A. Online Appendix

A.1. Medical Spending in Germany

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

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

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

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

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

	Cons. of Health Goods and Services$_i$	
Good Health$_i$	-118.2***	-119.6**
	(51.4)	(59.1)
Age$_i$	11.1***	10.5***
	(0.9)	(1.1)
Years of Education$_i$	40.6***	38.3***
	(7.6)	(4.8)
Earnings$_i$	0.9	
	(0.6)	
Wealth$_i$		0.08
		(0.05)
N	16,913	11,216
R^2	0.01	0.01

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

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

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

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

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

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

A.2. Comparison of Different Health Measures

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

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

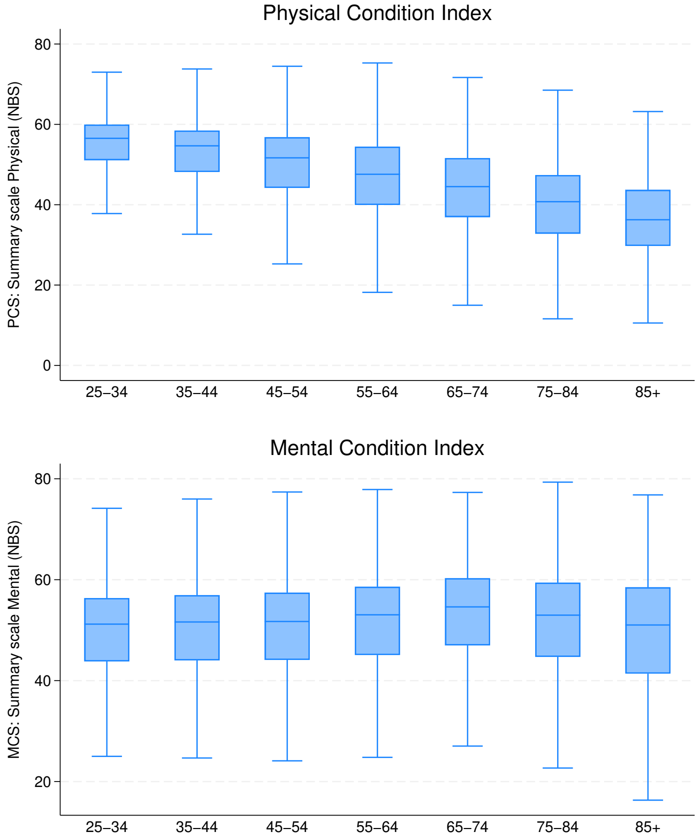
Table A.2 summarizes the correlation between our preferred binary health measure and these alternative, possibly more objective, health measures, as well as with the original 5-point self-reported health scale.[52] As expected, binary health is negatively correlated with frailty and positively correlated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

A.3. Construction of Health Effort

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

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

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



Notes: Box plots of Physical and Mental Health Summary Scores over 10-year age groups in the SOEP. The scores are calculated based on the SF-12 v2 series of questions on health-related quality of life. They are normalized to a mean of 50 and a standard deviation of 10 for 2004. A higher score indicates better health.

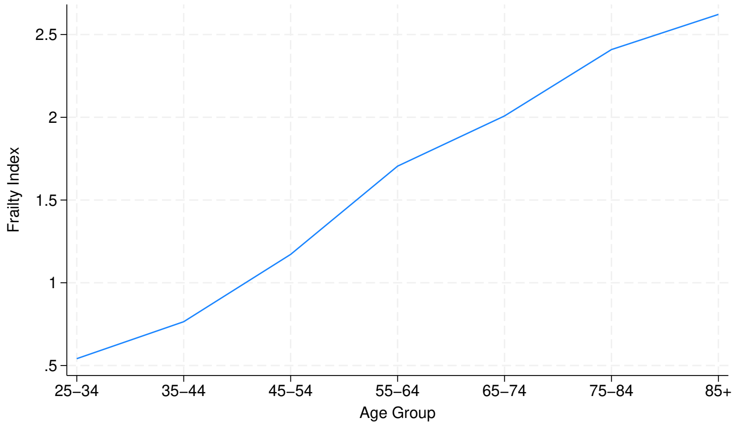
Table A.2: Correlations across Different Health Measures

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

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

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

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



Notes: Average frailty by 10-year age group. The frailty index is calculated by adding a 1 each time an individual is diagnosed with a specific health condition (Hosseini et al., 2022).

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

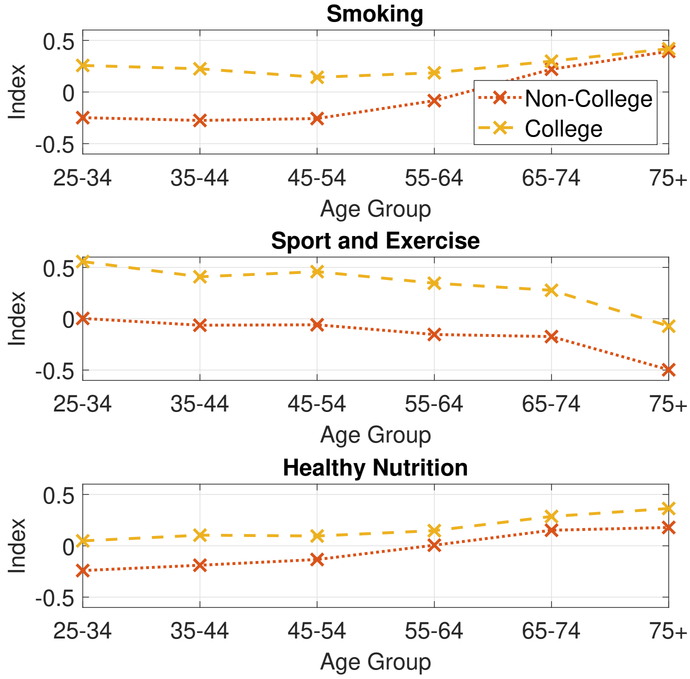
Table A.3: Health Effort Components and Weights

Health Behavior	Physical Exercise	Healthy Nutrition	Abstention from Smoking	Loading
Physical Exercise	1	0.17	0.15	0.592
Healthy Nutrition		1	0.21	0.587
Abstention from Smoking			1	0.553

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

Using the residualized effort measures, we perform a principal component analysis, where we take as the first principal component the measure that most closely

Figure A.3: Evolution of Each Standardized Lifestyle Behavior



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

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

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

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

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

where $y_{i,t}$ denotes either a dummy that equals 1 if individual i is working at time t and 0 otherwise, log labor income conditional on employment, or log hours worked

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

	(i) $work_{i,t}$	(ii) $\log(income_{i,t} \mid work_{i,t} = 1)$	(iii) $\log(hours_{i,t} \mid work_{i,t} = 1)$
$Health_{i,t}$	0.152	0.071	0.068
	(0.016)	(0.017)	(0.017)
N	104,085	61,185	61,185

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

conditional on employment. $\mathbf{X_{i,t}}$ includes a constant, age, age^2, marital status, type of health insurance (private or public), survey year, the number of children in the household, and dummies for the occupation in case of work. We also include individual fixed effects γ_i. We are interested in α_h, the contemporaneous effect of health on wage or hours worked.[54] In estimating such an effect, one concern might be simultaneity bias, which arises if labor income or hours worked themselves affect health status. We consequently instrument health status in year t by the number of doctor visits and the nights spent in the hospital in that same year. Given generous health insurance coverage benefits and sick-day regulations in Germany, the effect of the number of doctor visits or nights spent in the hospital on earnings and hours should work largely through health.

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

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

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

in higher wages per hour, and thus larger labor income gains from being healthy.

A.5. Details on the Estimation of Standard Errors

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

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

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

Table A.5: Empirical Moments and Standard Errors

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

A.6. Further Details on Structural Model Estimation

Classification of Fixed Health Types

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

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

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

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

Estimation of Wages and Productivity

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

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

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

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

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

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

A.7. Discussion of Estimated Health Technology Parameters

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

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

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

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

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

Variable	Model: Coef.	Endogenous Health Estimate	Endogenous Health Std.Error	Exogenous Health Estimate	Exogenous Health Std.Error
Current Health Effort	λ_1	0.693	0.138		
Past Health Effort	λ_2	0.734	0.137		
Current Health	$h_t = 1$	2.311	0.029	2.340	0.029
Age Group Dummies					
35		-0.289	0.079	-0.301	0.078
45		-0.644	0.074	-0.655	0.074
55		-0.881	0.074	-0.871	0.074
65		-1.138	0.074	-1.074	0.073
75		-1.586	0.077	-1.527	0.077
Health Type	$\eta = 1$	0.632	0.028	0.654	0.028
College	$e = 1$	0.238	0.033	0.388	0.032
Constant		-0.905	0.095	0.013	0.072
Pseudo R^2		0.242		0.237	

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Effort Tercile	Percent Change of Probability relative to the within-status Mean Diabetes	Cancer	Hypertension	Heart Condition
Current Effort				
Low	3.52	2.85	1.52	4.05
Middle	-0.52	-0.43	-0.21	-0.61
High	-3.35	-2.72	-1.45	-3.86
Past Effort				
Low	2.11	1.74	0.88	2.52
Middle	-0.26	-0.22	-0.10	-0.33
High	-2.12	-1.73	-0.90	-2.51
Both				
Low	4.26	3.5	1.81	5.06
Middle	-0.76	-0.62	-0.31	-0.92
High	-4.11	-3.36	-1.75	-4.87
Coleman & Dave	1.2-3% decrease		10-31% decrease	23-29% decrease

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

	Mortality Rates over 10 years (%) Knoops et al.	Implied by Simulation
Average Lifestyle	39.9	41.9
Healthy Lifestyle	35	40.6
Unhealthy Lifestyle		43.7

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

A.8. Sources of Lifetime Inequality

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

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

Statistic	Model
Fraction of variance in lifetime earnings	81.3%
Fraction of variance in wealth at age 65-66	53.0%
Fraction of variance in healthy years	24.9%
Fraction of variance in the share of healthy years in life	38.0%

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

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

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

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

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

We can rewrite the constrained optimization problem (20) as

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

which yields the following first-order conditions:

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

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

$$[f] \quad : \quad \varphi'(f) = \beta S'(h_1)\pi'(f)u_1(c_1, h_1) + \beta S(h_1)\frac{\partial u_1(c_1, h_1)}{\partial h_1}\pi'(f). \tag{A.6}$$

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

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

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

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

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

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

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

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

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

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

A.10. Additional Quantitative Exercises

Savings and Earnings Channel

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

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

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

	Earnings Channel								
	Total			Wage Loss Only			Disutil. Only		
Wealth	25th	50th	75th	25th	50th	75th	25th	50th	75th
Age Group									
35-44	98%	28%	21%	21%	0%	15%	-1%	11%	1%
45-54	15%	6%	15%	14%	5%	8%	-4%	0%	1%
55-64	34%	23%	6%	17%	12%	6%	5%	7%	0%
65-74	8%	19%	12%	7%	10%	11%	0%	7%	3%
	Savings Channel								
	Total			Length Only			Quality Only		
Wealth	25th	50th	75th	25th	50th	75th	25th	50th	75th
Age Group									
35-44	4%	1%	28%	-2%	0%	15%	-4%	-7%	11%
45-54	48%	42%	50%	16%	18%	36%	12%	2%	7%
55-64	55%	52%	69%	30%	19%	37%	17%	7%	9%
65-74	56%	51%	55%	32%	33%	40%	8%	5%	7%

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

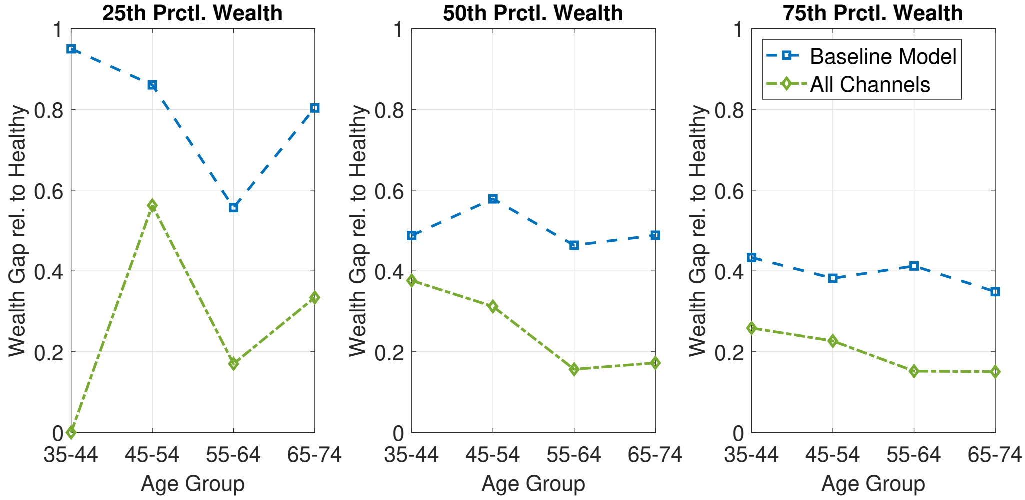
labor supply, wages, survival or consumption utility. This shrinks the wealth-health gaps considerably, by around 60%, on average. The remaining gaps in our model can be explained as individuals still differ in fixed characteristics that drive both wealth accumulation and the probability of being healthy,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

Equalizing Efforts

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

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

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



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

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

	Equal Efforts								
	Total			Direct Effects Only			Indirect Effects Only		
Wealth	25th	50th	75th	25th	50th	75th	25th	50th	75th
Age Group									
35-44	-1%	2%	26%	-1%	6%	26%	0%	2%	4%
45-54	10%	15%	20%	10%	16%	22%	5%	3%	1%
55-64	22%	28%	34%	20%	29%	35%	6%	5%	2%
65-74	27%	40%	40%	25%	39%	40%	4%	4%	2%

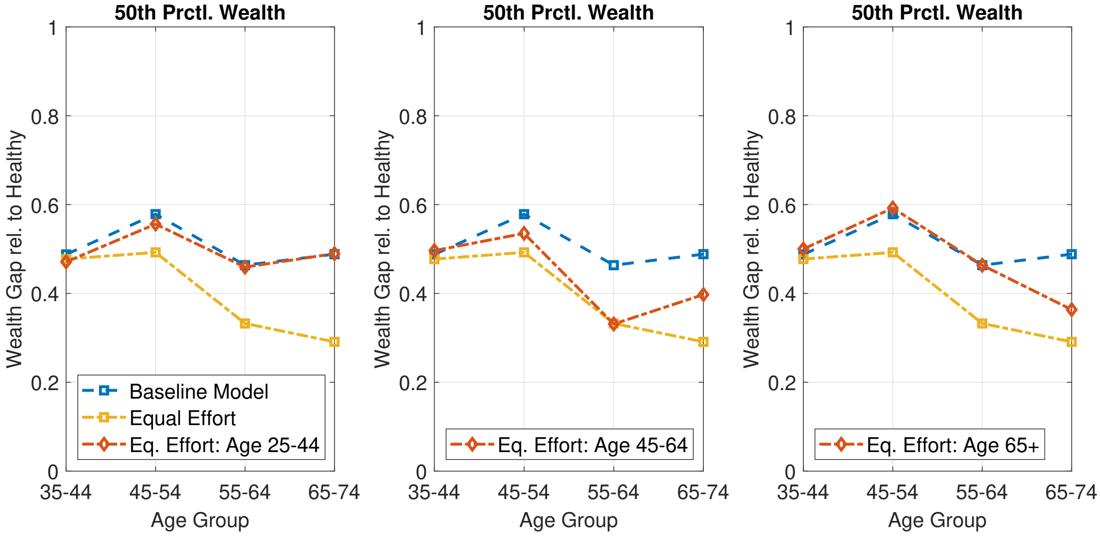
Notes: This table reports the proportions of the baseline relative wealth-health gaps that are explained by different effects. See the text for the definitions of direct and indirect effects.

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

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

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

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



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

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

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

A.11. Additional Figures and Tables

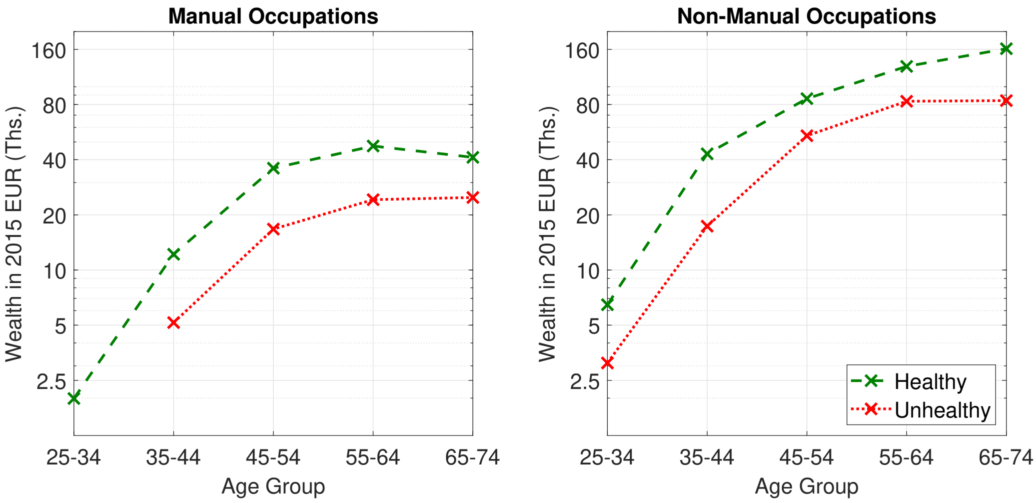
Table A.14 summarizes the initial distribution we estimate for our quantitative model. Several patterns are worth noting. Among college-educated individuals, 5% report being unhealthy between ages 25-30, while this number is over 8% among the non-college educated. Moreover, average initial health effort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

Table A.14: Initial Distribution

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

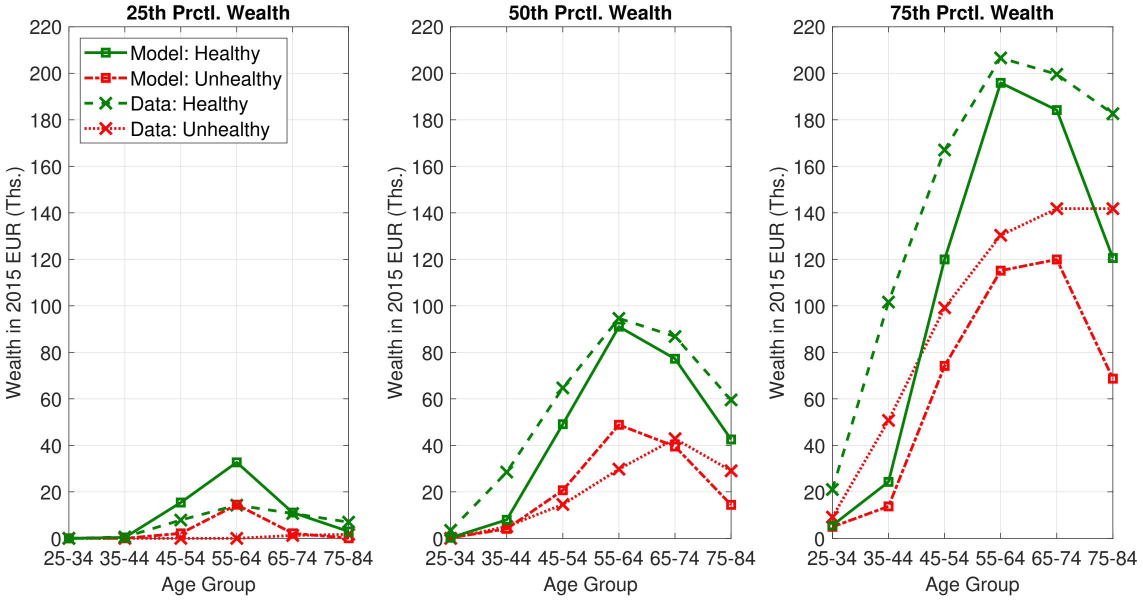
in both initial health and initial health effort are only marginal across productivity and discount factor types in the data, which is why we do not report them here.

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



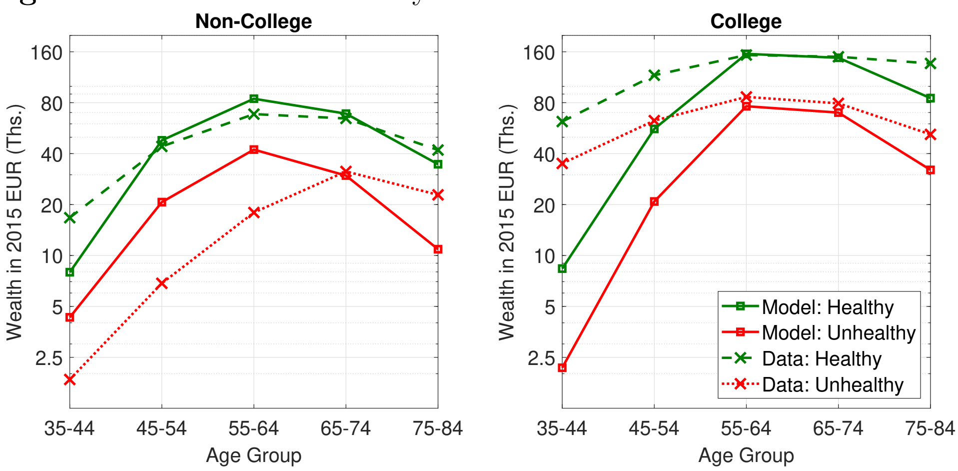
Notes: Median wealth per 10-year age group and health status for manual (left) and non-manual (right) occupations, separated by healthy (green) and unhealthy (red) status. Manual occupations include agricultural workers, craft and trades-persons, plant and machine operators, and other elementary occupations. The non-manual category includes all other occupations.

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



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

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



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

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