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 the empirical patterns in 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 various aspects of micro-level effort adjustment behaviors in the data. We find that our calibrated model generates around half of the wealth gaps by health observed in the German micro data, and that variations in health-related lifetime outcomes are largely explained by uncertainty realizations over the life cycle, rather than initial conditions at age 25. Our counterfactual experiments indicate that variations in individual health efforts account for over half of the model-generated wealth gaps by health status. Their importance is due not only to the fact that they affect labor income and savings rates, both of which influence wealth accumulation, but also because they act as an amplification device since richer households exert relatively more efforts to maintain a healthy lifestyle.

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, Pashchenko, and Porapakkarm (2018) 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 group. The gaps begin to open up at around the age of 25 and grow over the life cycle before stabilizing after retirement.[1]

What explains such large gaps in a country like Germany, characterized by universal health insurance, low out-of-pocket medical expenses, and generous sick-leave policies (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, French, and Jones (2010)), or the unilateral effect of health on labor supply and productivity coupled with the availability of disability insurance (Hosseini, Kopecky, and Zhao, 2021a).[2] 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, Kim, and Krueger, 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 (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 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).

[2]For a comprehensive review of the potential mechanisms underlying the positive relationship between health and socio-economic status more generally, see, for example, Cutler, Lleras-Muney, and Vogl (2008).

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.

Our calibrated model, using information from the German Socio-Economic Panel, is consistent with a number of salient features in the data. For example, the model-generated data align not only with the observed health gradients in labor supply and labor income but also the degree of wealth and income inequality seen in Germany. In particular, the model is calibrated to match various features of individual-level effort behaviors, and is able to match targeted moments such as their averages by age, dispersion, persistence, and the sizeable share of non-adjusting individuals that increases with age. Notably, our model reproduces more detailed non-targeted distributional aspects of effort adjustments, such as the share of individuals making large positive and negative adjustments, as observed in the data.

We find that the model accounts for between one- and two-thirds of the observed wealth-health gaps in the data, depending at which point of the distribution this is measured.[3] In addition, our model implies that variations in health-related outcomes over the lifetime (e.g., the fraction of healthy years) are largely due to factors occurring over the life cycle, as opposed to variations in lifetime earnings, which are largely (around 60%) accounted for by the initial conditions at age 25. Finally, we find that health behaviors have lasting effects. Given the presence of adjustment frictions in lifestyle behaviors, it is not possible to fully recover from poorer lifestyles at earlier ages over the course of the remaining lifetime. This results in persistently higher wealth-health gaps. The effect is particularly relevant for prime-aged individuals who begin to face a significant risk of becoming unhealthy, as compared to the younger age group who faces a lower health risk and smaller expected adjustment costs.

[3]While our model is rich, it still abstracts from alternative mechanisms through which money itself could affect health in the future. Such channels might include not only private medical expenditures (which are less relevant in Germany with a universal and generous health insurance) but also preventive monetary investments in health such as spending on relatively expensive organic items or health-related products (e.g., via GNC stores in the U.S.). These are also less relevant in the German context, since such goods are not as popular and price premiums on organic products are comparatively low. Appendix A.1 discusses the German healthcare system and provides suggestive empirical evidence on individual health-related consumption.

We then investigate the extent to which our main quantitative results are driven by different channels. Through counterfactual exercises, we observe that eliminating variations in individual lifestyle behaviors reduces the wealth-health gaps by over 50%, as compared to the baseline model economy. There are several reasons why health behaviors are such important drivers of the model-generated gaps. On the one hand, better lifestyles lead to improved health outcomes, which statically increase both labor income and the savings rate, as healthier individuals expect to have longer, higher quality lives. We find that these two channels together account for, on average, 40% of the model-generated gaps, with the labor income channel being particularly important for the young and asset-poor and the savings channel more consequential for older and asset-rich individuals. On the other hand, lifestyle behaviors are an important dynamic amplification vehicle, which fuels the wealth-health association over the life-course. This is because wealthier individuals, and especially the very wealthy, engage in more health-promoting efforts, which dynamically feeds back into better health and triggers the static labor income and savings channel.

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 (De Nardi, French, and Jones, 2010; French, 2005; French and Jones, 2011; 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.[4] Capatina (2015) and De Nardi, Pashchenko, and Porapakkarm (2018) 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, Pashchenko, and Porapakkarm (2018) 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, Pashchenko, and Porapakkarm (2018) study the interaction between wealth and health in an exogenous health framework, we

[4] See e.g., Attanasio, Kitao, and Violante (2010), Hall and C. I. Jones (2007), Jang (2020), Jung and Tran (2016), Kitao (2014), Pashchenko and Porapakkarm (2017), and Zhao (2014). 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. Cole, Kim, and Krueger (2019) and Low and Pistaferri (2015).

study this in a model with endogenous health.

In this regard, our paper is very 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, Kim, and Krueger (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, Keane, and Maruyama (2020), Hai and Heckman (2019), and Margaris and Wallenius (2020), 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, Feng, and Gu (2020), 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. Specifically, almost 90% of the total population is covered by public statutory health insurance.[5] 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).[6] 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.

[5]The remainder of the population is covered through private health insurance, available for individuals above a certain annual income threshold and self-employed individuals, or through special governmental insurance schemes (Fehr and Feldman, 2021). While the availability of private insurance for high-income individuals could theoretically drive the wealth-health gap if it consisted of better healthcare relative to the public option, this concern is negligible in Germany. The greater benefits offered by private health are typically limited to a small set of privileges that do not materially improve health outcomes, such as shorter waiting times.

[6]Germany's health 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.

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, Lleras-Muney, and Vogl (2008). We contribute to this body of work by providing an update on the state of health-related inequalities in Germany using the SOEP data. In doing so, we complement other studies using this same data set, such as Lampert et al. (2018), who employ the latter to compare the SES-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 calibration 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

2.1. Health and Lifestyle Behaviors

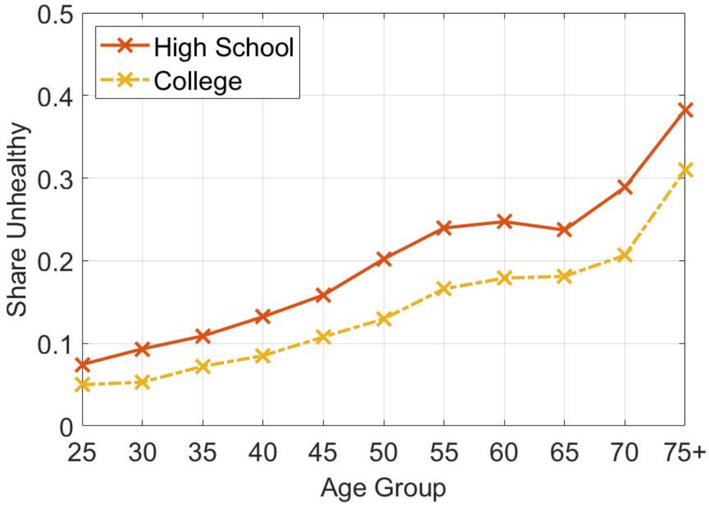
Throughout this paper, we rely on data from the German Socio-Economic Panel (SOEP). The SOEP is an annual representative longitudinal panel study of private households, conducted by the German Institute for Economic Research, DIW Berlin. We use information on individual wealth, employment, earnings, health, and lifestyle behaviors related to health from the 2004-2018 survey waves. We convert wealth and earnings data into 2015 Euros using a CPI index.

Health Dynamics

We measure individual health using information on self-rated health status in the SOEP. 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, Pashchenko, and Porapakkarm, 2018; French, 2005), we combine the first three categories into one *healthy* category and the last two into one *unhealthy* category.[7]

[7] 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, Kopecky, and Zhao (2021b), 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

Figure 1: Average Health over the Life Cycle



Notes: Share of unhealthy people in the SOEP over 5-year age groups, distinguishing between the high-school and college-education groups.

In Figure 1, we plot the average share of unhealthy individuals by 5-year age groups, starting at ages 25-29 and ending with ages 75 and older. We also distinguish between individuals according to their education level, where those in the high-school group completed a secondary but no tertiary education and those in the college group have at least some tertiary education. Already at ages 25-29, members of the high-school 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, almost 40% of high-school 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: (1) the frequency of sport or physical exercise; (2) health-conscious nutrition; and (3) 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

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Mental Component Summary scores (PCS and MCS, respectively). In Appendix A.2, we show the correlation of our benchmark binary health measure and these two alternatives. We focus on a binary self-reported health status measure rather than one of these alternatives for three reasons. First, 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. Second, this makes our study comparable to a number of existing papers in the structural health literature that also use a binary health measure. Finally, doing so provides a more parsimonious state space in our model in Section 3.

contributors to individual health risk (OECD, 2019). We normalize each measure to be in the unit interval and construct health effort as a weighted sum of these.[8] Overall, we end up with 104,603 individual-year health effort observations with a mean of around 0.63 and a standard deviation of 0.2. Moreover, we observe substantial path dependence in health efforts. For example, the autocorrelation of health efforts with a two-year interval is high at 0.82.

Comparing the average health effort levels of the various health and education groups (see Figure A.3 in Appendix A.3) allows us to draw two conclusions. First, unhealthy individuals consistently exert less health effort relative to healthy ones. Most of these differences are due to the fact that those in better health invest more in physical exercise. Second, college-educated individuals are characterized by higher health efforts than high-school educated individuals. Combining the two gradients, we find for example that a healthy person with a college education at ages 25-29 exerts on average a composite health effort that is over half a standard deviation higher than a unhealthy high-school educated person.

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.[9] To illustrate, Figure 2 shows the evolution of median wealth in the SOEP over the life cycle, separately for healthy and unhealthy individuals. The left panel uses the sample of high-school educated individuals, the right panel that of college-educated ones. For both education groups, the wealth levels of the healthy are consistently higher than those of the unhealthy. This *wealth-health gap* appears relatively early on in life and increases up until around the age 60 to 65. At this point, the median wealth of healthy individuals is about twice as large as the median wealth of unhealthy individuals.

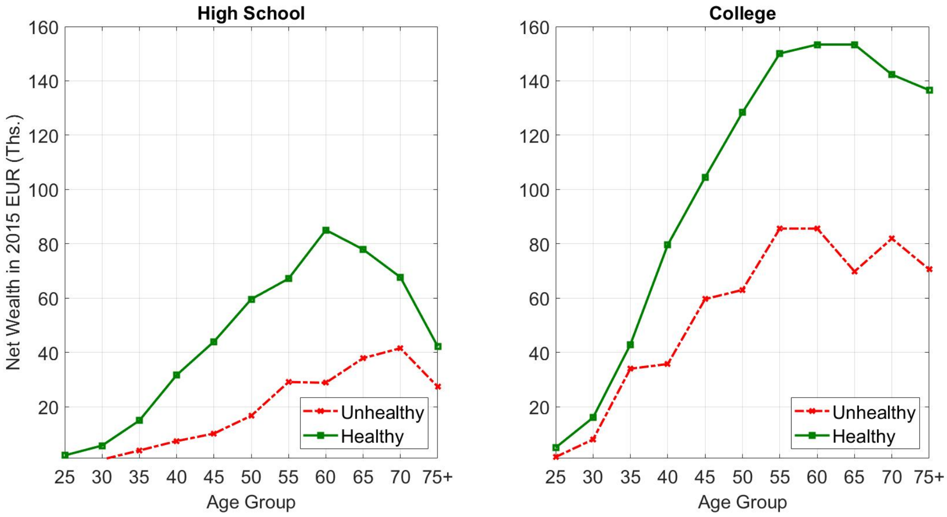
Moreover, the existence of these significant wealth-health gaps in both education groups means that the association between wealth and health cannot be explained solely by differences in education.[10] Similar exercises can, in fact, be carried out that consider different dimensions of socioeconomic status. For instance, occupations

[8]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 summarized in Appendix A.3.

[9]See Lampert et al. (2018) for a comparison of health inequalities in Germany over time and internationally. They find that health inequalities have widened in recent years.

[10]For example, by better educated individuals having more financial resources, for instance through better-paying jobs, or by being more knowledgeable about the efforts needed to lead a healthy life.

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



Notes: Median wealth by 5-year age-groups and health status for high school-educated (left panel) and college-educated (right panel) individuals in the SOEP.

could, through their potentially different toll on health, contribute to the wealth-health gap (see Appendix Figure A.7). Yet, in all cases, an independent correlation between wealth and health seems to persist, suggesting the existence of more direct 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., 2020). 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 various factors contribute to the significantly lower labor incomes observed for unhealthy individuals.[11] Worse health thus leads to lower available resources to accumulate wealth over the life cycle.

Yet, as pointed out by Poterba, Venti, and Wise (2017) and De Nardi, Pashchenko, and Porapakkarm (2018), a simple accumulation of lost labor income due to poor

[11]Relatedly, Hosseini, Kopecky, and Zhao (2021a) 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.5, 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 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.

health over the lifetime does not explain the majority of the association between health and wealth.[12] In light of these results, we explore the importance of individual health behaviors as an additional mechanism underlying the wealth-health relationship.[13]

Health Efforts and the Wealth-Health Relationship

Given that an individual's health outcomes benefit from better health behaviors, variations in that latter could in large 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 higher investments in health, we should expect richer people to devote comparatively more to such investments. Specifically, as consumption *levels* increase with wealth, the marginal utility of consumption falls and lifetime utility could be increased more effectively by extending life years. To achieve this, wealthier people dedicate relatively more of their resources to life-prolonging activities, such as healthy behaviors.[14]

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 high school or college education and age group. Health effort rises in wealth, with the exception of the young college educated individuals who are already in the 3rd wealth quartile. The increase is especially pronounced for high-school educated 45-64-year-olds, where average effort increases by almost 2/3 of a standard deviation.

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, in the case of abstention from smoking, higher health effort actually requires lower financial expenditure.[15]

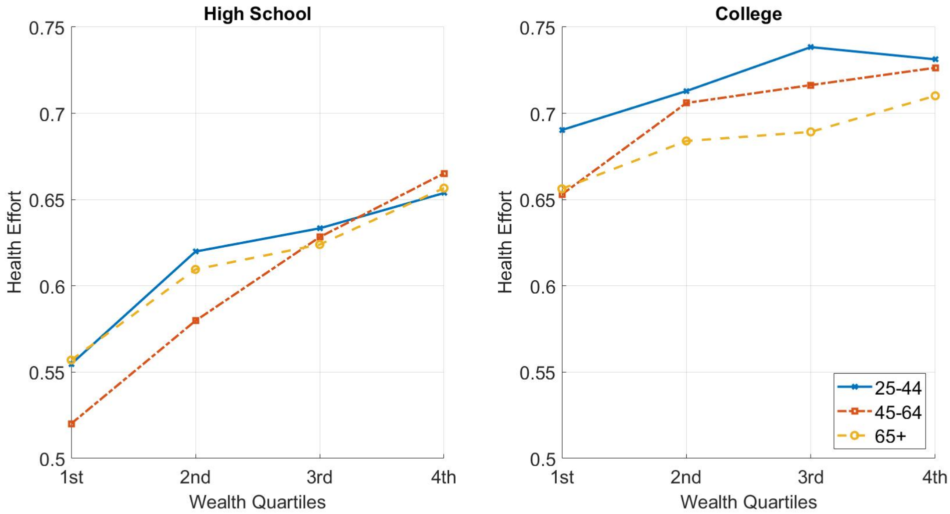
[12] In their findings for the U.S., Poterba, Venti, and Wise (2017) argue that between 20 and 40% of the asset costs of poor health are attributable to lower income and annuity income. We find similar effects in our quantitative results. De Nardi, Pashchenko, and Porapakkarm (2018) meanwhile estimate that even adding out-of-pocket medical expenses does not close the wealth-health gap.

[13] 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) and Schwandt (2018), and a survey in O'Donnell, Van Doorslaer, and Van Ourti (2015).

[14] This theory has been set forth in several seminal papers, such as Rosen (1988), Becker (2007), and Hall and C. I. Jones (2007), where it serves as the main explanation for the rising share in healthcare spending in the U.S.

[15] Cigarettes are quite expensive in Germany. Meanwhile, organic products are only slightly more expensive than non-organic ones.

Figure 3: Mean Health Effort by Wealth Quartiles



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

To further investigate the role of health effort in influencing the wealth-health relationship net of potentially confounding factors, we estimate the following regression:

$$Health_{i,t+k} = \beta_1 Wealth_{i,t}/1000 + (\beta_2 Effort_{i,t}) + \gamma \mathbf{X_{i,t}} + u_{i,t}, \tag{1}$$

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, and number of children in the households. Row (1) in Table 1 reports the estimated coefficients β_1 of wealth on health in the current year t and in a future year $t+k$ for $k = 0, 1, 2, 3$. The coefficients confirm a persistent positive correlation between wealth and current and future health, net of other confounding influences.

Row (2) reports the estimated coefficients on wealth, while *including health effort* in the same year as an additional regressor. The estimated coefficients on wealth, β_1, decrease by 15-25% across all horizons of health. That is, around 20% of the estimated effect of wealth on current and future health can be explained by variations in health effort. This suggests that health effort plays an important role in mediating the positive relationship between wealth and health.[16] At the same time, the estimated coefficients on health effort, β_2 are all positive and increase with the horizon of

[16]The estimated positive coefficients on wealth remain, however, statistically significant. This could indicate the presence of direct effects of material wealth, such as living conditions, on health. It could moreover also capture effects of wealth on mental health, as found for instance in Schwandt (2018), given that this aspect also appears in the self-reported health status.

health, indicating that our measure of health effort captures aspects of individual lifestyle behaviors that positively affect the probability of being healthy, and that some positive effects of lifestyle behaviors take time to materialize.

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)	$Wealth_{i,t}$	0.086***	0.078***	0.095***	0.117***
		(0.015)	(0.016)	(0.016)	(0.017)
(2)	$Wealth_{i,t}$	0.073***	0.061***	0.075***	0.095***
		(0.015)	(0.016)	(0.016)	(0.017)
	$Effort_{i,t}$	0.091***	0.119***	0.136***	0.148***
		(0.011)	(0.012)	(0.012)	(0.012)
(1) R^2		0.291	0.247	0.231	0.211
(2) R^2		0.293	0.251	0.235	0.215

Notes: Estimated coefficient β_1 from equation (1) in row (1), and β_1 and β_2 in row (2). Columns (i) - (iv) correspond to separate regressions for $k = 0, 1, 2, 3$. The estimated coefficients β_1 are multiplied by 10^6. Stars denote statistical significance at the 10%, 5%, and 1% level. $N = 25,541$.

The empirical observations presented in this section paint a clear picture. There exists a strong association between individual health and financial resources in Germany, which manifests in large wealth-health gaps. These gaps grow substantially 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 health lifestyles play an important role in explaining these gaps. Richer people tend to exert more effort to lead a healthy life. Over time, these efforts translate into better health outcomes, which in turn are associated with higher labor supply and, consequently, higher labor earnings. Higher financial resources are then likely to result in greater wealth accumulation, potentially further increasing the wealth-health gap.

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 develop and adopt a structural model providing an environment that allows us to disentangle the contribution of the different channels.

3. Model

Our model is built around the joint evolution of wealth and health of heterogeneous agents over the life cycle. In this setting, health affects individuals in multiple ways, but the dynamics of health can be endogenously influenced. Agents differ ex-ante in their level of education and time preference. They face uninsurable risk regarding their health, survival, labor productivity, and disutility shifters. Agents decide over consumption and savings as well as labor supply. Moreover, they choose how much costly health effort to exert.

3.1. Demographics

Agents enter the model at the beginning of their working career at age $t = 1$ and live at most for T periods. They decide whether and how much to work for every period until age t_R, when they retire and consume out of their savings and pension benefits.

Agents differ in their fixed education status e, which can either be high ($e = 1$), corresponding to at least some college education, or low ($e = 0$), consisting of a high school-only education. Moreover, following De Nardi, Pashchenko, and Porapakkarm (2018), we assume that agents also differ in their fixed discount factor β.[17]

3.2. Health and Lifestyle Behaviors

At every age, agents can be either healthy ($h_t = 1$) or unhealthy ($h_t = 0$). Being unhealthy affects economic outcomes in several ways. First, it decreases the survival probability from age t to $t + 1$, denoted by $S_t(h_t)$, which also depends on age. Second, it results in productivity loss when working, which manifests in a constant 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 $f_t \in [0, 1]$. Analogous to the definition in Section 2, we think of this level as a compound measure of all the efforts an individual makes to lead a healthy lifestyle, including physical exercise, health-conscious nutrition, and abstention from smoking. In period t, agents enter the period with a health effort level f_{t-1}, chosen in the past period. Agents then

[17] In their analysis of the joint wealth and health distribution in the U.S., De Nardi, Pashchenko, and Porapakkarm (2018) find that inherent differences in time preferences are a substantial driving force of the observed wealth-health gradient. They argue that differences in β, which affects the investments in health and savings, partly reflect genetic differences or the long-lasting effects of early childhood conditions.

decide whether to change their health effort level from f_{t-1} or not. This decision is subject to a stochastic adjustment cost $\chi_t \in \mathcal{U}[0, B_t] \equiv H_t(\chi)$, which has to be paid if the agent decides to change her effort level relative to her previous level f_{t-1}.[18] 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_t comes at a direct contemporaneous utility cost, as in Cole, Kim, and Krueger (2019). This utility cost $\varphi_t(f_t; h_t, e, \xi_t)$ is allowed to differ by health and education, and is subject to an idiosyncratic shifter, ξ_t, which follows a normal distribution in log. The latter plays a role of shifting agents' incentive to exert efforts in addition to other endogenous mechanisms, such as health and employment status, and provides flexibility in matching rich effort dynamics at the individual level, which we discuss in the next section in greater detail.

The benefit of leading a healthy lifestyle is that the latter increases the probability of being healthy in $t+1$, denoted by $\pi(h_{t+1} = 1 | h_t, f_t, f_{t-1}, e)$. Note that this probability not only depends on health efforts undertaken in period t, 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, Lleras-Muney, and Vogl, 2008). Through its effect on health, higher health effort is also associated with better survival prospects, given that survival probability increases in health. Finally, we let this probability be education-specific so as to allow for potential advantages associated with these efforts garnered by the more educated.

3.3. Preferences

Agents derive utility from consumption c_t and leisure $\bar{n} - n_t$, where $\bar{n}$ is the time endowment and n_t denotes hours worked. We assume that n_t can take a value from $\{0, n_p, n_f\}$, allowing for adjustments along both extensive and intensive margins. Working implies a utility cost $\phi_t(n_t; h_t, e)$ 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 poor health decreases the marginal utility of consumption, where the effect is governed by the constant κ, which takes a value of one if

[18]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.

healthy and 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:

$$u(c_t, n_t, f_t; h_t, e, \xi_t) = \kappa \frac{c_t^{1-\sigma}}{1-\sigma} - \phi_t(n_t; h_t, e) - \varphi_t(f_t; h_t, e, \xi_t) + b, \tag{2}$$

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.

The addition of this constant has implications for the levels of future utility (Hall and C. I. Jones, 2007). 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.

3.4. Taxes and Transfers

When working, agents receive gross labor income equal to $w_t(h_t, e)z_t n_t$, where $w_t(h_t, e)$ is a deterministic wage profile that increases with health h_t and education e, as will be made precise in Section 4. By z_t, we denote idiosyncratic productivity risk that follows a stochastic process, which is further specified in Section 4.

We incorporate progressive labor income taxation captured by $\mathcal{T}(y_t, \bar{y})$ (Heathcote, Storesletten, and Violante, 2017), where y_t denotes gross labor income and $\bar{y}$ refers to its average in the economy. In addition, we incorporate T, which the government guarantees to every individual.[20] This could capture means-tested social safety programs in Germany, such as sickness benefits and social security income, especially relevant to those with zero labor income. Finally, the government provides pension

[19]For example, Finkelstein, Luttmer, and Notowidigdo (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.

[20]In incomplete markets models with *extensive margin* labor supply, the presence of transfers given to non-working agents is crucial in mitigating over-precautionary motives among wealth-poor agents (Yum, 2018).

benefits $P(z_t, e)$, which are paid out in retirement periods.

3.5. Individual Optimization Problems

We first describe the individual optimization problem of a *working-age agent* $(t < t_R)$. At the beginning of each period t, the agent learns about current health realization h_t and productivity draw z_t. At this point, the state variables are composed of a vector given by $\mathbf{s}_t = (e, \beta, a_t, h_t, z_t)$, where e denotes education level, β the subjective discount factor, and a_t are assets in t, and the last period's health effort level f_{t-1}. Given $(\mathbf{s}_t, f_{t-1})$, the value function at the beginning of age t is then given by:

$$V_t(\mathbf{s}_t, f_{t-1}) = \mathbb{E}_{\xi_t,\chi_t} M_t(\mathbf{s}_t, f_{t-1}, \xi_t, \chi_t), \tag{3}$$

where M_t denotes the interim value after the effort disutility shifter ξ_t and the stochastic effort adjustment cost draw χ_t are realized. This is given by:

$$M_t(\mathbf{s}_t, f_{t-1}, \xi_t, \chi_t) = \max \left\{ \underbrace{W_t^{adj}(\mathbf{s}_t, f_{t-1}, \xi_t, \chi_t)}_{\text{value of } \textit{adjusting effort}}, \underbrace{W_t^{not}(\mathbf{s}_t, f_{t-1}, \xi_t)}_{\text{value of } \textit{not adjusting effort}} \right\}. \tag{4}$$

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

$$W_t^{adj}(\mathbf{s}_t, f_{t-1}, \xi_t, \chi_t) = \max_{\substack{c_t, a_{t+1} \geq 0 \\ f_t \in [0,1], n_t \in \{0, n_p, n_f\}}} \left\{ \begin{array}{c} u(c_t, n_t, f_t; h_t, e, \xi_t) - \chi_t \\ + \beta S_t(h_t) \mathbb{E}_{h_{t+1}, z_{t+1} | \Omega_t} V_{t+1}(\mathbf{s}_{t+1}, f_t) \end{array} \right\}, \tag{5}$$

subject to

$$\begin{aligned} c_t + a_{t+1} &\leq a_t(1+r) + T + w_t(h_t, e) z_t n_t - \mathcal{T}(w_t(h_t, e) z_t n_t, \bar{y}) \\ h_{t+1} &= 1 \quad \text{with prob. } \pi_t(h_{t+1} = 1 | h_t, f_t, f_{t-1}, e) \\ &= 0 \quad \text{with prob. } 1 - \pi_t(h_{t+1} = 1 | h_t, f_t, f_{t-1}, e). \end{aligned}$$

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

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

$$W_t^{not}(\mathbf{s}_t, f_{t-1}, \xi_t) = \max_{\substack{c_t, a_{t+1} \geq 0 \\ n_t \in \{0, n_p, n_f\}}} \left\{ \begin{array}{c} u(c_t, n_t, f_{t-1}; h_t, e, \xi_t) \\ +\beta S_t(h_t) \mathbb{E}_{h_{t+1}, z_{t+1}|\Omega_t} V_{t+1}(\mathbf{s}_{t+1}, f_{t-1}) \end{array} \right\}, \tag{6}$$

subject to

$$\begin{aligned} c_t + a_{t+1} &\leq a_t(1+r) + T + w_t(h_t, e) z_t n_t - \mathcal{T}(w_t(h_t, e) z_t n_t, \bar{y}) \\ h_{t+1} &= 1 \quad \text{with prob. } \pi_t(h_{t+1} = 1 | h_t, f_{t-1}, f_{t-1}, e) \\ &= 0 \quad \text{with prob. } 1 - \pi_t(h_{t+1} = 1 | h_t, f_{t-1}, f_{t-1}, e). \end{aligned}$$

During retirement periods ($t \geq t_R$), 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 (4) becomes:

$$M_t(\mathbf{s}_t, f_{t-1}, \xi_t, \chi_t) = \max \left\{ \underbrace{R_t^{adj}(\mathbf{s}_t, f_{t-1}, \xi_t, \chi_t)}_{\text{value of } \textit{adjusting}}, \underbrace{R_t^{not}(\mathbf{s}_t, f_{t-1}, \xi_t)}_{\text{value of } \textit{not adjusting}} \right\} \tag{7}$$

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

$$R_t^{adj}(\mathbf{s}_t, f_{t-1}, \xi_t, \chi_t) = \max_{\substack{c_t, a_{t+1} \geq 0 \\ f_t \in [0,1]}} \left\{ \begin{array}{c} u(c_t, 0, f_t; h_t, e, \xi_t) - \chi_t \\ +\beta S_t(h_t) \mathbb{E}_{h_{t+1}|\Omega_t} V_{t+1}(\mathbf{s}_{t+1}, f_t) \end{array} \right\}, \tag{8}$$

$$R_t^{not}(\mathbf{s}_t, f_{t-1}, \xi_t) = \max_{c_t, a_{t+1} \geq 0} \left\{ \begin{array}{c} u(c_t, 0, f_{t-1}; h_t, e, \xi_t) \\ +\beta S_t(h_t) \mathbb{E}_{h_{t+1}|\Omega_t} V_{t+1}(\mathbf{s}_{t+1}, f_{t-1}) \end{array} \right\}, \tag{9}$$

subject to the constraints

$$\begin{aligned} c_t + a_{t+1} &\leq a_t(1+r) + T + P(z_t, e) \\ h_{t+1} &= 1 \quad \text{with prob. } \pi_t(h_{t+1} = 1 | h_t, f_t, f_{t-1}, e) \\ &= 0 \quad \text{with prob. } 1 - \pi_t(h_{t+1} = 1 | h_t, f_t, f_{t-1}, e) \\ z_{t+1} &= z_t. \end{aligned}$$

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

Table 2: Externally Calibrated Parameters

Parameter	Value	Interpretation
t_R	21	Retirement age 65
T	28	Maximum age 99
σ	2	Inverse EIS
γ	1	Inverse Frisch Elasticity
r	$1.04^2 - 1$	Real interest rate
$S_t(h_t)$	SOEP	2-year Survival Probabilities
$\pi_t(h_{t+1}\|h_t, f_t, f_{t-1}, e)$	SOEP	Health Transition Probabilites
$w_t(h_t, e)$	SOEP	Determ. Wage Profiles
ρ	0.9409	Persistence of productivity shock
λ	0.321	Average tax rate
τ	0.128	Tax progressivity

4. Calibration

In this section, we describe the calibration of our model. As is standard in the literature, we externally calibrate a number of parameters while the remaining parameters are calibrated internally using the simulated method of moments approach. Table 2 summarizes the parameters calibrated externally by either estimating them directly from the SOEP data (waves 2004-2018) or by setting them to values commonly used in the literature. Table 5 displays the set of internally calibrated parameters along with their relevant target moments. In total, 26 parameters are calibrated to match 31 target moments in the data.

4.1. Calibrated Parameters

Demographics

We calibrate 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 ($t = 1$) 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 $T = 38$. Retirement age is set at 65 ($t_R = 21$).

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, κ, is calibrated internally to match the consumption differences between healthy and unhealthy 25-44, 45-64, and 65-and-older individuals in the data. Note that in the model, a certain degree of consumption differences across health types is also endogenously generated.

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

$$\phi_t(n_t; h_t, e) = \nu_0^h \exp(\nu_1^h(t-1) + \nu_2^h(t-1)^2 + \nu_e \mathbb{I}\{e=0\}) \frac{n_t^{1+1/\gamma}}{1+1/\gamma}, \tag{10}$$

for each health status h. Thus, the labor supply disutility shifter is an exponential function of a polynomial captured by health-specific coefficients—ν_0^h, ν_1^h, and ν_2^h—as well as ν_e, which determines extra disutility for those with a lower education level. We calibrate these parameters internally to match two sets of moments. First, we use the average employment shares among the healthy and unhealthy, by the age groups 25-34, 35-44, 45-54, and 55-64 in the data. Second, we use the educational gradient in employment rates: the ratio of the employment rate of the higher educated to the lower educated (1.16). 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 the equivalent of 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 largely 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_t as a combination of age-, education-, and health-dependent effort cost shifters, idiosyncratic shocks ξ_t, and a power function that increases with efforts, with the curvature parameter ψ shaping the degree of responsiveness in efforts:

$$\varphi_t(f_t; h_t, e, \xi_t) = \iota_0^h \exp(\iota_1^h(t-1) + \iota_2^h(t-1)^2 + \iota_e \mathbb{I}\{e=0\}) \xi_t \frac{f_t^{1+1/\psi}}{1+1/\psi}. \tag{11}$$

for each health status $h \in \{g, b\}$. The age polynomial coefficients, which are health specific, are calibrated internally to match the mean health effort observed in the data for the 25-44, 45-64, and 65-and-older age groups, separately for each health type. ξ_t follows a normal distribution with a mean of zero and a standard deviation of σ_ξ in logs, thereby centering around one. We internally calibrate σ_ξ to match the persistence of effort choices at the individual level (0.82), since a higher variability tends to reduce the persistence. Next, we internally calibrate the curvature parameter ψ to match the dispersion of efforts as in the data (standard deviation of 0.20). Finally, ι_e, which captures the additional disutility for the less educated, is internally calibrated to match the ratio of mean effort among the college-educated to that among the high school-educated: 1.16.

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 5. To replicate this pattern, we parameterize the age-dependent upper bound as

$$B_t = \varsigma_0 \exp(\varsigma_1(t-1) + \varsigma_2(t-1)^2). \tag{12}$$

and calibrate ς_0, ς_1, and ς_2 to match the share of individuals not adjusting efforts for three age groups: 25-44, 45-64, and 65-and-older.

Next, we internally calibrate the utility constant to $b = 17.21$, such that the model-implied value of a statistical life year (VSLY) is equal to 6.25 times average annual per capita consumption (Glover et al., 2021). 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. (2021)):[21]

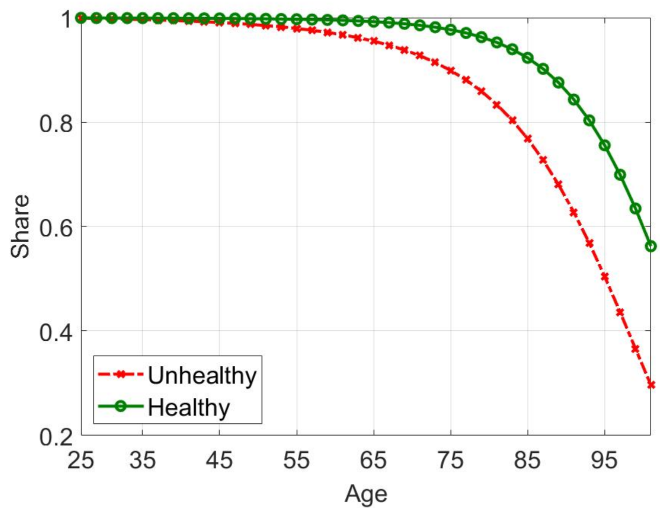
$$\bar{u}(c_t, n_t, f_t; h_t, e, \xi_t) + b = \frac{\partial \bar{u}}{\partial c} \times \underbrace{6.25\bar{c}}_{\text{VSLY}}$$

Initial Distribution

The distribution of agents over education, initial health, and initial effort levels is directly constructed from the SOEP data. In our sample, 68% of agents have a high-school education and 32% have some college education. Among college-educated individuals, 5% report being unhealthy at age 25, while this number is 8% among the high-school educated. The initial distribution over effort levels by education

[21] 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 calibrating b. Thus, we can still use the ratio of 6.25 as our target statistic.

Figure 4: Estimated health-dependent conditional Survival Probabilities



and health status is illustrated in the form of histograms in Figure A.8. Most noticeably, a larger fraction of college-educated healthy individuals have high effort levels compared to high school individuals. We interpret the initial heterogeneity in health and healthy lifestyles as reflecting differences in childhood and adolescent health and health-related behaviors that are exogenously given in the model, but may have important long-term consequences (Case, Lubotsky, and Paxson, 2002). Moreover, we assume that the fixed preference types β are drawn from a log normal distribution independently from all other initial states. The two parameters governing the mean and variance, μ_β and δ_β, are calibrated internally, such that our simulated data matches the Gini-index of wealth (0.77) as well as the aggregate wealth to labor income ratio (2.59) in the data. Finally, we assume that agents enter the model with zero savings and set the real interest rate to $r = 0.082$, which corresponds to an annual rate of 4%.

Survival Probability

We estimate the two-year, health-dependent survival rates $S_t(h_t)$ using information on deaths of survey respondents contained in the SOEP. Specifically, we fit a probit model of survival to age $t+2$ on health status at age t and a cubic polynomial in age. Thus, we assume that survival probabilities do not depend on level of education but purely on age and health. The resulting predicted conditional two-year survival rates are plotted in Figure 4.[22]

[22]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.

Health Evolution

We estimate the probability of being healthy in the next period conditional on current and past health effort, education, and health, $\pi_t(h_{t+2} = 1|h_t, f_t, f_{t-2}, e)$, directly from the data with the following linear model:[23]

$$h_{i,t+2} = \pi^0_{i,t} + \lambda_1 f_{i,t} + \lambda_2 f_{i,t-2} + \delta h_{i,t} + \gamma_1 e_i + \gamma_2 \mathbf{A}_{i,t} + \varepsilon_{i,t}, \tag{13}$$

where $h_{i,t}$ is a dummy variable that equals 1 if person i is healthy at age t, $f_{i,t}$ is our compound health effort measure, e_i is a dummy variable equal to 1 if person i has some college education, $\mathbf{A}_{i,t}$ is a vector of dummies that are equal to 1 when individual i is a member of a 10-year age group, and $\varepsilon_{i,t}$ is an error term. We estimate (13) as a probit model, such that the dependent variable gives the probability of being healthy in two years. Then, using the estimated coefficients λ_1 and λ_2, we calculate average marginal effects of current and past health effort on that probability separately for all combinations of health, education, and age groups.

Table 3 reports the estimated coefficients. The baseline probability of being healthy in two years in the absence of any past or present health effort, π^0, monotonically decreases with age. This is true among both high-school and college-educated individuals as well as among those who are currently unhealthy and those currently healthy. The estimated effects of current effort on the probability of being healthy, λ_1, are always positive and, conditional on age group and health status, quite similar to the effect of past effort, λ_2. Exerting health effort is estimated to be more effective in increasing the probability of future good health when the current health status is poor rather than good. However, this effectiveness decreases with age, whereas it increases with age when current health status is good.

In Appendix A.4, we gauge the empirical realism of our health transition parameter estimates, discussing their implications for disease prevalence and mortality and contrasting them with existing common 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 conservative.

Deterministic Wage Profile

In order to parameterize the wage process, we first follow Lagakos et al. (2018), and recover wage-experience profiles for workers in Germany, separately for high-school

[23] We also experiment with other specifications, such as that employed in Cole, Kim, and Krueger (2019). However, contrary to their non-linear effect of health effort, we opt for a more parsimonious linear specification with the advantage being that this allows us to include various potentially relevant control variables such as education and age.

Table 3: Estimated Coefficients governing Health Transitions

Age Group	**Estimated Coefficients**					
	High School $(e = 0)$					
	Unhealthy $(h_t = 0)$			Healthy $(h_t = 1)$		
	π^0	λ_1	λ_2	π^0	λ_1	λ_2
25-34	0.402	0.131	0.130	0.877	0.038	0.038
35-44	0.352	0.133	0.132	0.848	0.047	0.046
45-54	0.298	0.132	0.132	0.810	0.057	0.057
55-64	0.248	0.129	0.128	0.766	0.069	0.068
65-74	0.207	0.124	0.123	0.723	0.080	0.079
75+	0.144	0.109	0.109	0.636	0.099	0.098
	College $(e = 1)$					
	Unhealthy $(h_t = 0)$			Healthy $(h_t = 1)$		
	π^0	λ_1	λ_2	π^0	λ_1	λ_2
25-34	0.443	0.128	0.127	0.897	0.032	0.032
35-44	0.391	0.131	0.131	0.871	0.040	0.040
45-54	0.335	0.133	0.132	0.837	0.050	0.049
55-64	0.282	0.132	0.131	0.797	0.061	0.060
65-74	0.238	0.128	0.127	0.757	0.071	0.071
75+	0.169	0.116	0.115	0.674	0.091	0.090

and college-educated individuals. Formally, we estimate Mincer regressions of wages on years of schooling and potential work experience, controlling for time and cohort effects:

$$\log w_{ict} = \alpha + \theta s_{ict} + \delta x_{ict} + \gamma_t + \zeta_c + \epsilon_{ict}, \tag{14}$$

where w_{ict} is the wage of individual i, who belongs to birth cohort c and is observed at time t. Wages are defined as total annual labor earnings divided by hours worked. We denote by s_{ict} the years of schooling and by x_{ict} work experience, which is defined as follows:

$$\begin{aligned} x_{ict} &= age_{ict} - 18 && \text{if } s_{ict} < 12 \\ x_{ict} &= age_{ict} - s_{ict} - 6 && \text{else.} \end{aligned}$$

To disentangle time from cohort effects, we assume that there is no experience effect on wage growth in the last 10 years of work, following the HLT approach in Lagakos et al. (2018). The resulting experience-wage profiles are shown for 5-year experience bins in Table 4, expressed in growth relative to no work experience. We interpret these wage-experience profiles as the benchmark average deterministic productivity component of wages of a healthy worker, i.e. the equivalent to $w_t(1, e)$ in our model,

Table 4: Benchmark Wage Growth by Work Experience and Education

Experience (years)	Wage Growth	
	High School	College
0	1.00	1.00
5	1.22	1.29
10	1.46	1.61
15	1.56	1.90
20	1.71	2.07
25	1.77	2.17
30	1.85	2.21
35	1.97	2.37
40	1.98	2.47
45	1.97	2.37

and use the cubic spline interpolation to obtain values for each age t in the model based on these five-year bin estimates.

As discussed above, there are some contemporaneous effects of poor health on labor supply and earnings even among workers. We think of these effects as productivity losses due to poor health and parameterize them with a constant productivity differential w_p. To account for selection into employment based on health, we calibrate this productivity loss within the model, where agents endogenously decide whether or not to work based on their health.[24] Specifically, we calibrate the parameter to match the remaining average labor income difference among healthy and unhealthy 25-44- and 45-64-year-olds.

Labor Productivity Process

We assume that the stochastic component of labor productivity, z_t, follows an AR(1) process in logs:

$$\log(z_t) = \rho \log(z_{t-1}) + \varepsilon_t, \tag{15}$$

with

$$\varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2).$$

We use $\rho = 0.941$—based on our own estimate of the persistence of idiosyncratic productivity shocks. The variance of the idiosyncratic productivity component σ_ε^2 is calibrated internally to match the observed variance of log labor income (0.71) in the data.

[24] The issue of selection into employment based on health is discussed in De Nardi, Pashchenko, and Porapakkarm (2018).

Taxes and Transfers

We specify the progressive labor tax system using a commonly used parametric function (Heathcote, Storesletten, and Violante, 2017):

$$\mathcal{T}(y_t, \bar{y}) = y_t - \lambda y_t^{1-\tau} \bar{y}^{\tau}. \tag{16}$$

In this formulation, λ roughly represents the average tax rate and τ captures the degree of progressivity of the tax system. $\bar{y}$ is the average income. In accordance with the estimates in Kindermann, Mayr, and Sachs (2020) for Germany, we set to $\lambda = 0.321$ and $\tau = 0.128$.

In terms of pension benefits $P(z_t, e)$, 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. We then scale them by a constant ω and calibrate internally to match the average pension replacement rate of 40%, as in Kindermann, Mayr, and Sachs (2020).

Finally, lump-sum transfers T given by the government to all agents are particularly relevant for those who do not work. We set this to 10% of average income.

4.2. Model Fit

Table 5 summarizes the internally calibrated parameters, their target statistics, as well as the match between the actual and model-implied data moments. Recall that the model is over-identified, since there are 31 moments versus 26 parameters.

Figure 5 displays the annual employment rate by health status (left panel) and the average labor income by health status (right panel).[25] Both moments are reported by 10-year age groups over the working career. 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. Our model furthermore generates a slight hump-shaped pattern in employment rates that is similar to that seen in the data.

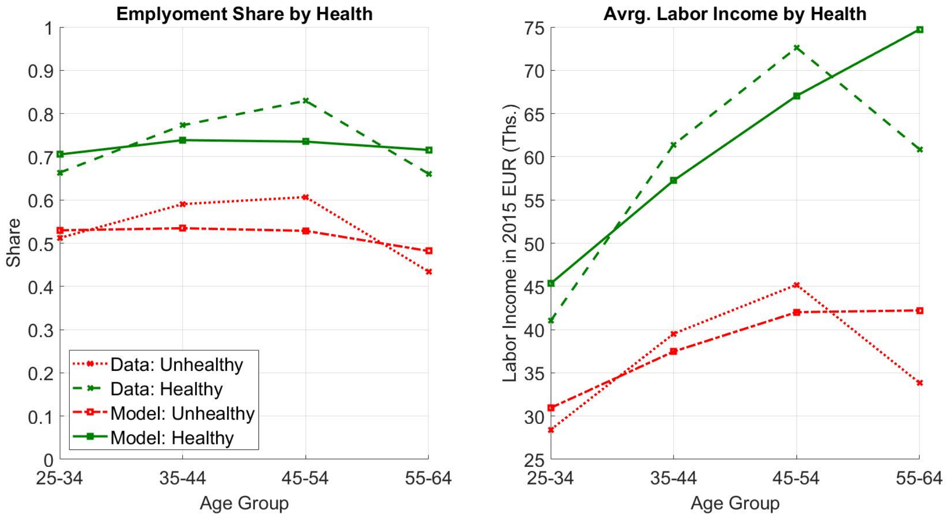
On average, healthy individuals earn substantially more labor income compared to unhealthy ones (right panel). In the data, this difference increases from around 12,000 EUR of labor income over a two-year span at ages 25-34 to almost 30,000 EUR right before retirement age. Our model matches this difference and quite aptly captures the increasing trend in labor income over the working career. These large

[25] In the data, we define workers as those who are recorded as employed part- or full-time, or having a labor income larger than 5,400 EUR in any given year.

Table 5: Internally Calibrated Parameters

Parameter	Value	Description	Target Statistics Model	Data	Description
$\nu_0^{h=1}$	2.20	Disutility of work	Figure 5		Age-Employment
$\nu_1^{h=1}$	-0.070	parameters			Profiles by
$\nu_2^{h=1}$	0.0021	(healthy)			Health
$\nu_0^{h=0}$	3.27	Disutility of work			
$\nu_1^{h=0}$	-0.081	parameters			
$\nu_2^{h=0}$	0.0031	(unhealthy)			
ν_e	0.399				
$\iota_0^{h=1}$	0.0382	Disutility of effort	Figure 6		Age-Effort
$\iota_1^{h=1}$	0.169	parameters			Profiles by
$\iota_2^{h=1}$	-0.0011	(healthy)			Health
$\iota_0^{h=0}$	0.160	Disutility of effort			
$\iota_1^{h=0}$	0.129	parameters			
$\iota_2^{h=0}$	-0.0016	(unhealthy)			
ι_e	0.377				
σ_ξ	0.192	Variance of ξ	0.79	0.82	$Corr(f, f_{t-1})$
ψ	0.702	f cost elasticity	0.20	0.20	Std.Dev.(f)
ς^0	0.00009	Adjustment costs	0.25	0.26	Share of
ς^1	0.168		0.30	0.32	Non-Adjusters
ς^2	0.00004		0.41	0.40	by Age
w_p	0.811	Product. loss (poor health)	Figure 5		$\frac{\bar{y}(h=1)}{\bar{y}(h=0)}$
κ	0.907	Cons. Util. shifter	1.12	1.15	$\frac{\bar{c}(h=1)}{\bar{c}(h=0)}$
μ_β	0.918	Mean of β	2.53	2.59	$\frac{Wealth}{Income}$
δ_β	0.064	Dispersion of β	0.769	0.77	Wealth Gini
σ_x	0.305	Productivity shock dispersion	0.73	0.71	Var(log income)
ω	0.237	Pension scale	0.38	0.4	Replacement rate
b	17.2	Utility constant	5.98	6.25	VSLY/$\bar{c}$

Figure 5: Model Fit of Labor Market Moments by Health



Notes: Annualized employment rate (left) and average two-year labor income (right) by 10-year age groups, distinguishing between healthy individuals (green) and unhealthy ones (red).

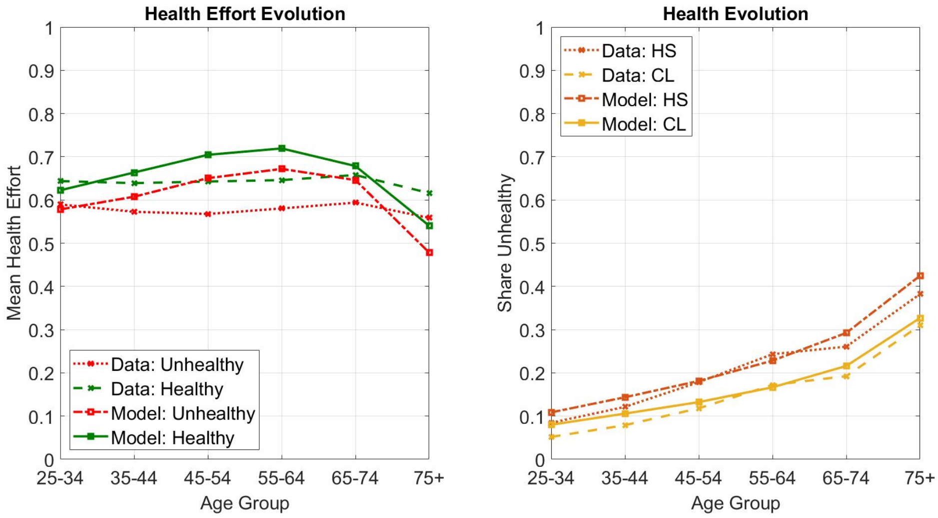
differences in labor income are due to an estimated productivity loss from being unhealthy of around 19%. Moreover, the calibrated model, using a variance of the innovations to the idiosyncratic productivity process, σ_ε^2, of 0.306, captures well the overall variation in labor income observed in the data, as this generates a variance in log incomes of around 0.73.

The left panel of Figure 6 displays the evolution of average health effort over the life cycle by health status. In the data, average health effort tends to be relatively stable over the life cycle, only dropping slightly at older ages. Importantly, healthy individuals always exert more health effort compared to unhealthy ones. Our calibrated model produces a similarly consistent difference, though the levels of health effort follow a somewhat less pronounced hump-shaped pattern compared to the data.

Our calibration 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 26% of young individuals (age 25-44) do not adjust their efforts, compared to a much higher share of 40% among the retired. Due to the adjustment costs that become more sizeable with age, our model replicates this pattern quite successfully.

In terms of the variability of effort choices, our model generates a standard deviation of 0.20, as in the data. Moreover, the calibrated model predicts a serial correlation in health efforts at 0.79, which is almost identical to that seen in the data (0.82).

Figure 6: Model Fit of Average Health Effort and Health Evolution



Notes: Left: Average health effort by 10-year age groups, distinguishing between individuals being healthy (green) and unhealthy (red). Right: Average share being unhealthy by 10-year age groups, differentiated by level of education: high-school and at least some college education.

4.3. Non-targeted Moments

We now turn to several relevant non-targeted moments generated by the model, which help us to validate the model. First, our model successfully captures the evolution of health status in the data. The right panel of Figure 6 displays the share of unhealthy people by 10-year age groups, differentiating between high-school and college-educated agents. As in the data, the share of unhealthy people among the college educated is always smaller than among the high school educated. Moreover, for both education groups, this share increases monotonically over age, starting at around 10% for unhealthy people, to 40% for high-school educated individuals at ages 75 and older, and 30% for the college educated at the same age.

In addition to the various data features we target in our calibration procedure, we also investigate how well our calibrated model captures the non-targeted adjustment patterns in individual lifestyle behaviors. In particular, since our model features non-convex adjustment costs, we compare the model-generated shares of individuals that change their health effort levels by more than 10% or 20% to their empirical counterparts. Table 6 displays theses shares, separately for increases (positive changes) and decreases (negative changes) in health effort, by three different age groups.

We find that our model is remarkably successful in reproducing these micro-level adjustment distributions observed in the data. Overall, the model generates relatively large adjustments of over 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 calibration does not directly target these moments.

Table 6: 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%	
	Data	Model	Data	Model	Data	Model	Data	Model
24-44	0.33	0.27	0.23	0.22	0.30	0.24	0.18	0.19
45-64	0.30	0.26	0.22	0.19	0.28	0.21	0.17	0.16
65+	0.28	0.18	0.21	0.14	0.28	0.28	0.18	0.20

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

Our model also speaks to gradients of health in dimensions other than wealth. For example, the literature highlights differences in health and health-related outcomes by education. While not the focus of our paper, in Appendix A.6 we discuss in greater detail the model's fit relative to education moments.

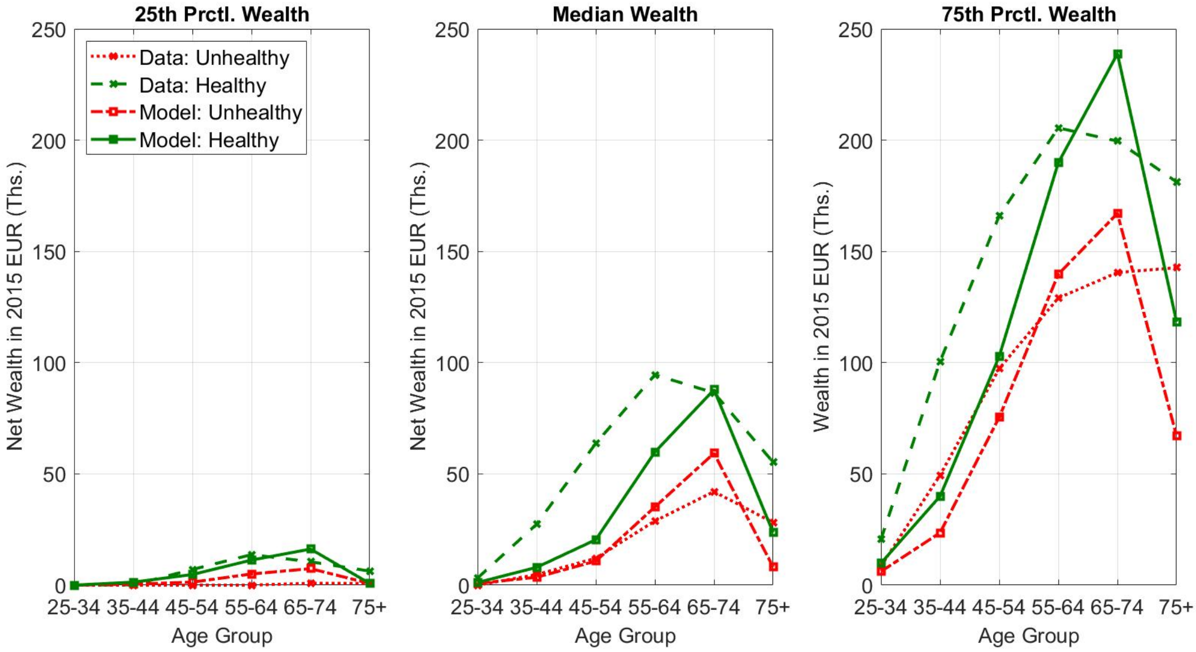
5. Quantitative Results

In this section, we present the main quantitative results and investigate their underlying factors.

5.1. Wealth and Health Inequality in the Baseline Model

We begin by presenting how much of the wealth-health gaps are generated endogenously by our baseline model. The wealth profiles of healthy and unhealthy people over their life cycle are plotted in Figure 7 at three points along the wealth distribution—the 25th percentile, the median, and the 75th percentile. We see, for example, that the gap in median wealth between the healthy (dotted green line) and the unhealthy (dotted red line) in the data begins to open up relatively early in life and increases to a maximum of over 60,000 EUR at ages 55-64. Our calibrated model is able to endogenously generate a wealth-health gap that amounts to around 65% of that observed in the data at ages 65-74. That said, the model-generated gaps tend to open up later than in the data. Overall, the wealth-health gaps generated by

Figure 7: Wealth Profiles by Health: Model vs. Data



Notes: Wealth by 10-year age groups, distinguishing between healthy individuals (green) and unhealthy ones (red) at the 25th percentile (left), the median (middle), and the 75th percentile of the wealth distribution (right).

the baseline model are, on average, around 46% at the 25th percentile, 35% at the median, and 70% at the 75th percentile of those observed in the data.[26]

Next, we use our model to quantify how much of the variance in lifetime outcomes between individuals is due to differences already established at an early age, as opposed to differences in uncertainty realizations experienced over the life cycle (Huggett, Ventura, and Yaron, 2011; S. Y. Lee and Seshadri, 2019). This is a relevant question in that it considers sources of lifetime inequality, as highlighted in the literature. In contrast to extant studies, we answer this query not only in terms of monetary lifetime outcomes, such as earnings that ultimately constitute wealth, but also in terms of health-related outcomes, such as life expectancy and the fraction of healthy years during one's life.

Specifically, following Huggett, Ventura, and Yaron (2011), we calculate the fraction of variance of the outcome variable that is due to the initial conditions at age 25 by computing conditional variances. The individual states at this age on which we condition include education, initial health, discount factor types, and initial labor

[26]In the next section, we investigate the factors driving these wealth-health gap generated endogenously in the model. The remaining wealth gaps across health types, as compared to the data, must then be due to reasons absent in our model. One such factor could consist of direct resource effects of more wealth on health, for instance through better housing.

productivity. Agents moreover differ in their initial health effort habits. Similar to S. Y. Lee and Seshadri (2019), we group individuals into three equally sized groups reflecting their initial health effort habits.

Table 7 shows that around 60% of the variation in lifetime earnings in our model is accounted for by differences in the initial conditions individuals face at age 25, remarkably similar to the 62% that Huggett, Ventura, and Yaron (2011) find for this outcome in the U.S. Yet, the differences in initial conditions seem to barely explain the variations in life expectancy, implying that events over the lifetime drive most of the latter. Finally, we find that 13.5% of the variation in the share of years that individuals spend being healthy during their lifetime is explained by the initial heterogeneity. Thus, while starting out in good health, with a high education, and good lifestyle habits do matter, our results suggest that the realization of health and labor market uncertainty over the rest of the life course in large part explains the variation in quality of life in terms of the share of healthy years.

Table 7: Contribution of Initial Conditions to Lifetime Inequality

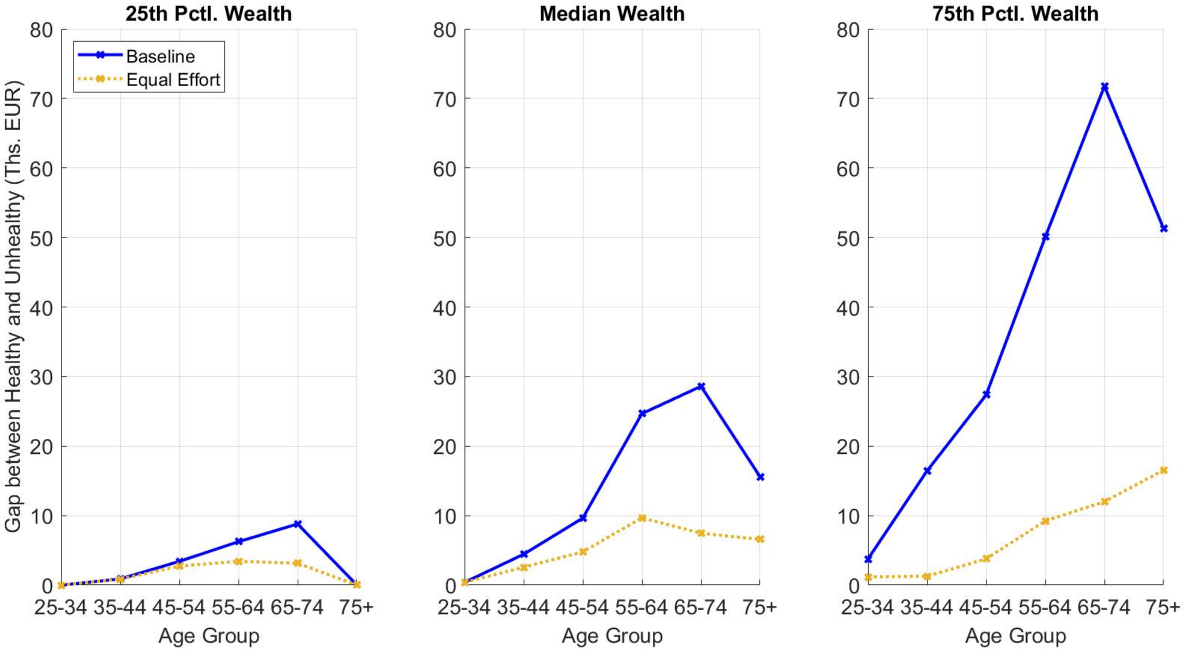
Statistic	Model
Fraction of variance in lifetime earnings	59.8%
Fraction of variance in life expectancy	0.8%
Fraction of variance in the share of healthy years	13.5%

5.2. Role of Heterogeneity in Lifestyle Behaviors

In the previous subsection, we saw that our model generates a substantial portion of wealth gaps by health and that variations in health-related outcomes are largely due to lifetime factors, as opposed to initial conditions. We now turn to the question that is the focus of our paper: to what extent do differing lifestyle behaviors across individuals explain the large wealth-health gaps observed in both the data and the model? To answer this, we perform a counterfactual experiment, in which we force all agents to choose the age-specific average health effort level at the baseline model economy. The rest of the model remains unchanged and we let the agents optimize given this constraint. Thus, the differences that arise between this counterfactual scenario and the baseline case are due to heterogeneity in individual health-related behavior.

Figure 8 summarizes the wealth-health gaps in the baseline model and in the counterfactual model with equalized health effort choices at three different points along the wealth distribution. Equalizing health efforts throughout the life span

Figure 8: 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).

reduces the wealth-health gaps across the wealth distribution. For example, the maximum difference in median wealth between those being healthy and unhealthy in the counterfactual case is reduced to less than 10,000 EUR at ages 55-64, while it is over 25,000 EUR in the baseline model. Across the life cycle, equalizing health efforts reduces the wealth-health gap at the median on average by 48%, at the 25th percentile by 42%, and at the 75th percentile by almost 80% relative to the baseline model.

The above results suggest that differences in individual health behaviors are an important driver of the observed wealth-health gaps. Their contribution is especially prominent for the asset-rich and for older individuals. Moreover, although the model on average does not fully account for the total wealth-health gaps observed in the data, these reductions are still economically meaningful. For example, our estimates suggest that differences in lifestyles can account on average for 15% of the observed median wealth-health gap in the data, 22% of the gap at the 25th percentile, and as much as 56% of the gap among asset-rich individuals at the 75th percentile.

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. To investigate the extent to which the wealth-health gaps are differently affected according to the timing of the heterogeneity in health behaviors, 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 9 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 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 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 calibrated adjustment costs are low when agents are young.

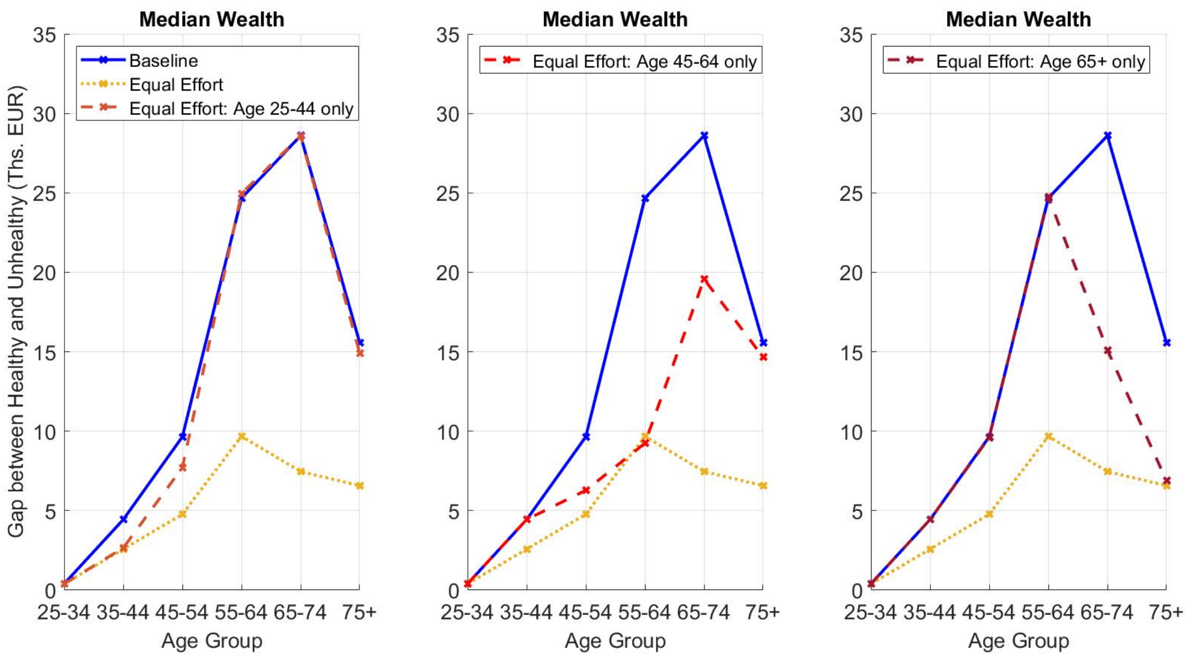
The lasting effect becomes more pronounced when equalizing efforts among prime-age workers (ages 45-64), who begin to face a more significant risk of becoming unhealthy. On the one hand, the gap at ages 45-54 is higher than in the counterfactual case with constant effort everywhere, as health behaviors 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 over 25% relative to the benchmark case even though health behaviors are allowed to vary, which reduces the gap with the counterfactual (with equal efforts everywhere) by over a third. Even in the oldest age group, the wealth gap between healthy and unhealthy individuals shrinks slightly relative to the baseline case. Finally, equalizing health effort among the 65-and-older group only reduces the wealth-health gap in that age group; yet again, at the oldest age group, the reduction only drops to the counterfactual level when efforts are equalized for all age groups.

5.3. How Lifestyle Behaviors Generate Wealth Gaps by Health

In our model, variations in lifestyle behaviors *in a given period* can contribute to the creation of a wealth gap across health types in the future, fundamentally because higher health effort leads to a lower risk of ending up being unhealthy in the next period. As depicted in Figure 10, being unhealthy, in turn, impacts wealth accumulation through two channels.

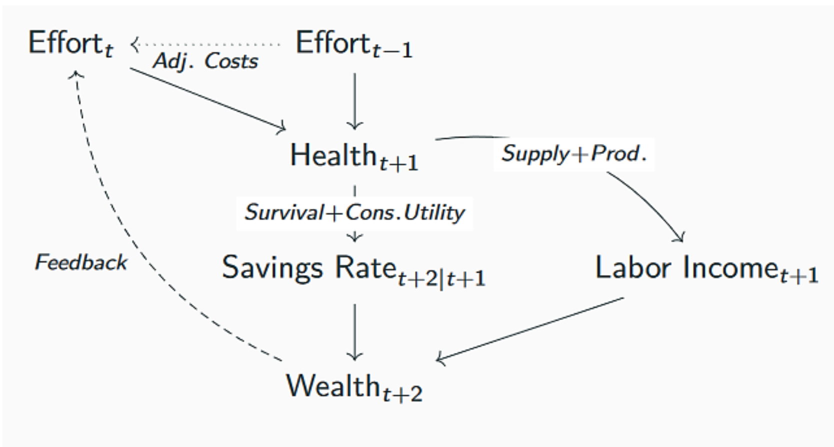
The first is a resource channel. Poor health is associated with more disutility from labor supply as well as less productivity when working. All else equal, this results in less labor income compared to a healthy individual. Thus, unhealthy individuals have access to fewer financial resources to use for wealth accumulation. This channel therefore works through differences in labor income flows.

Figure 9: Effect of Timing of Health Efforts on Wealth-Health Gaps



Notes: Differences in the wealth levels of those being healthy and unhealthy 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.

Figure 10: Channels behind Wealth-Health Gaps



The second is a savings rate heterogeneity channel across health. Since good health is associated with a higher probability of survival in the future, individuals with high health effort have a stronger motive to save for future periods as they expect to live a longer life. Good health in the current period is moreover likely to result in good future health thus allowing individuals to enjoy their consumption goods more, further reinforcing this motive. We therefore expect this channel to contribute to the wealth-health gaps endogenously generated in the model.

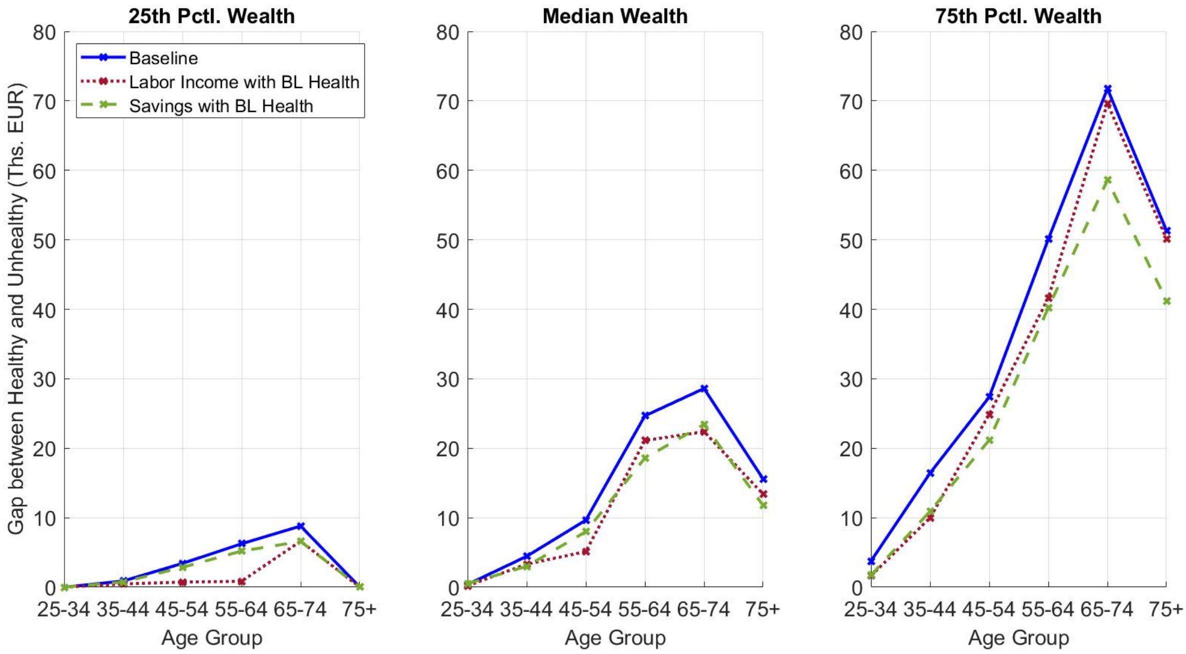
To gauge how important these channels are, we perform two further counterfactual analyses. First, we assume that both the disutility from work and labor productivity are no longer affected by health status (i.e., the disutility of labor supply is as if one was healthy for everyone and $w_p = 1$). This effectively shrinks the differences in labor incomes across health types.[27] Second, to quantify the savings heterogeneity channel, we assume that the savings decisions are no longer based on the actual health type, but are constructed using a weighted average across savings for those being healthy and unhealthy in every model period, while imposing $conp = 1$. In both exercises above, since the composition of agents across health types is affected by these counterfactual changes, we keep the benchmark distribution of health when we simulate the counterfactual experiment.

Figure 11 summarizes the resulting change in the wealth-health gaps at the different points of the wealth distribution. Both the red line, illustrating the experiment of closing the labor income channel, and the green line, which depicts the gaps after averaging savings rates, are below the benchmark blue line throughout the life cycle. This suggests that both channels contribute to the creation of the wealth-health gaps. Yet, their relative importance differs across age groups and wealth positions. The labor income channel seems quantitatively more important for the younger, and particularly asset-poor, agents, for whom wealth levels are relatively small such that differences in savings rates across health types are of little consequence. In contrast, differences in contemporaneous labor income across health types 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 during the working ages. At median wealth levels, the gaps between those in being healthy and unhealthy similarly narrow up until the 55-64-year-old age group, to a level resembling that of the counterfactual experiment where we equalize health efforts.

Quantitatively, equalizing savings rates across health types has a smaller effect on

[27] The remaining differences in labor incomes across health types arise due to correlation between health and education types.

Figure 11: Effects of the Labor Income and Savings Channels on Wealth-Health Gaps



Notes: Differences in the wealth levels of those being healthy and unhealthy at the three points along 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 types (green) across 10-year age groups. The counterfactual experiments were calculated using the baseline distribution of health.

closing the wealth-health gaps for asset-poor agents; a similar effect at the median of the assets distribution; and a stronger effect for asset rich agents. For example, among agents at the 75th percentile, equalizing savings rates reduces the wealth-health gap by over 25% on average. Particularly among older individuals, this means that heterogeneity in savings rates is a far more important contributing factor to the observed wealth differences across health types than are differences in labor income.

Averaged across the wealth distribution, simultaneously shutting down both the labor income channel and the savings channel results in a 41% reduction of the benchmark wealth-health gap. This effect is concentrated among the young and asset-poor model population, where the gaps are reduced by, on average, around 64%. However, even when accounting for both channels, substantial differences in the wealth levels across health types compared to the counterfactual with equalized efforts in Figure 8 remain. This means that equalizing health efforts also shuts down other forces in the model that contribute to the generation of wealth-health gaps over the life cycle but that are not captured by either the labor income or savings channel. In particular, equalizing healthy lifestyles everywhere also shuts down any

Table 8: Mean Health Effort by Age Group, Education, and Wealth Quartiles

Age Group	High-School				College			
	1st	2nd	3rd	4th	1st	2nd	3rd	4th
25-44	0.542	0.530	0.601	0.788	0.609	0.648	0.633	0.824
45-64	0.496	0.557	0.611	0.807	0.585	0.622	0.676	0.831
65+	0.572	0.541	0.572	0.802	0.634	0.660	0.679	0.814

dynamic feedback effects of higher wealth levels on health efforts that amplify the wealth-health relationship over time, as illustrated in Figure 10.

In line with the empirical observations and theoretical considerations outlined in Section 2.2, our model features a pronounced gradient of healthy behaviors in wealth. Table 8 summarizes average health effort levels for 25-44-year-olds, 45-64-year-olds, and the 65-and-older by education- and age-group specific wealth quartile. Going from the poorest to the richest quartile increases average health efforts by over one standard deviation for both high-school educated and college-educated individuals. While health efforts increase (almost) monotonically with wealth, by far the largest jump in effort can be seen when moving from the third to the fourth wealth quartile in all age groups.[28] This feature aligns well with the predictions made in the theoretical literature (i.e., Becker (2007) and Hall and C. I. Jones (2007)), where, with rising wealth levels, agents increasingly substitute additional utility from contemporaneous consumption with utility gained through prolonged longevity. Moreover, the fact that this jump is present for both education groups means that the effort-gradient in wealth cannot be attributed to just education-specific health technologies and education-specific health effort costs.

Thus, if richer people engage more in health-promoting activities as their marginal utility of additional consumption becomes smaller, the probability of being healthy in future periods increases. This, in turn, feeds back into the labor income and savings channels and ultimately results in more wealth at the end of the next period, which affects health efforts in the future, and so on. To render more concrete the presence of this *amplification* force of wealth, Table 9 reports the results from a similar regression as in (1) in Section 2 but using model-generated data. Concretely, we regress $Health_{i,t+k}$ on $Wealth_{i,t}$ and all model covariates $\mathbf{X_{i,t}}$, which include individual i's lagged health, her education, work status, income, age, and age^2. In row (2), we then also control for $Effort_{i,t}$ at the same period.

The results corroborate that wealth positively affects health at all future horizons.

[28] Average health efforts are always increasing in wealth with the exception of the college-educated second and third wealth quartile for the youngest age group. This illustrates that, especially for young workers, wealth levels are not necessarily the most important determinant of health efforts.

Table 9: Effects of Wealth on Health from Model Data

		Effect on $Health_{i,t+k}$		
		$k=1$	$k=2$	$k=3$
(1)	$Wealth_{i,t}$	0.101	0.106	0.111
(2)	$Wealth_{i,t}$	0.091	0.057	0.043
	$Effort_{i,t}$	0.024	0.112	0.155

Notes: OLS results from $Health_{i,t+k} = \beta_1 Wealth_{i,t}/1000 + (\beta_2 Effort_{i,t}) + \gamma \mathbf{X_{i,t}} + u_{i,t}$ on model-generated data conditional on survival from $k=0$ to $k=3$. Coefficients β_1 multiplied by 10^6.

We also see that this positive impact of current wealth increases going further into the future. This means that it takes some time for the positive effect of wealth on health to materialize. Finally, when controlling for individual health efforts in period t, the positive effect of wealth on health is substantially reduced, signifying that, especially the further into the future, the positive association between wealth and future health is driven by the positive correlation between wealth and contemporaneous health behaviors. Thus, net of effects through labor income, education, or age, today's wealth *dynamically* amplifies the wealth-health relationship because of its effect on today's health efforts.

6. Conclusion

We document a strong association between wealth and health over the life cycle in Germany, a country with a very generous and universal healthcare system. Empirical evidence on the dynamic relationship between health and wealth suggests that individual efforts to lead a healthy lifestyle could in part explain wealth-health gaps. With the aim of investigating the contribution of health efforts to these gaps, we build a structural life-cycle model of endogenous wealth and health evolution. Our calibrated model accounts for between one- and two-thirds of the empirical wealth-health gaps at different points of the distribution. We find that on average over half of these model-generated gaps are due to heterogeneity in individual lifestyle behaviors.

In our model, differences in healthy lifestyles affect the probability of good health outcomes in the future. Good health, in turn, affects wealth accumulation through differences in labor income and savings rates across health types. We find that, quantitatively, the labor income channel is most important for the young, and especially the asset poor, whereas the savings channel is more important at later ages, especially for retired and asset-rich individuals. Both channels together account for around 40% of the model-generated wealth-health gaps, on average. We argue that the remaining gaps are likely due to a dynamic feedback effect of wealth levels on healthy lifestyles. In our model, richer individuals exert higher health efforts, which results in being in better health in the future. Thus, contemporaneous wealth is especially positively associated with future health.

Our paper rationalizes that, because individual healthy lifestyles act as an amplifying force of the dynamic relationship between wealth and health, large and persistent wealth-health gaps can occur even in countries where the healthcare system does not frequently entail large out-of-pocket expenses. 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, strongly 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, Klein, and Ziebarth (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, Klein, and Ziebarth, 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).[29] 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).

[29]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 Labor Income and Wealth on Consumption 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)
Labor Income$_i$	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 SEs of Labor Income and Wealth multiplied by 1000. Stars denote statistical significance at the 10%, 5%, and 1% level.

Table A.1 shows the results of a linear regression of annual consumption on health-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.[30] 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, Lleras-Muney, and Vogl, 2008).

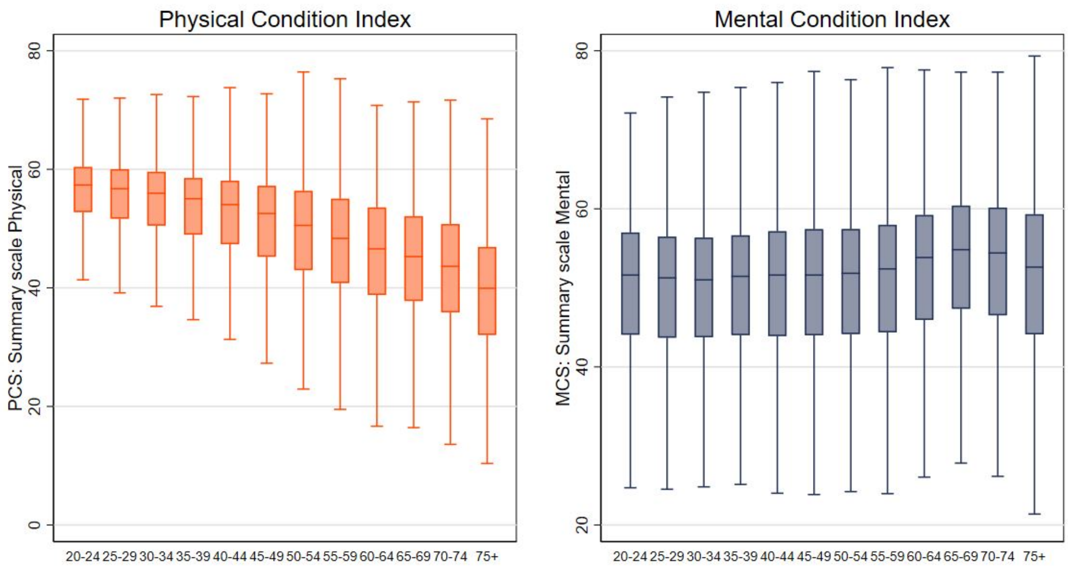
[30] Karlsson, Klein, and Ziebarth (2016) investigate individual medical spending using data from a private health insurer and find that medical spending increases over age and is particularly concentrated in the last three years before death.

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 that is frequently pondered as an important mechanism behind the wealth-health relationship: individual health behaviors (see Cawley and Ruhm (2011) and Cutler, Lleras-Muney, and Vogl (2008)).

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 5-year age group.

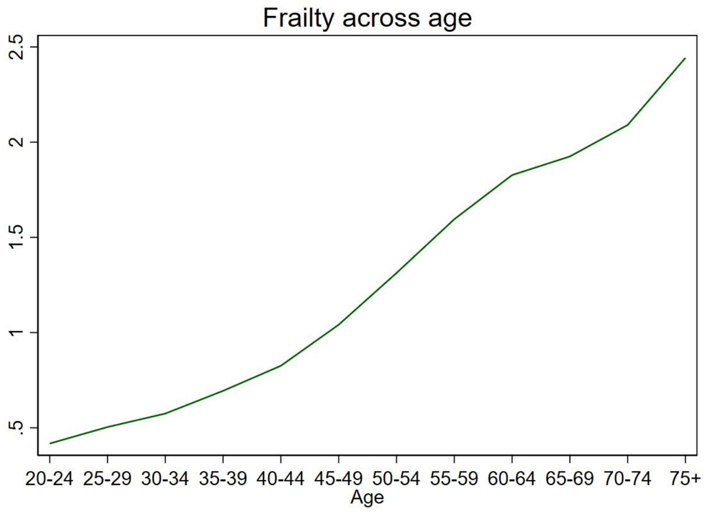
Figure A.1: Evolution of Physical and Mental Health Summary Scores in the SOEP over the Life Cycle



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.

Second, we construct a *frailty* index of individuals' health history as in Hosseini, Kopecky, and Zhao (2021b). 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 evolution of average frailty by 5-year age groups is depicted in Figure A.2.

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



Notes: Index is calculated by adding a 1 each time an individual is diagnosed with a specific health condition (Hosseini, Kopecky, and Zhao, 2021b).

Table A.2 then summarizes the correlation between our preferred binary health measure and these alternative, possibly more objective, health measures. 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).

Table A.2: Correlation between different measures of health

	Binary Health	Frailty	PCS	MCS
Binary Health	1	-0.4501	0.6285	0.2634
Frailty		1	-0.4622	-0.1401
PCS			1	0.9442
MCS				1

A.3. Construction of Health Effort

We use information on three individual health-related behaviors in constructing our health effort measure, following Cole, Kim, and Krueger (2019). First, the frequency of practicing a sport or exercising is given by never or almost never, several times a year, at least 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. Third, we use information on the number of cigarettes smoked in a day, which we cap at 50.

All of these behaviors are likely correlated with other observable characteristics, such as education, age, or work status. Given that the weight on each behavior should reflect its relative importance in explaining lifestyle variations *net of* potentially confounding factors, we first purge each behavior of variation coming from such factors, similar to Boar and Lashkari (2021). In particular, we regress physical exercise, healthy nutrition, and the number of cigarettes smoked on age, age squared, years of schooling, marital status, work status, insurance type, labor income, and wealth.

Next, we use the resulting residuals and 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 explains around 45% of all variance in the residualized physical exercise, nutrition, and smoking.

Finally, we calculate the weights as the relative loadings of each behavior, which are summarized in Table A.3.

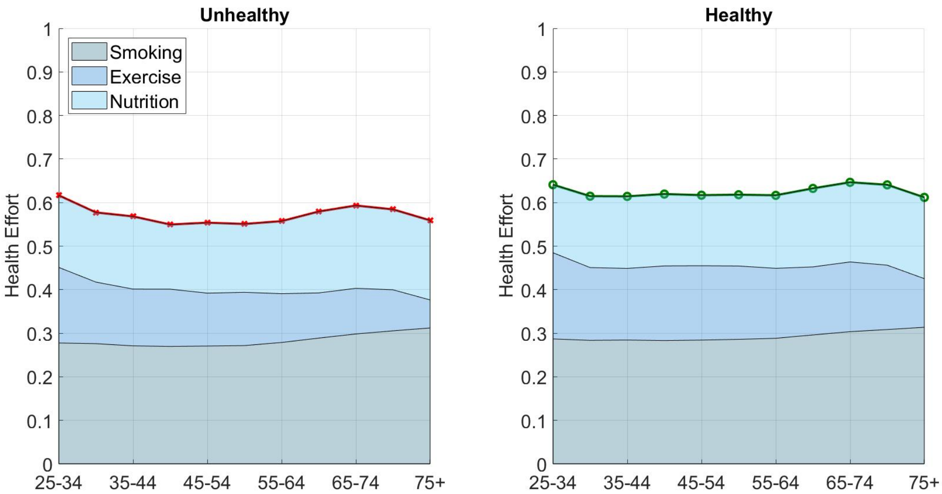
Table A.3: PCA for Health Effort Weights

Health Behavior	Loading
Physical Exercise	0.59
Healthy Nutrition	0.58
1 - no of cigarettes	0.55

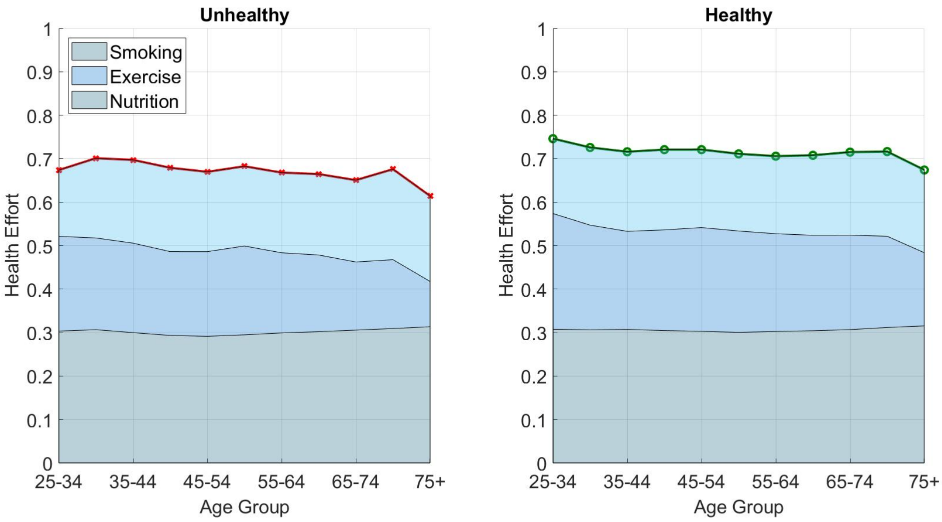
Figure A.3 shows average health effort for unhealthy and healthy individuals, separately for high school- (top) and college-educated (bottom) individuals. The life-cycle pattern for all health and education groups is relatively flat. The shaded areas illustrate the contribution of each of the three individual health behaviors to overall health effort. Smoking is the most important contributor, especially for those being unhealthy and with high school education. On top of this, the contribution of smoking becomes larger with age, relative to physical exercise and nutrition.

Figure A.3: Average Health Effort over the Life Cycle

(a) High School



(b) College



Notes: Average health effort by 10-year age groups for high school- and college-educated individuals in the SOEP, distinguished between unhealthy status (left) and healthy status (right). Health effort is a weighted, normalized sum of the average frequency of sport and physical exercise, health-conscious nutrition, and 1 minus the number of cigarettes smoked in a day. The shaded areas illustrate the contribution of these health behaviors to overall health effort.

A.4. Discussion of Estimated Health Technology Parameters

Much research, primarily medical, has aimed to causally identify the effect of different lifestyle components on good future health. For example, I.-M. 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, 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, Kim, and Krueger (2019), we use the SOEP data to map health status to the prevalence of a specific health condition (see Table A.4). 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, and current and/or past health effort tercile, which is implied by our estimated health technology parameters using the formula:

$$\begin{aligned}Pr(disease_{t+2}|h_t, f_t, f_{t-2}, e) =& \pi_t(h_{t+2} = 1|h_t, f_t, f_{t-2}, e) \times Pr(disease|h_{t+2} = 1, e) \\ &+ (1 - \pi_t(h_{t+2} = 1|h_t, f_t, f_{t-2}, e)) \times Pr(disease|h_{t+2} = 0, e)\end{aligned}$$

Finally, we calculate this implied probability of having a specific disease for individuals in the top, middle, and bottom terciles of the current health effort distribution and/or the past health effort distribution. We compare these implied probabilities to those in Colman and Dave (2013).

Table A.5 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 12%

Table A.4: Prevalence of Diseases in Population by Age Group and Health Status

		Health Condition Prevalence by Education							
		HS	CL	HS	CL	HS	CL	HS	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

compared to the mean.

Yet, the disadvantage of this approach, as mentioned earlier, is that it focuses on just one specific component of our compound health effort measure, namely exercise. We consequently 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 90 that are equipped with our estimated health transition technology, as specified in Section 4.1. As Table A.6 summarizes, our parameter estimates paired with the empirical average lifestyle effort results in a 10-year mortality rate of close to 44% 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 average health effort in the top effort quintile by age, the simulation-implied mortality rate drops to 40.8%. This drop is slightly smaller, yet comparable to that found in Knoops et al. (2004). We take this as confirmation that our estimated health technology parameters, and especially the effectiveness of health efforts, are conservative but

Table A.5: Implied Probability of Disease by Past and Current Effort Tercile

	Percent Change of Probability relative to the within-status Mean			
Effort Tercile	Diabetes	Cancer	Hypertension	Heart Condition
Current Effort				
Low	7.48	6.46	4.69	9.26
Middle	-1.94	0.19	-0.83	-3.10
High	-7.39	-8.32	-5.04	-8.43
Past Effort				
Low	10.58	9.36	7.03	12.72
Middle	0.07	2.17	1.10	-0.68
High	-7.20	-7.87	-3.96	-9.54
Both				
Low	10.86	9.90	7.60	12.74
Middle	-1.47	2.88	1.12	-3.58
High	-8.53	-9.85	-4.46	-11.84
Coleman & Dave	1.2-3% decrease		10-31% decrease	23-29% decrease

reasonable in light of the empirical medical literature.

Table A.6: Mortality among Older-Age Individuals implied by Our Estimates

	Mortality Rates over 10 years (%)	
	Knoops et al.	Implied by Simulation
Average Lifestyle	39.9	43.9
Healthy Lifestyle	35	40.8
Unhealthy Lifestyle		50.5

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.5. Similarly, Barbaresko, Rienks, and Nöthlings (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.5. 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:

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

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, years of schooling, gender, marital status, type of health insurance (private or public), survey year, the number of children in the household, and dummies for the occupation in case of work. We are interested in α, the contemporaneous effect of health on wage or hours worked.[31] 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.7. Column (i) gives the estimated effect of health in year t on the probability that individual i is working in the same year, estimated across the whole population. Going from being unhealthy to healthy increases this probability by an estimated 10.8%, even conditional on employment in the past two periods. Thus, 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 10%. The majority of this increase is due to longer working hours, which increase by over 6%. These finding suggest that,

[31] 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, Kopecky, and Zhao (2021a). However, our goal here is simply to quantify the contemporaneous effects of health on labor market outcomes, net of other confounding effects.

Table A.7: Effect of Health on Work Status, Labor Income, and Hours Worked

	(i) $\text{work}_{i,t}$	(ii) $\log(income_{i,t}\lvert\text{work})$	(iii) $\log(hours_{i,t}\lvert\text{work})$
$Health_{i,t}$	0.108***	0.097***	0.062***
	(0.006)	(0.010)	(0.009)
N	171,824	115,858	102,231
R^2	0.646	0.774	0.509

Notes: Estimated coefficient α 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, column (ii) and (iii) only on the sample of employed individuals. First-stage tests confirm relevance assumption of these instruments. Stars denote statistical significance at the 10%, 5%, and 1% level.

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.

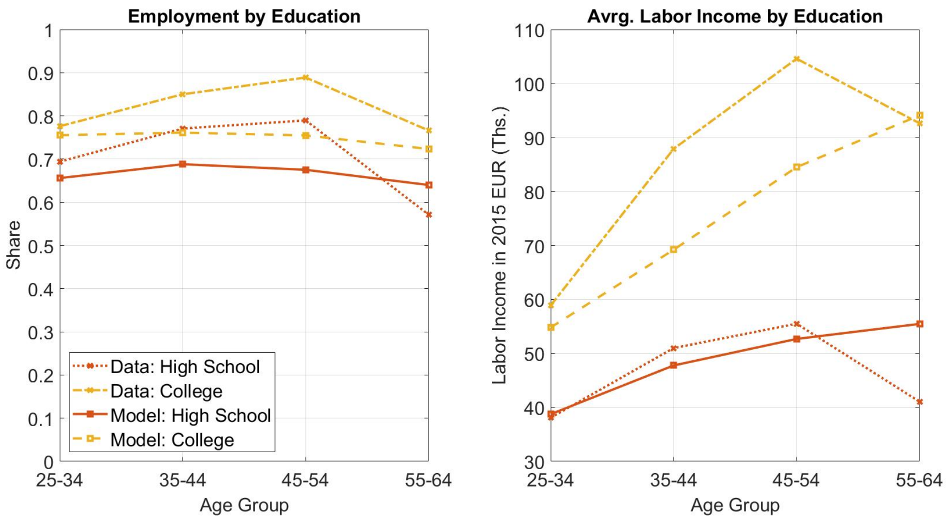
A.6. Model Fit regarding Education Groups

In this section, we present an additional analysis of the fit of the calibrated model. Figure A.5 shows the fraction of workers (left) and labor income conditional on working (right), differentiating between high-school (orange) and college-educated (yellow) individuals. The model captures well the empirical fact that a smaller fraction of the less educated group tends to work at all age groups. Additionally, high-school educated workers earn significantly less, as well as experience less earnings growth over their working career. This discrepancy in earnings growth rates is matched by the model.

Figure A.6 shows the evolution of average health effort among the two education groups over the life cycle, again contrasting the model-generated results with the observations in the data. As detailed in Section 2, higher-educated individuals exert substantially more effort in all age groups. The model captures this difference well. However, these differences in health effort only translate into relatively small differences in health by education.

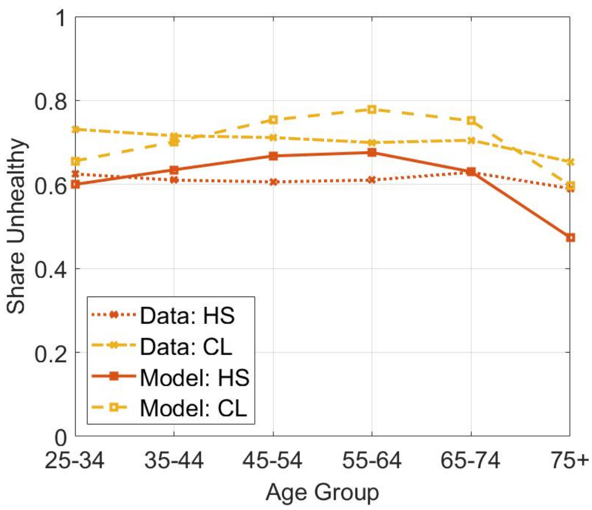
A.7. Additional Figures

Figure A.5: Model Fit of Labor Market Moments by Education Groups



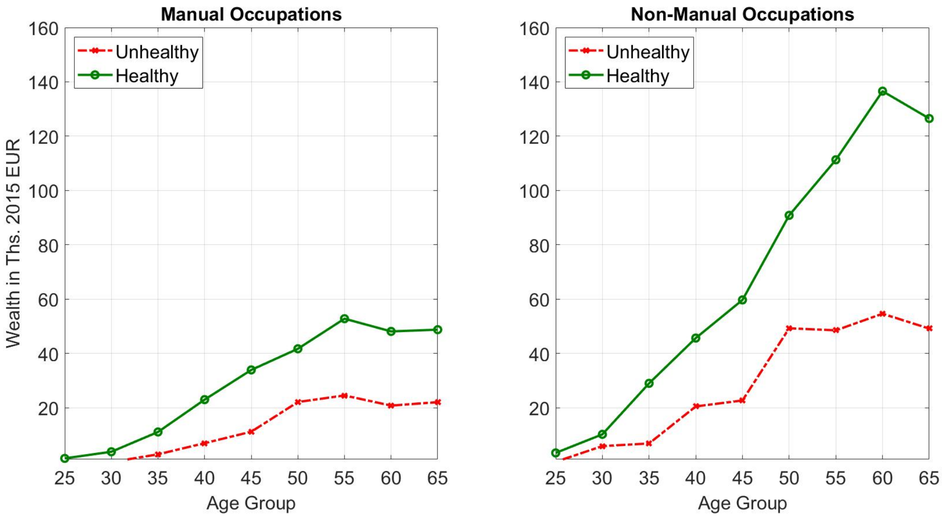
Notes: Share of people working (left) and average labor income conditional on working (right) by 10-year age groups, distinguishing between those with high school (orange) and college (yellow) education.

Figure A.6: Model Fit of Health Effort Evolution by Education Groups



Notes: Average health effort evolution by 10-year age groups, distinguishing between those with high school (orange) and college (yellow) education.

Figure A.7: Median Wealth Profiles of Unhealthy and Healthy Individuals by 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 tradespersons, plant and machine operators, and other elementary occupations. The non-manual category includes all other occupations.

Figure A.8: Histogram of Initial Effort Levels by Education and Health