Exercise or Extra Fries? How Behaviors Impact Health Over the Life Cycle*

Neha Bairoliya† Ray Miller‡ Vegard M. Nygaard§

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Abstract

Leveraging a unique thirty-year panel of U.S. registered nurses, we explore why individuals who appear ex-ante homogeneous in their health when entering adulthood experience divergent health outcomes as they age. We find that among those entering adulthood in good health, individuals in the top diet quality or exercise deciles at age thirty are roughly 50% more likely to maintain a healthy weight and have no chronic diseases three decades later, compared to those in the bottom deciles. Behaviors exhibit strong persistence, though exercise exhibits more long-term persistence than diet. While individuals might enter adulthood with healthy weight and no diseases, they vary in their *health types* due to factors like birth conditions, adolescent weight, and family disease history, which we find significantly affects weight and disease progression over time. To disentangle the role of initial conditions from behaviors in determining health trajectories, we propose a novel structural framework of endogenous health evolution. The model accounts for two sources of fixed heterogeneity—health types derived from data and unobserved exercise types inferred from long-term exercise patterns—in addition to differences in diet habits, weight, and diseases. We find that initial conditions account for one-third of the variance in weight at older ages. While course correction through behaviors can only partially make up for poor initial conditions at the onset of adulthood, promoting healthy behaviors can reduce total healthcare expenses by at least 8%, or $100 billion annually.

JEL classifications: I12, I14, H51, D15

Keywords: Obesity, diet, exercise, frailty, BMI, early childhood exposure, permanent health, medical spending, health production function

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†Marshall School of Business, University of Southern California, 701 Exposition Blvd, Ste 231 Los Angeles, CA 90089

‡Colorado State University, Clark C305B, Fort Collins, CO 80523

§University of Houston, 581 Cullen Boulevard Suite 230 Houston, TX 77204-5019

1 Introduction

The growing dispersion in health over the life cycle has been well-documented but remains poorly understood (Deaton and Paxson, 1998a,b). The need to comprehend the determinants of health is more pressing than ever following decades of rising healthcare spending, currently accounting for about 17% of annual GDP in the United States, or more than $13,000 per capita. This rise in spending has coincided with surging obesity rates (Cutler et al., 2003, 2006; Flegal et al., 2012).[1] Currently, more than 40% of Americans are classified as obese, with 6 in 10 living with at least one chronic disease such as cancer, heart disease, or diabetes according to statistics by the Centers for Disease Control and Prevention. However, despite the persistent growth in obesity and its health and macroeconomic consequences, questions remain regarding the determinants of health. Specifically, what determines the evolution of individual weight and chronic conditions over the life cycle, and why do individuals that appear ex-ante homogeneous in their health when entering adulthood experience divergent health outcomes as they age? How important are lifestyle choices compared to inherited health conditions at the onset of adulthood? We present a framework for answering these questions, leveraging a large longitudinal dataset of registered nurses in the U.S.

Our dataset, the Nurses' Health Study II (NHS II), is uniquely equipped for this purpose due to its thirty-year panel and detailed information on medical and health conditions, comprehensive measures of health behavior, including continuous measures of physical activity, food frequency, and dietary intake, as well as measures of early childhood circumstances and extensive family medical history. We first document several stylized facts relating health behaviors, as measured by diet and exercise choices, to long-run changes in weight and morbidities using our longitudinal data. Next, we develop a structural life-cycle model of endogenous health, specifically focusing on body mass index (BMI) and frailty evolution, to better understand the implications of the patterns observed in the data.[2] Finally, we use our model to conduct counterfactual experiments to understand the role of initial conditions and healthy behaviors in maintaining lower BMI and lower frailty over an individual's life, and consequently, on medical spending in the U.S.

Two aspects of our analysis warrant clarification at the outset. First, conventional wisdom posits that lifestyle factors most closely associated with changes in weight, through the creation of caloric deficit, are the amount of calories consumed and the degree of physical activity, with the latter also shown to improve overall health outcomes (Bleich et al., 2008; Booth et al., 2012). Nonetheless, more recent evidence indicates that the quality of diet serves as a more reliable predictor of both BMI changes and the onset of chronic diseases than simple calorie count.[3] Consequently, our framework focuses on diet quality and physical activity as key behaviors in understanding the evolution of BMI and health. Second, the NHS II dataset is an ongoing survey of female registered nurses that started in 1989. Focusing on nurses has significant advantages for

[1] The ongoing obesity epidemic is a significant population health concern due to its strong links to the development of major chronic illnesses and functional impairments, consequently leading to higher medical spending. For instance, Wolf and Colditz (1998) estimated the total economic costs attributable to obesity to be $99.2 billion dollars in 1995.

[2] For brevity, an index of the number of chronic conditions is referred to as frailty.

[3] A controlled experiment conducted by a recent influential study Hall et al. (2019) showed that poor quality diets, as represented by ultra processed foods, resulted in both higher caloric intake as well as weight gain among participants compared to those who consumed higher quality diets. See McCullough et al. (2002); Sotos-Prieto et al. (2015); Kant et al. (2000); Li et al. (2013); Lane et al. (2024) for the impact of diet on mortality and chronic conditions.

our study. Having a large but homogeneous sample helps us isolate drivers of healthy behaviors that cannot be fully attributed to socioeconomic characteristics such as income and educational attainment. The sample is also ideal for understanding the role of behaviors due to the shared health profession of the survey participants, which provides uniformity in factors such as health insurance coverage and consequent medical spending, as well as a similar information set regarding the health implications of these behaviors. Additionally, the study developers argue that using medical professionals as respondents helps mitigate the potential measurement errors that often arise in questions pertaining to health, nutrition, and eating patterns.

We utilize the NHS II panel data for nurses aged 25 to 30 at the time of the initial interview to document several novel facts. First, we observe that despite improvements in average dietary quality and physical activity levels over adulthood, both BMI and frailty prevalence tend to rise. Furthermore, within our sample, 9% of nurses were obese (BMI ≥ 30) in the initial survey wave, and over 90% of this group remained obese thirty years later, highlighting remarkably high obesity persistence throughout adulthood. In contrast, health trajectories diverged significantly among individuals with a healthy BMI (18.5–25) and no frailties in early adulthood. For instance, among the 74% of nurses with a healthy BMI and no frailties in the initial survey wave, 46% maintained a healthy BMI after 30 years, while 19% developed obesity. We label these 46% as healthy weight maintainers, or *stayers*, and the 19% as weight *gainers*. We find that diet and exercise patterns are strong predictors of membership in these two groups. For example, individuals ranking in the top deciles for exercise or diet at age 30 have approximately 50–60% higher odds of being in the *stayers* group compared to those in the bottom deciles. Additionally, they have roughly 30–40% higher odds of remaining free from frailties.

In addition to health behaviors, our empirical findings further emphasize the importance of *permanent health types*, as in De Nardi et al. (2022), in influencing the progression of both BMI and frailty throughout adulthood. These health types are inferred from data on early-life exposures, birth-related conditions, and family medical history. We document that these health types are also highly predictive of the long-run preservation of healthy weight and fewer chronic conditions, with nurses who are in the high (i.e., favorable) permanent health group having approximately 157% higher odds of being in the healthy BMI stayers group than those with low permanent health.

Finally, we document that diet and exercise exhibit differing patterns of persistence across the life cycle. While diet quality displays high levels of short-run persistence across the entire spectrum, physical activity demonstrates similar persistence mainly at the lower and upper extremes of the distribution (for brevity, referred to as the *inactive* versus *more active* groups). Moreover, diet displays somewhat less persistence than exercise over the very long run.

Despite our relatively homogeneous sample of nurses, there might be concerns regarding the sensitivity of our empirical findings to other factors, such as remaining socioeconomic disparities, additional health-promoting behaviors, various health metrics, or workplace advantages. However, our empirical findings remain robust within sub-groups based on marital or fertility status, educational level of the spouse, smoking habits, mental health status, and whether nurses primarily work day or night shifts.

We use the above stylized facts to discipline an endogenous health model of BMI and frailty evolution where individuals exert effort to maintain good health. The modeling framework posits that rational and forward-looking individuals face the following key trade-off: investing in costly health-maintaining activities now to enjoy the benefits of reduced frailty and a healthier BMI in old age. Individuals in the model differ in their permanent states in terms of their *permanent health*

type and exercise preferences, evolving states including their past frailty, BMI, and diet habits, and the realization of their i.i.d. idiosyncratic preference shocks to both diet and exercise. We exploit our rich panel data to estimate BMI and frailty laws of motion that depend on both permanent health type and health behaviors. Exercising and consuming a healthy diet both lead to lower weight and better expected health but come with utility penalties. A key modeling innovation is to treat the habitual nature of diet and exercise differently as suggested by our empirical observations. While the habitual nature of the former is captured through adjustment costs for any dietary improvements over past choices, the latter is modeled as permanent preference heterogeneity in attitudes toward physical activity, with the more active group incurring a lower disutility for the same levels of activity compared to the inactive group.

The model is estimated in two steps. First, the health production functions (i.e., the laws of motion for BMI and frailty) are estimated directly from our longitudinal data. Similarly, the initial idiosyncratic distribution of states corresponds to the equivalent distribution for our sample of nurses. Second, the preference parameters are calibrated by minimizing the distance between model and data moments. Although the modeling framework is kept intentionally simple, it does very well in capturing key non-targeted features of the cross-sectional and longitudinal relationships observed in the data. For instance, the model matches the life-cycle evolution of BMI, frailty, diet, and exercise as well as the cross-sectional distributions of diet and exercise. Even though not explicitly targeted, the model is broadly in line with the stylized facts and produces correlations between BMI, diet, and exercise similar to those observed in the data. Through the use of alternative and fully re-calibrated models, we further elucidate how some of our modeling choices, such as those related to diet habits and exercise preferences, are crucial in accounting for salient features of the data. For instance, while a model that abstracts from diet habits can replicate the distribution of diet quality *levels*, it falls short in matching the observed distribution of diet quality *changes* over time; specifically, agents exhibit unrealistically large adjustments in their diet quality in response to idiosyncratic shocks. We also show that an alternative modeling framework where we replace exercise types by heterogeneous discount factor types can replicate some features of the data but fails along certain dimensions, including substantially overestimating the rise in physical activity over adulthood and failing to account for the bottom third of exercise distribution.

Our model shows that initial conditions play an important role through a combination of direct and indirect mechanisms. Individuals entering adulthood with a healthy BMI and no frailties are more likely to sustain these favorable outcomes in the future due to the persistence in the associated laws of motion. Beyond these direct effects, however, there is an amplification effect through behaviors. A favorable health status facilitates higher levels of physical activity and healthier dietary choices because of the dependence of the disutility functions on existing health conditions. Similarly, starting adulthood with better diet habits and exercise preferences yield similar amplification effects. Consequently, equalizing initial conditions such as initial BMI, exercise preference types, and initial diet quality significantly affects the evolution of both effort and health outcomes in our model. For example, equalizing everyone's initial BMI at a healthy weight reduces the share of age-64 obese individuals (BMI $\geq$ 30) by 13 percentage points (pp) relative to the benchmark model; conversely, equalizing everyone's initial BMI at a class I obese level (BMI of 30–35) increases the rate of old age obesity by 30 pp. Overall, we find that about one-third of the variance in BMI of agents in their fifties can be explained by the variance in initial conditions. These experiments underscore the potential long-run negative implications of rising obesity trends among younger workers, which itself is partially driven by rising childhood obesity trends in the U.S., and

suggests that there are potentially high returns to policies that can influence adolescent BMI.

We further utilize our model to investigate the impact of health-promoting behaviors among adults on health outcomes. Equalizing effort levels at low or high values has a significant effect on obesity and frailty, underscoring the substantial influence of behaviors on health progression. Moreover, these experiments provide insights into potential policy implications for public health, suggesting that policies encouraging individuals to increase their effort could lead to substantial reductions in medical spending. For example, setting diet and exercise at the 90^{th} percentile of their respective distributions results in reductions in obesity rates by about 15 pp by age 64, as well as a 10 pp decline in the share of individuals with chronic conditions. We estimate that these health improvements could lead to an 8% reduction in aggregate annual healthcare expenditures, equivalent to approximately $100 billion based on 2022 national spending estimates. It is important to note that this is a conservative estimate of the total cost savings, as additional savings would occur among older individuals (age > 65) that are not captured in our model, since the data is restricted to working-age individuals. The estimate, however, is a simple extrapolation from our sample of nurses, who might engage in healthier behaviors than Americans on average. Nonetheless, these findings underscore the importance of both initial conditions and health-promoting behaviors in determining health outcomes over the life cycle, offering insights into potential strategies to improve public health and mitigate healthcare spending.

In summary, three insights emerge from our model about the role of initial conditions and behaviors:

INSIGHT 1: Because of the large effects of initial BMI on future BMI evolution, our paper highlights the potentially important role played by the increase in childhood obesity in the last few decades in causing high obesity prevalence among adult Americans (Ogden et al., 2012; Skinner and Skelton, 2014; Ogden et al., 2016).

INSIGHT 2: In equalizing all initial conditions to *poor* levels, we find large implications for old-age obesity and the share of those with multiple chronic conditions. This highlights that course correction through behaviors can only take individuals so far if their starting point is not favorable, especially when it applies to multiple factors. Policies that affect adolescent BMI, diet habits, and exercise preferences set early in life can therefore have large implications for adult health outcomes.

INSIGHT 3: Policies that promote healthy levels of diet and physical activity can have important implications for medical spending, a substantial share of which is tax-financed through Medicare or Medicaid in the U.S. The cost-savings of targeting healthy behaviors are likely larger than our estimates if the full impact on elderly health outcomes is considered.

Our paper contributes to several strands of the existing literature. First and foremost, it is closely related to a growing body of work using structural models to understand the evolution of health (Hall and Jones, 2007; Scholz and Seshadri, 2011; Ozkan, 2014; Jung and Tran, 2016; Cole et al., 2019; Fonseca et al., 2021; Bolt, 2021; Nygaard, 2021; Mahler and Yum, 2022). Among these papers, the three most closely related to ours are Cole et al. (2019), Bolt (2021), and Mahler and Yum (2022), who also focus on the role of lifestyle behaviors in explaining the evolution of health. We contribute to this line of research by focusing on the specific interplay of two behaviors,

physical activity and diet quality, on the evolution of weight and accumulated morbidities over the life cycle. Leveraging a unique thirty-year panel dataset, we incorporate continuous measures of effort alongside early childhood circumstances and family medical history to address additional permanent health heterogeneity. Moreover, BMI has received relatively less attention in this literature than other health measures such as self-rated health and frailty scores. However, it is a key objective health measure with strong implications for medical expenditure risk and documented links with the development of major chronic conditions and functional impairments. Finally, unlike other objective health measures that proxy an individual's health by the number of diseases and conditions that the person has ever been diagnosed with, BMI is not an absorbing state, presenting additional opportunities for investigating the role of behaviors.

Second, by highlighting the importance of physical activity preferences and diet habits at the onset of adulthood in shaping the evolution of health outcomes over the life cycle, our paper contributes to an extensive literature on early childhood investments and the role of family in shaping economic outcomes of future generations (Becker and Tomes, 1986; Aiyagari et al., 2002; Cunha et al., 2006; Heckman, 2006; Miller, 2020; Caucutt and Lochner, 2020). Our work reveals that early childhood investments in terms of exposure to healthy diet and exercise preferences can have far reaching effects on future health and weight trajectories, and in turn future earnings.[4] These effects hold even after controlling for the effects of genetic linkages between generations through family medical history.

Third and finally, our paper contributes to a growing body of work documenting the heterogeneity in population health outcomes (Deaton, 1999, 2007; Pijoan-Mas and Ríos-Rull, 2014; Miller and Bairoliya, 2023) and the impact of health on medical spending, economic outcomes, and welfare (De Nardi et al., 2010; Capatina, 2015; Conesa et al., 2018; Miller et al., 2019; Capatina and Keane, 2023; Hosseini et al., 2021; De Nardi et al., 2022). We extend this literature by documenting how BMI and frailty trajectories are shaped by individuals' behaviors over the life cycle and by quantifying the implications of behavior for aggregate healthcare expenses. While much of the recent literature has attributed health disparities to socioeconomic characteristics such as education, wealth, or access to health insurance, we intentionally abstract from these channels in our modeling framework for a simple reason—much of the variance in health remains even in socioeconomically homogeneous groups like the NHS II sample used in our analysis.[5] As such, we focus on examining the effects of dietary habits, differential preferences towards physical exercise, early exposure to healthy behaviors, and familial medical backgrounds in explaining health trajectories.

2 Data and key measures

We use data from the Nurses' Health Study II (NHS II), which is an ongoing longitudinal study of 116,429 female registered nurses from 15 US states who were between the ages of 25 and 42 in 1989. The goal of the study was to understand oral contraceptives, diet, and lifestyle risk factors. Every 2 years, a questionnaire was sent to each participant to assess lifestyle, health outcomes, and

[4] An extensive macro and labor literature has documented the impact of health on earnings and labor supply outcomes (Luft, 1975; Coile, 2004; French, 2005; Blundell et al., 2023).

[5] See for instance appendix Figure A1 which shows both within and across group variance in BMI for the US population.

medication use. Every 4 years, a validated food frequency questionnaire (FFQ) was sent to assess usual dietary intake. The survey had a high response rate (85-90% for each two-year cycle). See appendix A2 for attrition analysis.

Registered nurses were selected due to their health knowledge and ability to provide complete and accurate information on a brief, technically worded questionnaire. Additionally, they were expected to be relatively easy to follow over time and more likely to maintain participation in a long-term study than the general U.S. population. This unique survey design has two important benefits for our study. First, having a homogeneous group of individuals like female registered nurses helps us disentangle life-cycle habit-driven behavioral changes from socioeconomic determinants of health, including income, educational attainment, and occupation. Second, having medical professionals as survey respondents reduces the likelihood of measurement error in the key variables of interest for this analysis.

We select our analytic sample by applying two restrictions on the full NHS II sample. First, to limit potentially large cohort effects, we select a narrow birth cohort of those aged 25 to 30 at the time of their first interview in 1989.[6] This cohort was followed over the majority of their adult working-age lives. This restriction reduces the sample size from 116,429 to 26,589 registered nurses. Second, we exclude those reporting a BMI less than 18.5 in any survey wave. An underweight BMI is relatively uncommon in the U.S. population and is often tied to unique circumstances such as chronic diseases, eating disorders, or chronic food shortage (Uzogara, 2016). This second restriction reduces our final sample to 24,380 registered nurses.

Dietary score

We use a version of the *Alternate Healthy Eating Index* (AHEI-2010) developed by Chiuve et al. (2012) as a measure of diet quality. It is a score that measures adherence to a diet pattern based on foods and nutrients most predictive of disease risk in the public health literature. There are a total of 10 components, each of which has a minimum score of 0 and a maximum score of 10 (see details in appendix Table A1).[7] For example, fruit consumption scores range from 0 (no fruit) to 10 ($\geq$ 5 servings/day). Unhealthy consumption is reverse coded. For example, consuming one or more sugar-sweetened beverages a day receives a score of 0, while zero consumption receives a score of 10. A score between the minimum and maximum is assigned on a continuous basis (except for sodium). For example, if fruit intake is 2 servings/day, the score for this component would be 5. The sodium component was based on FFQ-specific deciles of sodium intake within the study population.

The AHEI-10 diet quality index is approximately normally distributed with a mean of 49 and standard deviation of 13 (see appendix Figure A3).[8] The average diet quality in the top percentile is 81 while that of the lowest percentile is 24. Figure 1 further shows the composition of various food components within each quintile of the diet quality index. We find stark gradients in the

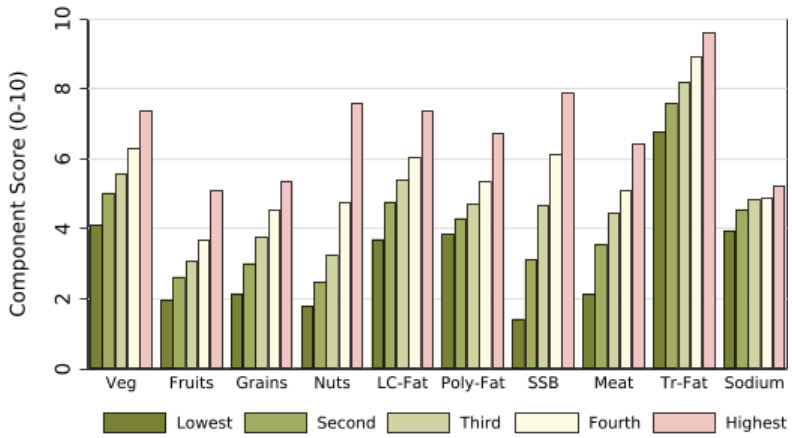
[6] Appendix Figure A2 shows the life-cycle evolution of BMI for different cohorts of nurses.

[7] Note that the full index treats small amounts of alcohol consumption (0.5 to 1.5 drinks per day) as diet improving. Given the lack of consensus in the medical literature about the impact of alcohol consumption (at low levels) on health outcomes (Stockwell et al., 2016; Corrao et al., 2004; Xi et al., 2017; Ma et al., 2021), we use a version of the AHEI-2010 index which does not include any scores due to alcohol consumption.

[8] The inclusion of alcohol does not change the shape of diet quality distribution in any noticeable way; its mean and standard deviation is 54 and 13, respectively.

consumption of fruits and vegetables, nuts and grains, as well as long chain and poly unsaturated fatty acids across quintiles of diet quality. For example, less than 1% of individuals in the top diet quintile consumed zero servings of nuts a day compared to almost 12% in the bottom quintile. Similarly, over 70% of individuals in the bottom quintile consumed at least one sugar-sweetened beverage (SSB) a day while this share was only about 7.2% for individuals in the top quintile.

Figure 1: Composition of AHEI-10 diet quality index



Notes: Figure shows average individual component score (between 0-10) for each food group within each quintile of diet quality. Food categories include vegetables, fruits, whole grains, nuts and legumes, long-chain fatty acids, polyunsaturated fatty acids, sugar sweetened beverages and fruit juices, red meat and processed meats, trans-fat, and sodium. Pooled diet data, for all nurses who were ages 25-30 in 1989, between the years 1991 and 2015 is used. Information on alcohol consumption is excluded from the construction of the diet score.

Physical activity

Physical activity (or exercise) is evaluated through survey questions about common leisure-time activities, which are then converted to metabolic equivalent (MET) hours per week.[9] Specifically, survey participants were prompted on the biennial questionnaire to report their average weekly hours devoted to various physical activities.[10] For each respondent, survey wave, and activity i, a MET score is computed by multiplying (1) the participant's reported median number of hours per week for that cycle and (2) the MET value assigned to the activity (refer to appendix Table A3).[11]

[9]This is a widely used measure in the medical literature to assess the level of physical activity. See for instance (Sallis et al., 1985; Jetté et al., 1990; Manson et al., 2002).

[10]Hours were selected from a discrete grid. Appendix Table A2 provides both the categorical responses for each activity and the corresponding median value in hours per week. This median value is used to generate a continuous measure of physical activity.

[11]MET values for each activity were obtained from Ainsworth et al. (1993). One MET is the energy expended while sitting quietly. Therefore, an activity with a MET score of 5 requires five times the energy of sitting quietly.

The total weekly MET score is then derived as the sum of all MET scores, as shown below:

$$\text{METs per week}_i = \text{median hours per week on } i \times \text{MET value of } i.$$
$$\text{Total METs per week} = \sum_i \text{METs per week}_i.$$

To provide an illustrative example, consider a nurse who reported jogging for 2-3 hours per week; she would have a MET-hours/week from jogging calculated as $2.5 \times 7.0 = 17.5$. The total MET-hours/week is then obtained by summing over each activity. Non-activity variables like standing/sitting at work/home and time spent sleeping are not included in an individual's total MET score.

In our sample, the mean physical activity is 23.2 MET-hours/week, with a median of 14.5 and a standard deviation of 29.4 (see appendix Figure A4). To contextualize these numbers, the physical activity recommendation for adults by the Centers for Disease Control and Prevention (CDC) is approximately 23 MET-hours/week (equivalent to 150 minutes of brisk walking with two days of muscle-strengthening activity). Thus, the sample mean aligns with the basic CDC recommendation for physical activity. However, the distribution of physical activity has a long right tail. For instance, individuals in the top 1 percent have a physical activity index of 134.6 MET-hours/week, more than 5 times the CDC recommended level. Simultaneously, approximately 15% of the sample does not engage in any physical activity, classified as having less than 3 MET-hours/week.

Figure 2 further illustrates the composition of various activity types and their associated MET values within each quintile of our physical activity index. Several noteworthy observations emerge. For example, sports activities like tennis, squash, racquetball, and swimming are less prevalent among our sample of registered nurses. In fact, those in the highest quintiles of the physical activity distribution are individuals engaging in extensive walking or aerobic and other vigorous physical exercises.

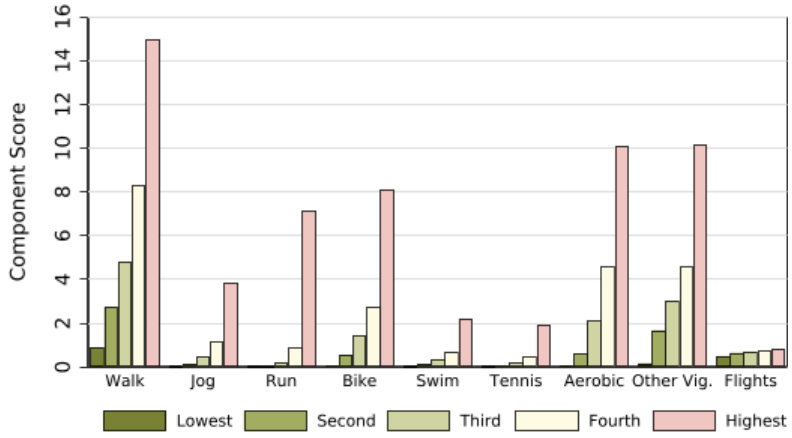
Body Mass Index

Every two years, the survey collects information on weight. Body mass index (BMI) is calculated as weight in kilograms divided by height (from the initial 1989 interview) in meters squared. Approximately half of our analytic sample (pooled across survey waves) falls within the healthy BMI range (between 18.5 and 25). However, the BMI distribution is substantially skewed to the right (see appendix Figure A5). For example, around 20% of the pooled sample is categorized as obese (BMI$\geq$ 30), with approximately 5% classified as class 3 obese according to the CDC definition (BMI$\geq$ 40).

While the NHS II is not intended to be a nationally representative sample, it is valuable to examine how it compares with a more representative survey. Although comparable representative surveys are not available for diet and exercise, we draw a comparison between BMI reported in the NHS II and the widely used National Health and Nutrition Examination Survey (NHANES).[12] Panel (a) of Figure 3 illustrates the BMI distribution for the pooled NHS II sample and NHANES for women aged 34-65. The shape of the BMI distributions generally align, although the NHS II

[12]The NHANES program began in the early 1960s and collects data on a nationally representative sample of about 5,000 persons each year.

Figure 2: Composition of physical activity index



Notes: Figure shows average individual component score (in MET-hours/week) for each activity within each quintile of physical activity index. Refer to appendix table A3 for individual components. Pooled data, for all nurses who were ages 25-30 in 1989, between the years 1991 and 2009 is used. Activities related to weight training were added to the questionnaire starting 2001 and are not included in the above graph but are used for constructing the total physical activity index. Running and Jogging activities were combined together starting 2013.

exhibits a somewhat lower overall BMI. This difference is perhaps unsurprising given the average education and socioeconomic status of nurses compared to the general US population. Nonetheless, the significant distributional overlap provides reassurance that insights from our analyses are not confined to an overly unique population. Panel (b) of Figure 3 presents an estimate of average medical expenditures by BMI category for the same demographic group. The steep gradient highlights the important link between weight and medical expenses across the entire BMI distribution.

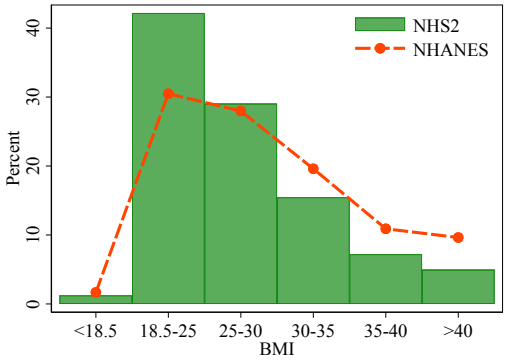
Frailty index

We follow the gerontology literature (see, for instance, Searle et al. (2008)) and approximate an individual's health by her *frailty index*. These indices have also been utilized in the economics literature (e.g., Braun et al. (2019); Nygaard (2021); Hosseini et al. (2022)). The gerontology literature constructs these indices by counting how many disabilities and diseases a person has, including functional limitations, cognitive impairments, and various morbidities. Because our goal is to understand how lifestyle choices affect BMI and health outcomes, we depart from the gerontology literature by restricting the components of our frailty index to morbidities with known hereditary links and medically proven relationships with lifestyle choices, including physical activity and diet quality. Specifically, we consider confirmed diagnoses for the following morbidities: stroke, coronary artery bypass surgery, myocardial infarction, all types of cancers[13], Type 2 dia-

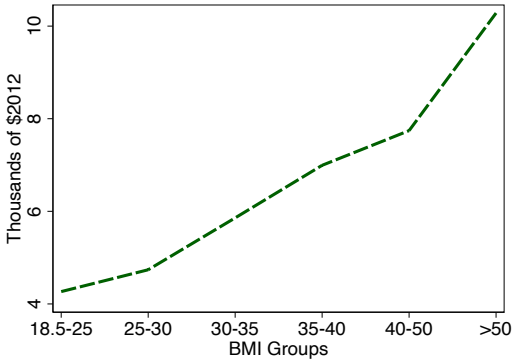
[13]The survey provides detailed diagnosis on six different types on cancers: (1) digestive organ cancers like oral, esophageal, stomach, intestine, liver, gall bladder, pancreatic, etc.; (2) respiratory cancers like larynx and lung; (3) bone, connective tissue and breast cancers; (4) genito-urinary cancers like uterine, ovarian, prostrate, bladder, kidney, etc.; (5) other and unspecified sites like brain and thyroid; and (6) lymphatic cancers like Hodgkins, non-Hodgkins

Figure 3: BMI distribution and medical expenditures

(a) BMI



(b) Medical expenditures



Notes: Panel (a) plots the BMI distribution in the NHS II and the NHANES surveys. Samples from both surveys are restricted to females between the ages of 34 and 65 pooled across survey years 1999 to 2015. Panel (b) plots the mean total medical expenditures for the same demographic across different BMI groups. Data from the Medical Expenditure Panel Survey is used.

betes, Parkinsons's disease, rheumatoid arthritis, multiple sclerosis, inflammatory bowel disease (IBD)/Chron's disease, hypertension, thyroid and kidney stones. Note that several methods were employed by the survey team to validate disease diagnosis reports among survey respondents, including medical record reviews, supplemental questionnaires, and, in some cases, self-reports. For many conditions (e.g., cancer, coronary heart disease), permission was obtained from the respondent to contact their doctor or hospital for medical records, pathology reports, etc., pertaining to the relevant disease. Among our pooled analytic sample, 83% have no morbidities and 3% have two or more morbidities (refer to appendix Figure A6).

Permanent health index

We construct a measure of permanent health type that impacts the evolution of BMI and health, but which is outside the control of an adult individual. Such factors could be those shaped by parents through early childhood exposures or circumstances surrounding birth, or those transmitted through genetics. Our measure is based on an extensive medical literature which shows that development of chronic conditions and weight gain at older ages is associated with birth weight (Yu et al., 2011; Oken and Gillman, 2003), breastfeeding (Arenz et al., 2004; Harder et al., 2005; Owen et al., 2005; Horta et al., 2015; Victora et al., 2016; Harder et al., 2005), preterm birth (Johansson et al., 2005), and childhood and adolescent obesity (Van Cleave et al., 2010; Reilly and Kelly, 2011). As such, we include information on each of these outcomes when constructing our permanent health types.

In addition, we incorporate family medical history of chronic conditions. It is widely recognized that certain diseases and obesity have hereditary links, attributed to genes that can be inherited from parents (Maes et al., 1997; Nabel, 2003; Foulkes, 2008). Individuals therefore have

lymphoma, multiple myeloma, lymphatic leukemia, etc.

heterogeneous likelihoods of developing these diseases and gaining weight over the life cycle based on their genetics. We approximate an individual's genetic type by considering the prevalence of specific morbidities in their biological family, as collected in the 2013 data wave. Specifically, we utilize responses indicating whether the individual's biological parents or family members have been diagnosed with three health conditions: diabetes, stroke, and myocardial infarction. These conditions have high incidence and known hereditary links to health outcomes and obesity (Friedlander et al., 1985; Seshadri et al., 2010; Grotto et al., 2003; Berentzen et al., 2016; Praveen et al., 2010; Chathurvedi et al., 2009). In our sample, 33% of nurses reported a family history of myocardial infarction, 19% stroke, and 40% diabetes.

We consolidate all the aforementioned information into a single measure, which we refer to as the individual's *permanent health index*, by tallying the count of "favorable" circumstances. This is analogous to how we construct the frailty index discussed above, with the exception that a higher permanent health index corresponds to better permanent health whereas a higher frailty index corresponds to worse (transitory) health. For birth weight, a favorable outcome is coded for those born within the normal weight range of 5.5 to 8.4 pounds. Concerning gestational length, we use an indicator if the birth was reported as full-term. For breastfeeding, an indicator is used on the extensive margin of being breastfed in childhood. Absence of adolescent obesity is approximated by age-18 BMI falling within the healthy range, $[18.5, 25)$. Lastly, for genetics, we code favorable outcomes for each of the three diseases as having zero instances in the family medical history. Figure 4 displays the distribution of the permanent health index in our selected sample.[14] Roughly 9% of registered nurses have all seven favorable permanent health outcomes, while approximately 3% have only one or two favorable outcomes (permanent health score ≤ 2).

3 Stylized facts

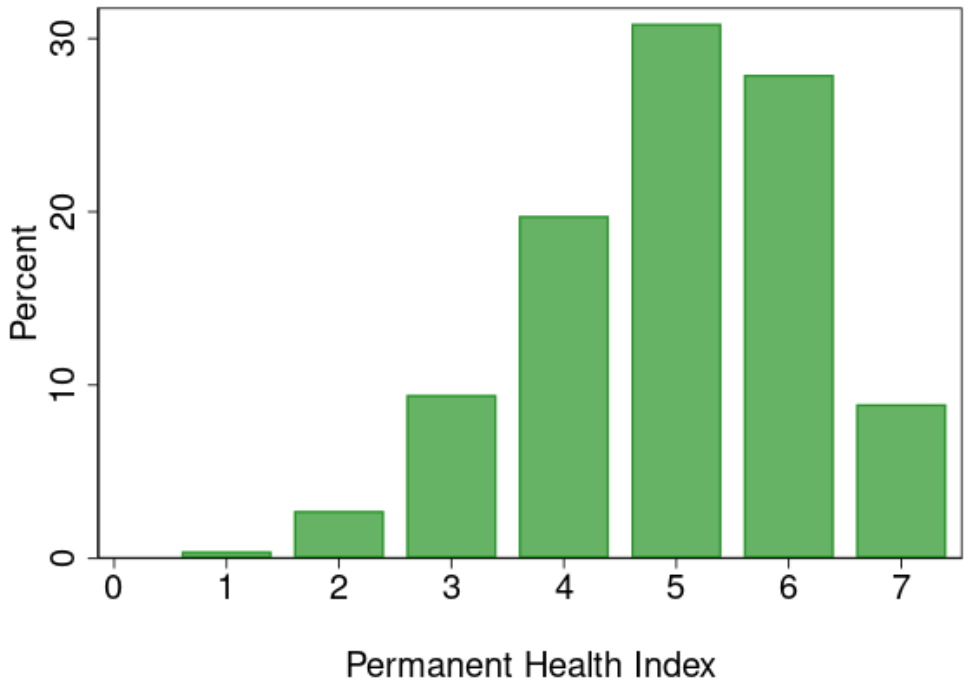
In this section, we present several stylized facts concerning life-cycle patterns and relationships between key variables used in the analysis. Importantly, while we showcase data from our full analytic sample, these stylized facts qualitatively hold for sub-groups of nurses based on marital or fertility status, spousal education, smoking habits, mental health status, and working shifts (refer to appendix A4 for more details).

Fact 1: **Average BMI, frailty, and diet quality increased over adulthood while exercise fell and then recovered.**

These observed trends are depicted in Figure 5. The first panel illustrates the evolution of BMI, showing the median, 10^{th}, and 90^{th} percentiles of the distribution by age. Each plotted percentile increases over the entire time horizon, indicating a continuous rightward shift of the BMI distribution throughout adulthood. The widening gap between the lines also reflects a substantial increase in the variance of BMI across the sample population. The second panel shows the steady decline in the share of nurses reporting no frailties over adulthood. This mirrors the observed increase in BMI.

[14] This simple permanent health index strongly correlates with changes in BMI and frailty later in life, even after controlling for health behaviors. The index also exhibits more predictive power for these changes than any single component (e.g., birth weight).

Figure 4: Distribution of permanent health index



Notes: Permanent health index is constructed as a total count of 7 indicator variables—(1) full-term gestational length, (2) breast fed in infancy, (3) normal birth weight, (4) healthy age-18 BMI ($[18.5, 25)$), and the absence of (5) diabetes, (6) stroke, and (7) myocardial infarction in the immediate biological family medical history.

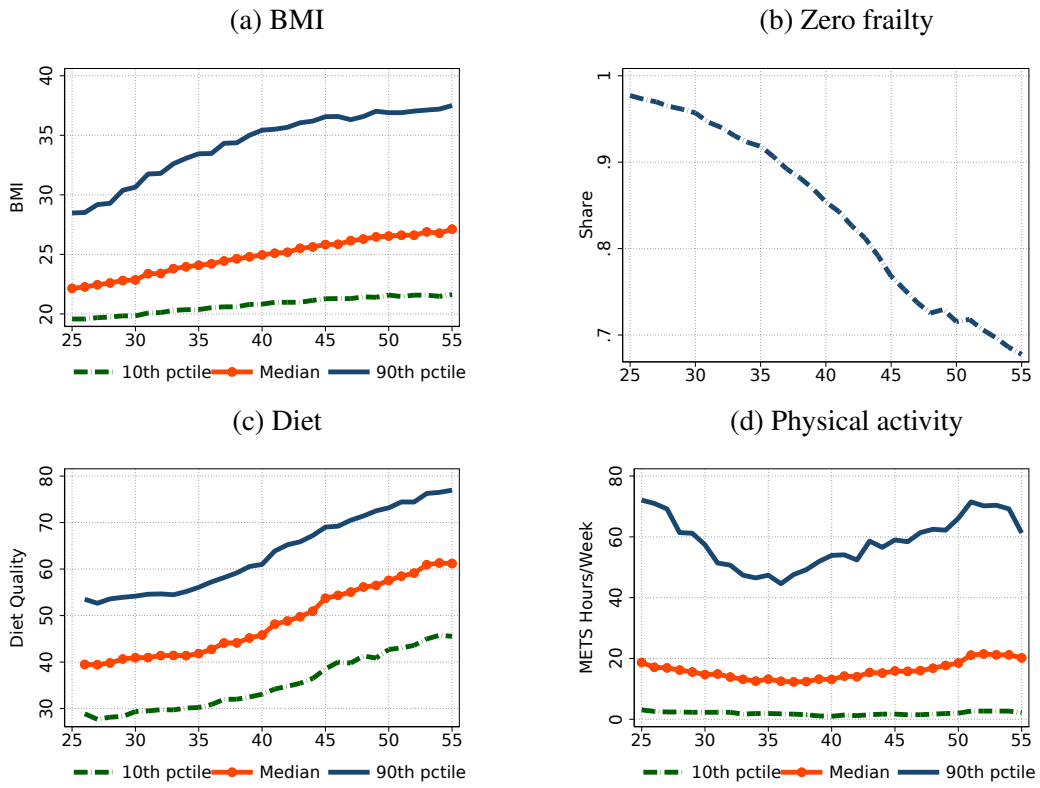
Shifting focus to trends in health behaviors, the third panel of Figure 5 demonstrates a similar rightward shift in diet quality as seen in BMI, suggesting that average diet quality improves over adulthood. Unlike BMI, the variance in diet quality remains relatively stable across the examined ages. The final panel shows life-cycle patterns for exercise. In contrast to BMI and diet quality, average exercise does not change monotonically over the examined ages. Specifically, average exercise decreases until the late thirties and then rises modestly until the early fifties.

Fact 2: **Health outcomes diverged significantly among individuals with similarly healthy BMI and no frailties in early adulthood.**

Table 1 reports long-term transition probabilities for BMI categories. Column two reports the share of nurses by BMI category in the first survey wave (1989) and columns three to five report the transition probabilities to BMI category in the final survey wave (2015).[15] Note that 9% of nurses were classified as obese (BMI ≥ 30) in the first survey wave. Among this group, over 90% remained obese in the final survey wave, demonstrating exceptionally high obesity persistence over adulthood. In contrast, 75% of nurses in the sample had a healthy BMI ($18.5 - 25$) in the

[15] We exclude the 3.3% of respondents with frailties in 1989 when deriving Table 1 to maintain a comparable sample for the analysis discussed below and illustrated in Figure 6.

Figure 5: Life-cycle patterns in BMI, frailty, diet Quality, and physical activity



Notes: Panels (a), (c), and (d) plot the distribution (median, 10th, and 90th percentile) of the evolution of BMI, diet quality, and physical activity index, respectively, over the life cycle for the sample of registered nurses in NHS II who were aged 25 to 30 in the initial 1989 wave. For frailty measure, a total count of morbidities is used. Panel (b) plots the share of those with zero frailty count by age.

first survey wave. Among this group, 46% maintained a healthy BMI in 2015 while 19% obtained an obese BMI. The final column reports the share of respondents with zero frailty in the final survey wave. Nurses that experienced weight gain were considerably more likely to experience an onset of morbidities. Among those that started with a healthy BMI in 1989, 77% remained free of morbidities in 2015, compared to less than half, or 47%, of the nurses that were obese during the first survey wave.

For illustrative purposes, we label the 46% that maintained a healthy BMI as healthy weight maintainers, or *stayers*, and the 19% as weight *gainers*. Figure 6 illustrates the differences in BMI evolution and the probability of zero frailty between these two groups by plotting average outcomes for weight gainers minus average outcomes for stayers. The first panel reveals that weight gainers consistently experienced widening average BMI gaps throughout adulthood, with the difference between the two groups growing by approximately 10 BMI points. The second panel illustrates a divergence in the probability of having zero frailty between the two groups over the life cycle, with stayers having a roughly 15 pp higher probability of maintaining zero morbidities compared to weight gainers by their fifties. These facts demonstrate that a significant share of nurses that appear ex-ante homogeneous in weight and frailty in early adulthood experience divergent health

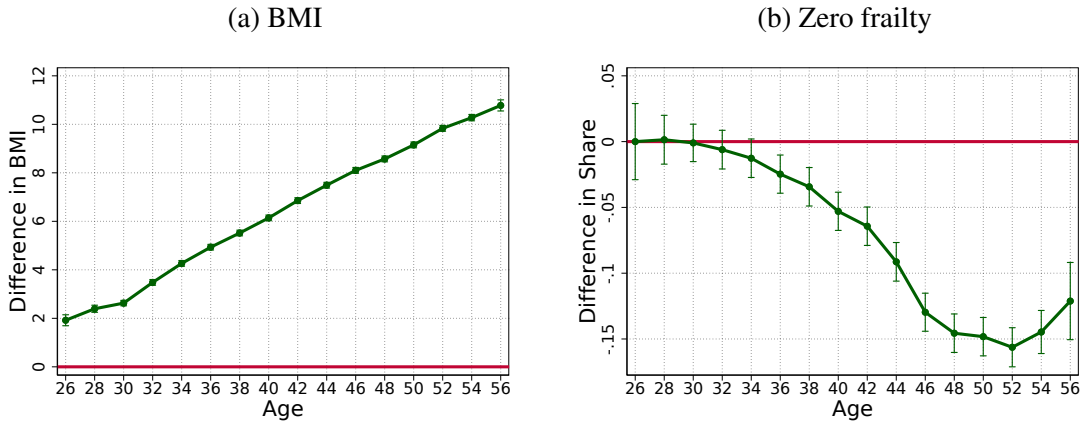
Table 1: Long-term BMI transition probabilities

1989 BMI		2015 BMI & frailty			
Groups	% share	Healthy	Overweight	Obese	Zero frailty
Healthy	75.15	46.17	35.10	18.74	76.68
Overweight	16.81	6.86	25.61	67.53	60.76
Obese	8.04	1.85	7.75	90.40	46.60

Notes: The first column reports the share of individuals across three BMI groups in the first survey wave (1989): 1) healthy BMI $\in [18.5, 25)$, 2) overweight BMI $\in [25, 30)$ and 3) obese BMI ≥ 30. Columns 3, 4, and 5 provide the transition matrix of BMI groups between 1989 and 2015. Column 6 provides the share of those with zero frailty in 2015 for each of the 1989 BMI groups. Note that the sample includes only those with zero frailty in 1989.

outcomes as they age.

Figure 6: Life-cycle health gaps between BMI gainers and stayers



Notes: The figures plot average outcomes for those whose BMI increased from healthy $(18.5 - 25)$ in 1989 to obese (≥ 30) in 2015 minus average outcomes for those who maintained a healthy BMI between 1989 and 2015. Bars denote 95-percent confidence intervals. NHS II respondents aged 25-30 in 1989 are considered, excluding the 3.3% of respondents with non-zero frailty in 1989.

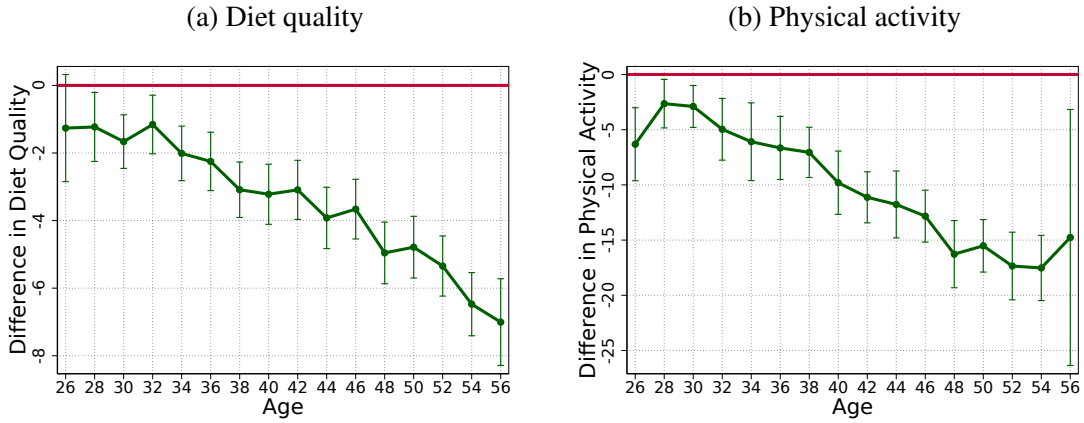
Fact 3: **Healthier diet and exercise behaviors, along with a favorable permanent health type, strongly predict long-run preservation of good health.**

Our next objective is to examine whether patterns of health behaviors are significant predictors of weight change over a span of approximately 30 years. Continuing our illustrative example of healthy weight maintainers compared to weight gainers, Figure 7 shows the evolution of diet quality and exercise for the two groups.[16] Before age thirty, there is a statistically significant but

[16]Recall that both groups start with healthy BMI and zero frailties at the beginning of their adulthood.

relatively small gap for both health behaviors. However, these gaps begin to widen substantially in the early thirties. By the time individuals reach their fifties, the average diet quality difference is six to eight points. The gap is even more striking for exercise, with stayers approaching double the METs of weight gainers by age 50 (a gap of nearly 20 METs per week between the two groups). This exercise surplus for stayers emerges through a combination of less reduction in exercise to the mid-thirties and a substantially larger increase in exercise thereafter.

Figure 7: Life-cycle behavior gaps between BMI gainers and stayers



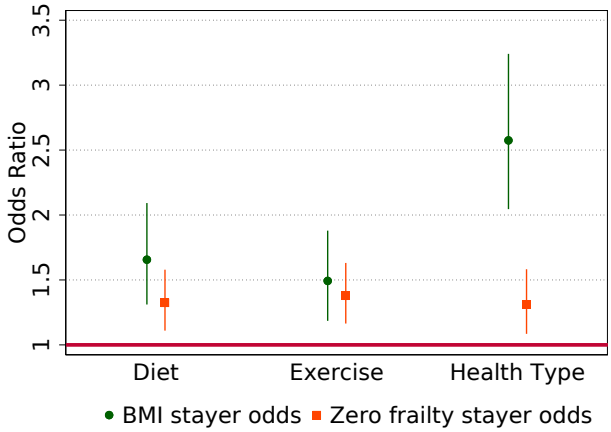
Notes: The figures plot average outcomes for those whose BMI increased from healthy ($18.5 - 25$) in 1989 to obese ($\geq$ 30) in 2015 minus average outcomes for those who maintained a healthy BMI between 1989 and 2015. Bars denote 95-percent confidence intervals. NHS II respondents aged 25-30 in 1989 are considered.

While health behaviors show comparatively modest gaps in early adulthood between stayers and gainers, early levels of diet and exercise are already strong predictors of long-run preservation of good health. For example, Figure 8 shows that those in the top exercise or diet deciles at age 30 have 49.2% and 65.6% (respectively) higher odds of belonging to the BMI stayers group compared to those in the bottom deciles. Additionally, the figure shows that nurses with a high (i.e., favorable) permanent health index (≥ 6) had 157% higher odds of being in the stayers group than those with a low permanent health index (≤ 3). This highlights that, in addition to healthy behaviors, initial conditions such as diet habits and exercise preferences established prior to adulthood are strong predictors of health divergence across nurses in the sample.

It is important to note that this relationship between health behaviors and the long-run maintenance of good health imply that cross-sectional relationships based on contemporaneous correlations can be very misleading. For example, compared to the long-run, the cross-sectional correlation between BMI, diet, and exercise are comparatively weak in our sample of nurses (see appendix Figure A7). Interpreting this as evidence of a limited role for behaviors in sustaining a healthy weight could be misleading, as it may not fully capture the long-term dynamics at play.

Mirroring the prior analysis contrasting weight maintainers with weight gainers, significant disparities were observed in health behaviors and health types between individuals experiencing frailty gain (i.e., those with at least one frailty by 2015) and those maintaining zero frailty (see appendix Figure A9). For instance, Figure 8 indicates that individuals ranking in the top deciles

Figure 8: Role of initial conditions



Notes: Sample includes NHS II respondents with healthy BMI and zero frailties in 1989. The figure plots the odds ratio of being a BMI stayer (healthy BMI in 2015) and frailty stayer (zero frailties in 2015) for permanent health types (top vs bottom groups), diet (top vs bottom decile) and exercise (top vs bottom decile). Diet and exercise taken from the 1991 wave (roughly age 30). Bars denote 95-percent confidence interval.

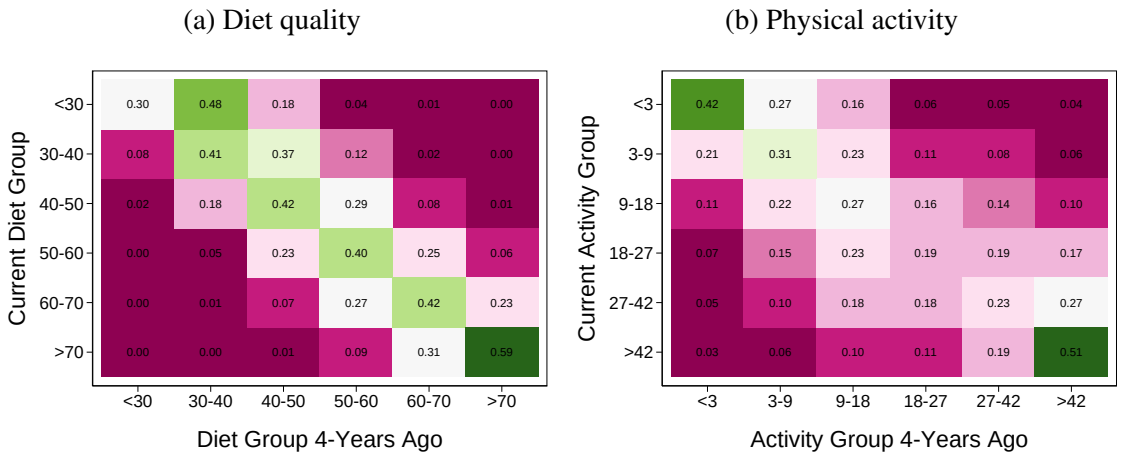
for diet and exercise at age 30 had 32% and 38% higher odds, respectively, of belonging to the zero frailty maintainers group compared to those in the bottom deciles. Likewise, individuals with high permanent health index had 31% higher odds of belonging to the zero frailty stayers group compared to those with low permanent health index. This underscores that both health behaviors and initial conditions serve as strong predictors for disease development.

Fact 4: **Health behaviors were highly persistent over adulthood, although diet showed less long-run inertia than exercise.**

Figure 9 presents four-year transition probabilities for six discrete diet and physical activity groups to examine persistence over time.[17] The first panel reveals several noteworthy features regarding the persistence in diet choices. First, persistence is observed across the board, from very low levels of diet quality to the healthiest diet groups. For instance, about 40% of nurses with a diet quality between 30-70 maintained their specific diet group four years later. The lowest persistence was noted for the bottom diet group (30%) and the highest for the top group (59%). Second, there is a rightward shift in diet quality at the lower end of the distribution. For example, over half of nurses in the 30 to 40 group reported an improvement in diet quality four years later. Third, reporting a drastic change in diet over a four-year period was highly unlikely. For example, those in the 30 to 40 range had only a 2% chance of reaching a diet score above 60.

[17] While the cut-offs for the six categories for each behavior are chosen somewhat arbitrarily, the top and bottom groups for each behavior are fixed from what is considered very low and high levels of diet and physical activity levels in the medical literature. Recall that the physical activity recommendation by the CDC for adults is 23 MET hours/week, equivalent to 150 minutes of brisk walking with two days of muscle-strengthening activity; thus, the top group with MET hours/week exceeding 42 reflects activity levels similar to those of some athletes.

Figure 9: Persistence of diet and physical activity



Notes: Panels (a) and (b) plot the 4-year transition probability between different diet and physical activity groups, respectively. NHS II respondents aged 25-30 in 1989 are considered. Pooled data between 1991 and 2015 is used to construct the 4-year transition probabilities.

Persistence was also observed for exercise, though transition probabilities reveal a somewhat different story compared to diet. Specifically, persistence was more concentrated at the tails of the distribution. For example, nurses reporting less than three METs of exercise per week had a 42% chance of remaining below this exercise threshold four years later. They also had only a 15% chance of moving above 18 METs per week (recall CDC guidelines recommend at least 23 METs per week). Conversely, nurses reporting more than 42 METs per week had a 51% chance of maintaining that high level of exercise four years later. Notably weaker evidence of persistence was observed in the middle of the distribution. For instance, a nurse reporting 9-18 METs per week had at least a 10% chance of landing in each of the six exercise categories shown in the figure four years later.

The above facts on dietary persistence suggest that habitual consumption patterns may drive the consistent selection of certain types of food, thereby impacting overall diet quality. However, dietary habits may not be entirely rigid, as evidenced by a gradual long-run improvement in diet quality over adulthood. This improvement is indicated by the rightward shift observed in the diet transition probabilities as well as the changing distribution of diet quality over time depicted in Figure 5c. In fact, when looking over a period of twenty years, a majority of nurses improved their diet (see appendix Figure A10) and only 3% of those who started in the lowest diet group stayed there, suggesting that dietary habits can evolve with age and health considerations.

In contrast, exercise demonstrates considerably more long-term inertia. For instance, 47% of nurses who started with the lowest activity levels (< 3 MET hours/week) maintained levels below 9 MET hours/week even two decades later. Additionally, the changes in reported exercise hours over twenty years were noticeably smaller than changes in diet quality (see appendix Figure A10), indicating a relative stagnation in physical activity levels over time. The long-run inertia in physical activity is plausibly influenced less by flexible habits and more by individuals' inherent dispositions towards exercise, ranging from high aversion (no exercise group) to a preference for

it as leisure, resulting in consistent activity levels. This distinction in the persistence of diet and physical activity is important because policy interventions will likely have different effects on behaviors that are somewhat flexible compared to those characterized by permanent preferences.

4 Structural framework

Informed by our empirical findings, we next develop a theoretical model to analyze the life-cycle evolution of BMI and frailty. This model posits that rational, forward-looking individuals face the following key trade-off: investing in costly health-maintaining activities now to enjoy the benefits of lower frailty and healthier BMI in old age. The economic and medical literature have identified several channels influencing population health outcomes: (1) uneven access to health-enhancing resources, both curative and preventive; (2) economic incentives influencing the extent of health-focused efforts; (3) habitual differences and early-life exposure to certain behaviors; (4) genetic factors related to disease susceptibility and weight gain; and (5) random life events or the influence of chance. Currently, no datasets exist that can be used to reliably estimate a model that accurately captures all of these different channels. However, our data is drawn from a homogeneous sample of registered nurses. Channels related to socioeconomic characteristics, such as educational attainment, occupation, health insurance coverage, or economic resources, therefore cannot account for the heterogeneous health outcomes and behavior of this sample.[18] Our theoretical framework therefore intentionally abstracts from the first two channels related to economic resources, significantly simplifying the model. This allows us to concentrate on understanding the impact of habitual behaviors and initial health conditions as individuals transition into adulthood.

4.1 Idiosyncratic type and choice variables

The economy is populated by heterogeneous agents whose idiosyncratic type is given by $(j, b, h, q_{-1}, \xi, \varepsilon_q, \varepsilon_e, \alpha)$, where j is age, b is BMI, h is frailty, q_{-1} is last period's diet quality choice, ξ is a fixed exercise type, ε_q is an i.i.d. preference shock to diet quality, ε_e is an i.i.d. preference shock to exercise intensity, and α is the agent's permanent health type. We focus on the life cycle of agents from when they enter the workforce until they retire. Agents trade-off the benefits associated with a lower terminal (i.e., end-of-working-life) BMI with the disutility of leading a healthy life. In each period, they choose how much to exercise, e, and the quality of their food consumption, q; exercising more (higher e) or consuming a healthier diet (higher q) reduces the likelihood of experiencing an increase in BMI or in frailty, both of which evolve stochastically over the life cycle. Following the findings in Section 2, we let the transition probabilities for BMI vary with the agent's current BMI and health type, $\mathbb{P}^b\left(b'|b, \alpha, e, q\right)$, and let the transition probabilities for frailty vary with the agent's current age, BMI, frailty, and health type, $\mathbb{P}^h\left(h'|j, b, h, \alpha, e, q\right)$.

The disutility of exercising depends on the agent's idiosyncratic type, $f\left(e|b, h, \xi, \varepsilon_e\right)$ (confer Section 6.3 for further details regarding our modeling choices). First, we assume that the disutility of exercising is increasing in both BMI and frailty. This is necessary to account for the negative

[18] Recall that our stylized facts are robust to possible variations in socioeconomic status for our sample of nurses, such as their marital status and the education of their spouse. All our empirical findings hold regardless of the sub-group examined. Moreover, all our respondents have an Associate or Bachelor's degree and 95.5% are white.

cross-sectional relationship in the data between BMI and physical activity and between frailty and physical activity. Next, we let the disutility vary with the agent's permanent exercise type to account for the high persistence at both the bottom and top of the exercise distribution documented in Figure 9. Lastly, we let the disutility vary with the realization of the agent's i.i.d. exercise preference shock. These sudden positive or negative "motivation shocks" enable us to account for variations in physical activity observed in the data that cannot be attributed to observable factors such as BMI or frailty.

The agent's idiosyncratic type similarly affects the disutility of healthy eating, $r\left(q|b,q_{-1},\varepsilon_q\right)$. As for exercising, we assume that the disutility of healthy eating is increasing in BMI. As discussed in Sections 5.2 and 6.3, this is necessary to match the observation that BMI and diet quality are nearly uncorrelated in the cross-section; in contrast, models without such BMI-specific disutility generate robust positive correlations because the return to healthy eating is higher for high-BMI agents in the model. Second, we allow for habit formation to account for the persistence in diet choices illustrated in Figure 9 by assuming that agents incur a utility loss from deviating from their past diet quality choice. Lastly, similarly to exercising, we let the disutility vary with the realization of the agent's diet quality preference shock to account for variations in diet quality observed in the data that cannot be attributed to observable factors.

4.2 Value function

The value function of an agent with idiosyncratic type $(j,b,h,q_{-1},\xi,\varepsilon_q,\varepsilon_e,\alpha)$ who discounts the future at rate β is given by

$$\begin{aligned} V_j^{\alpha,\xi}\left(b,h,q_{-1},\varepsilon_q,\varepsilon_e\right) \;=\; \max_{e\geq 0,q\geq 0} \;& -f\left(e|b,h,\xi,\varepsilon_e\right) - r\left(q|b,q_{-1},\varepsilon_q\right) + \beta\mathbb{E}\left[b'|b,\alpha,e,q\right] \\ & \times\mathbb{E}\left[h'|j,b,h,\alpha,e,q\right]\mathbb{E}\left[\varepsilon_q'\right]\mathbb{E}\left[\varepsilon_e'\right]V_{j+1}^{\alpha,\xi}\left(b',h',q,\varepsilon_q',\varepsilon_e'\right). \end{aligned} \tag{1}$$

Agents enter the model at age $j=1$ and retire at age $j=J$. Age-J agents solve the same problem as described in Equation (1) but with a continuation value that depends on the BMI-specific terminal condition, $V_{J+1}\left(b\right)$.

Before we turn to the calibration section, we briefly discuss two modeling choices that we have made.

REMARK 1: We assume that the terminal condition depends on BMI but not on frailty. We do so because the relative weights on terminal BMI and terminal frailty cannot be separately identified in our model. To understand why, recall that the law of motion for frailty depends on BMI, $\mathbb{P}\left(h'|j,b,h,\alpha,e,q\right)$, whereas the opposite is not the case, $\mathbb{P}\left(b'|b,\alpha,e,q\right)$. Therefore, a model that matches the evolution of BMI, exercise, and diet quality over the life cycle will also match the evolution of frailty even if frailty does not affect the terminal condition.

REMARK 2: We have abstracted from several features that are common in heterogeneous agents incomplete markets models, including consumption of non-durables and services, income uncertainty, and wealth. As discussed earlier, we have done so because our data sample is restricted to a sample of female working-age nurses with homogeneous socioeconomic characteristics, including identical educational attainment and similar income levels. Therefore, while it is well-known that health and behavior are correlated with education, income, and wealth, these variables cannot account for the heterogeneity in BMI, frailty, and lifestyle choices observed for

our data sample. We have therefore abstracted from such features in the model to isolate the role of non-socioeconomic determinants of BMI, frailty, and effort.

5 Calibration

We parameterize the model in two stages. In the first stage, we choose functional forms for the various model components and assign values to parameters that can be estimated without solving the model. In the second stage, we calibrate the remaining parameters by minimizing the distance between target moments calculated using data and their model counterparts.

5.1 First-stage calibration and estimation

5.1.1 Life-cycle parameters and grids

A period in the model is six years.[19] Agents enter the model at age 28 and exit the model at age $J = 7$, which corresponds to a retirement age of 64. Following the quantitative macroeconomics literature, we choose β to match an annual discount factor of 0.96. We follow the CDC and split BMI into six categories, $b \in \left\{\underline{b}, \ldots, \overline{b}\right\}$, where the six categories correspond to a BMI of 18.5–25 (healthy weight), 25–30 (overweight), 30–35 (obese class I), 35–40 (obese class II), 40–50 (obese class III), and 50+.[20] Following Braun et al. (2019), Nygaard (2021), and Hosseini et al. (2022), we proxy the agent's health by her frailty score as given by the number of morbidities that she has ever been diagnosed with, $h \in \left\{0, \ldots, \overline{h}\right\}$, where $\overline{h} = 2$.[21] Lastly, we proxy the agent's permanent health type, $\alpha \in \{1, \ldots, \overline{\alpha}\}$, by her permanent health index as illustrated in Figure 4. We allow for $\overline{\alpha} = 3$ permanent health types, where $\alpha = 1$, $\alpha = 2$, and $\alpha = 3$ correspond to individuals with a permanent health index of 0–3, 4–5, and 6–7, respectively.

5.1.2 Health production function

Law of motion for BMI: The evolution of BMI is stochastic and depends on the agent's current BMI, permanent health type, exercise level, and diet quality. We parameterize this stochastic process by means of an ordered logistic regression. The transition probabilities for each BMI-category $i \in \left\{\underline{b}, \ldots, \overline{b}\right\}$ are then given by the ordered logistic formula:

$$\mathbb{P}^b\left(b' = i | \boldsymbol{X}\right) = \frac{1}{1 + \exp\left(-\kappa_i + \boldsymbol{X}\boldsymbol{\beta}\right)} - \frac{1}{1 + \exp\left(-\kappa_{i-1} + \boldsymbol{X}\boldsymbol{\beta}\right)}, \tag{2}$$

where $\boldsymbol{X} = (b, \alpha, e, q)$, $\boldsymbol{\beta}$ is a vector of parameters, and the κ's are cutoffs for the ordered outcomes (see Appendix Table A5 for the regression results).

[19] The length of each model period is chosen to coincide with the estimation of BMI and frailty transition probabilities in the data. While BMI and frailty are reported bi-annually in the survey, we estimate six-year transition probabilities for these variables because effort choices (diet and exercise) are reported every four years. As in Cole et al. (2019), long time periods also help ensure that efforts choices have robust effect on BMI and frailty transitions.

[20] The CDC classifies individuals as underweight if their BMI is less than 18.5. We choose a lower BMI-bound of 18.5 in the model because only 1 percent of individuals are underweight in both the NHS II and NHANES datasets (see Figure 3).

[21] We top-code frailty at 2 because less than 0.3 percent of our sample have more than 2 frailties (see Figure A6).

Law of motion for frailty: An individual's frailty count is non-decreasing because we measure it by the number of morbidities that the individual has ever been diagnosed with. For more than 99% of the observations in our sample, frailty count increases in increments of one.[22] Given this, we let the frailty transition probabilities in the model be given by the likelihood that the frailty count will stay constant or increase by one between two periods. We parameterize this stochastic process by means of a logistic regression. The likelihood of experiencing a frailty increase is then given by the logistic formula:

$$\mathbb{P}^h\left(h' = h + 1 | \boldsymbol{X}\right) = \frac{\exp\left(\boldsymbol{X}\boldsymbol{\beta}\right)}{1 + \exp\left(\boldsymbol{X}\boldsymbol{\beta}\right)}, \tag{3}$$

where $\boldsymbol{X} = (j, b, h, \alpha, e, q)$ and $\boldsymbol{\beta}$ is a vector of parameters. (see Appendix Table A7 for the regression results).

Note that in our estimation of the health production functions, we make an important identifying assumption. We assume that while current BMI impacts the future evolution of frailty, the latter does not impact the BMI law of motion. This choice is driven by empirical observations where we find a strong and statistically significant impact of current BMI on future frailty but not vice versa (see appendix Table A6).

5.2 Second-stage: simulated moment matching strategy

In the second stage, we use the parameters from the first stage and the joint initial distribution of diet quality, frailty, BMI, permanent health index, and exercise group from the data to simulate the model. Appendix Table A9 provides the empirical joint distribution of the initial model states drawn from the data. Note that the data exhibits important correlations in these initial conditions. For example, individuals in the highest permanent health group have a 26 pp greater proportion of members within the healthy BMI category compared to those in the lowest group, while the corresponding figure for the highest versus lowest exercise type is 14.5 pp. The remaining parameters are then chosen to minimize the distance between model moments and their data counterparts. While these parameters are chosen jointly through the minimization procedure, each parameter is mostly informed by a specific targeted moment. A summary of the calibrated parameters, along with targets, data moments, and model moments, is given in Table 2.

5.2.1 Disutility from exercising

We normalize exercise intensity, e, from 0 to 1, where a value of 0 corresponds to no exercising (equivalent to 0 MET-hours per week) and a value of 1 corresponds to 100+ MET-hours per week.[23]

[22] We restrict our estimation to only the group for which the frailty count increases by at most one.

[23] We top-code MET-hours per week at 100 due to the long tail of the physical activity distribution illustrated in Appendix Figure A4. This top-coding applies to less than 2 percent of the sample.

Table 2: Calibrated parameters

Parameter	Value	Target	Data	Model
ψ_1	0.68	P90 exercise	54.5	55.1
ψ_2	3.51	Average exercise	23.5	25.3
λ_b	0.57	Exercise ratio (BMI <25 vs. BMI ≥ 30)	1.66	1.68
λ_h	0.18	Exercise ratio ($h=0$ vs. $h \geq 1$)	1.15	1.15
τ_1	0.66	P90 diet healthiness	64.1	63.1
τ_2	1.35	Average diet healthiness	47.2	48.4
υ_b	0.55	Diet ratio (BMI <25 vs. BMI ≥ 30)	1.00	1.02
υ_q	7.36	P90$-$P10 absolute gap in diet change ($\lvert q - q_{-1} \rvert$)	25.0	26.1
κ_b	0.77	Share of 58 year-olds with BMI <25	31.2%	32.7%
σ_e	0.67	P10 exercise	1.9	1.6
σ_q	0.70	P10 diet healthiness	32.1	32.4
$\overline{\xi}$	4.81	Exercise persistence (prob. remain above 42 METs)	42.3%	39.9%
$\underline{\xi}$	0.27	Exercise persistence (prob. remain below 3 METs)	50.6%	51.7%

Following (Cole et al., 2019), the disutility of exercising is given by:

$$\begin{aligned} f\left(e|b,h,\xi,\varepsilon_e\right) &= p^e\left(b,h,\xi,\varepsilon_e\right)\left[\tfrac{1}{1-e}-(1+e)\right]^{\psi_1} \\ p^e\left(b,h,\xi,\varepsilon_e\right) &= \psi_2\xi\exp\left(\varepsilon_e\right)\left(b-\underline{b}+1\right)^{\lambda_b}\left(h+1\right)^{\lambda_h}, \end{aligned} \tag{4}$$

where ψ_1 governs the elasticity of the disutility function with respect to exercise, ψ_2 governs the average disutility, and $p^e\left(b,h,\xi,\varepsilon_e\right)$ determines the BMI-, frailty-, exercise type-, and taste shock-specific slope of the function.

Because the first two parameters, ψ_1 and ψ_2, determine the average slope and the curvature of the disutility function, they can be identified by means of moments of the exercise distribution. We calibrate the elasticity parameter, ψ_1, to match the 90$^{\text{th}}$ percentile of the cross-sectional exercise distribution and calibrate ψ_2 to match the corresponding average exercise intensity.[24] The disutility of exercising must be increasing in BMI to account for the negative cross-sectional relationship in the data between BMI and physical activity; in the absence of such BMI-specific disutility, higher BMI would instead be associated with higher levels of physical activity because the return to exercising is higher for high-BMI agents in the model due to the BMI-specific terminal condition. Analogously, the disutility of exercising must be increasing in frailty to match the negative cross-sectional relationship between frailty and physical activity. We identify the parameters that govern the slope of the exercise disutility function with respect to BMI and frailty by comparing average exercise levels across BMI groups and across frailty groups, respectively. Given this, we calibrate the BMI-specific slope parameter, λ_b, to match the 66-percent higher average exercise intensity among healthy weight (BMI <25) individuals compared to obese (BMI ≥ 30) individuals. Similarly, we calibrate the frailty-specific slope parameter, λ_h, to match the 15-percent higher average

[24] For consistency with the data sample that we use to estimate BMI and frailty transition probabilities, we restrict both the data and model sample to individuals that are younger than 52 when calibrating parameters related to the disutility of exercising and healthy eating.

exercise intensity among individuals with zero frailties compared to those with at least one frailty.

Section 2 demonstrated that there is considerable persistence at both the bottom and top of the exercise distribution. As illustrated in Figure 9b, 42% of individuals whose exercise intensity is less than 3 METs and 51% of individuals whose exercise intensity exceeds 42 METs remain in the same exercise category four years later; comparatively high persistence within exercise categories is also observed two decades later. We account for this persistence by incorporating three exercise types in the model: high distaste for exercising ($\bar{\xi} > 1$), low distaste for exercising ($\underline{\xi} < 1$), and a middle group whose exercise type is normalized to one ($\xi = 1$). The values for those with a high and low distaste of exercising are calibrated to match the probabilities discussed above of remaining, respectively, below 3 METs and above 42 METs between two model periods. Lastly, the agent's disutility of exercising depends on the realization of her i.i.d. preference shock, ε_e. This shock, which is drawn from a normal distribution with zero mean and standard deviation given by σ_e, enables us to account for sudden positive or negative "motivation shocks" that affects willingness to exercise but that cannot be attributed to the realization of other variables in the model. We calibrate the dispersion of this taste shock to match the 10$^{\text{th}}$ percentile of the exercise distribution.

5.2.2 Disutility from healthy eating

Diet quality, q, is similary normalized from 0 to 1, where a value of 0 corresponds to the least healthy diet (equivalent to an AHEI-score of 0) and a value of 1 corresponds to the healthiest diet (equivalent to an AHEI-score of 100). The disutility of healthy eating is given by

$$\begin{aligned} r\left(q|b,q_{-1},\varepsilon_q\right) &= p^q\left(b,\varepsilon_q\right)\left[\tfrac{1}{1-q}-(1+q)\right]^{\tau_1}+\upsilon_q\mathbb{I}_{q>q_{-1}}\left[q-q_{-1}\right] \\ p^q\left(b,\varepsilon_q\right) &= \tau_2\exp\left(\varepsilon\right)\left(b-\underline{b}+1\right)^{\upsilon_b}, \end{aligned} \tag{5}$$

where τ_1 governs the elasticity of the disutility with respect to diet quality, τ_2 determines the average disutility, and $p^q\left(b,\varepsilon_q\right)$ governs the BMI- and taste shock-specific slope of the function.

Similarly to the identification of the parameters of the exercise disutility function, the first two parameters of Equation (5), τ_1 and τ_2, can be identified by means of moments of the diet quality distribution. We calibrate τ_1 to match the 90$^{\text{th}}$ percentile of the cross-sectional diet quality distribution and τ_2 to match the corresponding average value. The disutility of healthy eating must be increasing in BMI to match the observation that diet quality and BMI are cross-sectionally uncorrelated in the data. This follows because models without such BMI-specific disutility would generate a robust positive, and therefore inconsistent, cross-sectional relationship between BMI and diet quality because the return to healthy eating is higher for high-BMI agents in the model due to the BMI-specific terminal condition.[25] The parameter that governs the slope of the diet quality disutility function with respect to BMI, υ_b, can be identified by comparing average diet quality levels across BMI groups, and we therefore calibrate this parameter to match that average diet quality among healthy weight (BMI < 25) individuals is identical to that of obese (BMI ≥ 30)

[25] Unhealthy foods tend to be more caloric, are absorbed fast, and generate spikes of insulin. Higher-BMI individuals might have stronger incentives to opt for unhealthy foods because the calorie requirement necessary for satiation (in terms of maintaining current weight) increases with BMI and unhealthy foods lead to a quick, albeit transitory, feeling of satiation.

individuals.

The parameter υ_q governs the importance of habit formation. Consistent with the high degree of persistence in diet choices documented in Figure 9a, we assume that agents incur a utility loss from improving their diet quality relative to their last-period choice, $q > q_{-1}$, where the magnitude of the utility loss increases linearly with the size of the diet quality adjustment. Importantly, while agents in the model do not incur a direct utility loss from worsening their diet quality relative to last period's choice, $q < q_{-1}$, agents are forward-looking and thus internalize that eating less healthy this period makes it harder to eat healthy in future periods due to the adjustment cost. Hence, the higher the value of υ_q, the smaller are both the increases and the reductions in diet quality in the model and thus the lower is the absolute dispersion of $|\Delta(q)|$. We therefore calibrate υ_q to match the absolute gap between the 10th and 90th percentile of the diet quality change distribution.

Finally, we let the i.i.d. diet quality preference shock be drawn from a normal distribution with zero mean and standard deviation given by σ_q. Similarly to our approach for the calibration of the exercise taste shock, we calibrate the dispersion of the diet quality taste shock to match the 10th percentile of the diet quality distribution.[26]

5.2.3 Terminal condition

Agents in the model trade-off the cost of exerting effort with the benefits associated with a lower terminal-period BMI. We let the terminal condition be given by

$$V_{J+1}(b) = -\kappa_b (b - \underline{b})^2, \tag{6}$$

where the parameter κ_b determines the utility loss associated with reaching retirement age with a high BMI (e.g., due to higher mortality risk). Given that this parameter governs the willingness to lead a healthy life, we calibrate its value to match the 31.2% share of individuals at age 58 with a BMI no greater than 25.

6 Results

6.1 Model validation

Although the theoretical framework discussed above is quite simple, it is able to capture key non-targeted features of the data related to changes in healthy diet and exercise behaviors, along with health outcomes such as BMI and frailty. Below, we discuss these properties of the model in detail.

6.1.1 Cross-sectional distributions

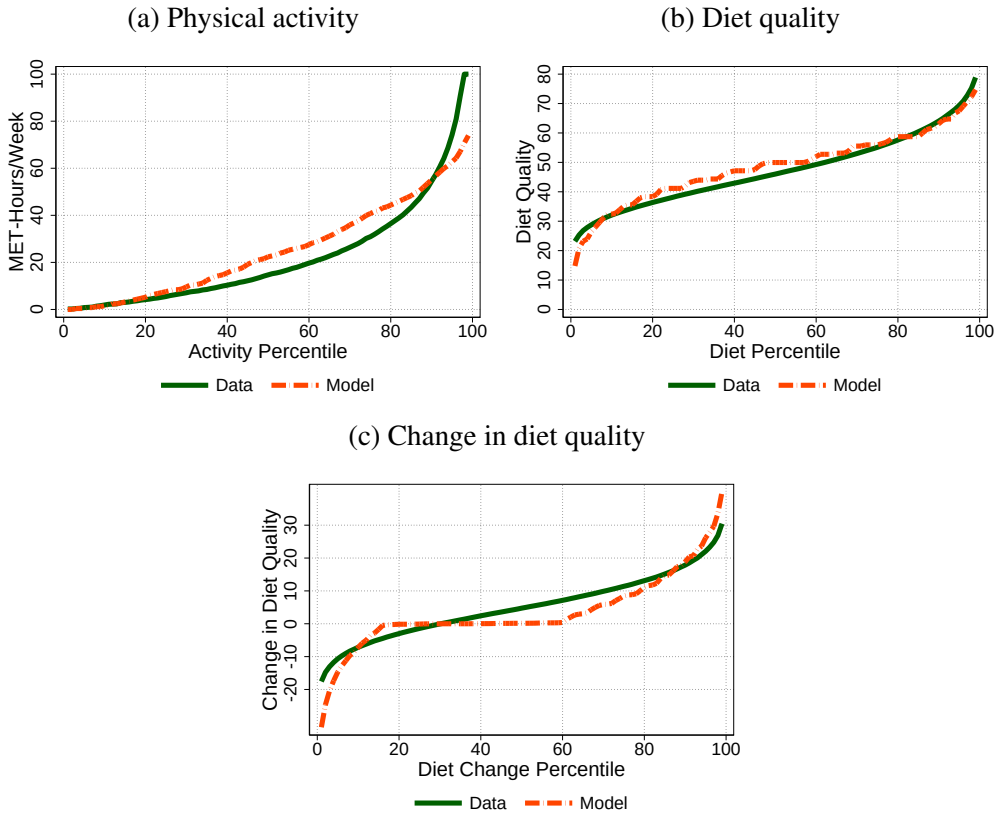
First, we examine how the benchmark model performs in matching the distribution of diet and physical activity. Note that some distributional moments were targeted in the calibration, while

[26] We allow for two independent preference shocks, ε_e and ε_q, to match that diet quality and exercise are only weakly related in the data with a correlation of 0.23. A simplified version of our model with one common taste shock to both exercise and diet quality incorrectly generates a large positive relationship between the two effort variables.

others were not. Notably, we explicitly targeted the 10th and 90th percentiles as well as the mean for both diet quality and exercise.

Panel (a) of Figure 10 displays the percentile distribution of physical activity levels for the benchmark model and our analytic sample of registered nurses. Due to the model's incorporation of fixed activity types, it closely aligns with the observed distribution, especially at very low activity levels. While it captures a substantial portion of the higher end of the activity distribution, it is important to note that the model's activity levels are capped at 100. This limits the model's ability to fully account for the upper extremes of the activity distribution observed in the data because the disutility of exercising in the model tends to infinity as exercise approaches 100 METs. Panel (b) illustrates the distribution of diet quality. The model effectively mirrors both the lower and upper extremes of the empirical diet distribution, despite not specifically targeting extreme diet levels in the calibration; for example, the 99th percentile is 76 in the data compared to 79 in the model.

Figure 10: Distribution of diet and physical activity



Notes: Panels (a), (b) and (c) plot, respectively, the percentile distribution of exercise (e), diet quality (q) and change in diet quality ($q - q_{-1}$) in the benchmark model and the data. We top-code the physical activity METs-hours/weeks to one hundred in the data to make it comparable to the model.

In addition to examining the static distribution of diet quality, observing sequential changes provides valuable insights into the persistence of dietary habits over an individual's life and the interplay between their current and past dietary choices. As individuals age, there is a growing motivation to improve their diet. In the absence of habitual influences, rational forward-looking

individuals might be inclined to make significant dietary changes to improve their late-in-life health outcomes, even if they had previously maintained poor dietary habits. However, this contradicts empirical observations where the magnitude of diet changes over a six-year period is modest, with a median change of 4.7 in our analytic sample. This data characteristic poses a stringent test for the model, challenging it to offer a plausible representation of the evolution of healthy behaviors. Panel (c) of figure 10 illustrates that our model effectively captures the range of 6-year dietary changes observed in the data, closely resembling both the lower and upper ends of the change distribution. Specifically, the model's mean change at the 10^{th} percentile of diet is -6.5, compared to -7.1 in the data, and at the 90^{th} percentile it is 19.2, compared to 17.8 in the data. While the P10-P90 *gap* in diet change was targeted in the calibration, other moments of the diet change distribution were not targeted. These results indicate a reasonable alignment of our model with observed dietary patterns.

In addition to replicating the distribution of healthy behaviors, the model also matches key patterns in the cross-sectional correlation between behaviors and BMI (see appendix Figure A35). Specifically, the model produces the weak correlation between diet quality and both BMI and physical activity levels observed in the data. Simultaneously, the model matches the stronger negative cross-sectional relationship between BMI and exercise.

6.1.2 Life-cycle evolution

Next, we would like to see whether the model is able to capture the evolution of diet, exercise, frailty, and BMI over the life cycle. Note that, besides terminal BMI, we do not target any of the age-specific moments in our calibration.

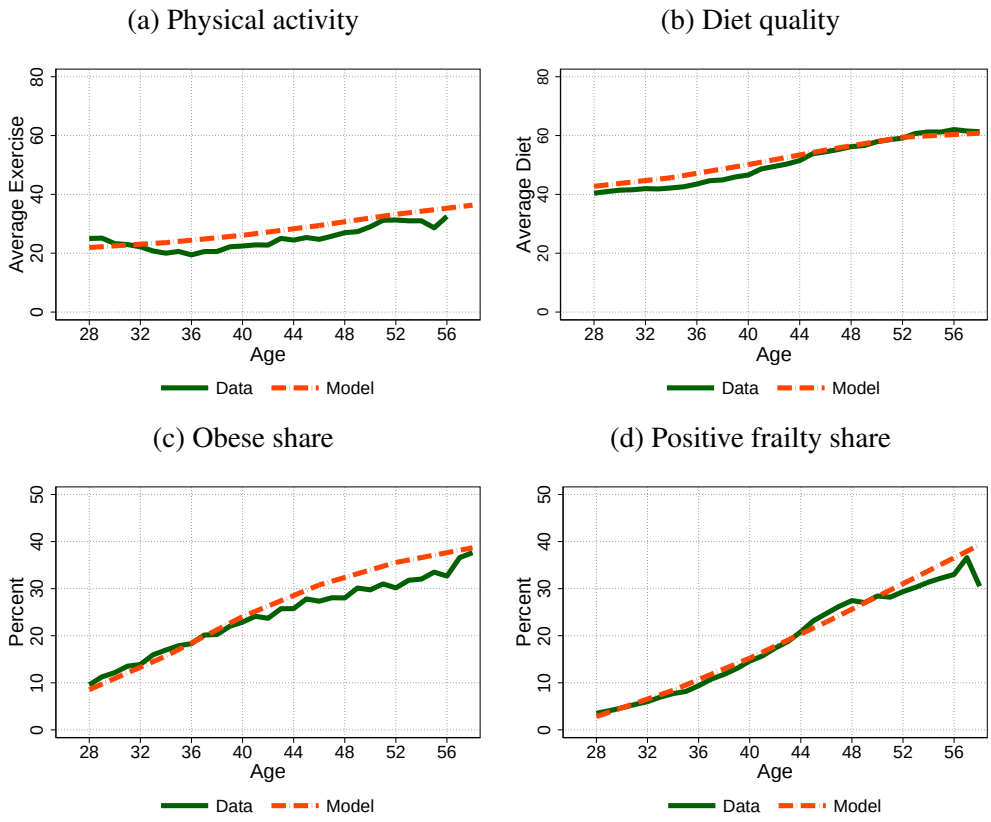
The first two panels of Figure 11 show average diet quality and physical activity levels over the life cycle for both our benchmark model and our analytic sample of registered nurses. The model does reasonably well in matching a key aspect of these behaviors: slow growth in both diet quality and physical activity levels over the life cycle. To reiterate, this is an important aspect of understanding how behaviors evolve. While simpler models without habits or exercise types might allow for a much faster growth in healthy behaviors, especially as individuals approach the terminal period, this is not the case in the data. Incorporating persistence through habits (diet) or permanent types (physical activity) is therefore key to capturing the evolution of healthy behaviors.[27]

Panel (c) of Figure 11 shows the age-specific share of obese individuals in the model and the data (see appendix Figure A36 for a further breakdown). The model tracks the evolution of BMI in the data. This is unsurprising given that (1) the model matches the evolution of healthy behaviors and (2) the BMI law of motion, conditional on current diet and exercise choices, was estimated directly from the data. Finally, panel (d) shows the age-specific share of individuals with at least one chronic condition (see appendix Figure A37 for a further breakdown). Similar to the case of BMI, the model closely tracks the evolution of frailty over the life cycle.

In addition to matching general life-cycle patterns across outcomes, the model is able to qualitatively capture several other important features observed in the data. For example, the model replicates the frailty gap between individuals that maintained or gained weight over the life cycle (see appendix Figure A38). The model also produces the BMI and frailty gaps between high and

[27]Note that, without additional age-specific factors in the disutility function with respect to exercising, our model cannot reproduce the initial decline in exercise observed in early adulthood. This limitation leads to a slight overestimation of the growth in exercise over the life cycle.

Figure 11: Effort and health over the life cycle: data vs. model



Notes: Figure plots age-specific averages for (a) exercise, (b) diet quality, (c) rate of obesity, and (d) share with at least one frailty in the benchmark model and the data.

low permanent health types (see appendix Figure A39) and the high short-run persistence in the tails of the exercise distribution as well as the mildly increasing persistence across the diet quality distribution (see appendix Figure A40).

6.2 Counterfactual experiments

In this section, we conduct counterfactual experiments to understand the role of initial conditions and healthy behaviors in maintaining lower BMI and fewer chronic conditions over adult life. We start by examining the impact of four specific initial conditions: permanent health (α), initial BMI (b_0), exercise type (ξ), and initial diet quality (q_0). Then, we explore how diet and exercise, done consistently across adult life, impact health outcomes. Our goal is to understand how health is shaped by inherent individual characteristics and health-promoting behaviors. These experiments shed light on factors that are more important in determining health outcomes and can provide insights for potential policies to improve public health.

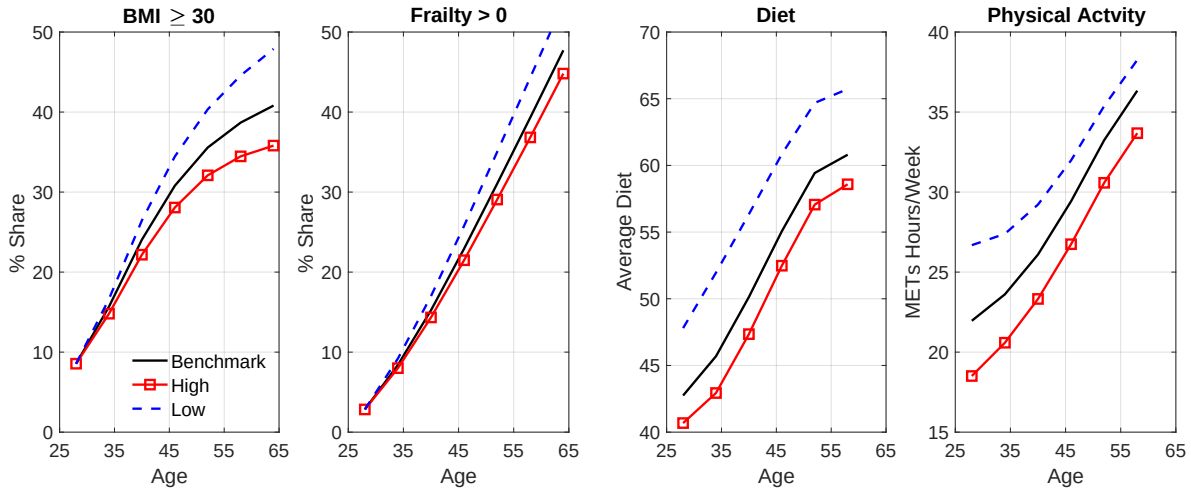
6.2.1 Role of initial conditions

Permanent health: First, we examine a scenario where all agents in the model are assigned the same value for the permanent health index. Recall that permanent health type can take three values: $\alpha \in \{1, 2, 3\}$. We conduct two experiments, initially assigning all agents the lowest value and then the highest value. It is important to note that this experiment does not alter the outcomes for those who were already in these groups. For instance, approximately 13% of nurses were in the bottom permanent health group and 37% in the top group in our benchmark model.

Figure 12 shows age-specific patterns of obesity, frailty, and health behaviors in the benchmark model alongside the two counterfactual experiments. As shown in the first panel, there is about a 7 pp increase in the share of obese individuals (BMI$\geq$ 30) by age 64 when every agent is assigned the lowest permanent health type. Equalizing permanent health at the highest level leads to the opposite effect, with the share of obese individuals decreasing by 4.9 pp by age 64. Similar effects are observed in the second panel for frailty. When assigned the highest permanent health type, the share of agents with at least one chronic condition decreases by 2.7 pp by age 64 compared to the benchmark model. Meanwhile, when assigned the lowest permanent health type, the share of those with at least one chronic condition increases by 6.1 pp at older ages.

Figure 12: Life-cycle evolution of health and effort: equalizing permanent health

(a) Health outcomes (b) Effort



Notes: Outcomes plotted for benchmark model and the experiments where permanent health is equalized at lowest value ($\alpha = 1$) and highest value ($\alpha = 3$) for all nurses.

To understand these results, it is important to recognize that permanent health plays a key role in the model both through its direct effect on the BMI and frailty laws of motion (refer to section 5.1) as well as an indirect effect through behaviors. The pace of BMI change, driven by permanent health type, makes it easier or harder for agents to sustain good health. This is due to the dependence of disutility of exerting effort on BMI. Specifically, the disutility of both higher diet quality and physical activity levels increases with BMI. Additionally, the disutility of exerting effort through physical activity goes up with the number of chronic conditions. A final

amplification effect occurs through the impact of BMI in the frailty law of motion. Lower future BMI due to higher permanent health also results in lower chronic conditions, which in turn makes it easier to maintain good health through behaviors.

However, having a higher permanent health partially distorts incentives to lead a healthy life in the model as forward-looking rational agents internalize that less effort is required to achieve favorable health transitions in this case. For example, mean exercise and diet quality levels decrease when we assign every agent to the highest permanent health group (see panel (b) of Figure 12). Conversely, assigning agents a lower permanent health group results in compensatory efforts to counter the losses from lower permanent health.

Initial BMI: Next, we consider a case where all agents are assigned the same BMI value in the initial model period (age 28). First, we assign all agents to the lowest BMI group ($b = 1$), representing a BMI within the range of 18.5–25.[28] Second, we assign all agents as class I obese ($b = 3$), corresponding to a BMI of 30–35. Again, this experiment does not change the outcomes for those who were already in these groups in the initial model period. For example, 74% of nurses were initially in the lowest BMI group and 6% in the class I obese group in our sample.

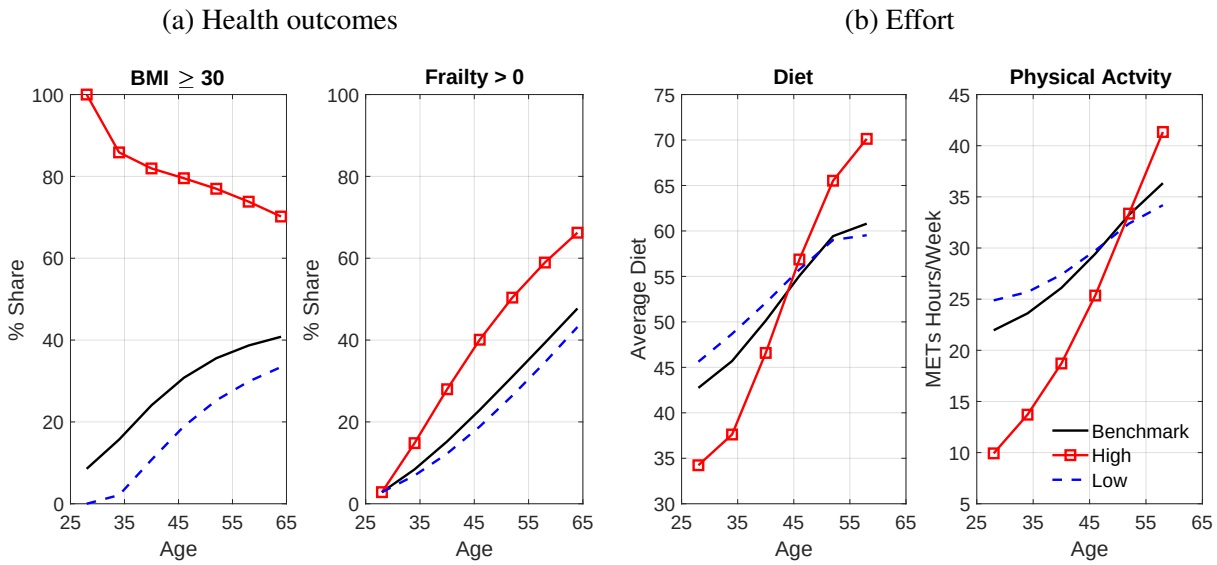
Figure 13 presents age-specific obesity, frailty, and health behaviors in the benchmark model and the BMI experiments. The first panel shows that the share of obese individuals (BMI$\geq$ 30) decreases by 7-13 pp over the life cycle when every agent is assigned the lowest starting BMI value. Similarly, the share of agents with at least one chronic condition decreases by 4.3 pp by age 64. Equalizing BMI at class I obese levels yields the opposite effect, with the obesity share remaining at least 30 pp higher than the benchmark across the life cycle. The share of those with at least one chronic condition at age 64 also increases by 18.7 pp. This experiment has particularly important implications for the role played by the recent increase in childhood obesity in causing high obesity prevalence among adult Americans (Ogden et al., 2012; Skinner and Skelton, 2014; Ogden et al., 2016).

Similar to the case of equalizing permanent health types, there are both direct and indirect effects operating through the BMI and frailty laws of motion, with further amplification through behaviors. Equalizing initial BMI, however, has more substantial effects on the evolution of both BMI and frailty than permanent health. This is primarily attributed to the stronger impact of lagged BMI in the BMI law of motion compared to permanent health. In terms of behavior, when BMI is equalized at the lowest (healthiest) levels, individuals initially increase effort in both diet and exercise relative to the benchmark model, as exerting effort is relatively less costly when BMI is lower (see panel (b) of Figure 13). However, having enjoyed the benefits of higher effort and a slower rise in obesity and frailty, they subsequently reduce effort compared to the benchmark model upon reaching older ages. The opposite pattern emerges when all agents are given class I obese levels of BMI, with considerable reductions in effort relative to the benchmark model during the early stages of life, but with higher effort later in life to partially compensate for their worse initial BMI.

Exercise type: Recall that in the benchmark model, we incorporate permanent heterogeneity through exercise types: agents have either a low ($\xi > 1$), medium ($\xi = 1$), or high ($\xi < 1$)

[28] Note that in the model, the group $b = 1$ is equal to the mean value of the healthy range (25–30) and corresponds to a BMI of 22.06, whereas the group $b = 3$ is equal to the mean value of the class I obese range (30–35) and corresponds to a BMI of 32.16.

Figure 13: Life-cycle evolution of health and effort: equalizing initial BMI



Notes: Outcomes plotted for benchmark model and the experiments where initial BMI is equalized at lowest value ($b = 1$, or BMI = 22.06) and highest value ($b = 3$, or BMI = 32.16) for all nurses.

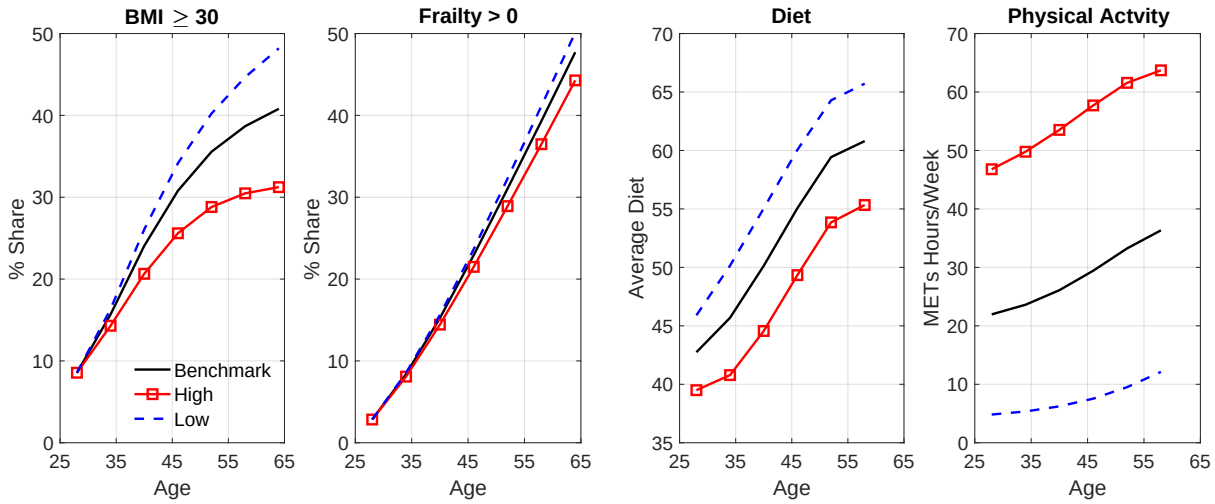
preference for exercise. This permanent type influences the agent's disutility from exercising each period, impacting the amount of effort exerted and, consequently, the evolution of BMI and frailty. To assess the quantitative role of exercise type heterogeneity in determining health evolution, we conduct two experiments where we assign all agents either the low or high exercise type. Similar to the above cases, this experiment does not alter the outcomes for those who were already in these groups—16% of the nurses were in the high exercise type and 17% were in the low type in our benchmark model.

Figure 14 illustrates age-specific patterns of obesity, frailty, and health behaviors in the benchmark model and the exercise type experiments. When all agents are assigned the high exercise type, the obesity share at age 64 decreases by 9.4 pp, and the share with chronic conditions experiences a more modest decline of 3.2 pp. Conversely, assigning all agents the low exercise type results in an increase in the obesity share by 7.5 pp and a rise in the share with chronic conditions by 2.6 pp.

There are notable differences between this experiment and those involving initial BMI and permanent health types that are worth highlighting. While equalizing exercise types has effects on BMI evolution similar in magnitude to equalizing permanent health types, the impact of the former on frailty is significantly more subdued. This difference arises because permanent health type directly influences both the frailty and BMI laws of motion, whereas exercise type has no direct impact on these processes. Even though acquiring a low exercise type leads to a substantial reduction in physical activity over the life cycle (65-77%), agents are able to counteract some of the detrimental effects of reduced physical activity by enhancing their diet quality by 6-8% (see panel (b) of Figure 14). Although this largely mitigates the adverse effects of lower activity levels on frailty evolution, BMI growth remains higher compared to the benchmark.

Figure 14: Life-cycle evolution of health and effort: equalizing exercise types

(a) Health outcomes (b) Effort



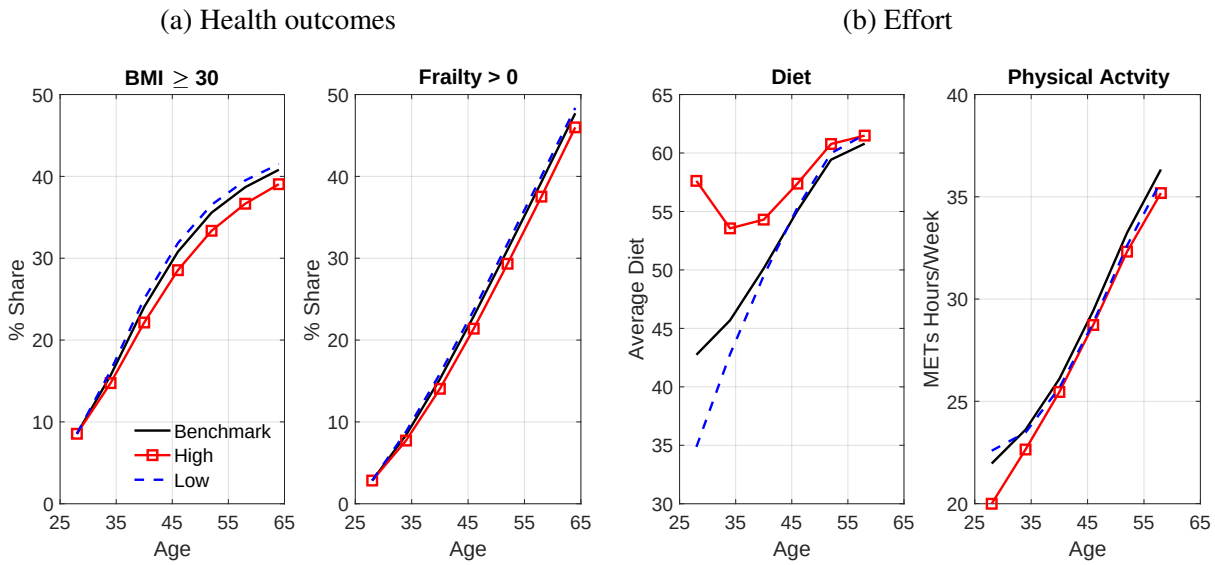
Notes: Outcomes plotted for benchmark model and the experiments where exercise type is equalized to low type ($\xi > 1$) and high type ($\xi < 1$) for all nurses.

Initial diet quality: Diet persistence in the benchmark framework is modeled as habits, where individuals incur utility losses from improving their diet quality levels relative to the previous period. This is in addition to the convex disutility costs associated with high levels of diet quality. Consequently, the initial diet quality, drawn from the data at the beginning of the life cycle, may play an important role. To assess its quantitative impact on health evolution, we conduct two experiments where we assign all agents at either low or high initial diet quality levels. Low levels are defined as those observed in the 10^{th} percentile of the pooled diet distribution in our analytic sample, while high diet corresponds to that observed in the 90^{th} percentile.

Figure 15 displays age-specific obesity, frailty, and health behaviors in the benchmark model and the diet quality experiments. In sharp contrast to earlier experiments, equalizing initial diet at either high or low levels does not significantly impact the evolution of BMI, frailty, or exercise. This is partly due to diet quality recovering towards benchmark levels relatively quickly. For example, agents starting with poor habits are willing to incur some early utility losses to improve diet quality and future BMI and frailty transitions. This underscores that initial diet habits, while important, are somewhat malleable, and agents can offset most of the effects of poor diet by exerting additional effort early on.

All initial conditions: Finally, we would like to gauge the overall importance of initial conditions in determining population health outcomes by equalizing all initial conditions explored above to either *poor* or *good* levels. For the former, we set all agents' starting BMI to class I obese levels ($b = 3$, or BMI = 32.16), one frailty ($h = 1$), low permanent health ($\alpha = 1$), 10^{th} percentile for diet habits, and low exercise types ($\xi > 1$). For the latter, we set all agents' starting BMI to healthy weight ($b = 1$, or BMI = 22.06), zero frailty ($h = 0$), 90^{th} percentile for diet habits, high permanent health ($\alpha = 3$), and high exercise type ($\xi < 1$). Appendix Figure A42 shows the impact

Figure 15: Life-cycle evolution of health and effort: equalizing initial diet habits



Notes: Outcomes plotted for benchmark model and the experiments where initial diet quality is equalized at the 10^{th} (low) and 90^{th} (high) percentile of the pooled diet distribution in our analytic sample of nurses.

of this for both behaviors and health outcomes. We find that equalizing all initial conditions at *good* levels results in a 21 pp reduction in the share of obese individuals and a 12 pp reduction in the share of agents with at least one frailty by age 64. Conversely, setting all initial conditions at *poor* values results in a 45 pp increase in the share of obese individuals and a 51 pp increase in the share with at least one frailty in old-age. Overall, by equalizing all initial conditions to their mean values (zero variance), we find that 30-40% of the variance in BMI of agents in their fifties can be explained by the variance in initial conditions. These experiments highlight a critical finding: course correction through behaviors can only take individuals so far if their starting point is not favorable, especially when it applies to multiple factors. Policies that affect adolescent BMI and diet habits can therefore have large implications for adult health outcomes.

6.2.2 Role of behaviors

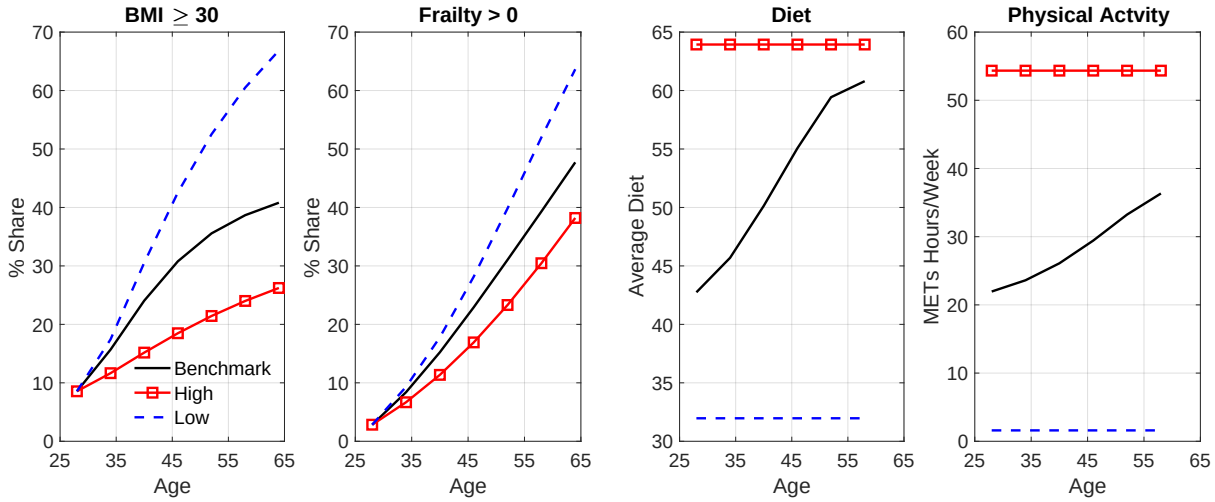
The above experiments highlight the significant role of initial conditions in determining both BMI and frailty over adult life. Next, we aim to understand the importance of behaviors in shaping these outcomes. To achieve this, we conduct two experiments where we first set effort (both diet and exercise) at the 10^{th} percentile of their respective distribution and then at the 90^{th} percentile, across the entire life cycle. These experiments serve two main objectives: first, to understand the potential impact of any policy inducing individuals to exert higher effort on population health and, consequently, medical spending; and second, to disentangle stochastic noise from behavioral channels in determining health outcomes.

Figure 16 shows age-specific obesity, frailty, and health behaviors in the benchmark model and the experiments where all effort is equalized at low or high values. The first panel indicates that

the share of obese agents decreases by 14.4 pp by age 64 when every agent is assigned the 90^{th} percentile of effort. Equalizing effort at the 10^{th} percentile has the opposite effect, with the obesity share increasing by 26.02 pp by age 64. Similar effects on frailty are observed in the second panel of the figure. When assigned high effort levels, the share of agents with at least one chronic condition decreases by age 64 (9.5 pp) compared to the benchmark model. Conversely, when assigned low effort levels, the share of those with at least one chronic condition increases by 15.9 pp.

Figure 16: Life-cycle evolution of health and effort: equalizing effort

(a) Health outcomes (b) Effort



Notes: Outcomes plotted for benchmark model and the experiments where exercise and diet quality are equalized at the 10^{th} (low) and 90^{th} (high) percentile of the respective pooled effort distribution in our analytic sample of nurses.

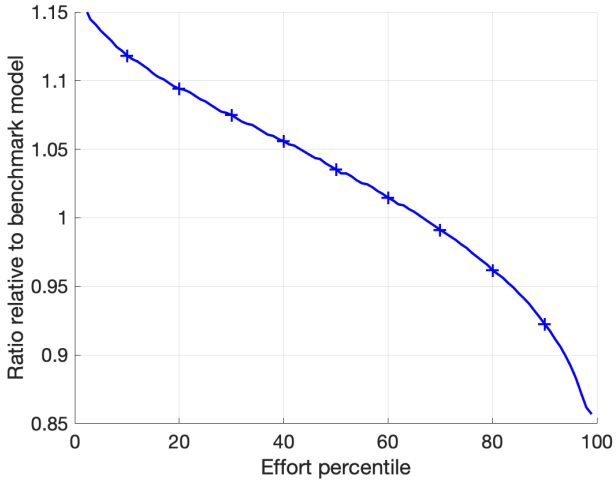
Implications for medical spending: Next, we aim to understand the implications of these experiments for total medical spending in the U.S. Note that our model does not feature health improving expenditures and the evolution of health (BMI and frailty) is completely governed by three factors: initial conditions, effort (diet and exercise), and stochastic shocks. To derive the medical expenditure implications, we first use data from the Medical Expenditure Panel Survey (MEPS) to compute the distribution of total medical expenses by age, BMI, and frailty (see appendix Section A3 for details.).[29] For each level of effort, we then combine the age-, BMI-, and frailty-specific medical expenditure distribution with the model-implied joint distribution over age, BMI, and frailty (which itself depends endogenously on the agents' effort choices over the life cycle) to calculate annual aggregate medical expenses for females aged 25-64.

The results are illustrated in Figure 17, which shows the ratio of total medical expenditures with counterfactual effort levels (both diet and exercise) relative to the benchmark model. In this experiment, we equalize agents' exercise and diet quality at a specific percentile of the respective distribution. For instance, the figure indicates that medical spending increased by 12% compared

[29]Total medical expenses includes both expenses covered by private and/or public health insurance programs as well as expenses covered out-of-pocket.

to the benchmark when both diet and exercise were permanently set at the 10^{th} percentile of their distributions (as in Figure 16). Conversely, spending decreased by 8% relative to the benchmark when exerted effort equalled the 90^{th} percentile of the distribution. To put these differences into perspective, total health spending in the working-age U.S. population surpassed $1.2 trillion in 2022 (MEPS). Therefore, an 8% reduction would translate to approximately $100 billion in aggregate annual savings, a substantial share of which is tax-financed through Medicare or Medicaid in the U.S. This value likely underestimates the scale of potential savings from higher effort because it does not consider any additional savings beyond age 64, where per-person expenditures are even higher; however, the estimate comes with the caveat that it is extrapolated from a specific cohort of registered nurses.

Figure 17: Total medical spending relative to benchmark model: equalizing effort



Notes: The graph plots the ratio of medical expenditures in the model with counterfactual effort levels relative to the model with benchmark levels for exercise and diet quality.

6.3 Alternative model specifications

To better understand the importance of some of the modeling choices in accounting for certain aspects of the data, we next simplify some features of our model. In each scenario, we re-calibrate the model to match the same targets (as discussed in Section 5.2) to give the simpler model the best chance of matching the data.

6.3.1 Exercise types and diet habits

In this set of experiments, we examine the importance of incorporating fixed exercise types and diet habits into our modeling framework to match the data. Specifically, we start by removing the fixed exercise types in the model by setting $\xi = 1$ for all groups in Equation (4) as follows:

$$f\left(e|b,h,\varepsilon_e\right) \quad = \quad \psi_2 \exp\left(\varepsilon_e\right)\left(b-\underline{b}+1\right)^{\lambda_b}\left(h+1\right)^{\lambda_h}\left[\tfrac{1}{1-e}-\left(1+e\right)\right]^{\psi_1}. \tag{7}$$

In the second experiment, we instead remove the dependence on previous diet quality by setting $\upsilon_q = 0$ in Equation (5), yielding the following disutility from diet:

$$r\left(q|b,\varepsilon_q\right) \quad = \quad \tau_2 \exp\left(\varepsilon\right)\left(b-\underline{b}+1\right)^{\upsilon_b}\left[\tfrac{1}{1-q}-(1+q)\right]^{\tau_1}. \tag{8}$$

In each of the above cases, the remaining parameters of the model are re-calibrated to match the same targets as the benchmark model (see parameter values in Table A10).

The first panel of Figure 18 shows that the model without fixed exercise types substantially overestimates the increase in physical activity over adulthood. Additionally, the second panel reveals a notable deficiency in explaining the low exercise levels among individuals in the bottom third of the distribution. The model also fails to match the persistence at the high end of the distribution. For example, the probability of remaining above 42 MET-hours/week is 31% in this version of the model compared to 42% in the data.

When focusing on diet, panels (c) and (d) show that ignoring dietary habits only marginally changes predicted average life-cycle and cross-sectional patterns of diet quality. However, the final panel demonstrates that such a model drastically fails to capture the distribution of *changes* in diet over successive periods. This discrepancy reveals that while models lacking habitual factors may capture some aspects of the diet distribution, they struggle to accurately represent changes in an individual's diet; in particular, it underestimates the persistence in diet choices. These limitations emphasize the complexity of exercise and dietary behavior and underscores the necessity of considering fixed and habitual influences in endogenous health models to achieve a more accurate understanding of the evolution of healthy behaviors like diet and exercise.

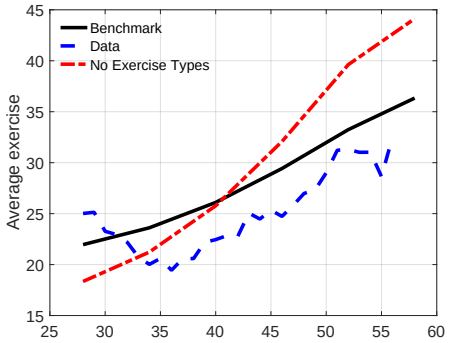
6.3.2 Discount rate heterogeneity

As observed above, both permanent activity types and diet habits are crucial for understanding the evolution of behaviors over the life cycle. An alternative hypothesis is that the data can instead be accounted for by a model with heterogeneous time preferences. We therefore explore a framework where agents are heterogeneous in their discounting of the future. Given our socio-economically homogeneous sample, it is difficult to credibly identify discount rate heterogeneity over and above the existing channels in the benchmark model. However, one could argue that the observed tails in the activity distribution (inactive versus the physically active types) could be attributed to heterogeneous discount factors. Hence, we propose a framework where exercise types are replaced by discount rate types, while maintaining alignment with the same calibration targets as the benchmark model. Specifically, preferences for physical activity remain determined by Equation (7), but we introduce three discount factor values across individuals (confer appendix Table A10 for values): low ($\underline{\beta} < \beta$), high ($\overline{\beta} > \beta$), and a middle group whose discount factor is given by the benchmark value, β (see Section 5.1).

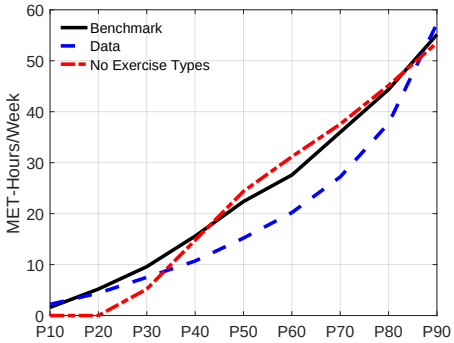
As this version of the model has both discount rate heterogeneity and diet habits, it is able to match the evolution of diet quality similarly well as the benchmark (see appendix Figure A43). Furthermore, compared to entirely excluding exercise types as in the previous section, integrating discount rate heterogeneity introduces additional free parameters, enhancing the model's capability to replicate the persistence of exercise across subsequent periods. However, compared to the benchmark with exercise types, discount rate heterogeneity still substantially overestimates the rise in physical activity over adulthood. The model also continues to miss the bottom third of the

Figure 18: Diet and physical activity: no habits and exercise types

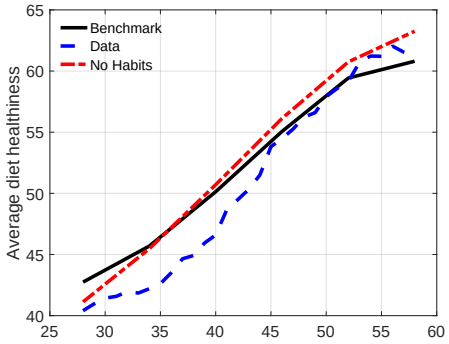
(a) Physical activity by age



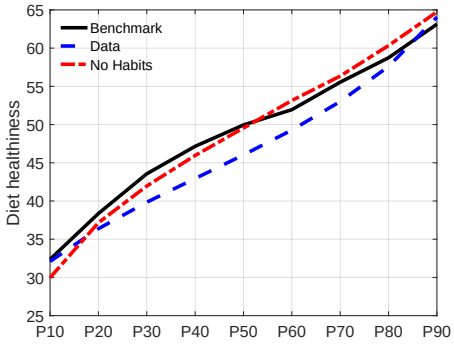
(b) Distribution of physical activity



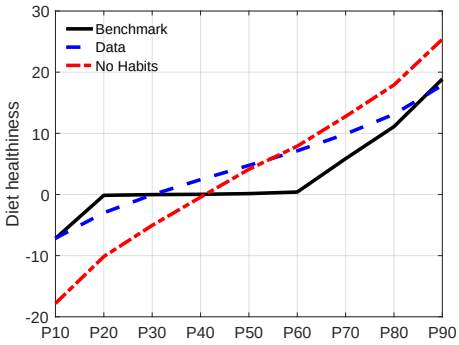
(c) Diet by age



(d) Distribution of diet



(e) Distribution of change in diet



Notes: Panels (a) and (c) plot, respectively, the age-specific averages for exercise and diet quality in the benchmark model and the re-calibrated model. Panels (b), (d) and (e) plot, respectively, the percentile distribution of exercise, diet quality, and change in diet quality ($q - q_{-1}$) in the benchmark model and the re-calibrated model.

exercise distribution almost entirely. These patterns again highlight the role of exercise types in replicating important features of the data.

7 Conclusion

We investigate the complex dynamics between lifestyle factors such as diet and physical activity and their long-term impacts on BMI and frailty using a comprehensive longitudinal dataset of registered nurses in the U.S. We document a striking persistence of obesity throughout adulthood, yet considerable divergence among nurses who began adulthood with a healthy weight and no frailties. We establish that diet and exercise strongly predict the long-term maintenance of good health, underscoring the pivotal role of lifestyle choices in shaping extended health outcomes. Moreover, our empirical findings underscore the influence of early-life circumstances and familial health histories on these health trajectories, indicating that both inherited health conditions and lifestyle behaviors significantly impact an individual's health over their lifespan.

Through the development and use of a structural life-cycle model, we quantify the effects of various factors on health outcomes and medical spending in the U.S. Our model substantiates the critical role of initial health conditions and lifestyle decisions in maintaining lower BMI and frailty, which, in turn, can significantly reduce medical expenses. For instance, aligning everyone's diet quality and exercise levels at the top decile of their respective population distributions would produce at least an 8% annual reduction in total health care expenses for females aged 25 to 65. This finding suggests that interventions aimed at improving lifestyle choices from a young age could have substantial economic benefits by mitigating healthcare costs associated with obesity and chronic conditions.

Our research contributes to a broader understanding of health evolution over the life cycle, emphasizing the interplay between diet, exercise, and inherited health predispositions. By focusing on a socioeconomically homogeneous sample of nurses, we highlight that significant health disparities can exist even within similar socioeconomic groups, driven by differences in lifestyle choices and early-life exposures. Our study opens several paths for future research in this direction that include embedding this framework within standard economic channels to achieve more comprehensive insight into health disparities both within and across socioeconomic groups.

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Appendix

A1 Data and measures

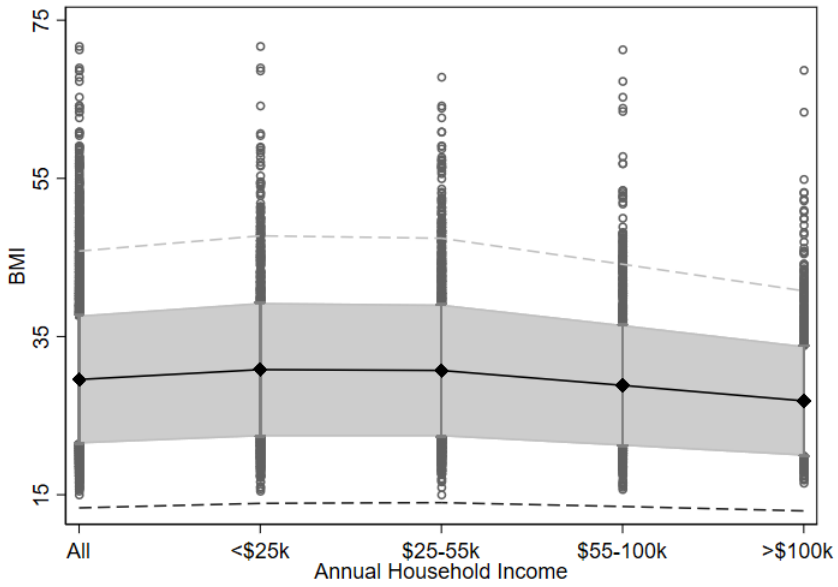


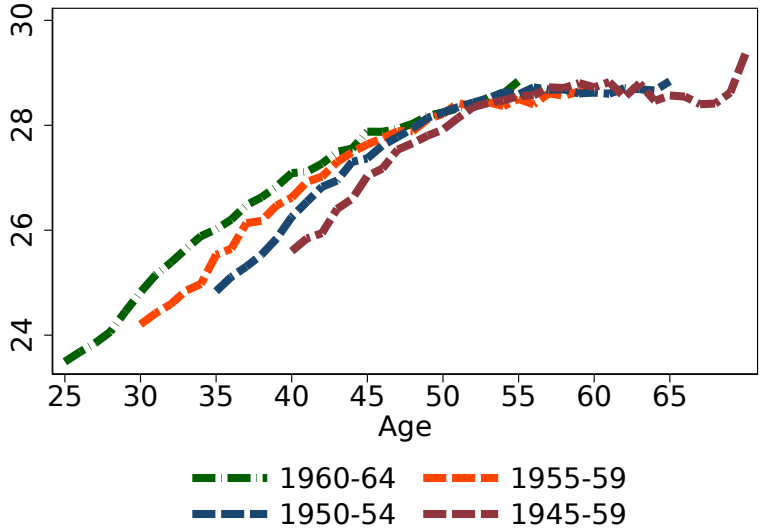
Figure A1: Within and across-group variation in BMI

Notes: Data comes from National Health and Nutrition Examination Survey. The figure plots means, standard deviation (shaded), and two standard deviations (dashed lines) of BMI across different income groups.

Table A1: Components and score for AHEI-2010 dietary index

Components	Minimum score 0	Maximum score 10
Vegetables, servings/day	0	≥ 5
Fruit, servings/day	0	≥ 4
Whole grains, grams/day	0	75
Sugar-sweetened beverages and fruit juice, servings/day	≥ 1	0
Nuts and legumes, servings/day	0	≥ 1
Red meat and processed meat, servings/day	≥ 1.5	0
Trans fat, % of energy	≥ 4	≤ 0.5
Long-chain (n-3) fats (EPA + DHA), mg/day	0	250
Poly-unsaturated fatty acids, % of energy	≤ 2	≥ 10
Sodium, mg/day	highest decile	lowest decile
Alcohol, drinks/day	≥ 2.5	0.5-1.5
Total	0	110

Figure A2: BMI evolution of different birth cohorts

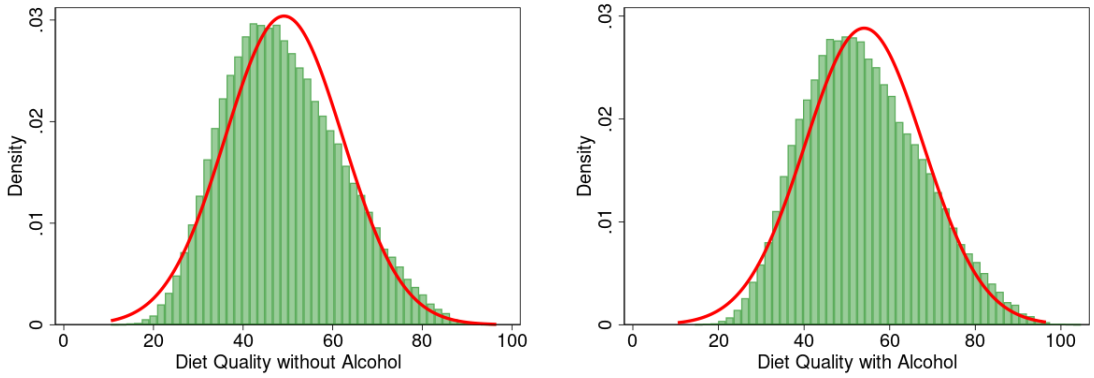


Notes: The figure plots the BMI-age profile of NHS II survey respondents of different birth cohorts. Pooled data between 1989 and 2015 is used and those with BMI less than 18.5 are dropped from the sample.

Figure A3: Distribution of diet quality index

(a) Without alcohol

(b) With alcohol



Notes: The figures plot the distribution of diet quality in our selected sample of the NHS II survey respondents — those aged 25-30 in 1989. Panel (a) plots the distribution of our preferred index that does not include alcohol consumption and panel (b) plots the distirbution including alcohol consumption. Pooled data between 1991 and 2015 is used. Note that even though the survey started in 1989, diet and physical activity variables were only available starting 1991.

Table A2: Categories of responses for the physical activity questionnaire

Categorical response	Median assigned value (hours/week)
1 = zero	0.0
2 = 1-4 minutes/week	0.03
3 = 5-19 minutes/week	0.20
4 = 20-59 minutes/week	0.67
5 = 1 hours/week	1.00
6 = 1-1.5 hour/week	1.25
7 = 2-3 hours/week	2.50
8 = 4-6 hours/week	5.00
9 = 7-10 hours/week	8.50
10 = 11+ hours/week	12.50

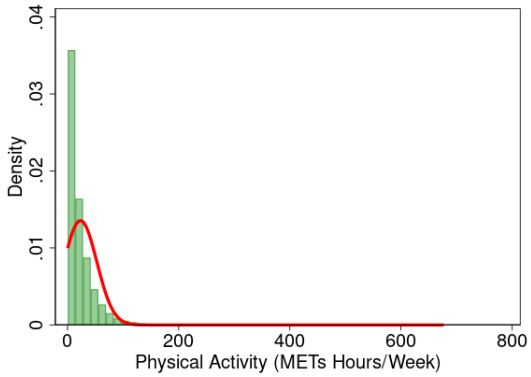
Table A3: Description of activities used in the computation of physical exercise index

Description	Assigned METs
Walking	
Easy pace	2.5
Average pace	3.0
Brisk pace	4.0
Very brisk pace	4.5
Unable to walk	1.0
Missing pace	3.0
Jogging (<10 minutes/mile)	7.0
Running ($\geq$ 10 minutes/mile)	12.0
Bicycling	7.0
Lap swimming	7.0
Tennis, squash, or racquetball	7.0
Other aerobic exercise calisthenics, aerobics, rowing machine	6.0
Lower intensity exercise (e.g., yoga, stretching)	4.0
Other vigorous activities (e.g., lawn mowing)	6.0
Weight training - arms	4.0
Weight training - legs	4.0
Stair-climbing	8.0

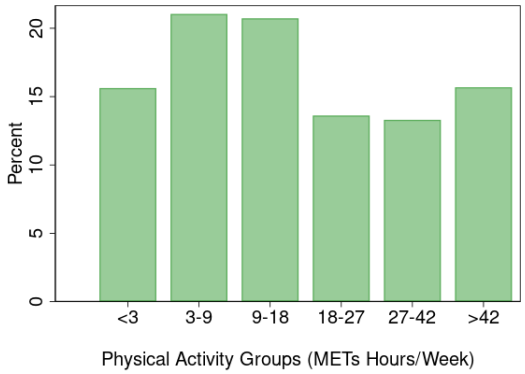
Notes: Activities related to weight training were added to the questionnaire starting 2001. Running and jogging activities were combined together starting 2013.

Figure A4: Distribution of physical activity

(a) Continuous measure



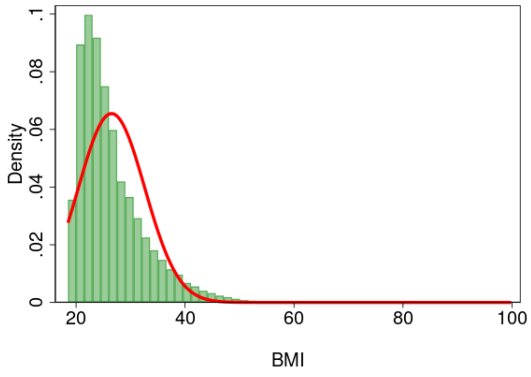
(b) Discrete groups



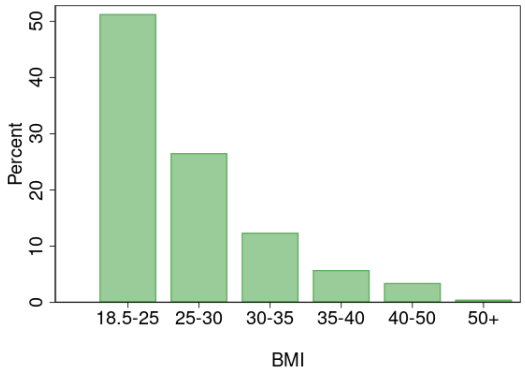
Notes: The figures plot the distribution of physical activity index (in METs hours/week) in our selected sample of the NHS II survey respondents — those aged 25-30 in 1989. Panel (a) plots the continuous distribution and panel (b) plots the distribution of select categories of physical activity. Pooled data between 1991 and 2015 is used. Note that even though the survey started in 1989, diet and physical activity variables were only available starting 1991.

Figure A5: Distribution of BMI

(a) Continuous index



(b) Discrete groups



Notes: The figures plot the distribution of Body Mass Index (BMI) in our selected sample of the NHS II survey respondents — those aged 25-30 in 1989. Panel (a) plots the continuous distribution and panel (b) plots the distribution of select categories of BMI (as defined by the Centers for Disease Control and Prevention). Pooled data between 1989 and 2015 is used.

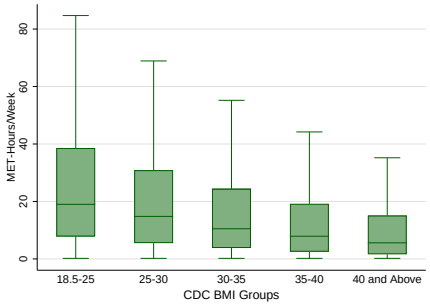
Figure A6: Distribution of frailty count



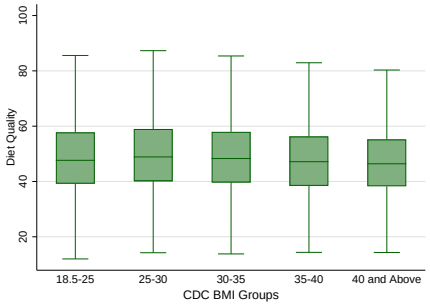
Notes: The figure plots the distribution of frailty count (measured as a count of chronic conditions) in our selected sample of the NHS II survey respondents—those aged 25-30 in 1989. Pooled data between the years 1989 to 2015 is used.

Figure A7: Joint distribution of BMI, frailty, diet quality, and physical activity

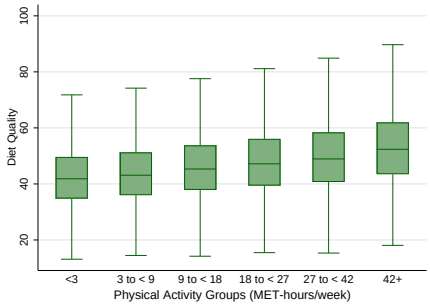
(a) Physical activity and BMI



(b) Diet quality and BMI



(c) Diet quality and physical activity

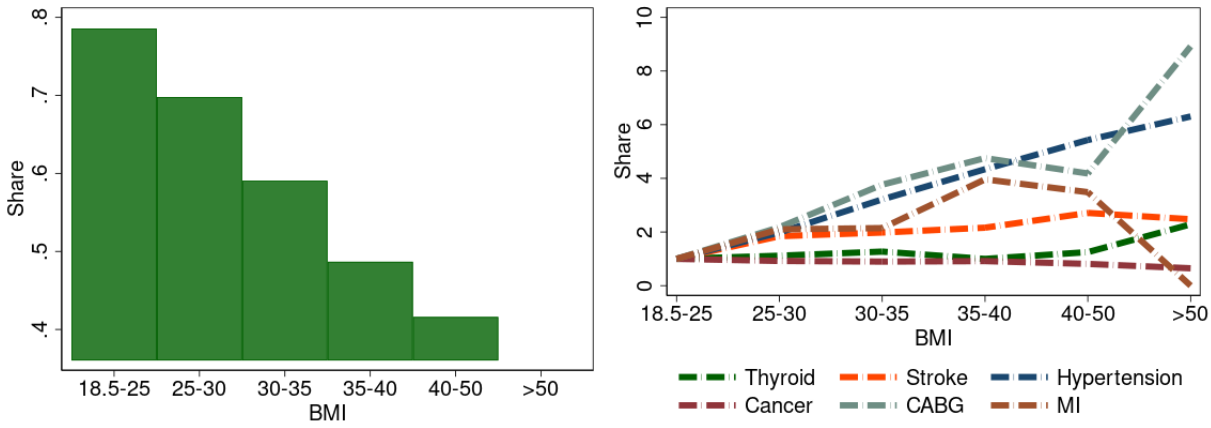


Notes: The figures plot joint distributions of a) physical activity and BMI, b) diet quality and BMI, and c) diet quality and physical activity in our selected sample of the NHS II survey respondents — those aged 25-30 in 1989. Pooled data between the years 1991 to 2015 is used. Note that even though the survey started in 1989, diet and physical activity variables were only available starting 1991.

Figure A8: Joint distribution of BMI and frailty

(a) BMI and Zero Frailty

(b) BMI and Chronic Conditions

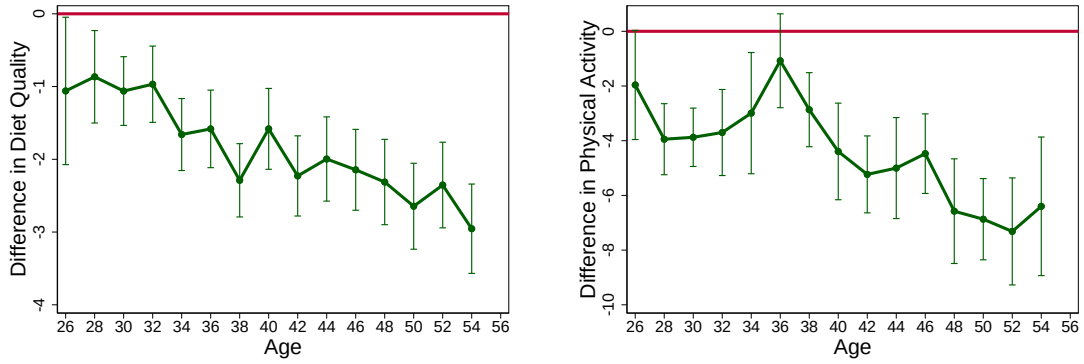


Notes: Panel (a) plots the share of those with zero chronic conditions in each BMI group (as measured in the final 2015 wave) and panel (b) plots the ratio of the share of those with particular chronic conditions in each BMI group relative to the healthy BMI group (18.5-25) in our selected sample of the NHS II survey respondents — those aged 25-30 in 1989.

Figure A9: Life-cycle gaps between frailty gainers and stayers

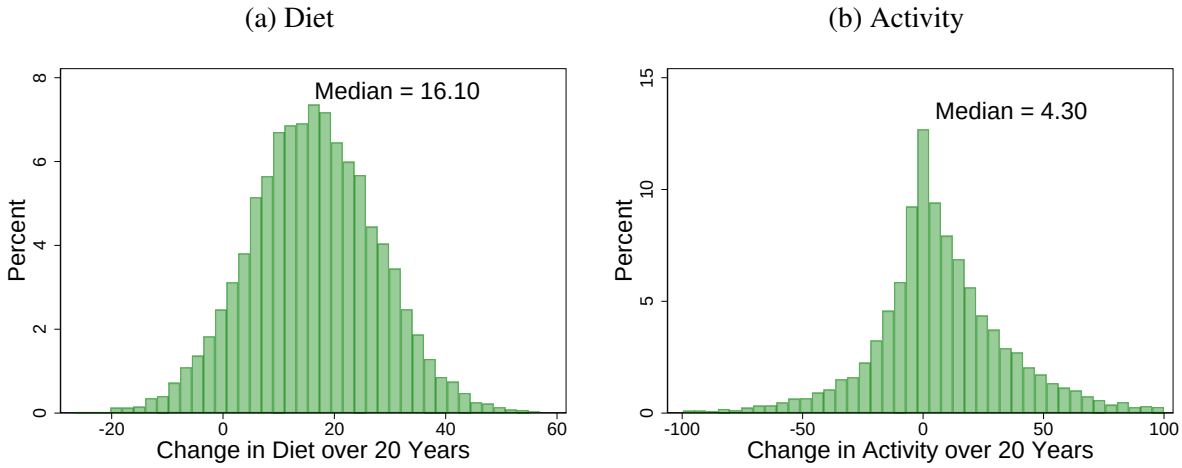
(a) Diet quality

(b) Physical activity



Notes: Panel (a) plots average diet quality for those who obtained at least one frailty between 1989 and 2015 minus average diet quality for those who maintained a zero frailty count between 1989 and 2015, conditional on both groups starting with zero frailty in 1989. Panel (b) plots the corresponding statistic for physical activity. Bars denote 95-percent confidence intervals. NHS II respondents aged 25-30 in 1989 are considered.

Figure A10: Long-run persistence in diet and physical activity



Notes: Figure plots the distribution of diet and physical activity change over a period of 20 years. NHS II respondents aged 25-30 in 1989 are considered. Pooled data between the years 1991 to 2015 is used. Note that even though the survey started in 1989, diet and physical activity variables were only available starting 1991.

A2 Sample attrition

Even though the survey has high response rate for each two-year cycle (85 to 90%), sample attrition could be a concern for the analysis, especially if it is systematically driven by those who are less healthy.[30] We find the attrition rates to be relatively low in the survey given that it is a long follow-up period. Specifically, roughly 70% of the registered nurses who were interviewed for the first time in 1989 also completed the survey in 2015. Table A4 shows the distribution of key baseline variables for nurses in our sample that completed a survey in 2015 (non-attrition sample) and those that did not (attrition sample). The attrition sample had a slightly higher, though statistically insignificant, baseline BMI, exercise score, and frailty count, and a slightly lower diet quality score and permanent health index.

Table A4: Sample attrition

	Non-Attrition Sample			***Attrition Sample***		
	Mean	Std.Dev.	Obs	Mean	Std.Dev.	Obs
BMI in 1989	23.48	4.28	17262	24.11	4.82	6946
Diet Quality in 1991	41.47	9.89	14885	40.68	9.97	4555
Physical Activity in 1991	23.64	29.94	15658	24.69	33.33	4925
Permanent health Index	4.52	1.28	10801	4.32	1.27	506
Frailty Count in 1989	0.03	0.17	17371	0.04	0.20	7009

Notes: Diet quality and physical activity were first reported in 1991. Attrition is defined as nurses who returned a filled questionnaire in 1989 but did not return their mailed questionnaire in 2015 (last period considered in the analysis).

A3 Medical expenditures

We use data from the Medical Expenditure Panel Survey (MEPS) to estimate age, BMI, and frailty-specific medical expenditure risk. Following classifications by the CDC, we categorize BMI into six groups: $18.5-25$ (healthy weight), $25-30$ (overweight), $30-35$ (obese class I), $35-40$ (obese class II), $40-50$ (obese class III), and $50+$. Consistent with our construction of the frailty index for the NHS II sample, we use data on whether the individual has ever been diagnosed with any of the following conditions: high blood pressure, diabetes, cancer, emphysema, angina, coronary heart disease, other heart disease, heart attack, stroke, asthma, arthritis, and high cholesterol. The frailty index is then given by the sum of these indicator functions, top-coded at 2 for consistency with the NHS II sample as discussed in Section 5.1.

To capture that the medical expenditure distribution has both a mass at zero and a long right tail, we categorize medical expenses into seven groups based on percentiles of the population distribution in the MEPS: $0-25$th percentile, $25-50$th percentile, $50-75$th percentile, $75-90$th percentile, $90-95$th percentile, $95-99$th percentile, and $99-100$th percentile. The medical spending level corresponding to each expenditure group is given by the weighted average spending

[30] In the survey, every cycle, questionnaires are sent to all surviving cohort members except those who have unforwardable addresses or who have refused further participation in the study.

level within that group in the MEPS. We then estimate the age, BMI, and frailty-specific likelihood of drawing one of these seven medical expenditure levels by means of an ordered logistic regression (with the probabilities obtained from the ordered logistic formula), using 6-year age groups for consistency with the model periods and restricting the sample to women. The regression results are reported in Table A8. Finally, we combine these medical expenditure levels and probabilities with the joint distribution of age, BMI, and frailty in the model, which itself is a function of the agents' specific effort levels (i.e., diet and exercise choices), to compute aggregate medical expenditures for the working-age population under different effort levels.

A4 Stylized facts by sub-groups

We test the robustness of our stylized facts to differences in marital and fertility status, spousal education, smoking habits, mental health status, and working night shifts. We use the marital status information from the 2013 wave to categorize nurses as married if they reported being married or living with a domestic partner. Non-married nurses included those who were divorced, widowed, separated, or never married. Based on this definition, 81.6% of the nurses in our sample were married. While the nurses all have similar education (an associate or a bachelor's degree), they could be married to spouses with varying education levels. Education of the spouse was reported in the 1999 survey wave. We construct an indicator for college educated spouse if the reported education levels were equal to a two-year college or above. Based on this definition, 80% of the married nurses in our sample had a college educated spouse. To understand the role of fertility, we look at nurses with and without children. However, the survey does not include any direct questions on the total number of children. We infer the number of living children by looking at responses on *parity*: total number of pregnancies that resulted in delivery at ≥ 6 months gestation, of either a live birth or a stillbirth. Note that while this measure should be a good approximation of the number children, it has two special properties: (1) this measure will include any instance of stillbirth and (2) it does not include non-biological children who may be living with the survey respondents. Based on this classification, roughly 18.4% of nurses in our sample were classified as without children (zero parity) and rest with at least one child (positive parity).

Smoking status was constructed from the 2015 survey wave. Nurses were designated as 0 if they never smoked or 1 if they had some smoking history. Based on this classification, 65% of the nurses in our sample were non-smokers. For mental health status, we use the SF-36 mental health index constructed from available information in the 1993 survey wave. This is a continuous index ranging from 0 to 100. We discretize the index into terciles and compare those in the top and bottom terciles. Finally, we use retrospective questions asked in the 2009 survey wave to categorize nurses who worked nights shifts versus those who did not. Nurses were asked to report their working shifts at various points in their life cycle: between ages 20-25, ages 26-35, ages 36-45, and after age 45. We categorize night shift nurses as those who only worked night-shifts during at least one of the four life phases mentioned above. Day shifters are then categorized as those who did not work night-shifts exclusively at any point during their lives up until the 2009 survey wave.

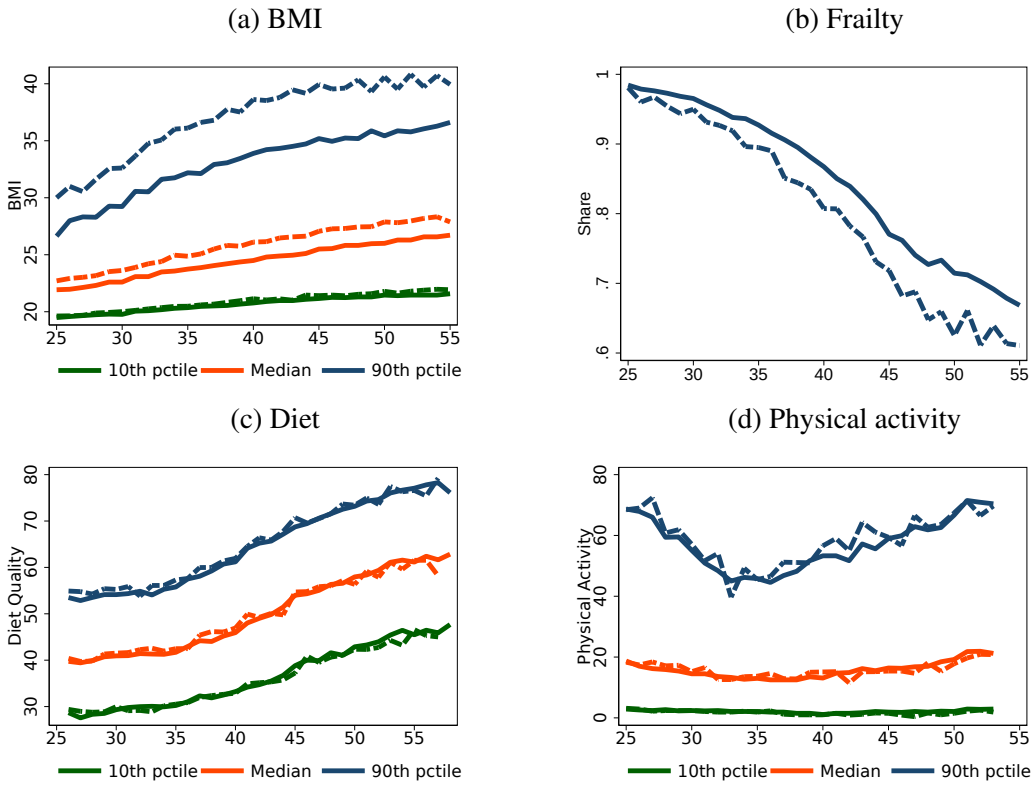
Figures in this appendix show that our stylized facts hold when broken down by the above sub-groups. For example, Figure A11 shows that while non-married nurses exhibited higher BMI and frailty than married nurses, the life-cycle patterns stated in stylized fact 1 hold for both groups. Figure A12 shows life-cycle patterns for BMI, frailty, and healthy behaviors by education of the

spouse (college vs. non-college). Similar to non-married nurses, the BMI and frailty levels are somewhat higher for nurses with non-college-educated spouses. In this case, we also observe somewhat poorer diet and exercise levels. However, we observe the same life-cycle improvements in behaviors and deterioration of health for both groups.

Concerns might arise about other factors influencing the observed life-cycle patterns highlighted in our stylized facts. For example, poor mental health and/or smoking could drive changes in BMI and frailty and deteriorate health behaviors over adulthood. At the same time, the nature of the working shift (night versus day) could also impact diet and physical activity behaviors by impacting circadian rhythms. Figure A14 indicates some increase in frailty and poorer health behaviors for nurses in the bottom tercile of the survey's available mental health index (SF-36). However, we once again observe life-cycle trends that align with stylized fact 1 for nurses with both high and low mental health scores. Similarly, Figure A15 shows some differences in outcomes for smokers, but the trends remain consistent between smokers and non-smokers. Finally, Figure A16 shows some differences in health outcomes for nurses who did and did not work night shifts between ages 20 and 46, but the trends remain consistent between the two groups.

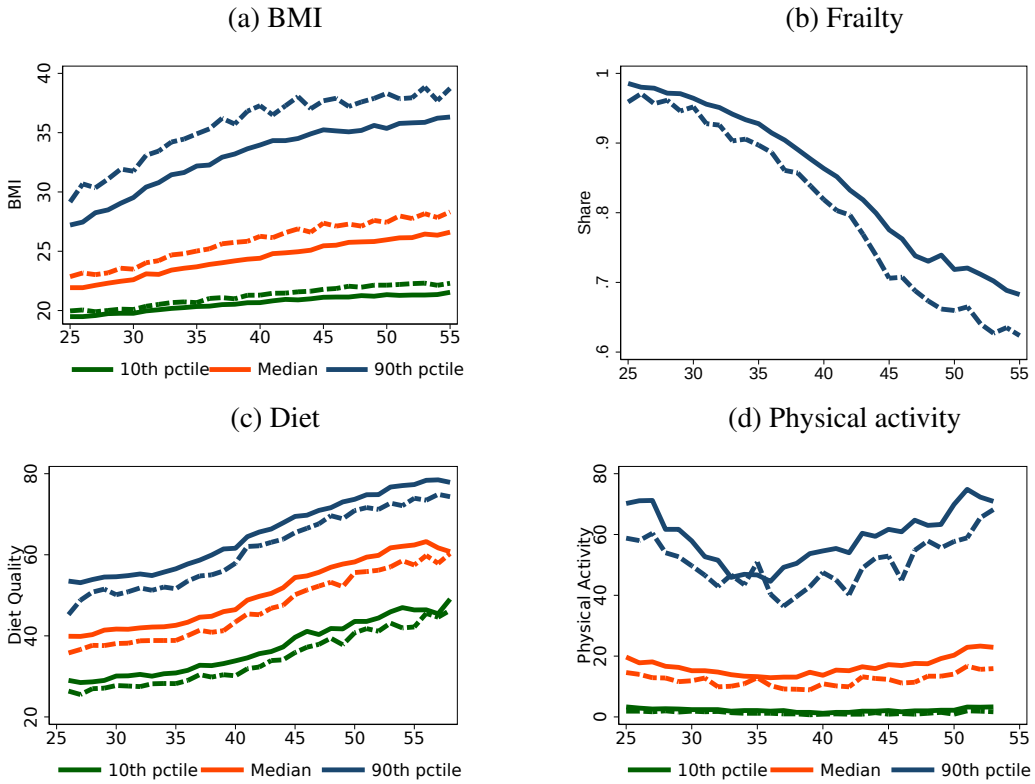
The remaining figures in this appendix show that the remaining stylized facts also hold for each of these sub-groups.

Figure A11: Life-cycle patterns in BMI, frailty, diet quality, and physical activity by marital status



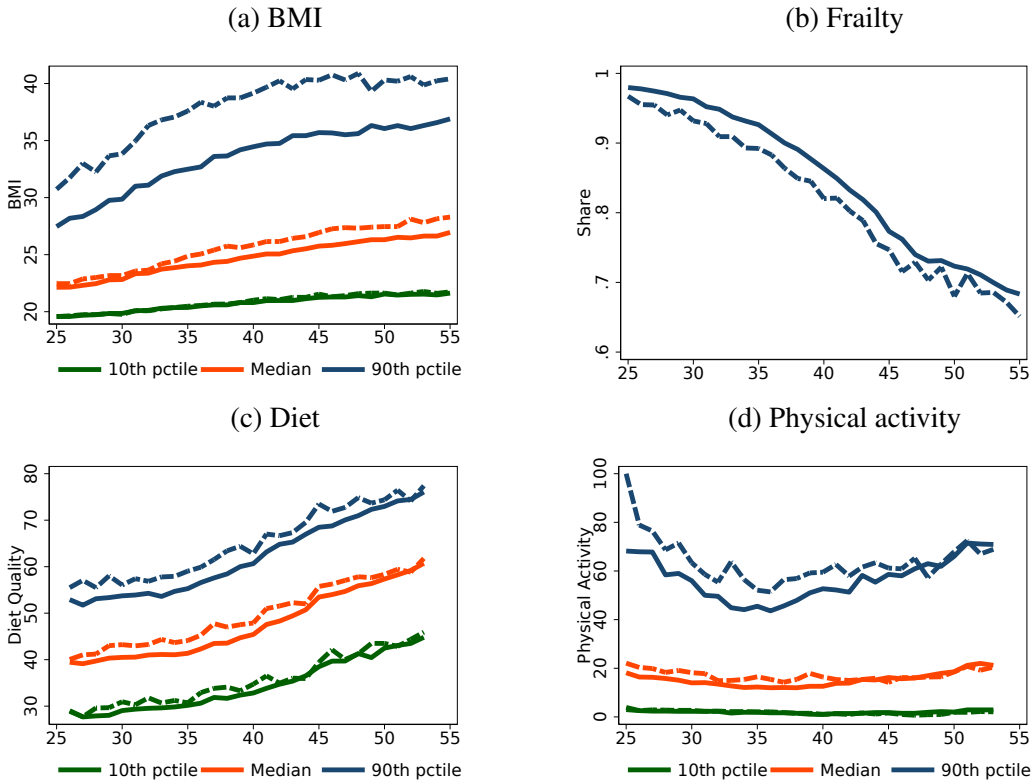
Notes: Panels (a), (c), and (d) plot evolution (median, 10th and 90th percentile) of BMI, diet quality, and physical activity index, respectively, over the life cycle of registered nurses in NHS II, who were aged 25 to 30 in the initial 1989 wave. Solid lines indicate those who were married and dashed lines are for non-married. For frailty measure, a total count of chronic conditions is used. Panel (b) plots the share of those with zero frailty count over the life cycle.

Figure A12: Life-cycle patterns in BMI, frailty, diet quality, and physical activity by education status of the spouse



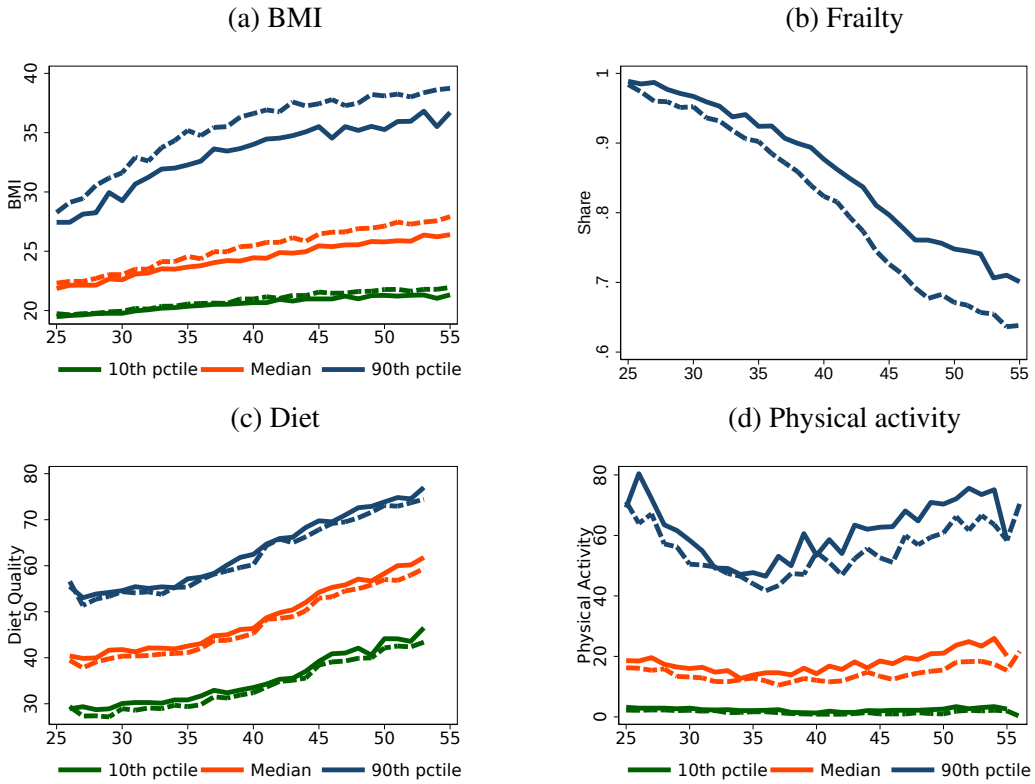
Notes: Panels (a), (c), and (d) plot evolution (median, 10th and 90th percentile) of BMI, diet quality, and physical activity index, respectively, over the life cycle of registered nurses in NHS II, who were aged 25 to 30 in the initial 1989 wave. Solid lines indicate those whose spouse had a college degree and dashed lines are for those whose spouse had less than college education. For frailty measure, a total count of chronic conditions is used. Panel (b) plots the share of those with zero frailty count over the life cycle.

Figure A13: Life-cycle patterns in BMI, frailty, diet quality, and physical activity by fertility status



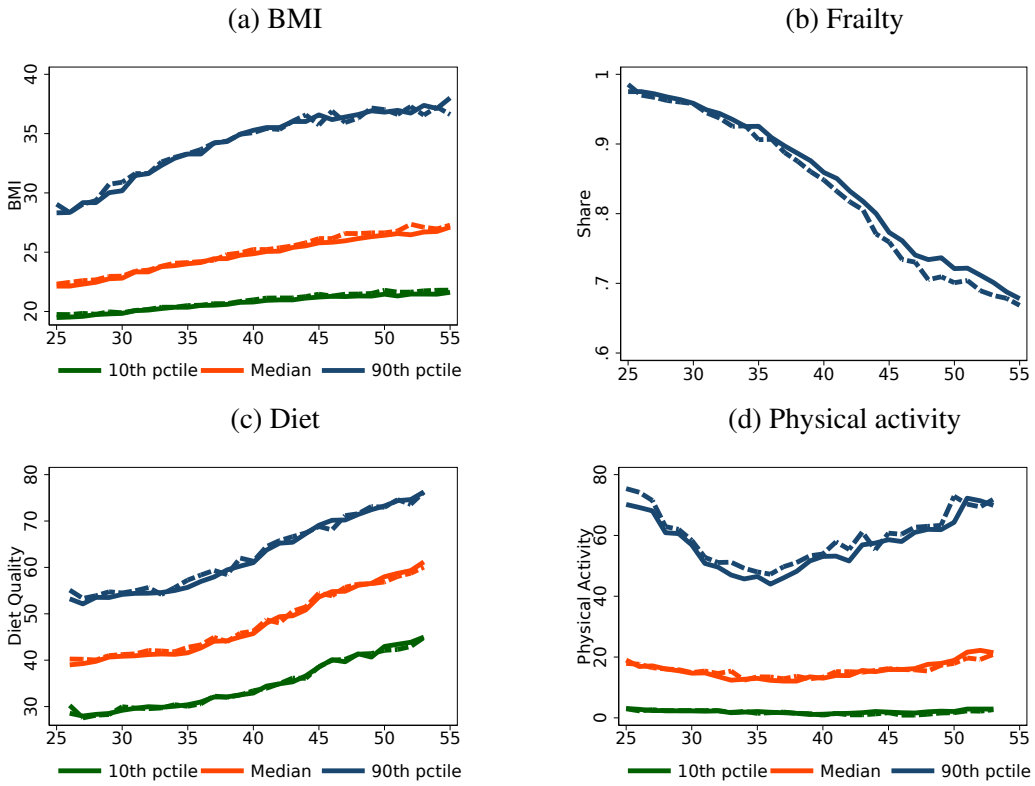
Notes: Panels (a), (c), and (d) plot evolution (median, 10th and 90th percentile) of BMI, diet quality, and physical activity index, respectively, over the life cycle of registered nurses in NHS II, who were aged 25 to 30 in the initial 1989 wave. Solid lines indicate those nurses who had at least one child (measured by pregnancies that resulted in the delivery at $\geq$6 months gestation) and dashed lines are for those with no biological children (zero parity). For frailty measure, a total count of chronic conditions is used. Panel (b) plots the share of those with zero frailty count over the life cycle.

Figure A14: Life-cycle patterns in BMI, frailty, diet quality, and physical activity by mental health status



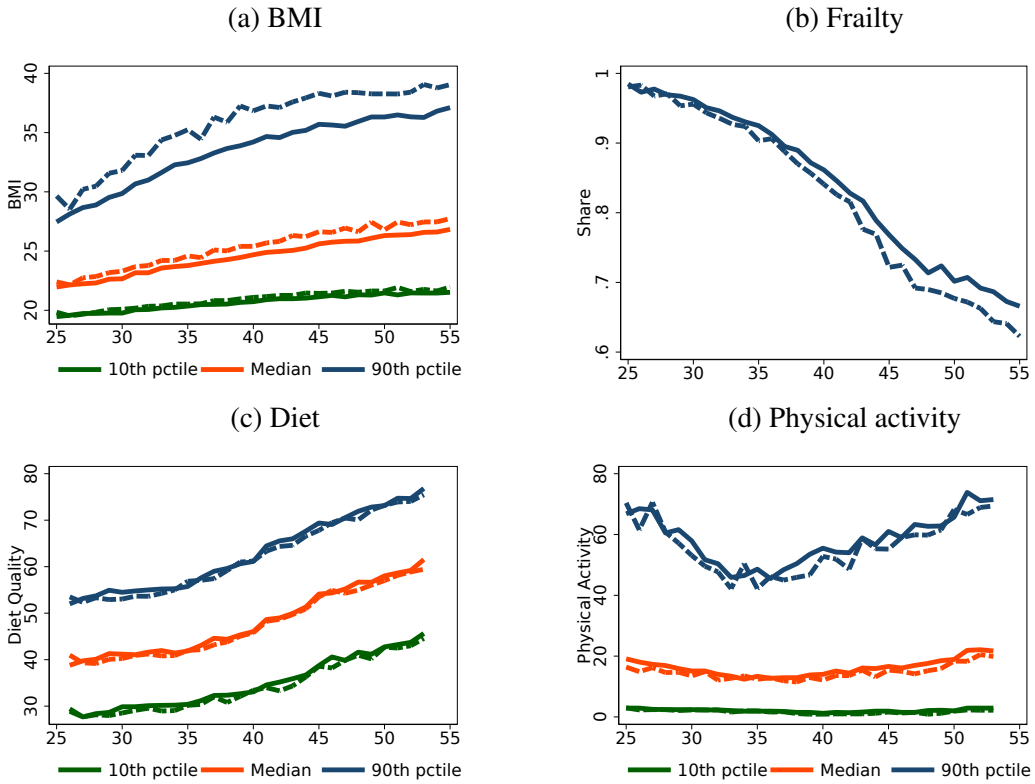
Notes: Panels (a), (c), and (d) plot evolution (median, 10th and 90th percentile) of BMI, diet quality, and physical activity index, respectively, over the life cycle of registered nurses in NHS II, who were aged 25 to 30 in the initial 1989 wave. Solid lines indicate those in the highest tercile of the mental health index and dashed lines are for those in lowest tercile. Mental health was measured in 1993 using SF-36 mental health index. For frailty measure, a total count of chronic conditions is used. Panel (b) plots the share of those with zero frailty count over the life cycle.

Figure A15: Life-cycle patterns in BMI, frailty, diet quality, and physical activity by smoking status



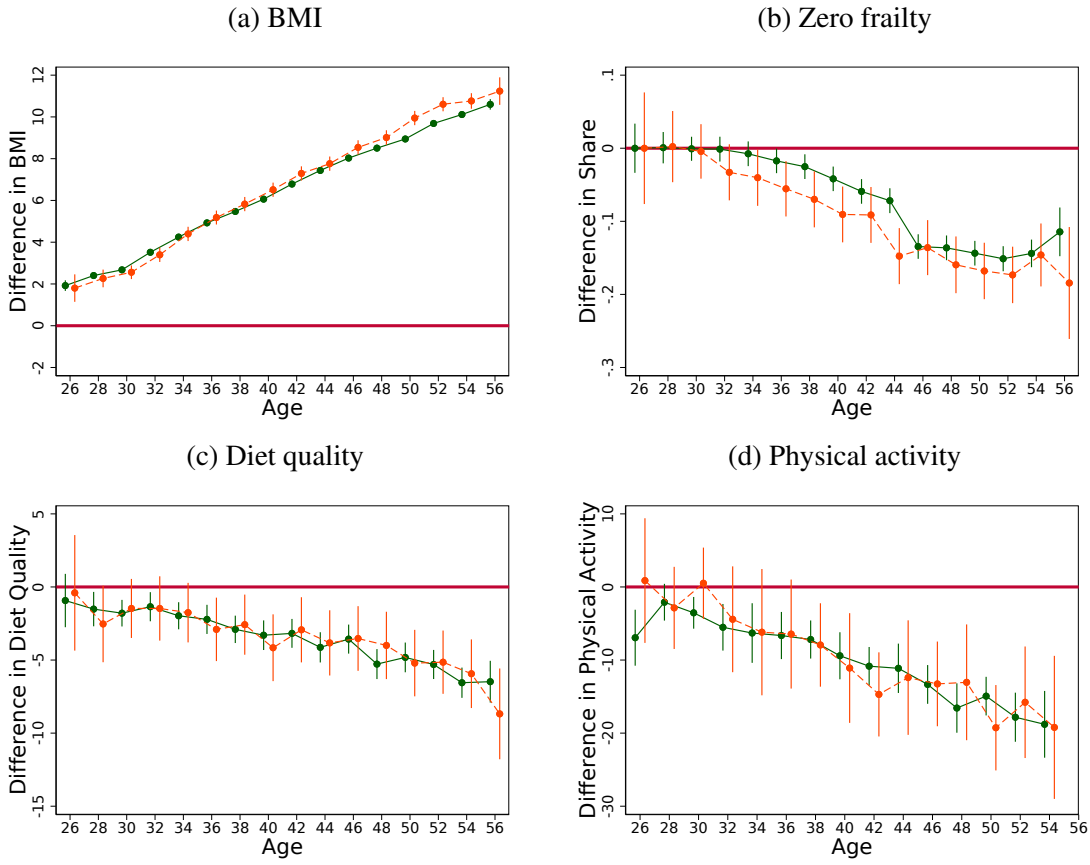
Notes: Panels (a), (c), and (d) plot evolution (median, 10th and 90th percentile) of BMI, diet quality, and physical activity index, respectively, over the life cycle of registered nurses in NHS II, who were aged 25 to 30 in the initial 1989 wave. Solid lines indicate those who never smoked and dashed lines are for those who smoked at some point. For frailty measure, a total count of chronic conditions is used. Panel (b) plots the share of those with zero frailty count over the life cycle.

Figure A16: Life-cycle patterns in BMI, frailty, diet quality, and physical activity by working shift status



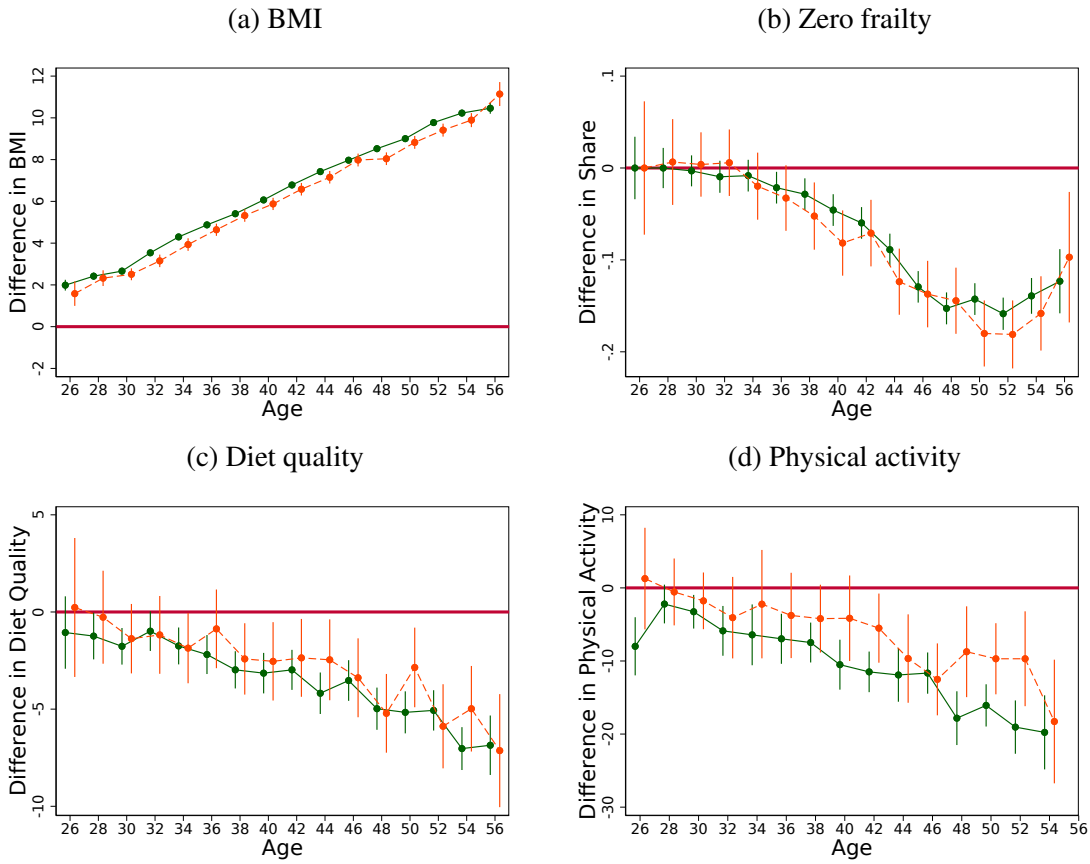
Notes: Panels (a), (c), and (d) plot evolution (median, 10th and 90th percentile) of BMI, diet quality, and physical activity index, respectively, over the life cycle of registered nurses in NHS II, who were aged 25 to 30 in the initial 1989 wave. Dashed lines indicate those who exclusively worked night shifts at some point between the ages of 20 and 46 and solid lines are for the rest. For frailty measure, a total count of chronic conditions is used. Panel (b) plots the share of those with zero frailty count over the life cycle.

Figure A17: Life-cycle gaps between BMI gainers and stayers by marital status



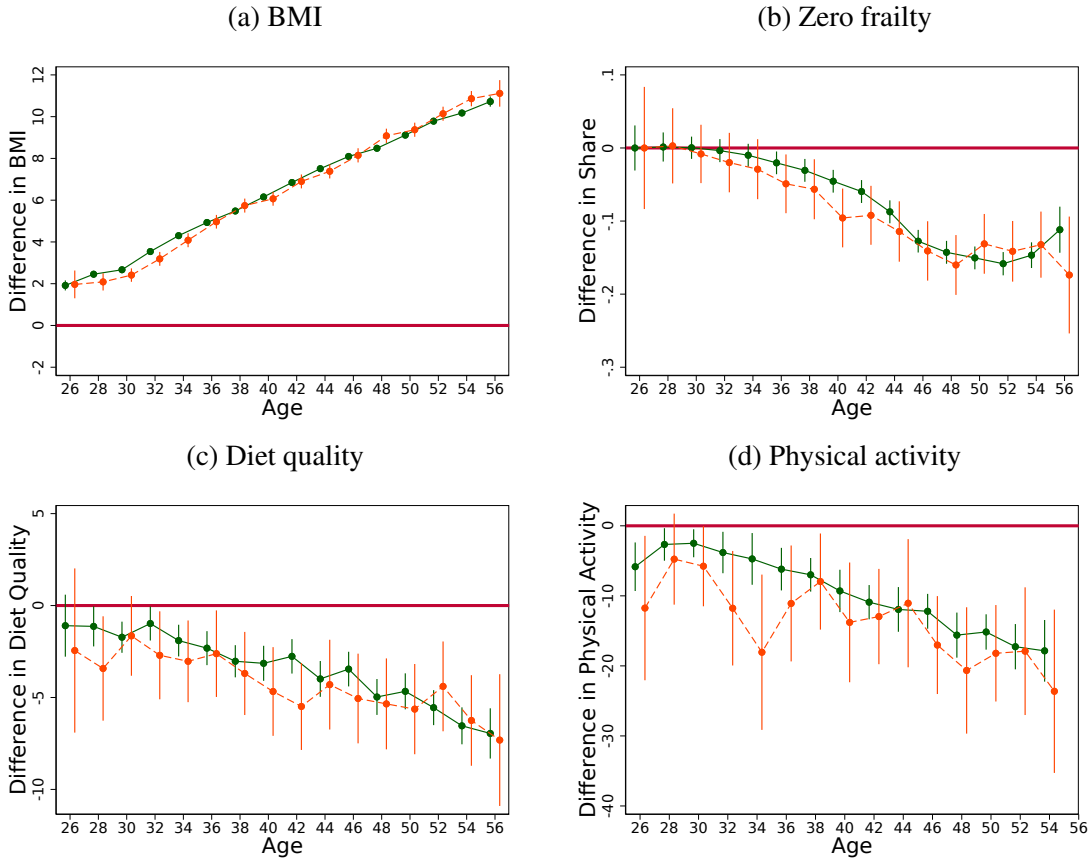
Notes: The figures plot difference in outcomes over the life cycle for those who maintained their healthy BMI (18.5-25) between the years 1989 and 2015 and those whose BMI increased from that in the healthy range in 1989 to BMI>30 in 2015 (last survey year). Solid green lines indicate these differences for married nurses and dashed orange lines for non-married nurses. NHS II respondents aged 25-30 in 1989 are considered. Panel (b) plots the difference in the share of those with zero frailty count between the two BMI-change groups.

Figure A18: Life-cycle gaps between BMI gainers and stayers
by education status of spouse



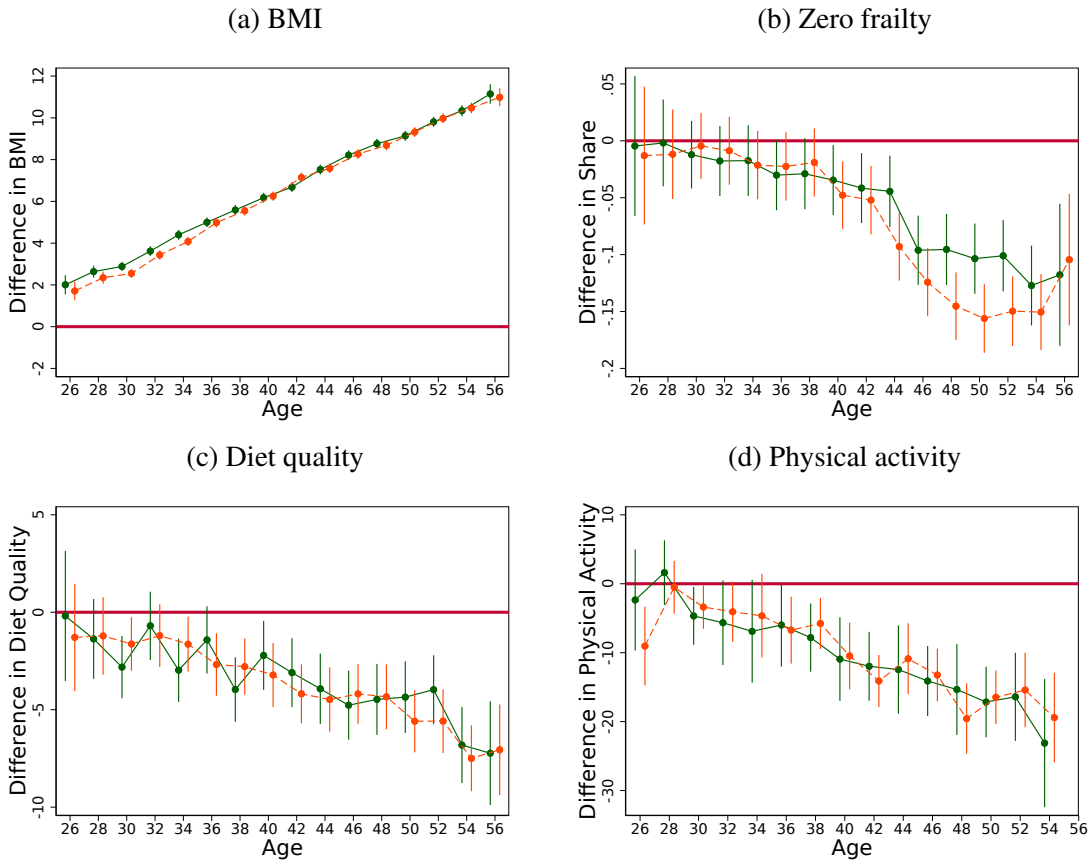
Notes: The figures plot average outcomes for those whose BMI increased from healthy (18.5-25) in 1989 to obese (>30) in 2015 minus average outcomes for those who maintained a healthy BMI between 1989 and 2015. Solid green lines indicate these differences for married nurses whose spouse have a college degree and dashed orange lines for those with non-college-educated spouses. NHS II respondents aged 25-30 in 1989 are considered.

Figure A19: Life-cycle gaps between BMI gainers and stayers by fertility status



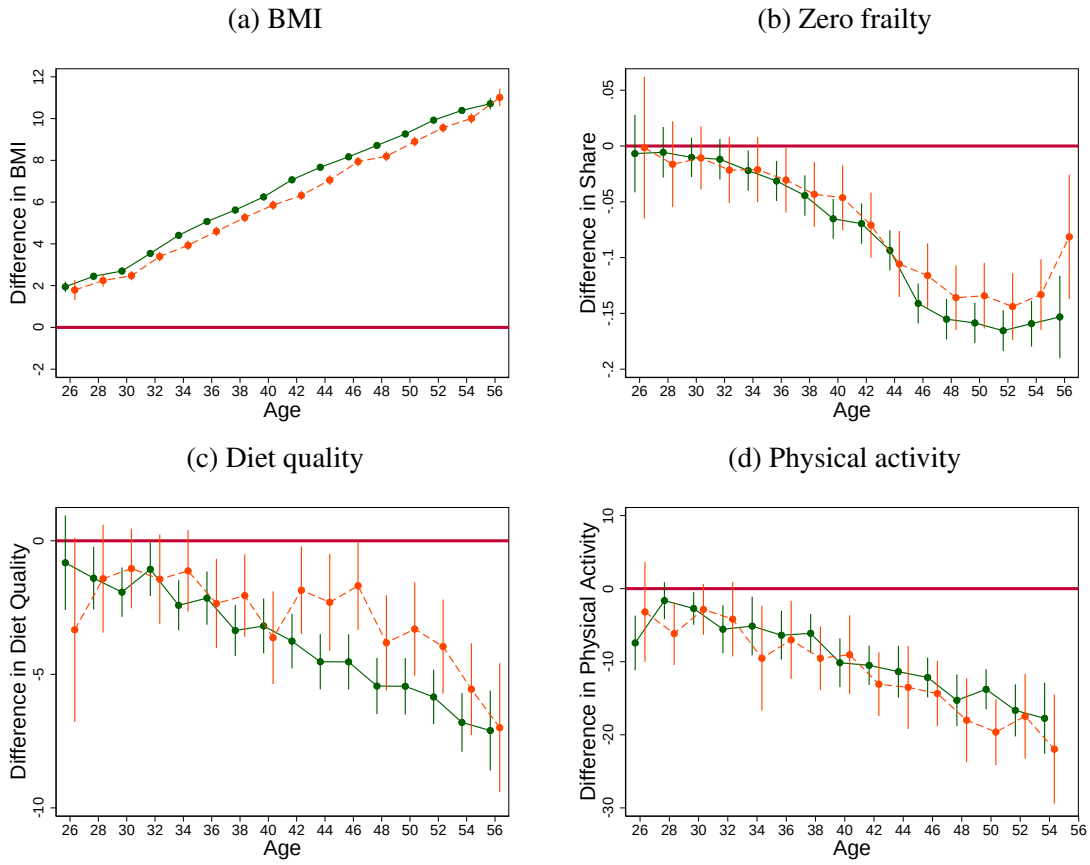
Notes: The figures plot average outcomes for those whose BMI increased from healthy (18.5-25) in 1989 to obese (>30) in 2015 minus average outcomes for those who maintained a healthy BMI between 1989 and 2015. Solid green lines indicate these differences for those nurses who had at least one child (measured by pregnancies that resulted in the delivery at ≥6 months gestation) and dashed orange lines are for those with no biological children (zero parity). NHS II respondents aged 25-30 in 1989 are considered.

Figure A20: Life-cycle gaps between BMI gainers and stayers by mental health status



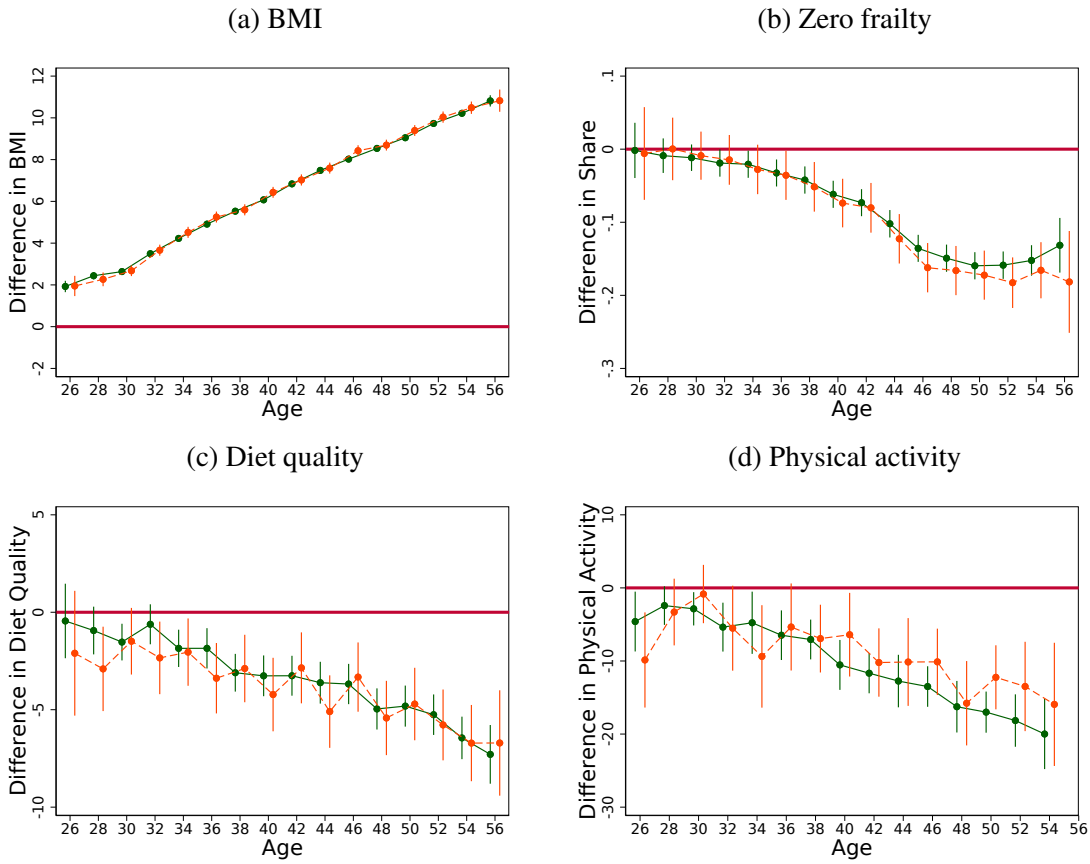
Notes: The figures plot average outcomes for those whose BMI increased from healthy (18.5-25) in 1989 to obese (>30) in 2015 minus average outcomes for those who maintained a healthy BMI between 1989 and 2015. Solid green lines indicate these differences for those in the highest tercile of the mental health index and dashed orange lines are for those in lowest tercile. Mental health was measured in 1993 using SF-36 mental health index. NHS II respondents aged 25-30 in 1989 are considered.

Figure A21: Life-cycle gaps between BMI gainers and stayers by smoking status



Notes: The figures plot average outcomes for those whose BMI increased from healthy (18.5-25) in 1989 to obese (>30) in 2015 minus average outcomes for those who maintained a healthy BMI between 1989 and 2015. Solid green lines indicate these differences for those who never smoked and dashed orange lines for those who smoked at some point. NHS II respondents aged 25-30 in 1989 are considered.

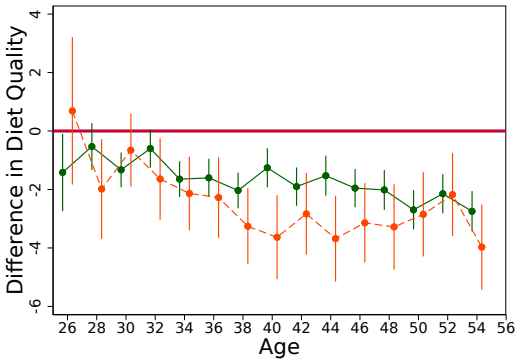
Figure A22: Life-cycle gaps between BMI gainers and stayers
by working shift status



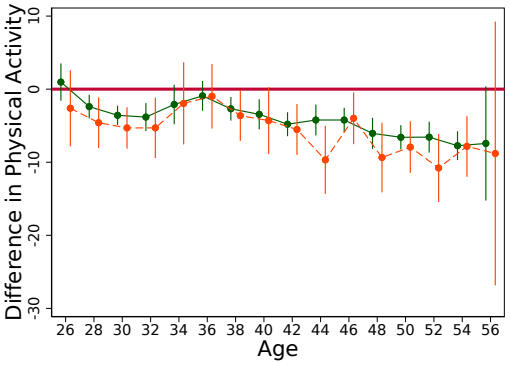
Notes: The figures plot average outcomes for those whose BMI increased from healthy (18.5-25) in 1989 to obese (>30) in 2015 minus average outcomes for those who maintained a healthy BMI between 1989 and 2015. Dashed orange lines indicate these differences for those who exclusively worked night shifts at some point between the ages of 20 and 46 and solid green lines are for the rest. NHS II respondents aged 25-30 in 1989 are considered.

Figure A23: Life-cycle gaps between frailty gainers and stayers by marital status

(a) Diet Quality



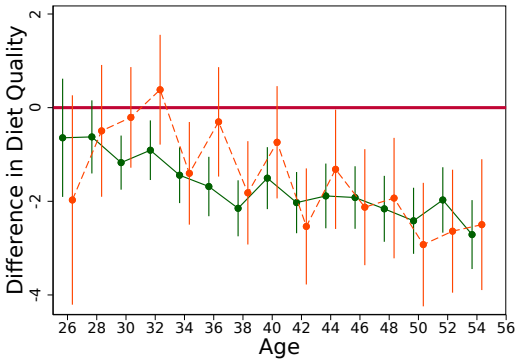
(b) Physical Activity



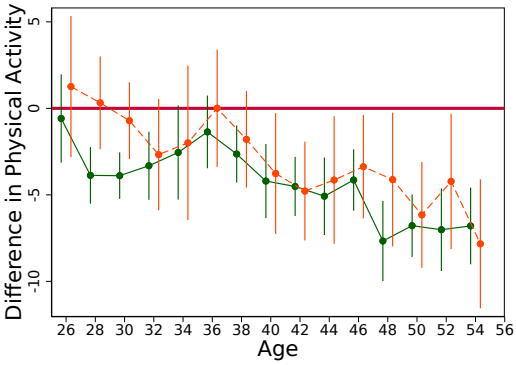
Notes: The figures plot average outcomes for those who obtained at least one frailty between 1989 and 2015 minus average outcomes for those who maintained a zero frailty count between 1989 and 2015. Solid green lines indicate these differences for married nurses and dashed orange lines for non-married nurses. NHS II respondents aged 25-30 in 1989 are considered.

Figure A24: Life-cycle gaps between frailty gainers and stayers by education status of spouse

(a) Diet Quality



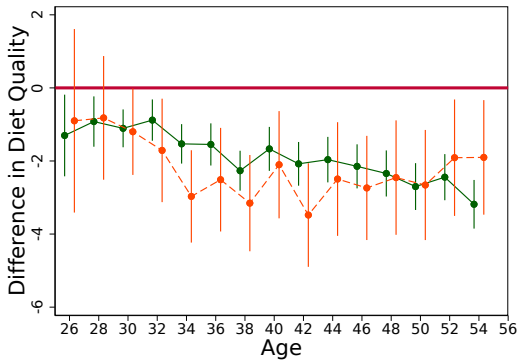
(b) Physical Activity



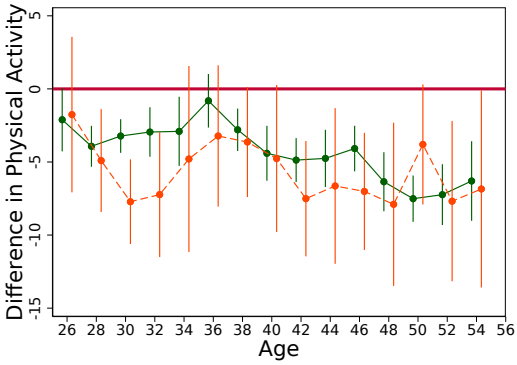
Notes: The figures plot average outcomes for those who obtained at least one frailty between 1989 and 2015 minus average outcomes for those who maintained a zero frailty count between 1989 and 2015. Solid green lines indicate these differences for married nurses whose spouse have a college degree and dashed orange lines for those with non-college-educated spouses. NHS II respondents aged 25-30 in 1989 are considered.

Figure A25: Life-cycle gaps between frailty gainers and stayers by fertility status

(a) Diet Quality



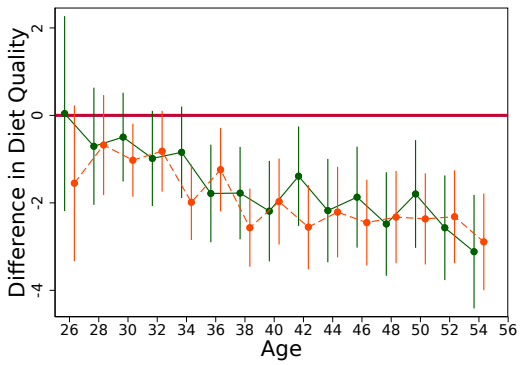
(b) Physical Activity



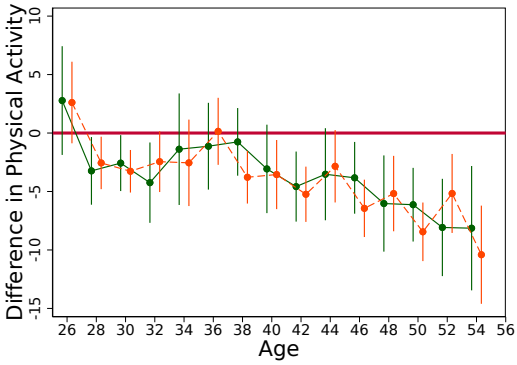
Notes: The figures plot average outcomes for those who obtained at least one frailty between 1989 and 2015 minus average outcomes for those who maintained a zero frailty count between 1989 and 2015. Solid green lines indicate these differences for those nurses who had at least one child (measured by pregnancies that resulted in the delivery at $\geq$6 months gestation) and dashed orange lines are for those with no biological children (zero parity). NHS II respondents aged 25-30 in 1989 are considered.

Figure A26: Life-cycle gaps between frailty gainers and stayers by mental health status

(a) Diet Quality



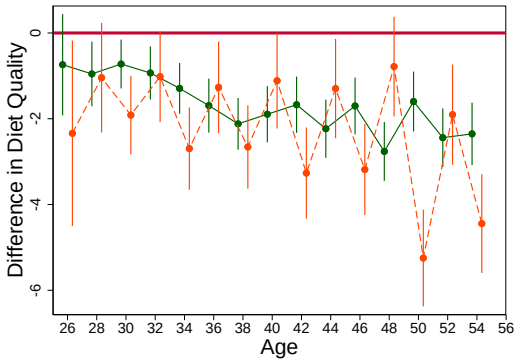
(b) Physical Activity



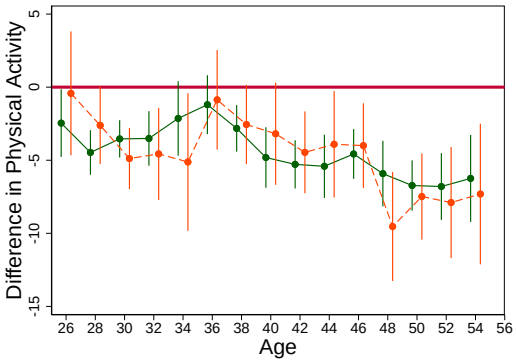
Notes: The figures plot average outcomes for those who obtained at least one frailty between 1989 and 2015 minus average outcomes for those who maintained a zero frailty count between 1989 and 2015. Solid green lines indicate these differences for those in the highest tercile of the mental health index and dashed orange lines are for those in lowest tercile. Mental health was measured in 1993 using SF-36 mental health index. NHS II respondents aged 25-30 in 1989 are considered.

Figure A27: Life-cycle gaps between frailty gainers and stayers by smoking status

(a) Diet Quality



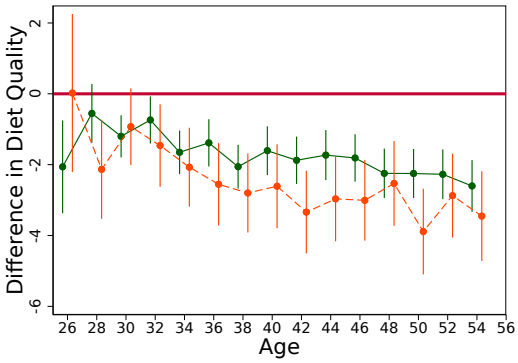
(b) Physical Activity



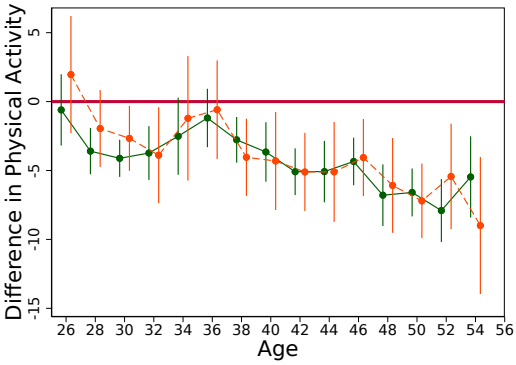
Notes: The figures plot average outcomes for those who obtained at least one frailty between 1989 and 2015 minus average outcomes for those who maintained a zero frailty count between 1989 and 2015. Solid green lines indicate these differences for those who never smoked and dashed orange lines for those who smoked at some point. NHS II respondents aged 25-30 in 1989 are considered.

Figure A28: Life-cycle gaps between frailty gainers and stayers by working shift status

(a) Diet Quality



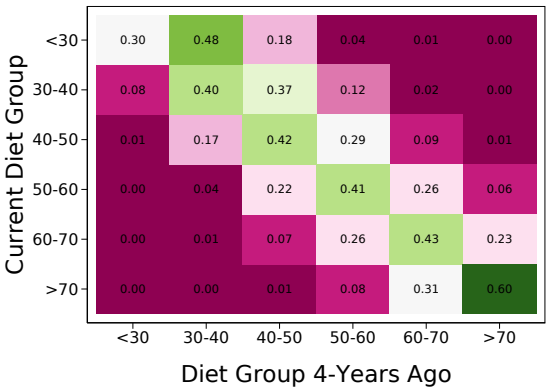
(b) Physical Activity



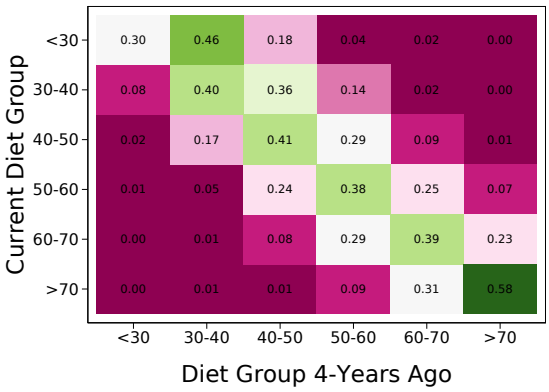
Notes: The figures plot average outcomes for those who obtained at least one frailty between 1989 and 2015 minus average outcomes for those who maintained a zero frailty count between 1989 and 2015. Dashed orange lines indicate these differences for those who exclusively worked night shifts at some point between the ages of 20 and 46 and solid green lines are for the rest. NHS II respondents aged 25-30 in 1989 are considered.

Figure A29: Persistence of diet
by marital status, education of spouse, and fertility status

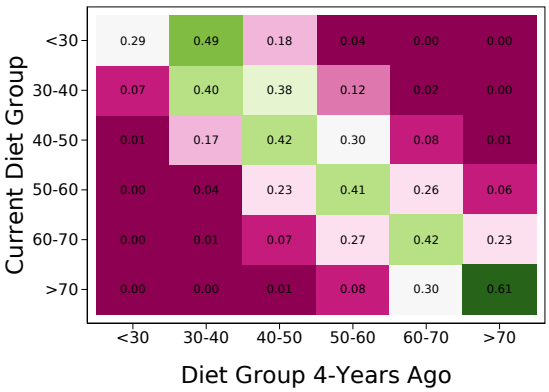
(a) Married



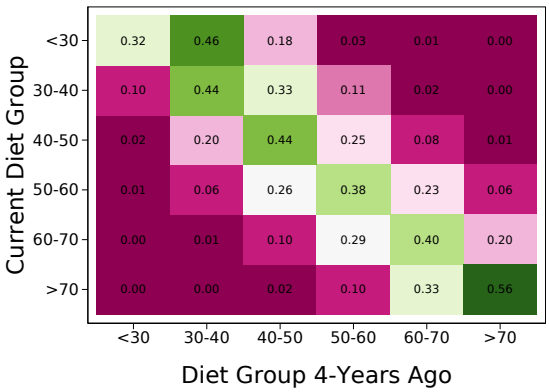
(b) Non-married



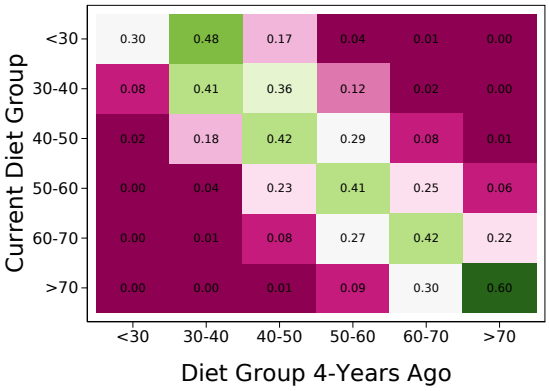
(c) Spouse college



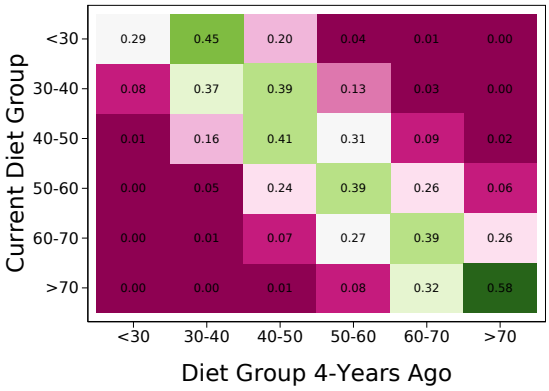
(d) Spouse non-college



(e) Children



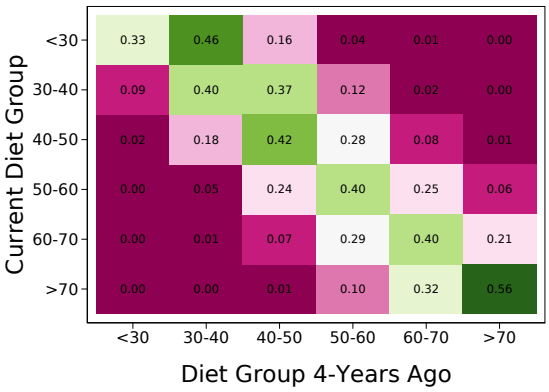
(f) No Children



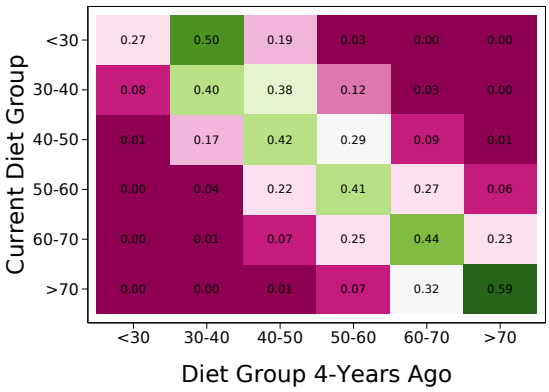
Notes: Figure plots the 4-year transition probability between different diet groups by marital status, education status of spouse, and fertility status. Having children indicate those nurses who had at least one child (measured by pregnancies that resulted in the delivery at $\geq$6 months gestation) and no-children outcomes are for those with no biological children (zero parity). NHS II respondents aged 25-30 in 1989 are considered. Pooled data between 1991 and 2015 is used to construct the 4-year transition probabilities.

Figure A30: Persistence of diet
by mental health, smoking and working shift status

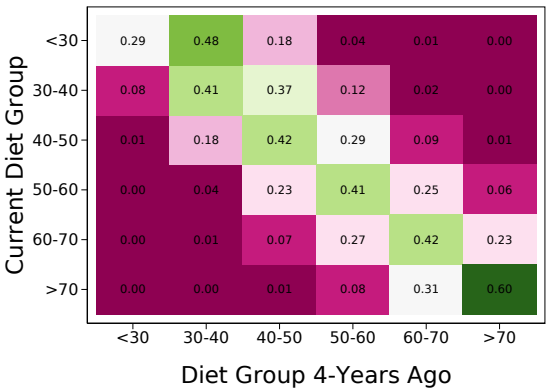
(a) Low mental health



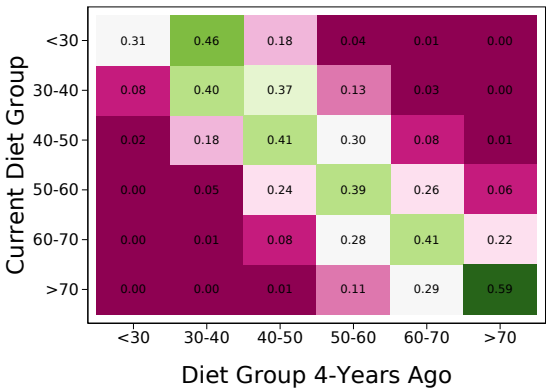
(b) High mental health



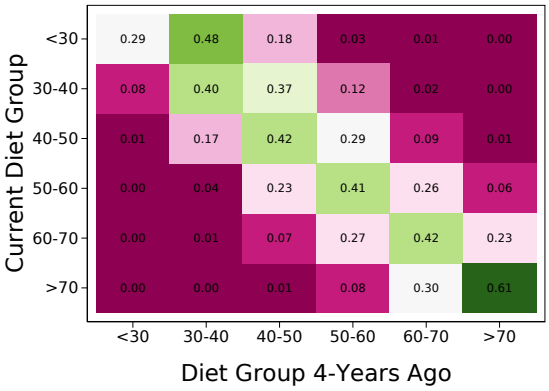
(c) Non-smokers



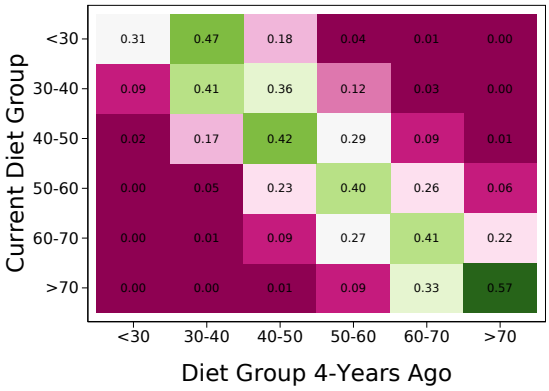
(d) Smokers



(e) Day shift



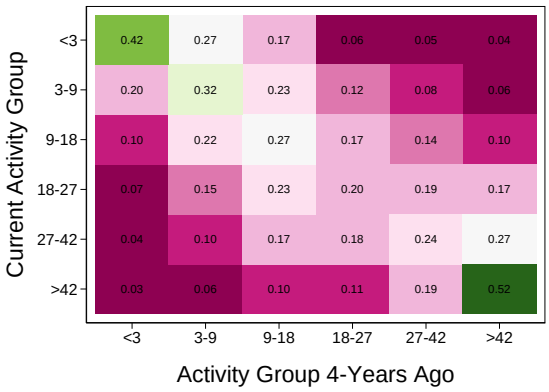
(f) Night shift



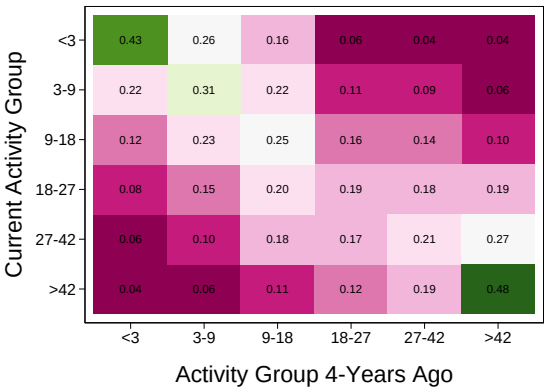
Notes: Figure plots the 4-year transition probability between different diet groups by mental health, smoking status and night shift working status. High mental health refers to those in the highest tercile of the mental health index and low refers to those in lowest tercile. Mental health was measured in 1993 using SF-36 mental health index. Smoking status was measured in 2015 as (1) smoked currently or in past and (2) never smoked. Working shift history was measured in 2009. We categorize night shift nurses as those who exclusively worked night-shifts during some point of their life as discussed in the text. NHS II respondents aged 25-30 in 1989 are considered. Pooled data between 1991 and 2015 is used to construct the 4-year transition probabilities.

Figure A31: Persistence of physical activity
by marital status, education of spouse, and fertility status

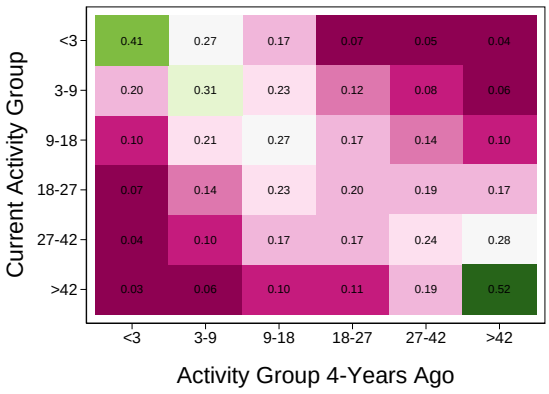
(a) Married



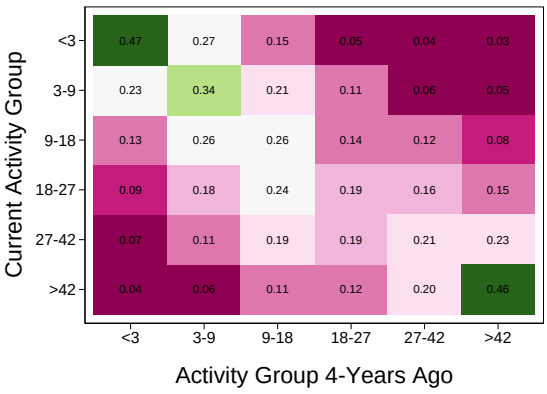
(b) Non-married



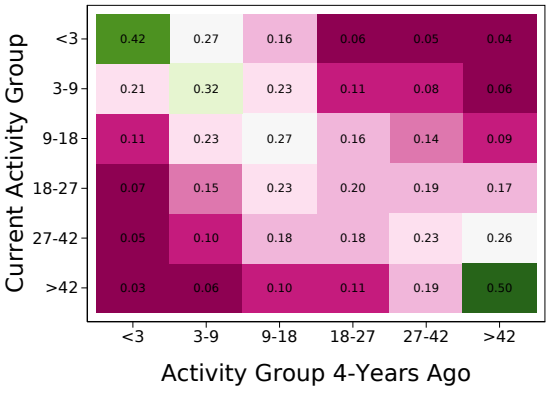
(c) Spouse college



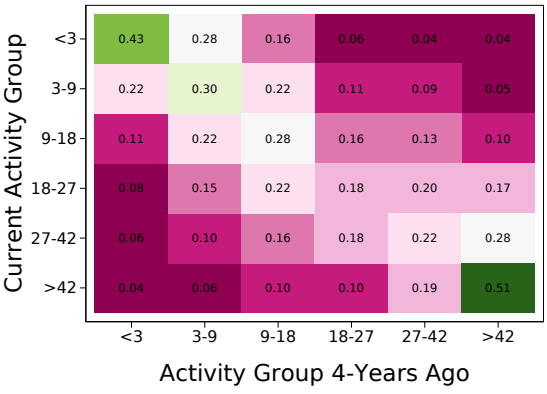
(d) Spouse non-college



(e) Children



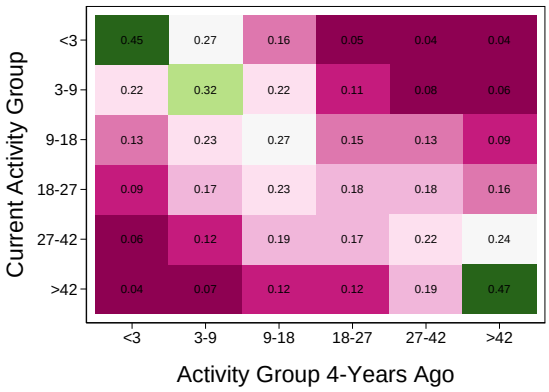
(f) No Children



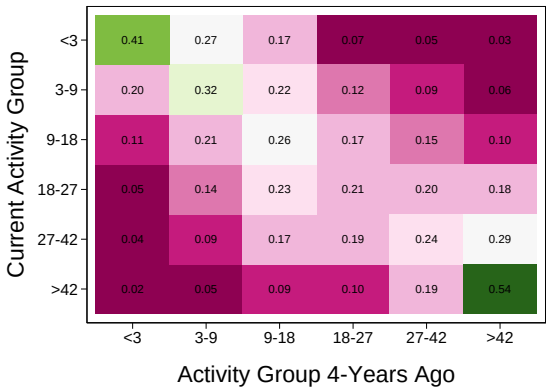
Notes: Figure plots the 4-year transition probability between different physical activity groups by marital status, education status of spouse, and fertility status. Having children indicate those nurses who had at least one child (measured by pregnancies that resulted in the delivery at $\geq$6 months gestation) and no-children outcomes are for those with no biological children (zero parity). NHS II respondents aged 25-30 in 1989 are considered. Pooled data between 1991 and 2015 is used to construct the 4-year transition probabilities.

Figure A32: Persistence of physical activity
by mental health, smoking and working shift status

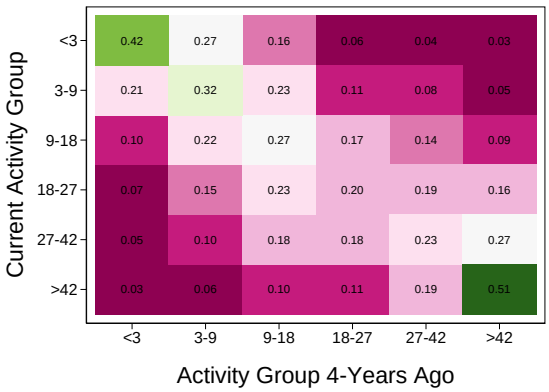
(a) Low mental health



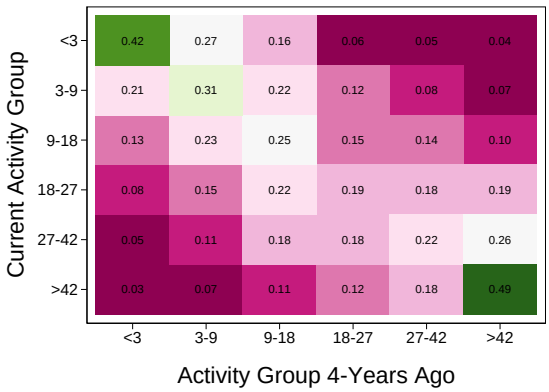
(b) High mental health



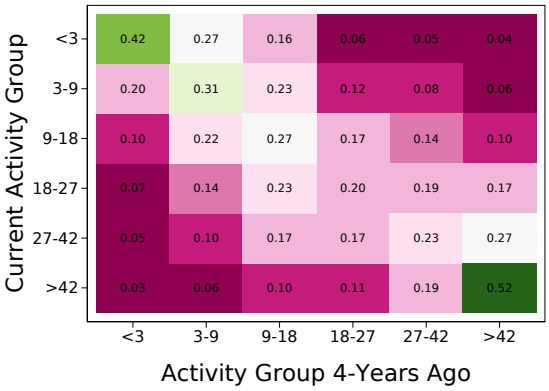
(c) Non-smokers



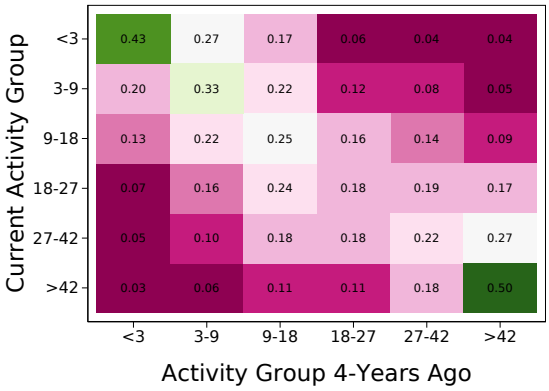
(d) Smokers



(e) Day shift

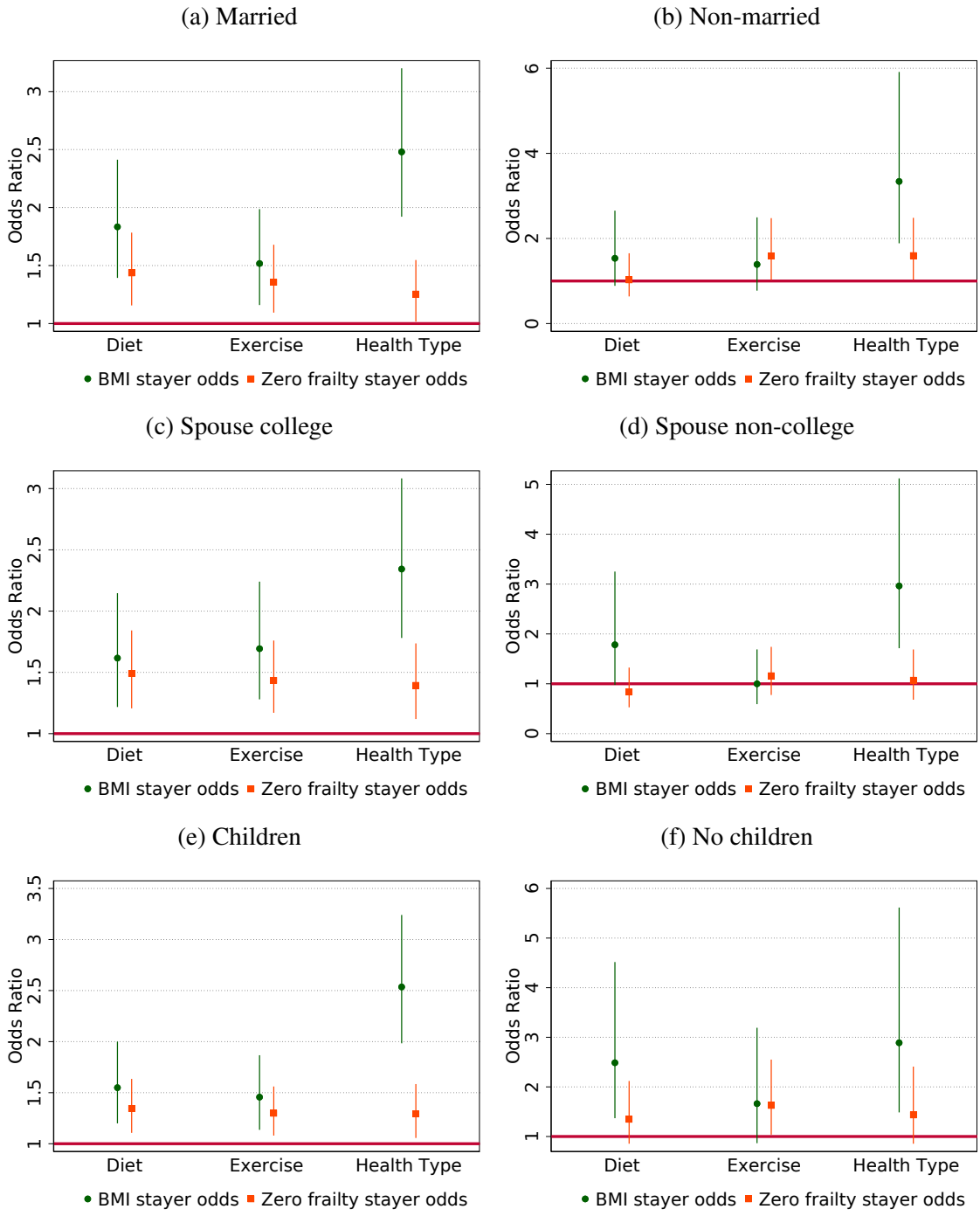


(f) Night shift



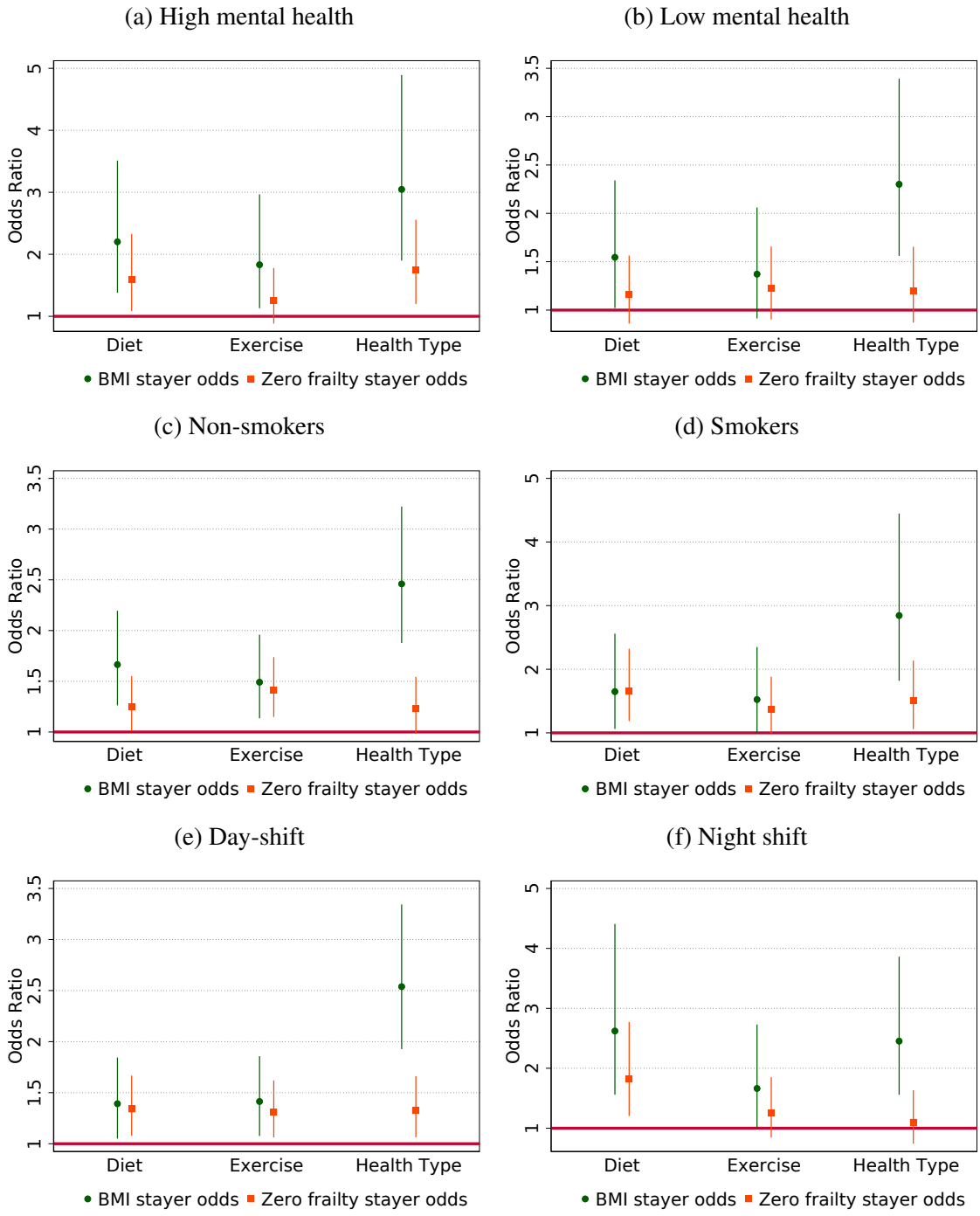
Notes: Figure plots the 4-year transition probability between different physical activity groups by mental health, smoking status and night shift working status. High mental health refers to those in the highest tercile of the mental health index and low refers to those in lowest tercile. Mental health was measured in 1993 using SF-36 mental health index. Smoking status was measured in 2015 as (1) smoked currently or in past and (2) never smoked. Working shift history was measured in 2009. We categorize night shift nurses as those who exclusively worked night-shifts during some point of their life as discussed in the text. NHS II respondents aged 25-30 in 1989 are considered. Pooled data between 1991 and 2015 is used to construct the 4-year transition probabilities.

Figure A33: Role of initial conditions
by marital status, education of spouse, and fertility status



Notes: Sample includes NHS II respondents with healthy BMI and zero frailties in 1989. The figure plots the odds ratio of being a BMI stayer (healthy BMI in 2015) and frailty stayer (zero frailties in 2015) for permanent health types (top vs bottom groups), diet (top vs bottom decile) and exercise (top vs bottom decile) by marital status, education of husband and fertility. Diet and exercise taken from the 1991 wave (roughly age 30). Having children indicate those nurses who had at least one child (measured by pregnancies that resulted in the delivery at $\geq$6 months gestation) and no-children outcomes are for those with no biological children (zero parity).

Figure A34: Role of initial conditions
by mental health, smoking and working shift status



Notes: Sample includes NHS II respondents with healthy BMI and zero frailties in 1989. The figure plots the odds ratio of being a BMI stayer (healthy BMI in 2015) and frailty stayer (zero frailties in 2015) for permanent health types (top vs bottom groups), diet (top vs bottom decile) and exercise (top vs bottom decile) by smoking status and night shift working status. Diet and exercise taken from the 1991 wave (roughly age 30). High mental health refers to those in the highest tercile of the mental health index and low refers to those in lowest tercile. Mental health was measured in 1993 using SF-36 mental health index. Smoking status was measured in 2015 as (1) smoked currently or in past and (2) never smoked. Working shift history was measured in 2009. We categorize night shift nurses as those who exclusively worked night-shifts during some point of their life as discussed in the text.

A5 Additional results

Table A5: Ordered logit estimates of BMI law of motion

	Estimates
BMI in $t-1$	
$b=2$	3.031***
$b=3$	5.385***
$b=4$	7.199***
$b=5$	8.977***
$b=6$	11.93***
Diet Quality	-0.209***
Physical Activity	-0.142***
Permanent Health Group=2	-0.187***
Permanent Health Group=3	-0.418***
cut 1	-0.0268
cut 2	2.760***
cut 3	4.986***
cut 4	6.998***
cut 5	10.40***
Observations	31102
Pseudo R^2	0.3667

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table A6: Ordered Logit Estimates of BMI Law of Motion with Frailty

	Estimates
BMI in $t-1$	
$b=2$	3.027***
$b=3$	5.378***
$b=4$	7.191***
$b=5$	8.974***
$b=6$	11.94***
Frailty in $t-1$	
h=1	0.108**
h=2	-0.282**
h=3	0.103
h=4	-1.173
h=5	-0.586
Diet Quality	-0.210***
Physical Activity	-0.142***
Permanent Health Group=2	-0.187***
Permanent Health Group=3	-0.418***
cut 1	-0.0251
cut 2	2.763***
cut 3	4.990***
cut 4	7.004***
cut 5	10.42***
Observations	31102
$PseudoR^2$	0.367

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: Logit estimates of frailty law of motion

	Estimates
Frailty=1	0.627
Age	0.0305***
Frailty=1 $\times$ Age	-0.0181
Diet Quality	-0.176***
Physical Activity	-0.0546*
BMI in $t-1$	
b=2	0.545***
b=3	0.983***
b=4	1.342***
b=5	1.482***
b=6	1.902***
Permanent Health Group=2	-0.200***
Permanent Health Group=3	-0.324***
Constant	-3.174***
Observations	31942
R^2	0.0495

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A8: Ordered logit estimates of medical expenditure Group

	Estimates
Age group	
$j = 2$	0.106**
$j = 3$	-0.000
$j = 4$	0.192***
$j = 5$	0.372***
$j = 6$	0.578***
$j = 7$	0.798***
BMI	
$b = 2$	0.057**
$b = 3$	0.167***
$b = 4$	0.318***
$b = 5$	0.406***
$b = 6$	0.702***
Frailty	
$h = 1$	0.803***
$h = 2$	1.563***
cut 1	-1.007
cut 2	0.104***
cut 3	1.384***
cut 4	2.601***
cut 5	3.452***
cut 6	5.346***
Observations	70519
Pseudo R^2	0.0335

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A9: Distribution of subset of initial conditions

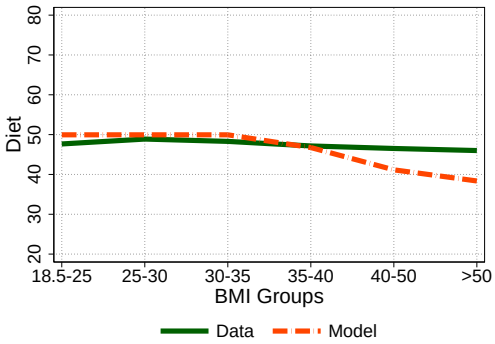
	Uncond. share (%)	Conditional share (%)					
		Permanent health group			Activity group		
		Bottom	Middle	Top	Inactive	Middle	Active
Unconditional share (%)		12.57	50.62	36.81	16.96	67.29	15.75
BMI groups							
18.5-24	74.10	55.50	71.37	81.52	66.54	74.42	81.01
25-29	17.12	24.86	18.81	15.10	19.76	17.26	13.75
30-34	5.64	11.56	6.39	2.63	7.77	5.52	3.76
35-39	2.14	4.91	2.51	0.59	3.50	2.02	1.12
40-49	0.90	2.93	0.84	0.13	2.08	0.73	0.37
50+	0.09	0.24	0.08	0.03	0.35	0.05	0
Frailty groups							
Zero morbidities	96.7	94.52	97.01	98.26	96.76	96.79	96.88
One morbidity	3.3	5.48	2.99	1.74	3.24	3.21	3.12
Average diet quality	41.28	41.61	41.32	42.19	37.60	41.25	45.42

Table A10: Calibrated parameters: Model validation experiments

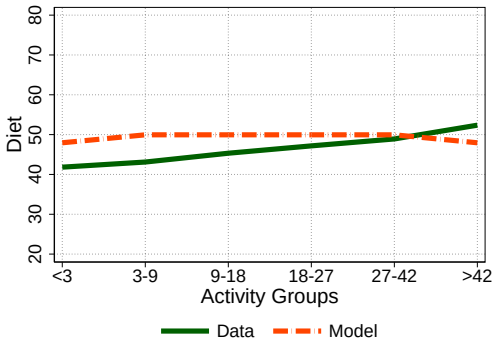
Parameter	Benchmark	No Diet Habits	No Exercise Types	Discount Rate Het.
ψ_1	0.68	0.68	0.51	0.51
ψ_2	3.51	3.51	2.70	2.60
λ_b	0.57	0.57	0.53	0.52
λ_h	0.18	0.18	0.18	0.17
τ_1	0.66	0.66	0.66	0.66
τ_2	1.35	2.00	1.35	1.61
υ_b	0.55	0.42	0.54	0.40
υ_q	7.36	-	7.36	4.36
κ_b	0.77	0.77	0.77	0.77
σ_e	0.67	0.67	0.45	0.48
σ_q	0.70	0.40	0.70	0.45
$\overline{\xi}$	4.81	5.12	-	-
$\underline{\xi}$	0.27	0.27	-	-
β	0.96	0.96	0.96	0.96
β_l	-	-	-	0.89
β_h	-	-	-	0.98

Figure A35: Correlations: Model vs. data

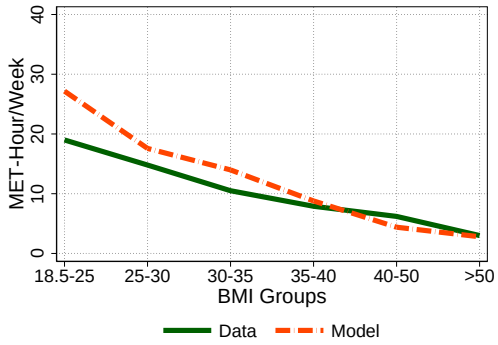
(a) Diet quality and BMI



(b) Diet quality and physical activity



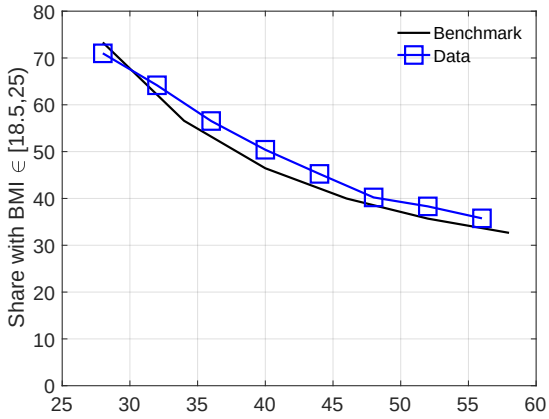
(c) Physical activity and BMI



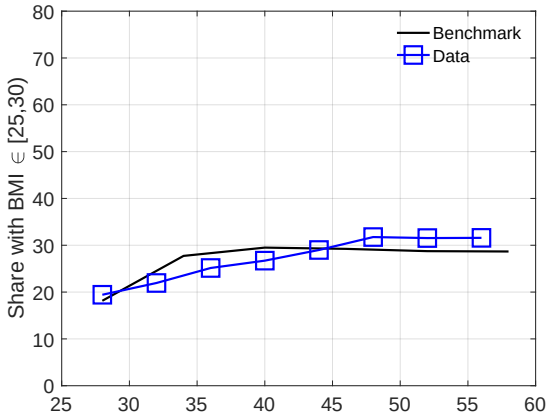
Notes: Panel (a) plots median diet quality for six BMI groups, panel (b) plots median diet quality for six exercise groups, and panel (c) plots median exercise for six BMI groups.

Figure A36: Life-cycle evolution of BMI: Data vs. model

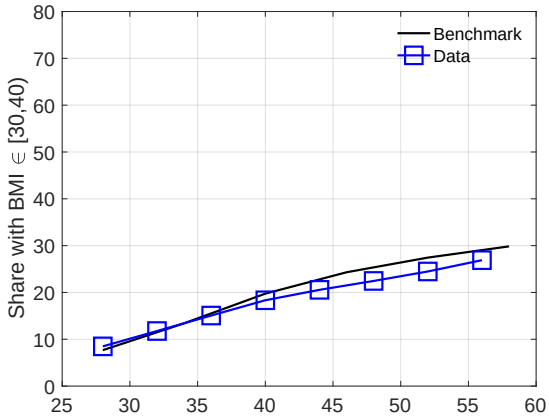
(a) Healthy weight



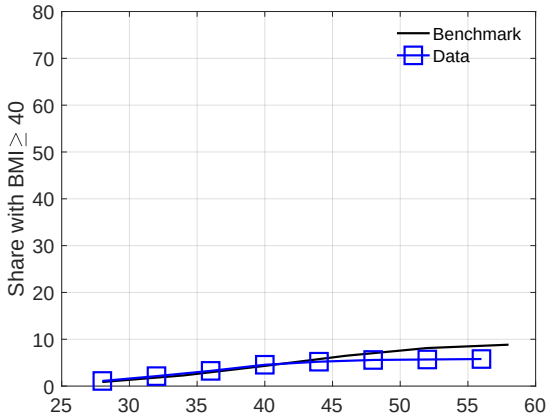
(b) Overweight



(c) Class I & II obese



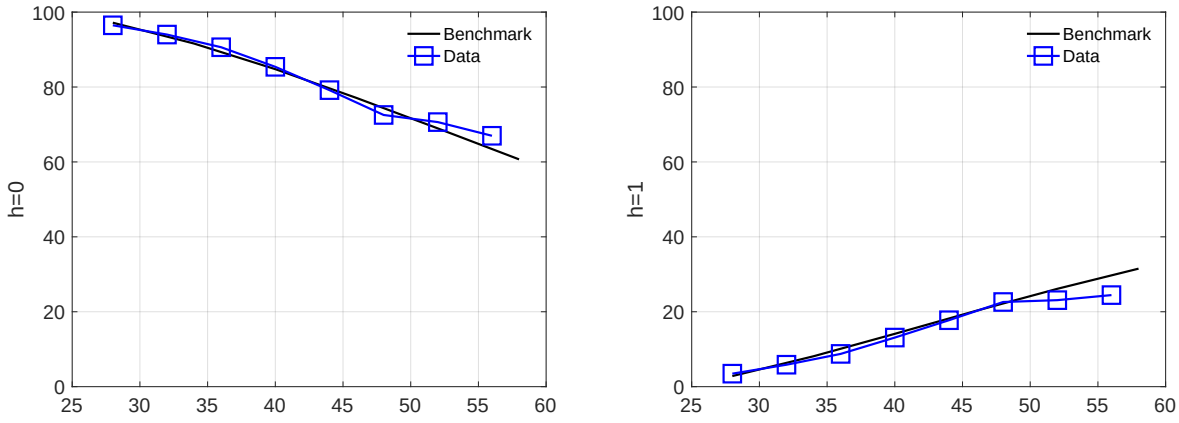
(d) Class III obese and higher



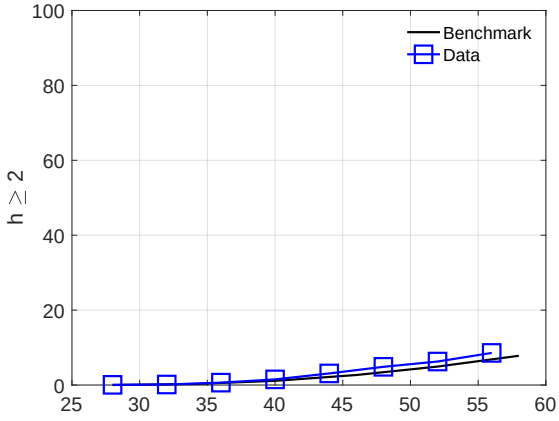
Notes: Panels (a), (b), (c), and (d) plot, respectively, the age-specific share of agents with a BMI between 18.5 and 25.0, between 25.0 and 30.0, between 30.0 and 40.0, and 40.0+ in the benchmark model (black) and the data (blue squares).

Figure A37: Life-cycle evolution of frailty: Data vs. model

(a) $h = 0$ (b) $h = 1$



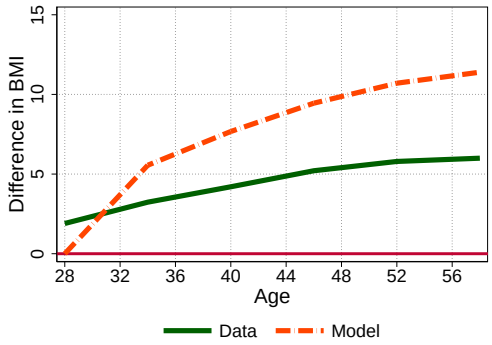
(c) $h \geq 2$



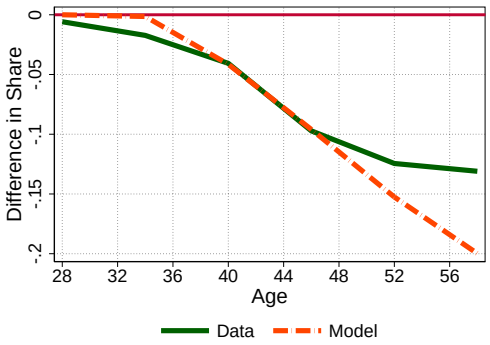
Notes: Panels (a), (b), and (c) plot, respectively, the age-specific share of agents with 0, 1, or 2+ frailties in the benchmark model (black) and the data (blue squares).

Figure A38: BMI and frailty divergence: Model vs. data

(a) BMI



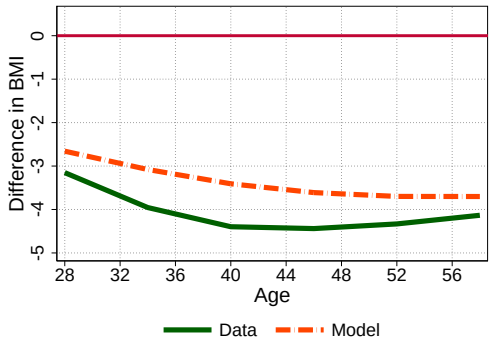
(b) Frailty



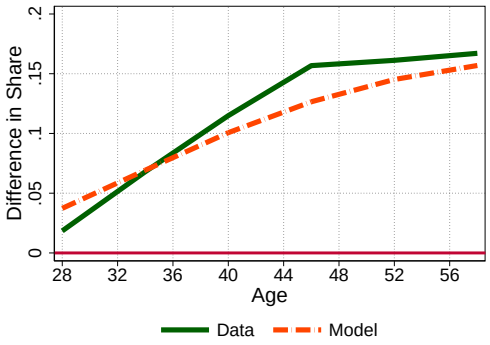
Notes: The figures plot the difference in average outcomes for those whose BMI increased from healthy (18.5-25) in 1989 to unhealthy (>25) at some point between 1989 and 2015 and average outcomes for those who consistently maintained a healthy BMI between 1989 and 2015 in both the data (solid line) and model (dashed line).

Figure A39: Permanent health: Model vs. data

(a) BMI



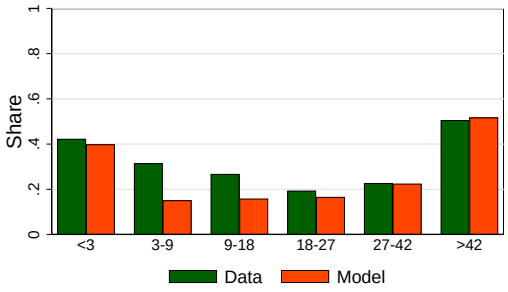
(b) Frailty



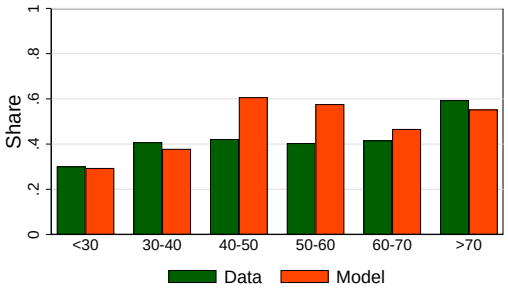
Notes: The figures plot the difference in average outcomes for those with a permanent health index ≥ 6 minus average outcomes for those with a permanent health index ≤ 3 both in the data (solid lines) and the model (dashed lines).

Figure A40: Persistence in diet and exercise: Model vs. data

(a) Exercise



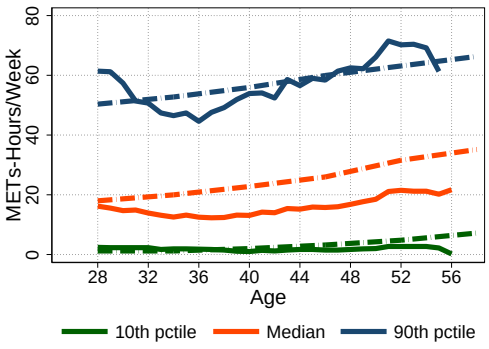
(b) Diet



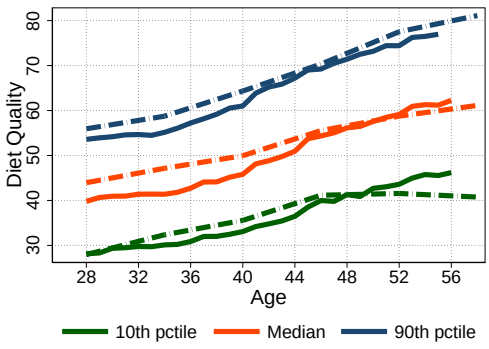
Notes: The figures plot the share of those who maintained their respective exercise and diet groups 4-years later, both in the model and the data.

Figure A41: Diet and exercise age distribution: Model vs. data

(a) Exercise



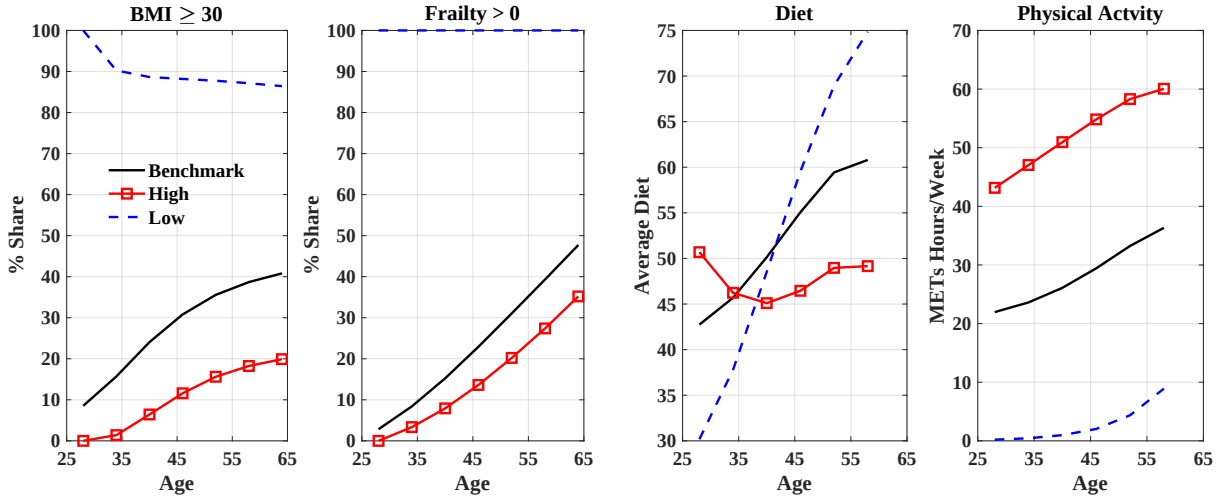
(b) Diet



Notes: The figures plot the life-cycle evolution of the exercise and diet distribution, both in the model and the data.

Figure A42: Life-cycle evolution of health and effort: Equalizing all initial conditions

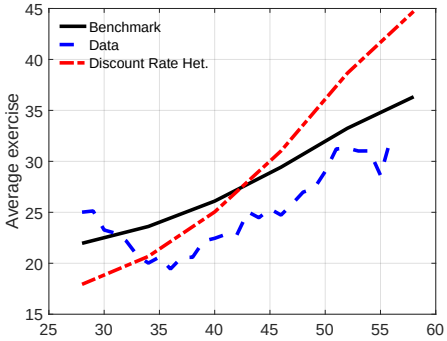
(a) Health outcomes (b) Effort



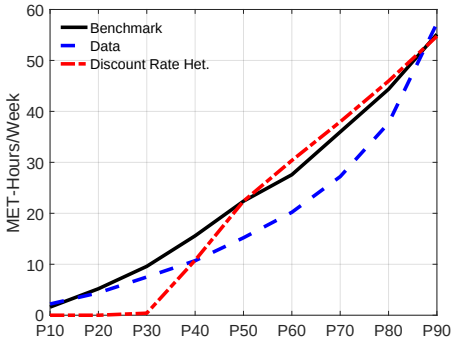
Notes: Outcomes plotted for benchmark model and the experiments where all initial conditions are equalized to their poor levels (dashed blue lines) and good levels (solid red lines) for all agents. The poor initial levels correspond to all agents being assigned obese class I ($b = 3$, or BMI = 32.16), one frailty ($h = 1$), low permanent health ($\alpha = 1$), 10^{th} percentile for diet habits, and low exercise types ($\xi > 1$). For good levels, everyone is assigned healthy weight ($b = 1$, or BMI = 22.06), zero frailty ($h = 0$), 90^{th} percentile for diet habits, high permanent health ($\alpha = 3$), and high exercise type ($\xi < 1$).

Figure A43: Diet and physical activity: Discount rate heterogeneity

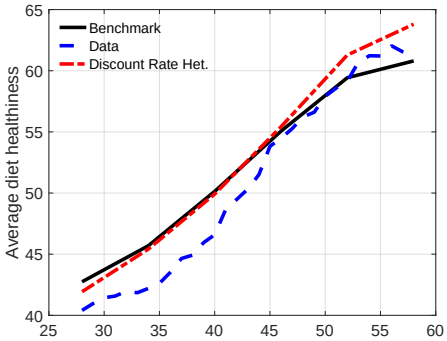
(a) Physical Activity by Age



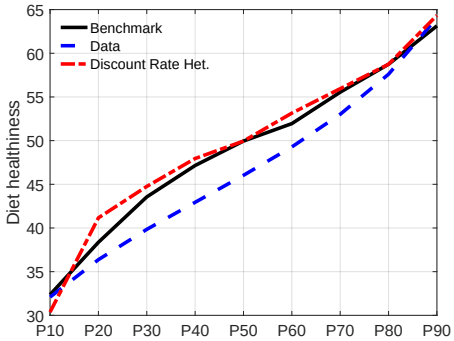
(b) Distribution of Physical Activity



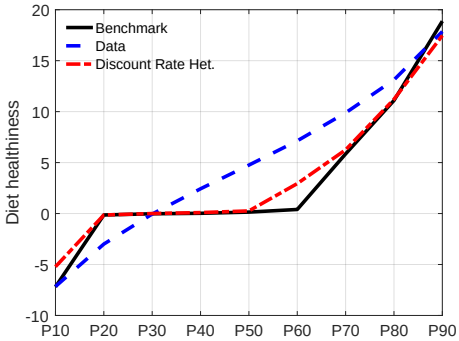
(c) Diet by Age



(d) Distribution of Diet



(e) Distribution of Change in Diet



Notes: Panels (a) and (c) plot, respectively, the age-specific averages for exercise and diet quality in the benchmark model and the re-calibrated model with discount rate heterogeneity replacing exercise types. Panels (b), (d), and (e) plot, respectively, the percentile distribution of exercise, diet quality, and change in diet quality ($q - q_{-1}$) in the benchmark model and the discount rate heterogeneity model.