at question. To construct the weights, we compute the Jacobian matrix that contains the derivatives of the model-implied moments with respect to the standard errors using first differences. The main assumption behind this method is a joint normality assumption of all empirical moments. We view this as reasonable in our context as all moments with the exception come from the same data set.

The algorithm to compute the efficient worst-case standard error for each component of $\hat{\Theta}$ then comprises the following steps (see Cocci and Plagborg-Møller (2021), page 11-12): First, we construct an efficient estimator $\hat{\Theta}$ using the weight matrix that has the inverse of each empirical moment's standard error on its diagonal, and zeros on the off-diagonals. Next, we construct the Jacobian matrix using first differences. Finally, we solve the median regression (eq. 6 in Cocci and Plagborg-Møller (2021)) that allows us to perform the efficient moment selection procedure for each parameter, which yields the standard error estimates as reported in Table 2.

Table A.5: Empirical Moments and Standard Errors

Description	Value	S.E.	Description	Value	S.E.
Employment Share	0.651	0.002	Median Wealth	0.062	0.003
among healthy	0.766	0.002	divided by average	0.516	0.015
by 10-year age group	0.823	0.002	2-year labor income	1.166	0.024
	0.619	0.002	by 10-year age group	1.651	0.037
Employment Share	0.506	0.008		1.567	0.043
among unhealthy	0.583	0.005		1.006	0.047
by 10-year age group	0.601	0.005	Education Gradient in Employment	1.237	0.003
	0.409	0.005	Non-Adjuster Shares	0.267	0.004
Average Effort among	0.678	0.002	by Long Age Group	0.328	0.003
non-college and healthy	0.677	0.002		0.404	0.004
by 10-year age group	0.680	0.002	VSL multiple	8.493	0.595
	0.699	0.002	Standard Deviation of Effort	0.161	0.000
	0.730	0.002	Consumption Ratio of Healthy/Unhealthy	1.163	0.022
	0.724	0.002	Average Labor Income	35.393	0.196
Average Effort among	0.643	0.007	in Ths for non-college	49.379	0.232
non-college and unhealthy	0.623	0.005	and healthy by 10-year age group	55.955	0.266
by 10-year age group	0.627	0.004		42.219	0.353
	0.655	0.003	Average Labor Income	24.948	0.563
	0.697	0.003	in Ths for non-college	33.166	0.519
	0.692	0.003	and unhealthy by 10-year age group	36.691	0.499
Average Effort among	0.779	0.002		25.311	0.499
college and healthy	0.770	0.002	Average Labor Income	59.483	0.488
by 10-year age group	0.766	0.002	in Ths for college	89.538	0.632
	0.763	0.002	and healthy by 10-year age group	107.928	0.761
	0.779	0.002		98.277	1.108
	0.769	0.004	Average Labor Income	50.388	1.849
Average Effort among	0.752	0.011	in Ths for college	66.253	1.656
college and unhealthy	0.744	0.008	and unhealthy by 10-year age group	78.318	1.688
by 10-year age group	0.737	0.006		63.133	1.786
	0.738	0.005	Variance of Log Labor Income	0.595	0.002
	0.751	0.005	Pension Replacement Rate	0.477	0.002
	0.734	0.006	Wealth Gini Coefficient	0.746	0.004

A.6. Further Details on Structural Model Estimation

Classification of Fixed Health Types

As explained in Section 4, the first step of estimating the probability of being in good health in the next period involves the classification of individuals in our data into fixed unobservable health type groups η using the *kmeans* algorithm. We construct the data moments used for the classification in the following way: First, we take all direct measures of health and health-related status that are available in our data for at least half of the sample period. These are (i) the number of annual doctor visits, (ii) self-rated health status on a 5-point scale, (iii) inpatient nights in a hospital, (iv) and (v) the Physical and Mental Component Summary scores (see

Appendix A.2), and (vi) the body-mass index.[55]

Second, we residualize these variables against age, age squared, a college education dummy, gender, health insurance type status, and cohort dummies. We do this because the individual health type should be informative about variation in health and health-related status *net of* variation that arises from other time-constant observable characteristics. Moreover, we strip the health moments from variation coming from mere satisfaction with own health (on a 10-point scale). This is to make sure that the classification into unobserved health types is based on fundamental factors that are no changed as a result from noisy reporting and measurement issues. Third we standardize the resulting residuals to give every variable the chance to be equally important for the health type classification. Since the health type is fixed over time, we take one average standardized residual per individual.

The fourth step comprises the clustering of individuals using the *kmeans* algorithm that assigns observations to the cluster with the smallest Euclidean distance. We repeat the clustering for randomly chosen initial group centers and for up to 5 clusters. We then calculate the within-cluster sum of squares for each cluster number. Our goal in selecting the number of clusters is to have intra-cluster variation that is as small as possible while maintaining computational feasbility in our model. Since the within-cluster sum of squares display a kink ("elbow") after 2 clusters, we opt to select two clusters.

Estimation of Wages and Productivity

Our estimation of the distribution of fixed productivity types and the persistence and variance of idiosyncratic shocks involves the following steps. First, we compute real hourly wages x_{ij} for individual i with age j in our data on the sample of workers that work for at least two consecutive years. We then recover combined residuals and individual fixed effects estimates from a regression of log wages on the full set of age and health dummies (D_{it}^{age} and D_{it}^{health}, respectively) according to:

$$\ln x_{ij} = \sum_{t=25}^{63} \sum_{h=\{0,1\}} d_t^h \times D_{it}^{age} \times D_{it}^{health} + \theta_i + u_{ij}, \tag{A.2}$$

as in De Nardi et al. (2023); French (2005). Here, the coefficients d_t^h capture the effect of the interaction of dummy variables for age and health status and θ_i captures unobserved fixed labor productivity. While we treat this fixed productivity

[55] We experimented with including individual fixed effects from a regression of future health on current and past health, effort and age as additional moments. However, this restricted our sample too much.

continuous in the estimation, we follow Low and Pistaferri (2015) in assuming discrete productivity "types" in the model as detailed in Section 4.2.

Next, we regress the combined estimated (predicted) residuals ($\hat{\theta}_i + \hat{u}_{ij}$) on cohort dummies and education to strip them from variation coming from these sources that we capture through $\lambda_j(h_j, e)$. We then estimate the parameters of the idiosyncratic components using a standard generalized method of moments (GMM) procedure that minimizes the distance between the empirical age-profile of the variances of the combined residuals and the population analogue following Storesletten et al. (2004).[56] We obtain the estimated persistence of idiosyncratic productivity shocks $\rho = 0.975$.

A.7. Discussion of Estimated Health Technology Parameters

Table A.6 shows the results of estimation of (16) along with the estimates of the exogenous health model. All estimates are statistically significant at the 95% level. Table A.7 reports average marginal effects calculated from the estimated parameters for the baseline model.

The estimates from the columns for the baseline model with endogenous health imply that the probability of being healthy in the next period, conditional on effort, current health, education and health type, decreases monotonically over age. Individuals with the high health type consistently have, ceteris paribus, a larger probability of being healthy than those with the low health type. The same, albeit to a smaller degree, is true for agents with college rather than non-college education. However, the largest differences in the probability of being healthy conditional on all other covariates, arise between individuals who are currently unhealthy and individuals who are currently healthy. For example, a healthy 75-year-old college-educated individual of the high health type has a 67% probability of being healthy in two years absent any effort (past and present) if she is currently healthy, while this probability is only 16% if she is currently unhealthy.

Much research, primarily medical, has aimed to causally identify the effect of different lifestyle components on good future health. For example, Lee (2003) review data from 50 epidemiological studies on the relationship between physical activity and cancer incidence. Similarly, Colman and Dave (2013) analyze the connection between physical activity and the prevalence of hypertension, diabetes, and heart disease. Other papers, such as those by LaCroix et al. (1991) and Van Oyen et al. (2014) highlight the impact of smoking on mortality and disability. More recently,

[56] Concretely, to distinguish the variance of the fixed effect from the variance of transitory shock, we again follow Storesletten et al. (2004) and references therein by computing the sum of three consecutive residuals for 25-year olds.

Table A.6: Logit Estimation of Probability of being Healthy in 2 years

Variable	Model: **Coef.**	Endogenous Health **Estimate**	**Std.Error**	Exogenous Health **Estimate**	**Std.Error**
Current Health Effort	λ_1	0.693	0.138		
Past Health Effort	λ_2	0.734	0.137		
Current Health	$h_t = 1$	2.311	0.029	2.340	0.029
Age Group Dummies					
35		-0.289	0.079	-0.301	0.078
45		-0.644	0.074	-0.655	0.074
55		-0.881	0.074	-0.871	0.074
65		-1.138	0.074	-1.074	0.073
75		-1.586	0.077	-1.527	0.077
Health Type	$\eta = 1$	0.632	0.028	0.654	0.028
College	$e = 1$	0.238	0.033	0.388	0.032
Constant		-0.906	0.095	0.013	0.072
Pseudo R^2		0.242		0.237	

Notes: $N = 43,336$. Standard Errors are heteroscedasticity robust.

Cena and Calder (2020) review evidence on the health-promoting effects of more plant-based diets. Generally speaking, there is a strong consensus in this literature on the beneficial effects of healthy lifestyle behaviors, such as physical activity, a healthy diet, and abstention from smoking, on morbidity and mortality. However, since these studies typically focus on the effect of a specific lifestyle behavior on the onset of a specific disease, such as hypertension or diabetes, it is not possible to directly compare their estimates with our health transition technology parameters, which are estimated based on self-reported health status.

To facilitate a meaningful comparison, we accordingly employ three approaches. First, similar to Cole et al. (2019), we use the SOEP data to map health status to the prevalence of a specific health condition, conditional on age group and education (see Table A.8). We use this information to construct the probability of the onset of a specific disease in the future, conditional on current health status, age group, fixed health type, as well as current and past health effort, which is implied by our estimated health technology parameters using the formula:

$$\begin{aligned} Pr(disease_{j+1}|h_j, f_j, f_{j-1}, e, \eta) =& \pi_j(h_{j+1} = 1|h_j, f_j, f_{j-1}, e, \eta) \times Pr(disease|h_{j+1} = 1, e) \\ &+ (1 - \pi_j(h_{j+1} = 1|h_t, f_t, f_{j-1}, e, \eta)) \times Pr(disease|h_{j+1} = 0, e) \end{aligned}$$

Table A.7: Average Marginal Effects from Health Technology Estimates

	Low Health Type ($\eta = 0$)											
	No College ($e = 0$)						*College* ($e = 1$)					
	Unhealthy ($h_t = 0$)			Healthy ($h_t = 1$)			Unhealthy ($h_t = 0$)			Healthy ($h_t = 1$)		
Age	π^0	λ_1	λ_2	π^0	λ_1	λ_2	π^0	λ_1	λ_2	π^0	λ_1	λ_2
25-34	0.29	0.17	0.18	0.80	0.05	0.06	0.34	0.17	0.18	0.84	0.04	0.05
35-44	0.23	0.17	0.18	0.75	0.07	0.07	0.28	0.17	0.18	0.79	0.05	0.06
45-54	0.18	0.16	0.17	0.68	0.09	0.09	0.21	0.17	0.18	0.73	0.07	0.08
55-65	0.14	0.15	0.16	0.63	0.10	0.11	0.18	0.16	0.17	0.68	0.09	0.09
65-74	0.11	0.13	0.14	0.57	0.12	0.12	0.14	0.15	0.16	0.62	0.10	0.11
75+	0.08	0.11	0.11	0.45	0.15	0.15	0.10	0.12	0.13	0.51	0.13	0.14
	High Health Type ($\eta = 1$)											
	No College ($e = 0$)						*College* ($e = 1$)					
	Unhealthy ($h_t = 0$)			Healthy ($h_t = 1$)			Unhealthy ($h_t = 0$)			Healthy ($h_t = 1$)		
Age	π^0	λ_1	λ_2	π^0	λ_1	λ_2	π^0	λ_1	λ_2	π^0	λ_1	λ_2
25-34	0.43	0.15	0.16	0.88	0.03	0.03	0.49	0.14	0.15	0.91	0.02	0.03
35-44	0.36	0.16	0.17	0.85	0.04	0.04	0.42	0.15	0.16	0.88	0.03	0.03
45-54	0.29	0.17	0.18	0.80	0.05	0.06	0.34	0.17	0.18	0.84	0.04	0.05
55-65	0.24	0.17	0.18	0.76	0.06	0.07	0.29	0.17	0.18	0.80	0.05	0.06
65-74	0.20	0.17	0.17	0.71	0.08	0.08	0.24	0.17	0.18	0.76	0.07	0.07
75+	0.13	0.15	0.115	0.61	0.11	0.11	0.16	0.16	0.17	0.67	0.09	0.10

Finally, we average this implied probability of having a specific disease over individuals in the top, middle, and bottom terciles of the current health effort distribution and/or the past effort distribution, conditional on age group, current health and education but averaging over health type. To be comparable to Cole et al. (2019), we use only individuals between the age of 25 and 75. We then calculate the average percent deviation of the implied disease probabilities in each effort tercile relative to their within-status mean and compare the results to those in Colman and Dave (2013).

Table A.9 shows the results. Overall, the effectiveness of health efforts in reducing the probability of disease onset implied by our estimated health technology parameters seems lower than that reported in Colman and Dave (2013) for the case of exercise. For example, while they find that exercise can reduce the prevalence of heart conditions by between 23-29%, our estimates imply that being in the top effort tercile for current and past health effort lessens the prevalence of heart conditions by around 5% compared to the mean.

Yet, the disadvantage of this approach is that it focuses on just one specific component of our compound health effort measure, namely exercise. We consequently

Table A.8: Prevalence of Diseases in Population by Age Group and Health Status

		Health Condition Prevalence by Education							
		No CL	CL	No CL	CL	No CL	CL	No CL	CL
Age	Health	Diabetes		Cancer		Hypertension		Heart Condition	
25-34	Unhealthy	0.038	0.000	0.015	0.006	0.111	0.073	0.029	0.011
	Healthy	0.007	0.006	0.006	0.005	0.042	0.028	0.013	0.011
35-44	Unhealthy	0.055	0.034	0.035	0.029	0.201	0.118	0.062	0.044
	Healthy	0.018	0.011	0.015	0.011	0.104	0.067	0.015	0.012
45-54	Unhealthy	0.116	0.064	0.074	0.075	0.327	0.286	0.118	0.084
	Healthy	0.039	0.022	0.025	0.030	0.201	0.162	0.032	0.019
55-64	Unhealthy	0.200	0.177	0.094	0.113	0.525	0.462	0.213	0.172
	Healthy	0.089	0.063	0.051	0.047	0.342	0.328	0.075	0.058
65-74	Unhealthy	0.263	0.243	0.164	0.179	0.575	0.593	0.348	0.347
	Healthy	0.147	0.123	0.084	0.104	0.456	0.423	0.149	0.150
75+	Unhealthy	0.262	0.251	0.138	0.221	0.583	0.621	0.460	0.491
	Healthy	0.179	0.171	0.102	0.135	0.490	0.508	0.248	0.276

implement a second approach, again in an effort to gauge our estimated health technology parameters against the literature, this time using a mapping between health status and survival in old age to benchmark our estimates against the results found in Knoops et al. (2004). Their study not only explores the effect of a comprehensive lifestyle measure, comprised of a Mediterranean diet, moderate alcohol use, physical activity, and nonsmoking, but also uses data on European men and women between ages 70 and 90 and is thus closer to our German data source.

To compare their estimate of the impact of healthy lifestyles on mortality, we simulate the random health and survival evolution of 100,000 individuals between the ages of 70 and 84 that are equipped with our estimated health transition technology, as specified in Section 4.2.[57] As Table A.10 summarizes, our parameter estimates paired with the empirical average lifestyle effort results in a 10-year mortality rate around 42% percent, which is slightly above the rate reported in Knoops et al. (2004). When restricting everyone to have a healthy lifestyle, which we assume to be the effort at the 90th percentile by age, the simulation-implied mortality rate drops to 40.6%. This drop is slightly smaller, yet comparable to that found in Knoops et al. (2004). Vice versa, if we assume everyone exerts efforts equal to the 10th percentile, mortality over 10 years is increased by half a percentage point. We take this as confirmation that our estimated health technology parameters, and especially the effectiveness of health efforts, are conservative but reasonable in light of the empirical medical literature.

[57]We choose 84 instead of 90 to have ample sample size to measure 10-year mortatiliy. We assume that initial age is drawn uniformly between 70 and 84.

Table A.9: Implied Probability of Disease by Past and Current Effort Tercile

Effort Tercile	Percent Change of Probability relative to the within-status Mean Diabetes	Cancer	Hypertension	Heart Condition
Current Effort				
Low	3.52	2.85	1.52	4.05
Middle	-0.52	-0.43	-0.21	-0.61
High	-3.35	-2.72	-1.45	-3.86
Past Effort				
Low	2.11	1.74	0.88	2.52
Middle	-0.26	-0.22	-0.10	-0.33
High	-2.12	-1.73	-0.90	-2.51
Both				
Low	4.26	3.5	1.81	5.06
Middle	-0.76	-0.62	-0.31	-0.923
High	-4.11	-3.36	-1.75	-4.87
Coleman & Dave	1.2-3% decrease		10-31% decrease	23-29% decrease

Table A.10: Mortality among Older-Age Individuals implied by Our Estimates

	Mortality Rates over 10 years (%) Knoops et al.	Implied by Simulation
Average Lifestyle	39.9	42.3
Healthy Lifestyle	35	40.6
Unhealthy Lifestyle		42.8

Finally, several papers investigate the causal effect of compound measures of healthy lifestyles on specific disease prevalence. For example, Schlesinger et al. (2020) find, in a meta-analysis of the literature, that adherence to healthy lifestyle behaviors (i.e., a favourable diet, physical activity, nonsmoking, moderate alcohol intake, and normal weight) lowers the risk of type 2 diabetes by almost 80%, which qualifies the numbers found in column 1 in Table A.9. Similarly, Barbaresko et al. (2018) survey 22 research papers that analyze the effect of adhering to a healthy lifestyle on the onset of various serious conditions, and find a reduced risk of 66% for cardiovascular disease, 60% for stroke, and 69% for heart failure.

A.8. Sources of Lifetime Inequality

To get a sense of the importance of initial conditions in shaping inequality in lifetime outcomes, we follow the strategy in Huggett et al. (2011) and calculate the

Table A.11: Contribution of Initial Conditions at Age 25 to Lifetime Inequality

Statistic	Model
Fraction of variance in lifetime earnings	81.3%
Fraction of variance in wealth at age 65-66	53.0%
Fraction of variance in healthy years	24.9%
Fraction of variance in the share of healthy years in life	36.5%

share of (the present value of) lifetime earnings, of the variance in the wealth at retirement ages, of the number of healthy years, and of the the share of healthy years to overall life years that can be explained by variation in the individual states at age 25. Specifically, following Huggett et al. (2011), we compare the conditional variance in these outcomes, where we condition on all individual state variables at age 25, with the unconditional variance. The state variables are education, discount factor type, productivity type, and health type, as well as initial health and initial health effort habits. For the latter, we group individuals into three equally sized groups reflecting their initial health effort habits. If a significant share of wealth and health inequality can be explained by initial conditions, the positive association between wealth and health is more likely to be predetermined at age 25. On the other hand, if the explained share is small, this points to the significance of luck in terms of economic but also health shock realizations during life in determining inequalities.

Table A.11 summarizes the results. We find that around 81% of the variation in lifetime earnings in our model is accounted for by differences in the initial conditions individuals face at age 25, similar to the 62% that Huggett et al. (2011) find for this outcome in the U.S. The corresponding statistic for wealth at the retirement age (i.e., age 65-66) is lower but is quite large at 53%. By contrast, the differences in initial conditions explain much smaller fractions of the variations in healthy years (25%), and the share of healthy years in life (37%), implying that events over the lifetime largely drive the health-related outcomes. Overall, our results indicate the the role of both initial conditions and lifecycle events (and choices made by agents) in accounting for health and wealth inequality over the lifecycle.

A.9. Details about the Conceptual Two-Period Model

We presented a simple two-period model with endogenous health and wealth accumulations in Section 5.1 to build insights on key channels. Here we provide more details such as a full set of assumptions, derivations for the optimality conditions, and further results with different assumptions.

In addition to the key assumptions laid out in Section 5.1, we further assume that utility is positive ($u_t > 0$ for $t = 0, 1$) and that the survival probability is positive ($S(h_1) > 0$). For simplicity, we assume zero interest rate, which is not important for our results. Current health (h_0) is assumed to be a state variable, and future health (h_1) can be shaped by the effort choice through $\pi(f)$. Having endogeneity of current health is feasible, yet complicates the analytic results. Similarly, we abstract from several mechanisms that are present in our quantitative life-cycle model to focus on illustrating our key channels of interest. These include the effect of current health on effort cost disutility, the effect of current health on current consumption utility and the effect of current health on future health. We provide implications of incorporating these extra effects below.

We can rewrite the constrained optimization problem (20) as

$$\max_{c_0,f,n} \{u_0(c_0) - \varphi(f) - \phi(n, h_0) + \beta S(\pi(f))u_1(w(h_0)n - c_0, \pi(f))\} \tag{A.3}$$

which yields the following first-order conditions:

$$[c_0] \quad : \quad u_0'(c_0) = \beta S(h_1)\frac{\partial u_1(c_1, h_1)}{\partial c_1} \tag{A.4}$$

$$[n] \quad : \quad \frac{\partial \phi(n, h_0)}{\partial n} = \beta S(h_1)\frac{\partial u_1(c_1, h_1)}{\partial c_1}w(h_0) \tag{A.5}$$

$$[f] \quad : \quad \varphi'(f) = \beta S'(\pi(f))\pi'(f)u_1(c_1, \pi(f)). \tag{A.6}$$

The first equation A.4 describes the optimal savings choice, as discussed in Section 5.1. As noted earlier, one could consider the health-dependence on u_0 as well. Then, the condition would read

$$\frac{\partial u_0(c_0, h_0)}{\partial c_0} = \beta S(h_1)\frac{\partial u_1(c_1, h_1)}{\partial c_1}. \tag{A.7}$$

Therefore, if we consider a health penalty in the form of a multiplicative constant $\kappa(h)$, one can see that the relative health status would shape the strength of the savings motive. For example, if $h_0 < h_1$, then it could reinforce the savings motive. On the other hand, for those with $h_0 = h_1$, the savings channel we discussed in Section 5.1 would only work through the length channel (i.e., $S(h_1)$).

Combining equations (A.4) and (A.5), we can obtain:

$$\frac{\partial \phi(n, h_0)}{\partial n} = u_0'(c_0)w(h_0), \tag{A.8}$$

which is the labor-leisure condition (21). As is standard in any labor-leisure condition, the effects of higher wages due to health on labor supply depends on whether the substitution effect is stronger than the income effect, which is shaped by the functional form on utility. In practice, it would also matter if the wage decline is temporary or not, since a temporary change would induce a stronger positive effect on labor supply than a permanent change.

Finally, (A.6) describes the optimality condition for the effort choice. As in the labor disutility, one could potentially introduce health-dependence on the disutility of efforts. The implication is going to be parallel: poor health would shift the left-hand side up, which would increase the marginal cost of efforts.

Moreover, we note that if we assume that health for the working period (i.e., h_0) can also be endogenously affected by the effort choice, the right-hand side would additionally include:

$$\beta S(\pi(f)) \frac{\partial u_1(c_1, \pi(f))}{\partial c_1} w'(\pi(f))\pi'(f), \tag{A.9}$$

which captures an effect coming through higher expected future wages when healthy. Interestingly, this motive can be decreasing in wealth, as it is weighed by the marginal utility of future consumption, which decreases with wealth. In other words, the motive to exert efforts to be healthy in the future and therefore be more productive, is weaker with rising income, which we can interpret as an income effect of effort. This force would mitigate the earnings channel in generating wealth-health gaps.

A.10. Additional Quantitative Exercises

Savings and Earnings Channel

Table A.12 reports the proportions of the baseline relative wealth-health gaps that are explained by different channels. With *Wage Loss Only*, we only impose $w_p^e = 0$ for both education groups. With *Disutil. Only*, we only impose that the disutility of labor supply is as if one was healthy for everyone. With *Length Only*, we only equalize the survival probability at the healthy level: $S_j(h_j = 1, e) \forall j, e)$. With *Quality Only*, we only impose that the consumption utility and value of life is not reduced from being unhealthy ($\tilde{\kappa} = 1$). In all exercises, we keep the distribution of health fixed at the baseline economy.

Figure A.4 shows the results of a counterfactual experiment, in which we shut down both savings and earnings channel, and leave the distribution of health free to adjust to different health effort choices. This effectively takes away any incentive to exert efforts, as being unhealthy is no longer different from being healthy in terms of

Table A.12: Contributions to Wealth-Health Gaps of the Baseline Model

	Earnings Channel								
	Total			Wage Loss Only			Disutil. Only		
Wealth	25th	50th	75th	25th	50th	75th	25th	50th	75th
Age Group									
35-44	100%	28%	21%	21%	0%	15%	-1%	11%	1%
45-54	15%	6%	15%	14%	5%	8%	-4%	0%	1%
55-64	34%	23%	6%	17%	12%	6%	5%	7%	1%
65-74	8%	19%	12%	7%	10%	11%	0%	7%	3%
	Savings Channel								
	Total			Length Only			Quality Only		
Wealth	25th	50th	75th	25th	50th	75th	25th	50th	75th
Age Group									
35-44	4%	1%	28%	-2%	0%	16%	-4%	-7%	11%
45-54	48%	42%	50%	16%	18%	36%	12%	2%	7%
55-64	55%	52%	69%	30%	19%	37%	17%	7%	9%
65-74	56%	51%	55%	32%	33%	40%	8%	5%	7%

Notes: This table reports the proportions of the baseline relative wealth-health gaps explained by different components of the earnings and savings channels. See the text for their definitions.

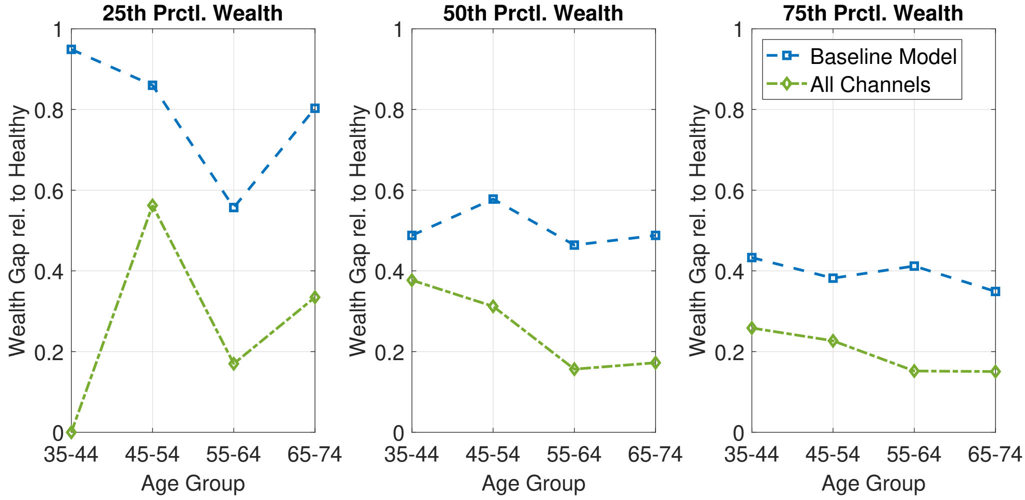
labor supply, wages, survival or consumption utility. This shrinks the wealth-health gaps considerably, by around 60%, on average. The remaining gaps in our model can be explained as individuals still differ in fixed characteristics that drive both wealth accumulation and the probability of being health, most notably education.

Equalizing Efforts

In this subsection, we first explain how to quantify the contributions of the two different (direct versus indirect) effects that we discussed in Section 5.2 to the wealth-health gaps of the baseline economy separately at different ages and points of the wealth distribution in Table A.13.

Specifically, we quantify the contribution of *direct* effects of health effort equalization that work through the health distribution by simulating our baseline economy but, unexpectedly to the model agents, changing the health distribution to be the same as in the equal efforts counterfactual. That is, all decisions on savings, labor supply and health efforts are the same as in the baseline economy but the health evolution of every agent is as if she would have exerted the average effort level. Analogously, we quantify the contribution of the *indirect* effects of the equal efforts experiment that work through choices, by simulating the counterfactual economy, but keeping the health distribution of the baseline case. The results clearly suggest

Figure A.4: Effect of Both Earnings and Savings Channels



Notes: Differences in the wealth levels of those being healthy and unhealthy at the 25th (left), 50th (middle), and 75th (right) percentile of the wealth distribution in the baseline model (blue) and in the counterfactual scenario when shutting down both earnings and savings channel together (green). Differences are expressed relative to the wealth levels of the healthy.

Table A.13: Contributions of Equal Efforts to Baseline Wealth-Health Gaps

	Equal Efforts								
	Total			Direct Effects Only			Indirect Effects Only		
Wealth	25th	50th	75th	25th	50th	75th	25th	50th	75th
Age Group									
35-44	-17%	3%	26%	0%	6%	24%	-2%	-4%	1%
45-54	10%	14%	20%	12%	14%	17%	-3%	-2%	2%
55-64	22%	28%	34%	21%	29%	33%	-3%	-1%	2%
65-74	28%	41%	40%	25%	40%	41%	2%	3%	2%

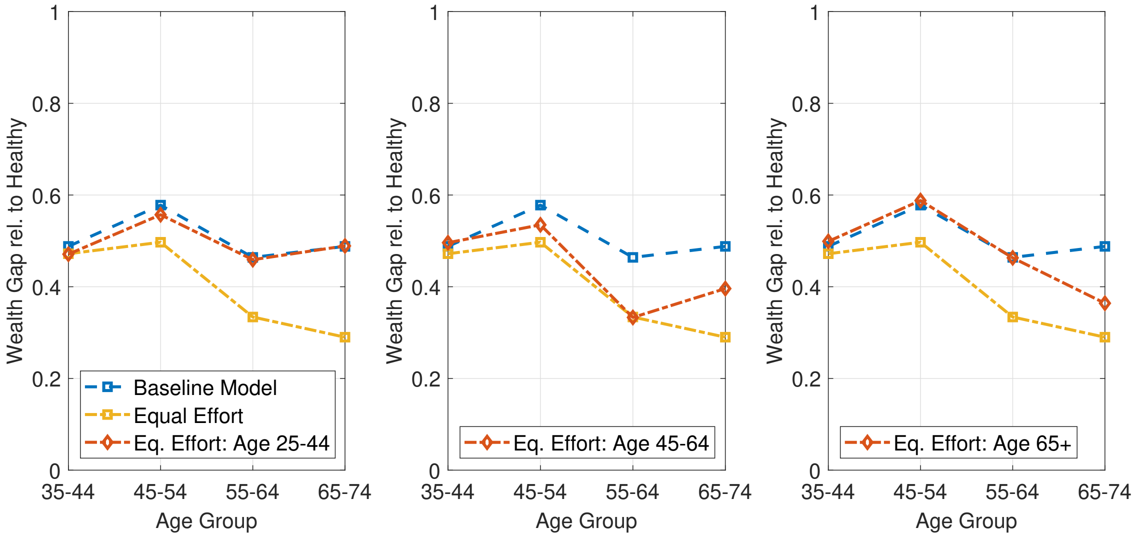
Notes: This table reports the proportions of the baseline relative wealth-health gaps that are explained by different effects. See the text for the definitions of direct and indirect effects.

that the total effects of equalizing efforts works primarily through its direct effect on the health distribution rather than the indirect effects.

Next, in addition to equalizing efforts at all age groups, we perform a series of further counterfactual exercises, in which we separately equalize individual health efforts for the following ages groups: 25-44-year-olds, 45-64-year-olds, and 65-and-older (i.e., retired individuals).

Figure A.5 displays the resulting wealth-health gaps at the median for different scenarios. The left panel suggests that when equalizing health efforts among the young working-age agents only (ages 25-44), the wealth-health gaps are also slightly reduced in the 45-54-year-old age group. For older individuals, however, the gaps remain as large as in the baseline economy, meaning that eliminating effort variation

Figure A.5: Effect of Timing of Health Efforts on Wealth-Health Gaps



Notes: Differences in the wealth levels by health status at the median of the wealth distribution in the baseline model (blue), in the counterfactual scenario with constant health effort choices across all age groups (yellow), and in the counterfactual scenarios where health efforts are equalized separately for the 25-44-year-old (left), 45-64-year-old (middle), and 65+ (right) age groups.

early on has some moderately lasting effects in terms of closing the wealth-health gaps during the working ages. This is sensible given that the estimated adjustment costs are low when agents are young.

The lasting effect becomes more pronounced when equalizing efforts among prime-age workers (ages 45-64), who begin to face a more significant risk of becoming unhealthy. On the one hand, the gap at ages 45-54 is higher than in the counterfactual case with constant effort everywhere, as health behaviors are allowed to vary at young ages and this spills over into the age groups where efforts are held constant. On the other hand, the gap at ages 65-74 is diminished by almost 20% relative to the benchmark case even though health behaviors are allowed to vary.

A.11. Additional Figures and Tables

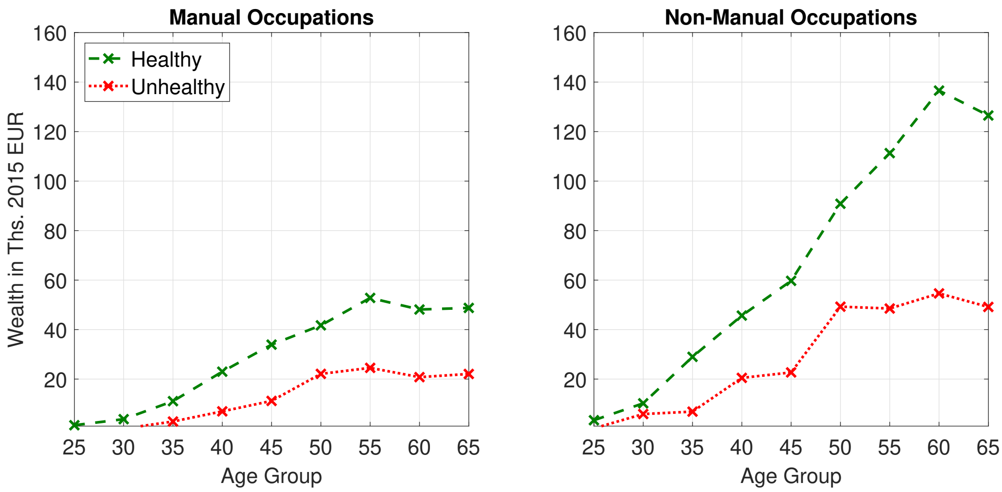
Table A.14 summarizes the initial distribution we estimate for our quantitative model. Several patterns are worth noting. Among college-educated individuals, 5% report being unhealthy between ages 25-30, while this number is over 8% among the non-college educated. Moreover, average initial health effort is almost two-thirds of a standard deviation higher for the college educated. The fixed health type is strongly correlated with initial health. Over 11% of those with the low health type are on average unhealthy, while it is less than 6% for the high health type. In contrast, initial health effort levels differ only little across health types. Generally, differences

Table A.14: Initial Distribution

	No College ($e = 0$)							
	$\beta = \beta_l$				$\beta = \beta_h$			
$\theta =$	θ_l		θ_h		θ_l		θ_h	
$\eta =$	η_l	η_h	η_l	η_h	η_l	η_h	η_l	η_h
Prob. Mass	0.062	0.133	0.070	0.101	0.061	0.099	0.063	0.102
Avg. h	0.878	0.937	0.878	0.937	0.878	0.937	0.878	0.937
Avg. f	0.663	0.690	0.663	0.690	0.663	0.690	0.663	0.690
	College ($e = 1$)							
	$\beta = \beta_l$				$\beta = \beta_h$			
$\theta =$	θ_l		θ_h		θ_l		θ_h	
$\eta =$	η_l	η_h	η_l	η_h	η_l	η_h	η_l	η_h
Prob. Mass	0.034	0.033	0.024	0.045	0.029	0.047	0.025	0.072
Avg. h	0.926	0.960	0.926	0.960	0.926	0.960	0.926	0.960
Avg. f	0.773	0.785	0.773	0.785	0.773	0.785	0.773	0.785

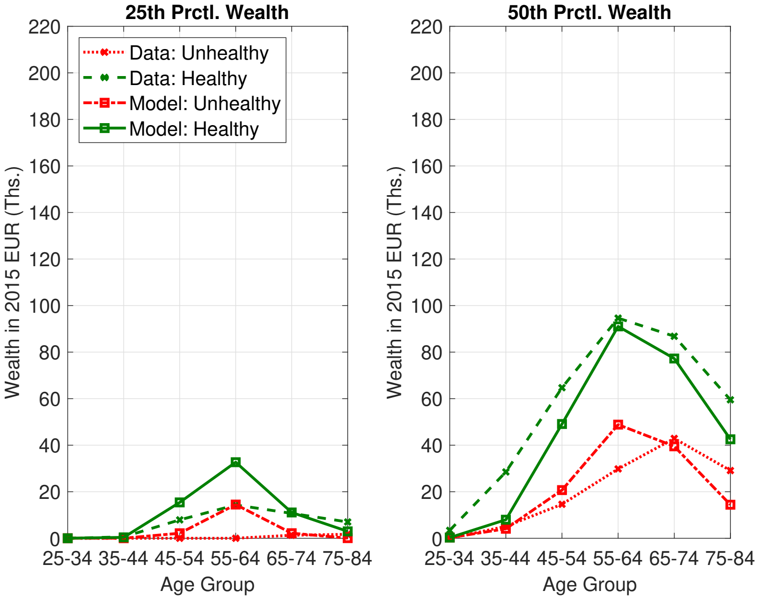
in both initial health and initial health effort are only marginal across productivity and discount factor types in the data, which is why we do not report them here.

Figure A.6: Median Wealth Profiles by Health Status and Occupation



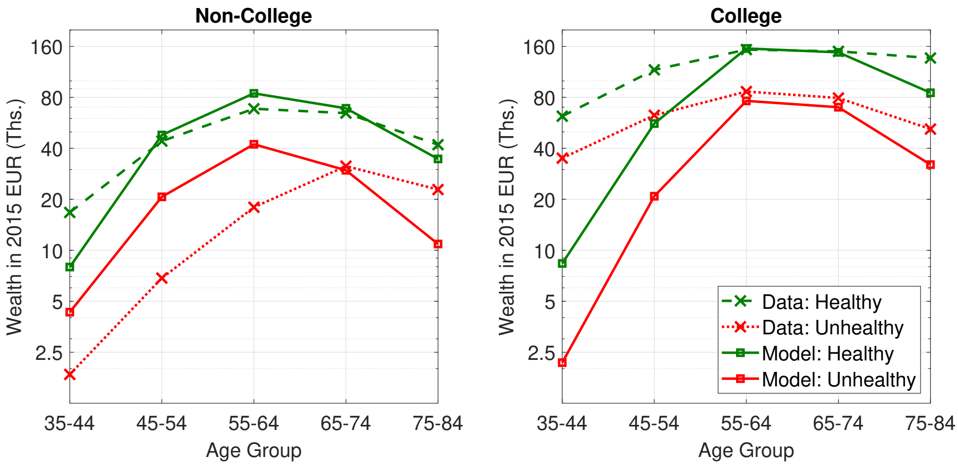
Notes: Median wealth per 5-year age group and health status for manual (left) and non-manual (right) occupations, separated by healthy (green) and unhealthy (red) status. Manual occupations include agricultural workers, craft and trades-persons, plant and machine operators, and other elementary occupations. The non-manual category includes all other occupations.

Figure A.7: Wealth-Health Gaps at Different Distribution Points: Model vs. Data



Notes: Wealth by 10-year age groups, distinguishing between healthy individuals (green) and unhealthy ones (red) in the model relative to the data at different point of the wealth distribution. Left panel: 25th percentile. Central panel: 50th percentile. Right panel: 75th percentile.

Figure A.8: Wealth Profiles by Health and Education: Model vs. Data



Notes: Wealth by 10-year age groups, distinguishing between healthy individuals (green) and unhealthy ones (red) in the model relative to the data. Left panel: Non-college educated individuals. Right panel: College educated individuals.

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