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Estimating Transition Probabilities Between Health States Using U.S. Longitudinal Survey Data*

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Abstract

We use data from two representative U.S. household surveys, the Medical Expenditure Panel Survey (MEPS) and the Health and Retirement Study (RAND-HRS) to estimate transition probability matrices between health states over the lifecycle from age 20–95. We compare non-parametric counting methods and parametric methods where we control for individual characteristics as well as time and cohort effects. We align two year transition probabilities from HRS with one year transition probabilities in MEPS using a stochastic root method assuming a Markov structure. We find that the non-parametric counting method and the regression specifications based on ordered logit models produce similar results over the lifecycle. However, the counting method overestimates the probabilities of transitioning into bad health states. In addition, we find that young women have worse health prospects than their male counterparts but once individuals get older, being female is associated with transitioning into better health states with higher probabilities than men. We do not find significant differences of the conditional health transition probabilities between African Americans and the rest of the population. We also find that the lifecycle patterns are stable over time. Finally, we discuss issues with controlling for time effects, sample attrition, the Markov assumption, and other modeling issues that can arise with categorical outcome variables.

JEL: I10, C14, C23, C25, D15

Keywords: Lifecycle profiles of health transition probabilities, Medical Expenditure Panel Survey (MEPS), Health and Retirement Study (RAND-HRS), health transition matrices, conditional health transition probabilities, Markov property, age-time-cohort effects.

1 Introduction

Modeling health risk over the lifecycle has become an important component in recent studies assessing public policy reforms and the macroeconomic effects of demographic change (e.g., French and Jones, 2011; İmrohoroğlu and Kitao, 2012; Pashchenko and Porapakkarm, 2013; Jung and Tran, 2016; Jung, Tran and Chambers, 2017; Fonseca et al., 2021). In this literature household income, health spending, as well as survival probabilities are often modeled as functions of age and health. Since the evolution of

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an individual's health tends to be driven by relatively rare but potentially large adverse effects, precise estimates of health or health shock processes require large data sets. In this paper we combine information from two large U.S. household surveys—the Medical Expenditure Panel Survey (MEPS) and the RAND version of the Health and Retirement Study (RAND-HRS)—and estimate transition probabilities between self-reported health states.[1] A key advantage of our method is that our combined data set is large enough to produce very precise estimates over the entire lifecycle from age 20–95, even for transitions into relatively rare states of health.

In addition to being important building blocks for lifecycle modeling, health transition probabilities are also of interest to a wider variety of stakeholders working in the fields of economics, epidemiology, insurance, and public policy. As such the analysis of health states using survey data has spawned a large literature. This paper contributes to this literature as follows:

First, we combine the latest available data from two representative U.S. surveys in order to construct a representative sample of the U.S. population over the entire lifecycle. The MEPS and the RAND-HRS provide suitable panel data for the construction of health transition probabilities since they both include a self assessment health (SAH) question that asks respondents to assess their current health according to five categories indicating either 1. Excellent, 2. Very Good, 3. Good, 4. Fair, or 5. Poor health. Since the surveys also record if an individual has died, we include a 6^{th} state of death. We then use a non-parametric counting method as well as parametric regressions based on categorical outcome variables, to estimate conditional health transition probabilities for individuals between the age of 20–95. The combination of the two surveys allows us to base our estimates on representative samples of all age groups. Prior research is typically more narrowly focused on specific age groups with more targeted data sets (e.g., Diehr and Patrick, 2001; Kapteyn and Meijer, 2014).

Second, we compare non-parametric and parametric estimation methods and show that non-parametric counting methods that only condition future health states on current ones (i.e., first order Markov assumption) can replicate the overall trend of health transitions over the lifecycle but do significantly overestimate health risks. While modeling health states as a Markov switching process is a parsimonious way to describe the evolution of health over the lifecycle, its assumption that tomorrow's health state is exclusively a function of today's health state and that all past health information is contained in the present health state, is not likely to hold for health transitions. Recent research into the health accumulation/depreciation process suggests that health evolves as a result of the accumulation of health deficits over time (e.g., Rockwood and Mitnitski, 2007; Dalgaard and Strulik, 2014), so that individuals who currently report identical health states may nevertheless have accumulated different health deficit levels. This would result in different transition probabilities into future health states and violate the Markov property. Chronic conditions are additional examples of strong links between past and current health. As a consequence a strict Markov assumption may be too strong and the inclusion of more explanatory factors into the econometric specifications of health transition processes is warranted. In fact, tests for homogeneity (time invariant Markov transition probabilities) and first vs. second order Markov property with respect to lagged health states are rejected based on frequency counts from the non-parametric setup. In our parametric specifications we therefore include additional factors such as income, gender,

[1] MEPS is a representative household survey of the U.S. working population while the HRS is a survey representative of the older population in the U.S.

race, education, life-style choices such as smoking, initial health as well as cohort and time effects while maintaining the assumption that tomorrow's health state is strongly determined by today's health. Using this richer setup will make model predictions more accurate as different types of individuals with identical self reported current health, can now differ in their probabilities to transition into specific future health states.

Third, we resolve a survey frequency issue using an algorithm based on stochastic root methods which allows us to produce consistent annual transition probabilities over the entire lifecycle from both surveys. We demonstrate that once period length is adjusted, the health transition probabilities become more aligned which highlights the fact that the five state SAH variable is interpreted consistently by the respondents to the two surveys.

Fourth, we show that while it is not possible to simultaneously control for age, cohort, and time effects when estimating transition probabilities due to perfect multicollinearity, controls for time periods (as opposed to every year) are statistically significant and should therefore be added to soak up some of the time effects between 2000–2017, a period with significant innovations in health care that have been linked to a 1.5 year increase in life expectancy.[2]

Finally, we are able to show a systematic trend of higher health risks for females when young which is subsequently reversed once individuals pass age 50. We do not find statistically significant differences of conditional health transitions over the lifecycle by race.

Related Literature. The epidemiological literature has used non-parametric counting methods to estimate future years of healthy life using SAH variables. Siebert et al. (2012) provides a summary of the issues involved in health transition modeling in clinical decision analysis. Diehr et al. (1998) and Diehr and Patrick (2001) are two examples using non-parametric counting methods and data on older individuals in the U.S. Adding to this literature we present precisely estimated health transition probabilities over the entire lifecycle based on representative U.S. data for a large number of age groups over the lifecycle. In addition, since we work with survey data, we also include parametric models to parsimoniously account for survey weights and individual heterogeneity.

There is a large literature that focuses on tracking health inequalities using SAH questions (e.g., Kakwani, Wagstaff and van Doorslaer, 1997; Deaton and Paxson, 1998; Doorslaer and Jones, 2003; Ziebarth, 2010). More recently this literature expanded into studying the intergenerational links of health (Halliday, Mazumder and Wong, 2020, 2021). The most prevalent SAH question that is used in many nationally representative household surveys—such as the MEPS, HRS, NLSY, PSID (all for U.S.), HILDA (Australia), SOEP (Germany), NPHS (Canada), BHPS (UK) to name just a few—asks respondents to assess their general health status (often in comparison to one's peer age group) using five categories: Excellent, Very Good, Good, Fair, or Poor. These type of variables have been shown to be good predictors of mortality across many studies as discussed in Idler and Benyamini (1997). In addition, Gerdtham et al. (1999) have shown that a continuous variable constructed from categorical SAH measures based on the method in Wagstaff and Doorslaer (1994) is highly correlated with other continuous health measures that are often elicited from respondents in household surveys. As such, categorical SAH variables carry important information despite their "subjectivity." For these reasons SAH variables have been widely used in economics

[2]Compare Catillon, Cutler and Getzen (2018) and life tables from the CDC at: https://www.cdc.gov/nchs/nvss/life-expectancy.htm

since the mid eighties (e.g., Okun et al., 1984; Idler and Kasl, 1995; Deaton and Paxson, 1998). More recent studies point towards reporting inconsistencies of the categorical SAH variable described above and the importance of framing the question in a survey context (Crossley and Kennedy, 2002; Clarke and Ryan, 2006; Juerges, 2007). New statistical approaches address some of these issues and attempt to achieve consistency of this variable across surveys—including cross country consistency (Doorslaer and Jones, 2003; Lindeboom and van Doorslaer, 2004; Meijer, Kapteyn and Andreyeva, 2011). While our project does not attempt to track health inequality or explain the nature of the elicited information contained in the categorical SAH variable, our conditional health transition probabilities do show significant differences by gender and age groups and also show strong consistency across two representative U.S. household surveys once the transition matrices are weighted properly and adjusted for period length.

More recently the literature on estimating health states has addressed issues of endogeneity and unobserved heterogeneity with finite mixture models and partially structural systems estimation techniques such as conditional mixed processes (Contoyannis and Jones, 2004; Balia and Jones, 2008; Balia, 2014). Closest to our study is Contoyannis, Jones and Rice (2004) who estimate health transitions with panel data from a British household survey using an ordered probit model. Different from their paper our focus is not the identification of marginal effects of specific input variables into the health production process. And, while we do provide some results based on mixture and mixed processes models, our overall focus is on mapping conditional health transition probabilities for different types of individuals over the entire lifecycle combining information from two large representative U.S. household surveys. This will be useful to researchers interested in lifecycle modeling of economic behavior affected by health and health policies. To the best of our knowledge the literature has not yet presented a consistent treatment of health state observations across MEPS and HRS.

Finally, the empirical labor economics literature has investigated the effects of (self-reported) health on labor market decisions, especially towards the end of the lifecycle (e.g., Kerkhofs and Lindeboom, 1995; Lindeboom and Kerkhofs, 2009; Kapteyn and Meijer, 2014). This literature is often linked to the health capital model by Grossman (1972) which provides a theoretical framework for health investment decisions over the lifecycle while also accounting for labor market decisions.[3] SAH measurements are often used in empirical implementations of this model which has spawned a large literature.[4] As such, health transition probabilities have begun to play an important role in lifecycle models with health uncertainty and health spending heterogeneity. While lifecycle consumption models have been a standard vehicle for modeling tax and pension reforms for a long time (e.g., Bewley, 1986; Huggett, 1993; Aiyagari, 1994; İmrohoroğlu, İmrohoroğlu and Joines, 1995), the addition of health risk into these frameworks is relatively new. In light of recent developments in the U.S. healthcare sector such as the introduction of the Affordable Care Act in 2010 but also issues of sustainability of the two large public health insurance programs, Medicare and Medicaid, it has become more important to include health risk into the aforementioned decision frameworks (e.g., Palumbo, 1999; French, 2005; De Nardi, French and Jones, 2010; French and Jones, 2011; İmrohoroğlu and Kitao, 2012; Pashchenko and Porapakkarm, 2013; Jung and Tran, 2016;

[3] A related approach by Dalgaard and Strulik (2014) has focused on modeling the dynamics of health as a health deficit accumulation process that eventually ends in death which can be measured with a frailty index. An introduction to the frailty index measure can be found in Rockwood and Mitnitski (2007).

[4] Cutler and Richardson (1997) and more specifically Grossman (2000) provide summaries of this empirical literature concerning health capital.

Jung, Tran and Chambers, 2017; Fonseca et al., 2021). In this recent literature household income, health spending, as well as survival probabilities are often modeled as functions of age and health. Our study will be informative for quantitative modelers of the lifecycle effects of health and health risk as conditional health transition probabilities represent an important building block in these types of models.

The paper is structured as follows. The next section describes the data. Section 3 introduces the non-parametric counting method. Section 4 discusses the parametric logit and probit models. Section 5 present the results and section 6 concludes the paper.[5]

2 Data

2.1 Medical Expenditure Panel Survey (MEPS)

We use data from the Medical Expenditure Panel Survey (MEPS) from the years 2000–2017. MEPS provides a nationally representative survey about health care use, health expenditures, health insurance coverage as well as demographic data on income, health status, and other socioeconomic characteristics. The original household component of MEPS was initiated in 1996. Each year about $15,000$ households are selected and interviewed five times over two full calendar years using an overlapping panels design.[6] MEPS groups individuals into Health Insurance Eligibility Units (HIEU) which are subsets of households. We do abstract from family size effects and concentrate on adults aged 20 to 65 who are the head of the HIEU.

We focus our analysis on the economically active population from age 20 upwards. Since MEPS is not representative of the older population and since attrition issues have been reported for individuals older than 65 we limit the sample to individuals up to age 65.[7] In addition, we limit the sample to head of HIEUs as standard lifecycle models are traditionally calibrated or estimated using head of household information. The restricted sample is based on observables used in a regression framework which uses next periods health state as dependent variable and a series of demographic and household specific control variables such as age, gender, partnership status, smoking behavior, race, education status, household income, and census region. We therefore lose information from the last wave of MEPS in 2017 as we only use the health status information from that year. Since information about smoking behavior is only available from 2000 onward, we use observations from 2000–2017.

2.2 RAND-HRS

We use 13 waves of the RAND-HRS. The HRS collects data every two years and data is available from 1992–2016.[8] It is a composite data set that combines seven cohorts to construct a nationally representative panel of the older population in the U.S. The cohorts comprise the AHEAD cohorts born before 1924, the

[5] Appendices A–I contain additional results including additional summary statistics, ordered probit models, multinomial logit and probit models, transition probabilities based on samples from two different time periods, detailed lifecycle transition probabilities by gender, race, and race and time, as well as results from finite mixture and mixed processes models.

[6] Chowdhury, Machlin and Gwet (2019) provides details about the MEPS survey designs.

[7] Section 5.8 contains a more detailed discussion about attrition bias issues in MEPS and HRS.

[8] The RAND-HRS is developed from the HRS and comprises a cross-wave file with variables derived consistently across waves. The RAND-HRS is maintained by the RAND Center of Aging. More information is available at: https://www.rand.org/well-being/social-and-behavioral-policy/centers/aging/dataprod/hrs-data.html

CODA cohorts born between 1924–1930, the HRS cohorts born between 1931–1941 and the War Baby cohorts born between 1942–1947, Early Baby Boomer cohort born between 1948–1953, Mid Baby Boomer cohort born between (1954–1959), and most recently the Late Baby Boomer cohort born between 1960–1965. It is a longitudinal survey conducted every two years starting from 1992. A particular strength of the HRS is its use of a steady-state sampling design that introduces a new cohort of individuals age 51–56 very 6 years (e.g., 1998, 2004, 2010, and 2016). The survey covers a broad range of topics, including health, income, assets, employment, retirement, insurance, and family structure.[9]

Survey respondents are non-institutionalized individuals and we exclude individuals living in nursing homes from the analysis. The majority of them were between 51 and 61 years old when the survey was first conducted in 1992. The baseline survey included $12,652$ persons, or $7,600$ households, with over sampling of Mexican Americans, African Americans and residents of Florida. Juster and Suzman (1995) present a general overview of the HRS and Wallace and Herzog (1995) review the health measures in particular. We limit the sample to heads of households and to the age group of 50–95 year olds as the HRS is not representative of the younger population and attrition bias has been reported for the very old age groups.

2.3 Construction of Health Status Variables in MEPS and HRS

MEPS. Unlike the HRS, the MEPS is an overlapping/rotating panel. A person is interviewed 5 times in a two-year time frame which results in three health state observations for each of the two years that an individual is present in the survey. Round three in the first year and round one in the second year do overlap. In order to correct for missing health state values, we interpolate missing health state information and then calculate average health states for each year using the available health state data points (up to three are available for every year that an individual responds). We then round to the nearest integer value and record the health state in variable h_t.

If a person dies in period 1 (of the two observed years) and a health state has been recorded prior to death, a forward looking health state variable is generated indicating a health state $h_{t+1} = 6$ (i.e., dead) and a death transition from the recorded health state h_t prior to death is recorded. Similarly, if a person dies in period 2, and a health state is recorded in h_{t+1}, we generate $h_{t+2} = 6$ and count this person as a transition to death from her last recorded health state h_{t+1}.

HRS. HRS data is available every two years. Whenever an agent leaves the survey due to death it is reported and, if that happens, usually very few other variables are reported in the same year (or wave). We therefore count this death event as a transition to a forward looking health state $h_{t+2} = 6$ (i.e., dead) with respect to the person's health state h_t two years prior (in the previous wave). All other individuals leaving the survey are assumed to be alive with unknown health state.

If health state information is missing we interpolate health measures with health state information in the previous and next round of the interview. Diehr and Patrick (2001) report that interpolated values tend to be under dispersed and they suggest to add a small random error. Given the two-year observational lags and leads in the HRS (as opposed to the much shorter lags/leads of less than half a year in MEPS where we have roughly three health state observations per year), we follow their method

[9] Fisher and Ryan (2017) provides a recently published summary of the Health and Retirement Study

and add a small random error after interpolation and then round to the nearest health category. Engels and Diehr (2003) report that this method is less biased than other methods.

2.4 Summary Statistics

Table 1 shows the number of observations and the average (unweighted) age of each wave of the restricted sample.[10] MEPS observations are available annually whereas HRS observations are only available every other year. The average (unweighted) age in MEPS is around 45 years and fairly constant over time. The average (unweighted) age in the HRS sample is 56 in 1992 and then increases to around 67 for the remaining waves. This means that despite the fact that the HRS is a true panel in the sense that a household can be tracked over multiple years, entering new households in specific waves ensure that the sample remains representative of the older population with an average age of around 67 years. Unweighted summary statistics of the dependent and control variables of the restricted samples are presented in Table 2. All dollar values are denominated in 2010 dollars using the OECD-CPI for the U.S.[11]

3 Non-Parametric Estimation

The first method to calculate transition probabilities between health states is a simple non-parametric counting method. Since we have panel data with health state observations from two consecutive years in MEPS and HRS (in HRS the time dimension is from 1992–2916 with two-year gaps) we can simply count health transitions between the different health states and calculate their respective relative frequencies.

We count the realization of a particular transition by first defining the random variable of a health state realization at time t as $Y(t)$. The possible realizations of this variable are $y_t \in \{1,2,3,4,5,6\}$ where the numbers indicate one of six possible health states: 1 Excellent, 2 Very Good, 3 Good , 4 Fair, and 5 Poor. Health state 6 indicates that the individual has died in this period. Next we define the realization of a particular transition from state h at time t to state j at time $t+k$ as $1\left(y_{i,t+k}=j,\, y_{i,t}=h\right)$ where 1 is an indicator function equal to one if the particular case in the data is indeed a transition from state h to state j and zero otherwise. We can now count all possible transitions between the six health states as

$$N_{h,j} = \sum\nolimits_{i=1}^{I} \sum\nolimits_{t=1992}^{T=2017} 1\left(y_{i,t}=h,\, y_{i,t+k}=j\right),$$

where k equals 1 in the MEPS sample (which we observe annually) and k equals 2 in the HRS sample which we only observe every two years. Variable $y_{i,t}$ is the health state of individual i in year t. Thus $N_{h,j}$ counts all transitions from health state h to j for all individuals over the entire time period in the respective sample. The sixth health state, death, is of course absorptive. Once an individual reaches that state, she exits the sample. We then calculate the conditional transition probability $\Pr(y_{t+k}=j|y_t=h)$ from state h to j as the relative frequency of transition cases defined as

$$\hat{p}_{h,j} = \frac{N_{h,j}}{\sum\nolimits_{i=1}^{I} \sum\nolimits_{t=1992}^{T=2017} 1\left(y_{i,t}=h\right)}. \tag{1}$$

[10] A frequency distribution of the full sample is available in Figure A.1 and Table A.1 in Appendix A.

[11] OECD (2018), Inflation (CPI) (indicator). doi: 10.1787/eee82e6e-en (Accessed on 29 June 2018) at https://data.oecd.org/price/inflation-cpi.htm

We report these estimated (unweighted) probabilities in Table 4 for the MEPS sample and Table 6 for the HRS sample. Both tables report absolute and relative frequencies of these transitions. In MEPS the cumulative frequency of individuals transitioning to excellent and very good health is 58.3 percent—the sum of 18.4 and 39.9 percent in the "Total" row of the first two columns. In the HRS sample it is much smaller at 36.3 percent. On the flip side, transitioning into worse health states is more likely in the HRS where 8.5 percent transitioned into poor health and 6.5 transitioned to death compared to only 2.3 percent into poor health and 0.3 percent into death.[12]

The estimated probabilities in the main diagonal of the table are the probabilities that an individual maintains the current health state into the next period. These estimates indicate that health states are highly persistent. In the younger MEPS sample the probability to transition into an identical health state next year is fairly large. The probability to remain in Excellent health is 68.6 percent, the probability to remain in Very Good health is not much smaller at 68.3 percent and the smallest probability, the transition from Fair to Fair, is still 57.5 percent. In the older HRS sample the probabilities to maintain the current health state are somewhat lower but still rather high at about 50 percent across all health states.

These results become slightly stronger when we calculate population weighted frequencies in Tables 5 and 7, respectively. The weighted health transition probabilities show a slightly larger persistence of health states as can be seen by comparing the numbers in the main diagonal of the tables. In addition, we also observe much lower transition probabilities into worse health states in the tables based on sample weights. This can be seen by comparing numbers in the upper right corner of Table 4 to the respective numbers in Table 5 for MEPS. We find even larger differences in the HRS sample comparing the upper right numbers in Tables 6 and 7. Overall, these differences are be expected as both, MEPS and HRS over sample minority populations who are known to have worse health prospects than the general population. The raw sample counts therefore put too much emphasis on these groups so that weighting the data becomes important, especially for the HRS sample.

4 Parametric Methods

The literature analyzing self-reported health measures often assumes a true latent health state process $h_{i,t}$ for individual i in period t with the self-reported health measure being a categorical representation of the true state of health. Since there is a natural ordering in the health states we can put more structure on the model. We assume that the true state of health depends on a vector of covariates $x_{i,t}$ (e.g., Cutler and Richardson, 1997; Lindeboom and van Doorslaer, 2004; Juerges, 2007; Meijer, Kapteyn and Andreyeva, 2011; Kapteyn and Meijer, 2014). In addition, we assume that health states are driven by past health states so that the specification for the true (latent) health state evolves according to

$$h^*_{i,t+1} = \alpha \times h_{i,t} + {x_{i,t}}'\beta + \epsilon_{i,t}. \tag{2}$$

[12] It should be noted that the observed frequencies of the respective health categories are much more uneven in MEPS than in the HRS. For instance, only 391 individuals transition to death and $3,172$ into poor health states whereas much larger numbers of individuals transition into the other health states. Uneven counts of observations of different categories in the outcome variable can lead to convergence issues in multinomial models. We discuss some of these issues in Sections 4.3 and 5.4.

The vector of covariates $x_{i,t}$ includes controls for age, age squared, age to the power three, a dummy for gender, an interaction dummy for gender and age, an indicator variable for whether a person lives with a partner (married or unmarried), an indicator for current smoking behavior, race dummies for African American and Hispanic, education dummies for high school and college degrees, pre-tax household (or HIEU in the case of MEPS) income, a region dummy, a cohort dummy (we use 5-year birth cohorts), and two time period dummies (one for observations from $t \leq 2001$ and the second for observations from $t \geq 2012$).[13]

Alternatively we could split the sample in five health categories according to the observed health state variable $h_{i,t}$ and then separately specify the latent variable as

$$h^{*}_{i,t+1} = {x_{i,t}}'\beta_j + \epsilon_{i,t}, \tag{3}$$

conditional on $h_{i,t} = j$.[14] This is less restrictive as it allows for health state specific β_j parameters. However, splitting the sample increases the computational burden as we now have to estimate five specifications for each model type and it leads to less precise estimates, especially if the number of observations for a health category is small.

4.1 Ordered Logit Model (OLM) and Ordered Probit Model (OPM)

In an OLM, the observed health response variable takes on values 1–6 depending on whether the latent health state crosses a certain threshold τ so that

$$h_{i,t} = \begin{cases} 1\,\text{Excellent} & \text{if } \tau_0 = -\infty \leq h^{*}_{i,t} < \tau_1 \\ 2\,\text{Very Good} & \text{if } \tau_1 \leq h^{*}_{i,t} < \tau_2 \\ 3\,\text{Good} & \text{if } \tau_2 \leq h^{*}_{i,t} < \tau_3 \\ 4\,\text{Fair} & \text{if } \tau_3 \leq h^{*}_{i,t} < \tau_4 \\ 5\,\text{Poor} & \text{if } \tau_4 \leq h^{*}_{i,t} < \tau_5 \\ 6\,\text{Dead} & \text{if } \tau_5 \leq h^{*}_{i,t} < \tau_6 = \infty \end{cases}$$

is observed. The probability of an observed outcome j in the next period can now be stated as the probability that the latent health variable falls within the j^{th} thresholds, so that

$$\Pr\left(h_{i,t+1} = j | x_{i,t}, h_{i,t}\right) = \Pr\left(\tau_{j-1} \leq h^{*}_{i,t+1} < \tau_j | x_{i,t}, h_{i,t}\right),$$

and given our parameterization of the latent health state this probability becomes

$$\Pr\left(h_{i,t+1} = j | x_{i,t}, h_{i,t}\right) = F\left(\tau_j - \alpha \times h_{i,t} - {x_{it}}'\beta\right) - F\left(\tau_{j-1} - \alpha \times h_{i,t} - {x_{i,t}}'\beta\right),$$

[13] Increasing the polynomial order of age does not affect our results.

[14] It should be noted that $t+1$ refers to the future period which in the econometric implementation could mean a one year ahead variable for MEPS data and a two-year ahead variable for HRS data.

where F is the CDF of error term ϵ_{it}. In the OLM the error follows a logistic distribution and the probability is therefore

$$\Pr\left(h_{i,t+1}=j|x_{i,t},h_{i,t}\right) = \frac{\exp\left(\tau_j-\alpha\times h_{i,t}-x_{it}'\beta\right)}{1+\exp\left(\tau_j-\alpha\times h_{i,t}-x_{it}'\beta\right)}-\frac{\exp\left(\tau_{j-1}-\alpha\times h_{i,t}-x_{i,t}'\beta\right)}{1+\exp\left(\tau_{j-1}-\alpha\times h_{i,t}-x_{i,t}'\beta\right)} \tag{4}$$

for all $j\in[1,6]$. This results in the following log likelihood function:

$$\ln L\left(\beta,\alpha,\tau\right) = \sum_i\sum_t\sum_j 1_{[h_{i,t}=j]}\times\ln\left(\Pr\left(h_{i,t+1}=j|x_{i,t},h_{i,t}\right)\right),$$

where $1_{[h_{i,t}=j]}$ is an indicator function for observed health state category j. This function is well behaved and can be estimated for α,β and τ. We then calculate mean values of predicted probabilities conditional on the current health state to fill a 6×6 health transitions probability matrix. The mean is over all individuals in the respective MEPS or HRS sample.

Similarly, the ordered probit model (OPM) defines the CDF of the error terms as the CDF of the standard normal distribution Φ so that

$$\Pr\left(h_{i,t+1}=j|x_{i,t},h_{i,t}\right) = \Phi\left(\tau_j-\alpha\times h_{i,t}-x_{i,t}'\beta\right)-\Phi\left(\tau_{j-1}-\alpha\times h_{i,t}-x_{i,t}'\beta\right) \quad \text{for all } j\in[1,6]. \tag{5}$$

As can be seen from expressions 4 and 5, both models implicitly assume that the slope coefficients α and β are not outcome specific. This is often referred to as the parallel regression assumption or the proportional odds assumption. Brant (1990) developed a statistical test for this assumption.

4.2 Multinomial Logit Model (MLM) and Multinomial Probit Model (MPM)

The multinomial logit model specifies each categorical outcome probability as a non-linear function of covariates $x_{i,t}$ and $h_{i,t}$ that do not vary over alternative outcomes. This results in

$$\Pr\left(h_{i,t+1}=j|x_{i,t},h_{i,t}\right)=\frac{\exp\left(\alpha_j\times h_{i,t}+x_{i,t}'\beta_j\right)}{\sum_{m=1}^{6}\exp\left(\alpha_m\times h_{i,t}+x_{i,t}'\beta_m\right)},$$

if we assume that error terms are independently and identically distributed (iid) following a type I extreme value distribution (log Weibull). This specification embeds the independence of irrelevant alternatives (IIA) assumption when forming odd ratios. The odds of outcome j over outcome k will only depend on parameters $\alpha_j,\alpha_k,\beta_j$, and β_k but not on slope parameters of the other outcomes. A Hausman test (Hausman and McFadden, 1984) can be used to test for this assumption.[15]

Multinomial probit models (MPM) can also be derived from the index model in equation 2 where we can express the probability of category j relative to the other categories as

$$\Pr\left(h_{i,t+1}=j|x_{i,t},h_{i,t}\right)=\Pr\left(\epsilon_{i,t,j}>\epsilon_{i,t,m}\text{ for all } m\neq j\right),$$

which can be written as a series of integrals over the joint normal density. The MPM does not assume IIA but is computationally burdensome.

[15] Other tests for IIA are based on Small and Hsiao (1985). Compare Long and Freese (2014) for further details on testing for IIA.

4.3 Model Issues

Ordered Models. The OLM and the OPM both depend on the parallel regression (or proportional odds) assumption. It describes the implicit model feature that the slope coefficients β of a series of binary regressions that can be derived from the ordered logit or probit models have to be equal. Unfortunately, it is very common that the OLM fails the test of proportional odds. We implement a test based on Brant (1990) and indeed, proportional odds is rejected. This failure hints at a probable misspecification of the model.

Multinomial Models. Since the ordered models fail the test of the parallel regression assumption we also estimate multinomial models that do not rely on the proportional odds assumption. While the MLM does not make the proportional odds assumption, it does assume independence of irrelevant alternatives (IIA) in the choice set. A Hausman test of IIA does not reject the IIA assumption. A Small Hsiao test of IIA does reject IIA under certain sample divisions. The Small-Hsiao test for IIA divides the sample randomly into two sub-samples fitting a restricted and an unrestricted model. Depending on how the sample is subdivided the test gives different results.[16] Issues with IIA tests have been raised in Vijverberg (2011) and Long and Freese (2014). It is therefore often recommended to not use the IIA test in practice.

In general, results based on the OPM are very similar to the results from OLM regressions. However, the OPM also assumes proportional odds. Since tests do reject the proportional odds assumption, as mentioned above, the MPM seems to be a good alternative candidate. This model does not assume proportional odds and it does also not assume IIA. However, in a series of simulations Kropko (2008) has been shown that the MPM is a very inefficient estimator and that a biased and inconsistent MLM that violates IIA "nearly always" provides more accurate results than the correctly specified MPM. As such, Kropko (2008) recommends multinomial logit over multinomial probit, even if tests of IIA reject it.

Unobserved Heterogeneity. Unobserved heterogeneity, such as an unobserved health risk type or an unobserved health preference type, can lead to endogeneity issues and biased estimates. We therefore implement a finite mixture model that allows for two such unobserved types or classes. In general, in finite mixture models the responses to the SAH question are allowed to come from a number of distinct and unobserved classes. These latent classes are modeled according to a multinomial logit model (McLachlan and Basford, 1988; Deb and Trivedi, 1997).

Endogeneity issues can arise from the inclusion of lifestyle variables such as smoking. Balia and Jones (2008) and Balia (2014) use multivariate probit models to address issues of simultaneity and cross correlation of error terms of the health production process and the reduced form lifestyle regression. Similar to their setup we can write the model as a system of equations with correlated error terms where the lifestyle variable is also an outcome variable. More formally this can be expressed as

$$\begin{aligned} h_{i,t+1} &= H\left(h_{i,t}, \text{smoking}_{i,t}, x_{i,t}, \epsilon^h_{i,t}\right), \qquad (6) \\ \text{smoking}_{i,t} &= S\left(h_{i,t}, x_{i,t}, \epsilon^s_{i,t}\right), \end{aligned}$$

where $x_{i,t}$ is the same covariate vector as in the benchmark model (i.e., the ordered logit model in expression 4) excluding the smoking status variable. The first equation is estimated using an ordered probit specification and the second equation is a probit model. The two error terms follow a joint normal

[16] See Long and Freese (2014) for details.

distribution that allows for correlation between the errors. Exclusion restrictions typically result in more robust identification of such systems but are difficult to find.[17] However, under certain conditions, exclusion restrictions are not necessary for identification in models with categorical outcome variables according to Wilde (2000).

5 Results

5.1 Ordered Logit Models

Average Predicted Conditional Transition Probabilities. We report the average conditional probabilities for transitioning into a specific health state one year from the current period conditional on the current health state in Tables 8(a) and 8(b). The first table shows estimates based on an ordered logit regression with age, age^2, and age^3 as sole explanatory variables whereas the second table shows the results of the ordered logit model in equation 4 with the full control vector including cohort and time controls using observations from 20–65 year old individuals from the MEPS sample.

First, comparing Table 8(a) to the weighted frequency counts in Table 5 we see that the transition probabilities are roughly in line with the ordered logit model, especially for transitions that are based on high frequency observations. We observe the largest difference in the transition probability from *Poor* to *Poor* health states which is 60.6 percent based on weighted counts but only 50 percent based the ordered logit regression with the age polynomial. Furthermore, if we estimate the ordered logit model using the full control vector including cohort and time dummies, we find slightly lower persistence with respect to the better health states *Excellent*, $Very\,Good$, and *Good* but much lower persistence in the worse health states *Fair* and *Poor* in Table 8(b). The transition probability from fair-to-fair drops from 56 percent to 53.1 percent and the transition probability from poor-to-poor drops from 50 percent to 46.1 percent between Tables 8(a) and 8(b).

Overall, in the full model we observe a high level of persistence of all health states (compare numbers in the main diagonal of Table 8(b)) with the possible exception of the already discussed poor-to-poor transition probability which is the only one that drops below 50 percent. If an individual is in excellent health, she has a 67.6 percent probability of being in excellent health a year from now. The $Very\,Good$ health state is even more persistent at 70 percent. The probabilities then begin to decline for the lower health states.

For the older age group based on HRS data we get similar results. However, the differences between the weighted count frequencies in Table 7 and the predicted probabilities based on the weighted ordered logit model in Tables 9(a) and 9(b) are more pronounced. In addition, the estimated health state persistence is much lower in the full model compared to the ordered logit model with age as the only control variable. Another reason, why this difference is so much more pronounced in the HRS sample is that the full model includes controls for initial health conditions. Once we factor in a possible control for the inherent health or risk type, the period by period persistence of health states decreases. It stands to reason that some of the observed year-to-year persistence of health states in MEPS is due to an underlying risk type. Unfortunately the short time dimension in the MEPS panel does not allow us to control for initial health

[17] The number of children in a household is sometimes added to the lifestyle equation as the number of children could affect smoking behavior but not one's assessment of health.

state.

Overall, the probabilities to remain in the same health state in the older HRS sample are much lower. The probability to transition from excellent-to-excellent health is only 31.3 percent and the transition probability from poor-to-poor is also much lower at 22.4 percent as a large fraction of individuals with poor health dies. These lower probabilities are of course expected as Tables 7, 9(a) and 9(b) report two-year transition probabilities which naturally makes them less persistent than the one year transition probabilities in the MEPS sample.[18]

Marginal Effects. We report average marginal effects of the ordered logit model in Table 10 based on MEPS data and Table 11 based on HRS data. Almost all regressors are highly statistically significant. Note that the marginal effect of a categorical variable is measured relative to its dropped base category. The base category for race indicators is "white", the base category for education status is "No High School Degree", and the base category for the current health state is "Excellent" health. The reported standard errors are clustered at the individual level. This accounts for the fact that an individual can contribute more than one transition observation, especially in the HRS data where individuals are observed over multiple years.

Current health states are highly significant and demonstrate the persistence of health states across time. With "Excellent" health as the omitted base category, the negative coefficient estimate of "Very Good" health in the first column of Table 10 indicates that an individual in "Very Good" health today is less likely to transition to "Excellent" health than an individual who is currently already in "Excellent" health. Similarly, the positive coefficient in the second column suggests that an individual in "Very Good" health today is more likely to be in "Very Good" health tomorrow than in an individual who is currently in "Excellent" health. This is again the already discussed pattern of "persistence" of remaining in one's current health state as indicated by the large transition probabilities in the main diagonals of Tables 5, 8(a), and 8(b). Furthermore, a specific self-reported health state will, at the margin, always increase the probability to transition to even worse health stats in the future compared to the base category health state of "Excellent." Being in "Very Good" health today (as opposed to "Excellent" health), makes it less likely to be in "Excellent" health in the next period but more likely to be again in "Very Good" health or any health state that is worse.

The long time dimension in our HRS sample—the median panel length is $T = 5$ periods which spans 10 years—allows for adding initial health conditions into the regression specifications.[19] From Table 11 it is apparent that initial health conditions do have significant marginal effects but they are much smaller in magnitude than current period health conditions. Unfortunately controlling for similar initial conditions is not possible in the MEPS sample due to the shortness of the panel.

The marginal effects of age are highly significant and show the direction of the effects that we would expect. An increase in age decreases the probability to transition into the "better" health states and increases the probability to transition into the "worse" health states. The magnitudes of these marginal effects are small. This is not necessarily surprising given that MEPS represents the younger cohorts.

[18]We will discuss methods to transform two-year transition probabilities into one-year frequencies probabilities in the next Section.

[19]Compare Contoyannis, Jones and Rice (2004) for a discussion of using initial condition to control for individual effects in dynamic panel regressions.

The marginal effects of age in the HRS sample are larger in general which shows that the impact of age on health transition probabilities increases on average for older individuals. We will discuss age specific effects on lifecycle transition probabilities in more detail in Section 5.3.

The effect of gender is interesting when comparing the MEPS and HRS samples. Being female decreases the probability to transition into better health states for the younger cohorts in MEPS while it increases the probability for the same transitions for the older cohorts in HRS. Similarly, being female increases the probability to transition into the worse health states in MEPS while it decreases the probability to transition into the worse health states in the HRS. Being married or partnered makes transitions into better health more likely and decreases transitions into worse health states. This is true in both samples but the magnitudes of the effect are much higher in the HRS sample.

The race indicator variables for Hispanic and Black show that minorities are more likely to transition into worse health states than their white counterparts. Increases in household income increase the probability to transition into the "better" health states in both samples.

Finally, we construct dummy variables indicating observations from the "early" period before 2002, the "middle" period from 2002–2011, and the "late" period from 2012–2017. While this does not completely control for time effects, it will allow us to detect differences across time periods. We use the middle period as reference category and find no significant difference between the early and middle period in terms of transition probabilities into any of the six states in the MEPS sample according to Table 10. On the other hand, the table indicates that transition probabilities into the better health state decrease in the latest time period whereas transitions into the worse health states increase. These results are also observed in the HRS sample which covers older individuals. Table 11 shows that in the early period the probabilities to move into the better health states are significantly larger than in the middle period and the probabilities that indicate a move into the worse health states are significantly smaller. The late period shows the already familiar pattern from the MEPS sample that in more recent years the transition probabilities to the better health states (excellent and very good) decrease and the probabilities to transition to worse states increase. These findings are somewhat surprising and not consistent with the reported increases in life expectancy at age 20 (from 57.9 years in 2001 to 59.4 years in 2016) and age 65 (17.9 years to 19.5 years).[20] Having said that, while some of these statistical significant time effects are attributable to technological progress as argued by Catillon, Cutler and Getzen (2018), the counter intuitive effects could also be due to confounding business cycle effects. We therefore also compare estimation results based on two samples from non-recession periods in Section 5.5.

Unobserved Heterogeneity. We next present results based on finite mixture and mixed processes models in Appendix H and I, respectively. In addition to being computationally very intensive, finite mixture models exhibit poor convergence in our setup. The low frequencies of adverse health states in the MEPS sample create either very flat or non-concave likelihood functions which prevents convergence of the optimizing algorithm. A similar issue arises in the HRS sample with a full control vector. The only version of the finite mixture models that does successfully converge is the most parsimonious one, where we only control for age including a higher order age polynomial. We present these results in Appendix H and compare them to the corresponding ordered logit model with age as only control variable. Not

[20] Life expectancy numbers are from CDC life tables for the year 2001 and 2016 retrieved in June 2021 from https://www.cdc.gov/nchs/nvss/life-expectancy.htm:

surprisingly, the results based on the finite mixture model show much higher probabilities to remain in the current health state (i.e., health state persistence) as the model allows for agent grouping into separate classes according to a latent type specifier.

Results from the mixed process model in expression 6 where smoking is added as additional equation in reduced form to account for the possible endogeneity of this type of risky health behavior are presented in Appendix I. The overall trend in health transitions is fairly similar between this version of the model and the "regular" ordered probit model (i.e., expression 5 in Section 4) with all control variables. However, the mixed process model shows slightly lower persistence across all health states.

5.2 Using Markov Assumption to Transform Two-Year Transition Probabilities into One-Year Transition Probabilities

HRS data is only available every two years. Transition probability matrices based on HRS estimates therefore describe two-year transitions as opposed to the one-year transitions we observe in MEPS. In order to present consistent one-year conditional transition probability matrices between health states over the entire lifecycle we therefore transform the two-year matrices into one-year matrices based on an algorithm described in Chhatwal, Jayasuriya and Elbasha (2016). The algorithm implements a stochastic root and first attempts to translate the stochastic transition probability matrix of period length 2 (HRS estimates only result in 2-year transition probabilities) into an instantaneous intensity rate matrix based on eigendecomposition and then converts it back into the desired stochastic transition matrix (i.e., a matrix whose rows sum to one) of period length one. Israel, Rosenthal and Wei (2001) have derived necessary conditions for the eigendecomposition approach to work. Even if the necessary conditions are met, the eigendecomposition can still result in a non-stochastic transition probability matrix. If this is the case, the algorithm will attempt to approximate a stochastic matrix using a matrix norm distance minimization technique based on theoretical results developed in Lin (2011) and Higham and Lin (2011).[21]

This method rests on the assumption that the health transition probabilities remain stable over the two year period and that health states, conditioned on age and agent type, follow the Markov assumption so that next period's health state is primarily a function of today's health state (and other conditioning variables) and all past health risk information is contained in the present health state. If this is the case then health states would follow a first order Markov chain and we can back out the annual transition probabilities from the two year ahead estimates described above.

The literature on statistical inference for Markov chains dates back to the fifties (e.g., Anderson and Goodman, 1957; Billingsley, 1961; Kullback, Kupperman and Ku, 1962). In the following we primarily follow Anderson and Goodman (1957) and test for (i) homogeneity and (ii) first vs. second-order Markov chain length using the weighted frequency counts from the non-parametric model in Tables 5 and 7.[22] The homogeneity test assesses whether the transition probabilities remain constant across time t or more specifically whether

$$H_0 : p_{h,j}\left(t\right) = p_{h,j}$$

[21] The Python version of the algorithm is available on the author's website at: `https://juejung.github.io/research.htm`

[22] We skip the test for state dependency as it is pretty clear that consecutive health states are not independent from each other as shown by the highly significant coefficients of current health states in the marginal effects estimations of Tables 10 and 11.

where the estimate for the transition probability from state h to state j in time t is calculated as

$$\hat{p}_{h,j}(t) = \frac{N_{h,j}(t)}{\sum_{i=1}^{I} 1(y_{i,t} = h)},$$

where $N_{h,j}(t) = \sum_{i=1}^{I} 1(y_{i,t} = h,\, y_{i,t+k} = j,)$ and the estimate for the overall transition probability across all time periods $\hat{p}_{h,j}$ is defined in expression 1. The resulting likelihood ratio test between the time dependent and time independent probability estimates from a starting health state h follows a Chi-square distribution with $(6-1) \times (T-1)$ degrees of freedom where T is the number of observed time periods and the test criterion is[23]

$$\alpha_h = 2 \times \sum_{t,j} \left(N_{h,j}(t) \times \ln \left(\frac{\hat{p}_{h,j}(t)}{\hat{p}_{h,j}} \right) \right).$$

We next test the null hypothesis that the Markov chain is first-order against the alternative that it is second-order. More formally this can be stated as:

$$H_0 : p_{1,h,j} = p_{2,h,j} = p_{3,h,j} ... = p_{5,h,j} = p_{h,j}, \text{ for } h \text{ and } j = 1, ..., 6,$$

where $p_{1,h,j}$ is the probability that an individual was in health state 1 (Excellent Health) in $t-1$, in health state h in t and in health state j in $t+1$. The remaining probabilities $p_{2,h,j} ... p_{5,h,j}$ are defined similarly with different starting health states in $t-1$. The estimators for these probabilities are the relative frequencies defined as

$$\hat{p}_{g,h,j} = \frac{N_{g,h,j}}{N_{g,h}},$$

where the absolute frequency counts are defined as $N_{g,h,j} = \sum_{t=1993}^{T=2017} \sum_{i=1}^{I} 1(y_{i,t-k} = g,\, y_{i,t} = h,\, y_{i,t+k} = j)$ and $N_{g,h} = \sum_{t=1993}^{T=2017} \sum_{i=1}^{I} 1(y_{i,t-k} = g,\, y_{i,t} = h)$. The resulting test criterion

$$\alpha_h = 2 \sum_{g,j} (N_{g,h,j}) \ln \left(\frac{\hat{p}_{g,h,j}}{\hat{p}_{h,j}} \right),$$

where $\hat{p}_{h,j}$ is defined in expression 1 follows a Chi=square distribution with $(6-1)^2$ degrees of freedom.[24]

The test for homogeneity rejects the null hypothesis in both samples. This highlights the importance of controlling for time variation. The test for second-order Markov chains can only be implemented in the HRS sample as the MEPS sample does not allow to control for additional lags of health state variables due to the shortness of the panel ($T = 2$ years). The second order test hypothesis is rejected as well which indicates that the Markov assumption could be problematic if health heterogeneity and risk factors are not adequately controlled for.[25] In light of these issues it will be informative to compare health transition probabilities of 50–60 year olds from the HRS sample to health transition probabilities of 50–60 year olds from the MEPS sample where probabilities are estimated without assuming a Markov structure.[26]

[23] A joint hypothesis over all initial health types h can easily be implemented by summing up the individual α_n over all health states with then follow a Chi-square distribution with $6(6-1)(T-1)$ degrees of freedom.

[24] The joint distribution over all health states h follows a Chi-square distribution with $6 \times (6-1)^2$ degrees of freedom.

[25] Tests for subcategories of individuals for whom we control in the parameterized version of the model are difficult to implement as some transitions between rare health states would not show up in the divided sample and the tests would have diminished statistical power.

[26] The age group of 50–60 year olds has good representation in both surveys as can be seen from Figure A.1 in Appendix

5.3 Lifecycle Patterns of Age Dependent Health Transition Probabilities

In this and the following sections we will first estimate a specific parametric model (such as ordered logit, ordered probit, etc.) using HRS data. We will then predict two year conditional transition probability matrices connecting current to future health states. We then run these matrices through the adjustment algorithm described in the previous section and transform them into one year stochastic matrices. Finally, we plot these one year "adjusted matrices" together with the one year matrices we directly get from predictions based on estimates from the MEPS sample which is available annually. This consistent treatment results in comparable one year conditional health transition probabilities.

We first investigate how these health transition probabilities are shaped by age over the lifecycle. In Figures 1–5 we compare the age-conditional health transition probabilities based on frequency counts for age groups 20–24, 25 ± 2, $30 \pm 2, \ldots, 90 \pm 2$ to health transition probabilities based on predictions of the ordered logit model in expression 4 for age groups $20, 25, \ldots, 90$. All statistical models are estimated separately for each survey sample and survey weights were used to estimate the ordered logit model. Figures $1(a)$–$5(a)$ show the lifecycle profiles based on weighted frequency counts and Figures $1(b)$–$5(b)$ show lifecycle profiles based on weighted ordered logit estimates. Conditional transition probabilities from the HRS sample are subsequently transformed into one-year transition probabilities using the stochastic root method described earlier in Section 5.2. All probabilities are averages of predicted probabilities for a specific age based on either weighted frequency counts or the ordered logit model. We also report 95 percent confidence intervals for the predicted probabilities of the ordered logit model. Confidence intervals widen in both samples for the older age groups but overall the transition probabilities are estimated fairly precisely.

From the figures we can see that the patters of the weighted frequency counts and the patterns based on the weighted parametric model match up but the lifecycle probabilities based on the regression model that also controls for cohort and partial time effects show the already discussed higher likelihood of recovery from worse health states due to appropriately weighting observations from over sampled minority groups. In addition, we clearly see that after we adjust the probabilities from the HRS to one year frequencies, we achieve much greater continuity of the lifecycle profiles between the two samples. Next, transition probabilities to the better health states such as $Excellent$ and $Very\,Good$ are declining functions of age, whereas transition probabilities to the "bad" health states such as $Poor$ and $Dead$ are increasing functions of age. This makes intuitive sense as one would expect that health deteriorates as a function of age and transitions to the better health states become less likely as an individual ages.

Similarly, transition probabilities to the intermediate health states of $Good$ and $Fair$ are increasing functions of age when the current health state is better than $Good$ or $Fair$. If the current health state is worse than $Good$ or $Fair$, then the respective transition probabilities are declining functions of age. Both these observations are again consistent with the idea that health is likely to deteriorate as an individual gets older.

The probability to remain in the same health state is decreasing for "Excellent" and for "Very Good" health and hump-shaped for the remaining health states. The peak of the hump-shaped profiles moves to higher age ranges, the worse the current health state gets. The transition probability from Good to Good is highest at almost 70 percent for 55 year olds. The transition probability from Fair to Fair is highest

A.

at around 55 percent for 60–70 year olds and the transition probability from Poor to Poor is highest at around 50 percent for 80 year olds. Again this persistence of remaining in worse and worse health states as one ages, is consistent with the biological aging process and the deterioration of an individual's health over time.[27]

5.4 Multinomial Models

Multinomial models rely on fewer assumptions than models with a specified order in the outcome variable which increases the computational burden of estimating them. In addition, if the categories of the outcome variables differ in their respective observed frequencies, convergence issues can arise. The multinomial logit and multinomial probit models do not converge in our MEPS sample since the "Poor" and "Dead" health states are only observed at very low frequencies compared to the other health states. We are therefore only able to present estimation results from multinomial logit and probit models using the HRS data, where the frequency distribution of the outcome categories is more even.

Table 12 shows predicted two-year transition probabilities based on a multinomial logit model and Table 13 shows similar probabilities based on a multinomial probit model. We do not observe large differences between the two multinomial model types. However, compared to the ordered logit model from Table 9(a), the resulting health transition probabilities from the multinomial models do show higher probabilities to remain in identical health states across a two year period. The probabilities based on multinomial models differ more from the probabilities based on raw frequency counts as well, especially when it comes to transition probabilities into the very worse health states.[28] Given the already discussed convergence issues with multinomial models and the often reported issues with inaccurate estimates—as discussed in Section 4.3—our preferred model specification is still the ordered logit model.

5.5 Time Effects

Indicator variables of age, birth year, and observation year are perfectly collinear. We are therefore not able to directly control for age, cohort and time effects simultaneously.[29] The literature (e.g., Kaplan (2012)) often suggests to conduct two analyses and separately controlling for cohort effects and time effects. In this work we explicitly control for cohort effects. In order to investigate whether transition probabilities have changed over time we follow two procedures.

The model so far accounted for differences across time periods via a time period indicator variable which allows for different intercepts for the early (<2002), middle (2002–2011), and late (2012–2017) periods. In addition, these intercept terms confound business cycle effects from recession periods with non-recession periods and as such cannot be interpreted as long-term trends in conditional health transition probabilities. In order to investigate the presence of a possible time trend over the lifecycle (net of business cycle effects), we next use a less parsimonious model that allows for differences in all coefficients, not just period intercepts. In order to accomplish this, we break the sample into observations from 2002–2006 and

[27] In order to assess the robustness of our results based on the ordered logit model we also report estimation results from an ordered probit model in Figures B.1–B.5 in Appendix B. The results are almost identical to the ordered logit model.

[28] Marginal effects estimates for both the MLM and MPM using HRS data are available in Appendix C. They are very similar to the marginal effects based on the ordered logit model from section 5.1.

[29] For more detailed discussions of age, cohort, and time effects see Fernández-Villaverde and Krueger (2007) and Jung and Tran (2014).

observations from 2012–2016. Both samples cover post-recession or recovery periods. This comparison accomplishes two goals. First, it will highlight any systematic differences between health risk exposure or possible systematic changes in the perception of health for different age groups over time. Second, these estimates will inform us about the robustness of our earlier results with respect to time effects that we were not able to directly control for due to multicollinearity problems.

We present summary statistics of the resulting four sub-samples: (*i*) MEPS in 2002–2006, (*ii*) MEPS in 2012–2016, (*iii*) HRS in 2002–2006 and (*iv*) HRS in 2012–2016 in Appendix D. The overall conclusion from the comparison of these summary tables is that both MEPS and HRS samples are fairly similar across the two time periods with an average age of 40.97 compared to 41.52 in the MEPS samples and an average age of 68.34 compared to 68 in the HRS samples. The fraction of individuals without a high school degree decreases over time in both MEPS and HRS and the fraction of individuals with college degree increases. Labor income drops by roughly USD 1,000 in MEPS and increases about the same amount in the HRS samples. The health state measures are very similar as is the death rate. We do, however, observe a notable drop in out-of-pocket health expenditures at the individual and household (or in case of MEPS the HIEU) level. These numbers are unweighted but inflation adjusted using the urban CPI. This is somewhat remarkable as the number of individuals with health insurance barely increases in the MEPS sample and noticeably drops in the HRS sample.

We next estimate the ordered logit model from expression 4 separately for each of the four sub-samples and plot the health transition probabilities based on predictions from these model estimates. These graphs are similar to the graphs presented in Section 5.1 and shown in Appendix D. Due to the smaller sample sizes the confidence intervals are larger and the age profiles of the transition probabilities are statistically indistinguishable across the two time periods in the MEPS sample. However, we do find some statistically significant differences in the HRS sample but these tend to be very small and primarily manifest among the oldest age groups which are based on few observations and imprecisely estimated.[30] This is encouraging when it comes to interpreting the estimation results of earlier sections that are based on the full sample.

5.6 Gender Differences in Conditional Health Transition Probabilities

We next compare health transition probabilities by gender. The marginal estimates in Tables 10 and 11 with respect to gender hint at contrary effects in the younger MEPS vs. the older HRS sample. The average marginal effect of being female is negative for excellent and very good health and subsequently switches to being positive for the good, fair, and poor health states. Among the younger group, being female appears to significantly decrease the probability of moving into the better health states. These marginal effects, while being highly statistically significant, are very small. In the older HRS sample the marginal effects are reversed so that being female is associated with a higher probability of transitioning into better health states and a lower probability of transitioning into the worse health states.

In order to more systematically investigate how the effects of gender change by age, we again plot predictions of health transition probabilities based on estimates of the ordered logit model from expression 4 over the lifecycle similar to the graphs in Section 5.1. The model is estimated separately for the MEPS and HRS samples and predictions by gender are based on a gender dummy variable as well as an interaction

[30]This does not contradict our earlier result that finds some significant differences in the early and late time period dummy variables as differential effects from periods of recessions are potentially driving the results.

dummy variable between gender and age.[31] The graphs are available in Appendix E and confirm what we have already found based on the marginal effects estimates we just discussed. The stated differences are persistent across the lifecycle and the direction of the effects (where being female switches from having a negative to having a positive effect towards transitioning into better health states) seems to change around age 50. Females exhibiting higher conditional probabilities of transitioning into worse health states while young can of course be related to childbearing or labor market status. Women having lower conditional probabilities moving into worse health states than men past age 50, is of course a reflection of biological differences and the much higher life expectancy of women in the U.S. in general.

5.7 Race Differences in Conditional Health Transition Probabilities

We next compare health transition probabilities of black and non-black respondents. Tables 10 and 11 show significant negative marginal effects to transition into the Excellent and Very Good health states for the black indicator variable. On the flip side, the marginal effects of this indicator variable on transitions into the relatively worse health states (good, fair , or poor) are positive and statistically significant. Being black can be associated with a lower probability of transitioning into better health states and a higher probability of transitioning into the worse health states. This is true for both, MEPS and HRS samples.

We next compare these race effects by age and plot predictions of health transition probabilities based on estimates of the ordered logit model from expression 4 over the lifecycle similar to the graphs in Section 5.1. The model is again estimated separately for the MEPS and HRS samples and predictions by race are based on a race dummy variable as well as an interaction dummy variable between race and age. The graphs are available in Appendix E and confirm the direction of the marginal effects estimates we just discussed over the entire lifecycle. It should however be noted that the averages of the predicted conditional transition probabilities by age and current health state are not statistically different by race for any of the age groups in the lifecycle graphs and that we only found a statistically significant marginal effect of race when we pool all age groups. This seems to suggest that some of the observed marginal race effects work through the age channel and once we condition on age, these differences disappear. In other words, if an African American individual who reaches say age 45 in good health has a similar probability to move into any of the six health states in the next period than a non African American while overall an African American has a lower probability of reaching age 46 in good health.

We have established earlier, see Section 5.5, that between 2002–2006 and 2012–2016 time effects play a very minor role if any. We next investigate whether there are any significant time trends in conditional transition probabilities into health states of the black vs. non-black population. We again form two samples, the first from 1996–2001 and the second from 2013–2017. This is the widest possible time gap we are able to generate with our data while also maintaining enough observations in the MEPS (we use 2000–2001 because the smoking variable is only available from wave 2000 onward) and HRS sample to analyze transitions. We compare the differences of predicted conditional health transition probabilities between non-black and black responders, that is $\hat{\Pr}\left(h_{t+1}|h_t, \text{age}_t, \text{non-black}\right) - \hat{\Pr}\left(h_{t+1}|h_t, \text{age}_t, \text{black}\right)$ for each of the two periods over the lifecycle where predictions are averaged over the remaining control variables of the ordered logit model in expression 4. We are not able to identify any significant differences

[31] Adding additional interaction terms of gender with a higher order age polynomial does not change the resulting graphs in a statistically significant way.

for any of the age groups between the two time periods. As such, our earlier result from Section 5.5 where we also found no significant time effects between periods 2002–2006 and 2012–2016 is confirmed.[32]

It should be noted that black individuals on average report worse health states in any of the analyzed time periods and samples. This is obvious from the summary statistics. However, we cannot establish that conditional on being in a specific health state at a specific age, the transition probability from this health state differs significantly by race.

5.8 Sample Attrition

Sample attrition in longitudinal surveys can lead to selective samples which introduce attrition bias into estimates of parametric models. For the following discussion we distinguish between three types of attrition: (*i*) passive attrition due to death, (*ii*) active attrition due to non-reporting of health status, and (*iii*) active attrition due to non-response to the survey in a given year. Table 14 shows the frequencies of the attrition types in the MEPS and the HRS respectively.

Since the dependent variable in this study is a one period ahead health state variable including death, the parametric models from Section 4.1 explicitly incorporate death as one of the possible outcomes and, as long as deaths are reported, do therefore not add to estimation bias of the age gradient on conditional health state transition probabilities.

The second type of attrition due to not reporting health state information is very rare. If individuals respond to either survey, they typically report their health state. In MEPS only 78 out of 167,251 second year observations (from individuals who also respond in the second year) do not contain a health status report. In HRS, which is a deeper panel in which individuals are followed until they either die or become otherwise non-responsive, it is possible to have partial attrition for some periods. After implementing the interpolation routine described in Section 2.3 we are left with only three observations with missing health information out of 204,492 person/year observations in years following the initial entry into the survey.

This leaves us with the issue of possible attrition bias generated by complete non-response to the survey. We do not know whether these individuals died or stopped responding for other reasons. After generating an attrition indicator for this type of attrition and running the attrition probit test described in Fitzgerald, Gottschalk and Moffitt (1998) as well as the attrition pooling test described in Becketti et al. (1988), we are not able to reject attrition bias in either MEPS or the HRS.[33] In order to minimize the estimation bias in our econometric specifications in Section 4.1, we implement three strategies. First, we limit the upper age range of the MEPS sample to 65 years and the HRS sample to 95 years. Cohen, Machlin and Branscome (2000) report that individuals older than 65 and individuals who were never married or partnered are more likely to drop out of MEPS which causes MEPS to be non representative for older age cohorts. In MEPS, death is observed at very low frequencies as individuals typically exit the survey when they become institutionalized. By limiting our sample to individuals up to 65 years of age, this issue is partly mitigated. We also remove the very old age group (older than 95) in the HRS sample for similar reasons.

We then use probability weights provided in MEPS and HRS to counteract the effects of attrition

[32] Appendix G presents the lifecycle profiles of the differences in the conditional transition probabilities as well as summary statistics by race across the two time periods.

[33] Baulch and Quisumbing (2010) contains detailed descriptions including Stata codes for these type of tests.

on observables. As the MEPS is sampling from NHIS cohorts (another national health survey), MEPS survey weights account for both NHIS and MEPS differential sampling probabilities and non-response as described in Chowdhury, Machlin and Gwet (2019). The sampling weights in the HRS do reflect the complex survey design and adjust for survey non-response and post-stratifying the HRS sample to national population data such as the U.S. Current Population Survey up to year 2004 and the American Community Survey for 2006 and later.[34]

For the HRS, Kapteyn et al. (2006) find very little evidence of attrition bias from selection on observables that would warrant the use of more complicated weights than the HRS weights which do condition on race, ethnicity, gender, and age, the main drivers of attrition from observables. A similar result is demonstrated in Cao and Hill (2005) who further distinguish between passive (through death) and active (non-death) attrition. Kapteyn et al. (2006) recommend the use of the unbalanced panel that includes individuals that have attrited in the past but have subsequently been recruited back into he survey. We follow their advice and use the unbalanced panel with HRS weights for estimation. While using sampling weights or inverse probability weights can account for attrition on observables, attrition on unobservables would require selection models and exclusion restrictions which are often impossible to find.[35] Many studies, however, point to very mild attrition effects even in longitudinal surveys with high attrition rates (Fitzgerald, Gottschalk and Moffitt, 1998; Lillard and Panis, 1998; Alderman et al., 2001).

6 Conclusion

We use data from two representative U.S. household surveys, the Medical Expenditure Panel Survey (MEPS) and the Health and Retirement Study (RAND-HRS) and estimate transition probability matrices between self reported health states. We condition these probabilities on various individual characteristics such as age, gender, race, education, smoking behavior, income, initial health conditions, and the current health state. We use a non-parametric method based on weighted frequencies of self-reported health as well as different parametric models such as ordered logit and probit models, multinomial logit and probit models, as well as finite mixture and mixed process models. We also resolve a data inconsistency issue that only allows for the direct estimation of two-year transition probabilities in the HRS. Assuming a Markov structure, we transform two-year into one-year transition probabilities using a stochastic root method. This allows us to consistently present one year health transition probabilities between health states over the entire lifecycle of the working and retired population aged 20–95.

We find that the non-parametric counting method and the regression specification based on the ordered logit model produce similar results over the lifecycle. However, the counting method overestimates the probabilities of transitioning into worse health states. In addition, we find that young women have worse health prospects than their male counterparts but once individuals get older, being female is associated with transitioning into better health states with higher probabilities than men. We do not find significant

[34] See Heeringa and Connor (1995) and Ofstedal et al. (2011) for more detail about the HRS sample design and sample weights.

[35] Attrition on observables occurs when the dependent variable is independent of the attrition process conditional on the explanatory variables. Attrition on unobservables occurs when this conditional independence does not hold. A sample selection model can account for attrition on unobservables but requires an exclusion restriction for identification, that is, an instrumental variable that affects attrition only but not the dependent variable (Hausman and Wise, 1979; Ridder, 1992). Fitzgerald, Gottschalk and Moffitt (1998) point out that it is almost impossible to find plausible exclusion restrictions.

differences in the average predicted health transition probabilities by race if we condition on current health state and age simultaneously. Finally, we discuss issues of attrition bias, time effects, unobserved heterogeneity, and other modeling issues that can arise with categorical outcome variables. While the estimated health transition probabilities show interesting patterns across different groups, they also serve as an important building block in computational lifecycle models with health uncertainty. As such the techniques and results presented in this paper will be of value to researchers with an interest in lifecycle modeling of economic behavior affected by health and health policies.

Compliance with Ethical Standards/Declarations

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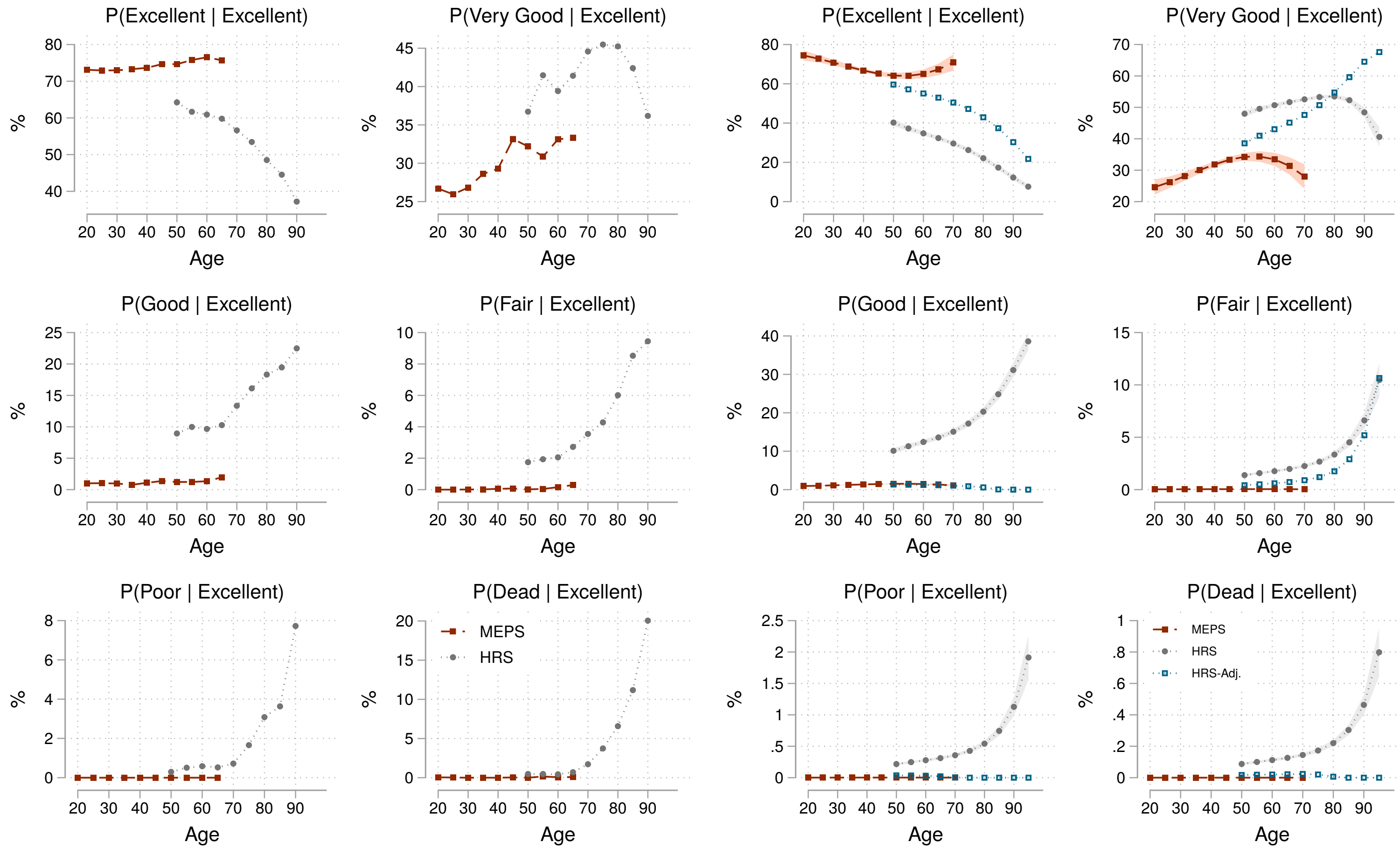
Figures



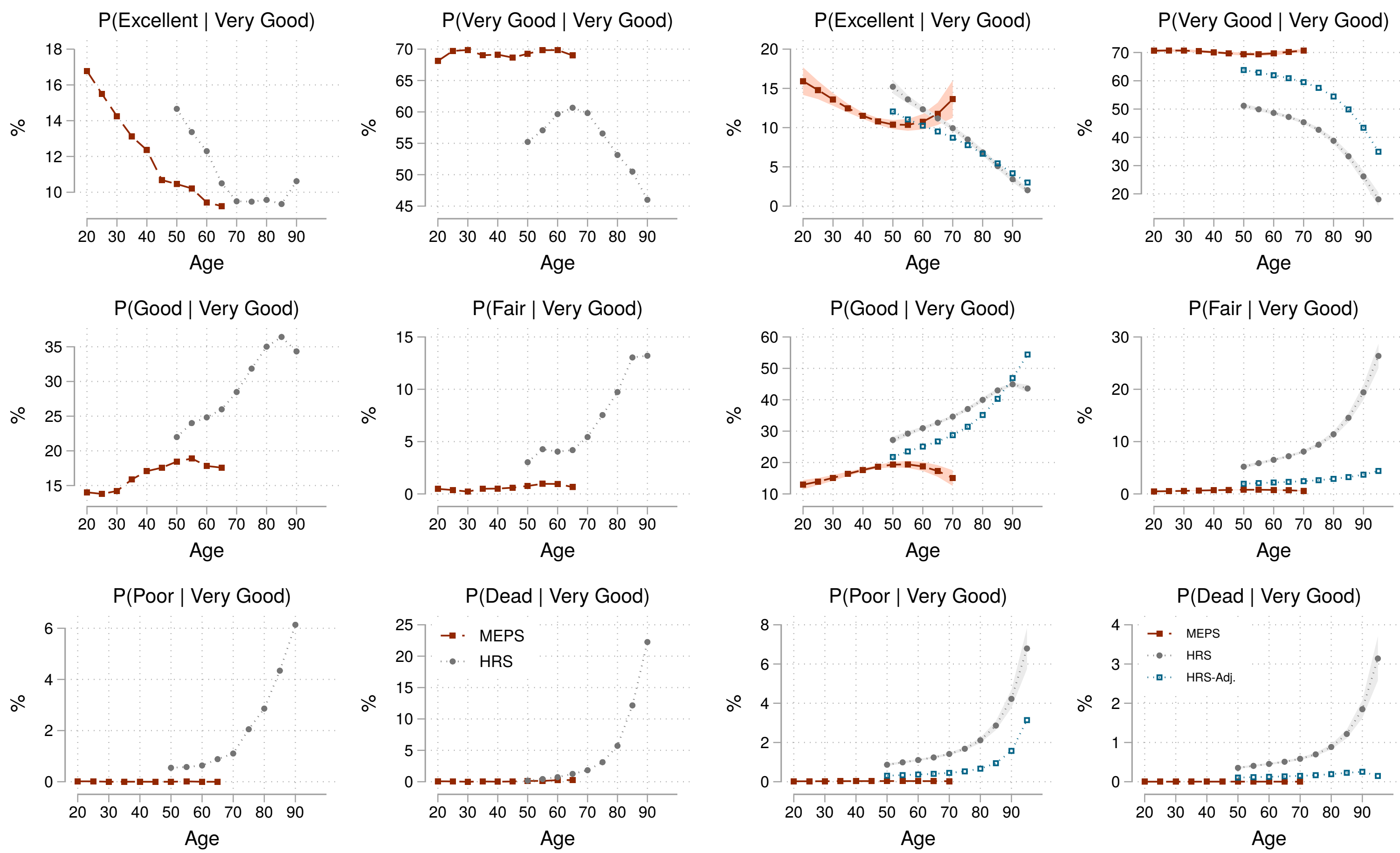
(a) Weighted Count

(b) Ordered Logit

Figure 1: **Transition Probabilities from Excellent Health State**

Note: **Panel** (*a*) reports relative frequencies of counts of **weighted** transitions from **excellent** health states to one of six possible health states for individuals belonging to the following five-year age groups: 20–24, 25 ± 2, $30 \pm 2, \ldots, 90 \pm 2$.

Panel (*b*) shows average predicted conditional probabilities based on separate **Ordered Logit** model estimates using **weighted** observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016. The predictions are shown with 95 percent confidence bounds. Since HRS estimates are based on two-year predictions, we transform the two-year predictions (gray lines with circle marker) into one-year predictions (blue lines with square marker). [back to page 8, 17]



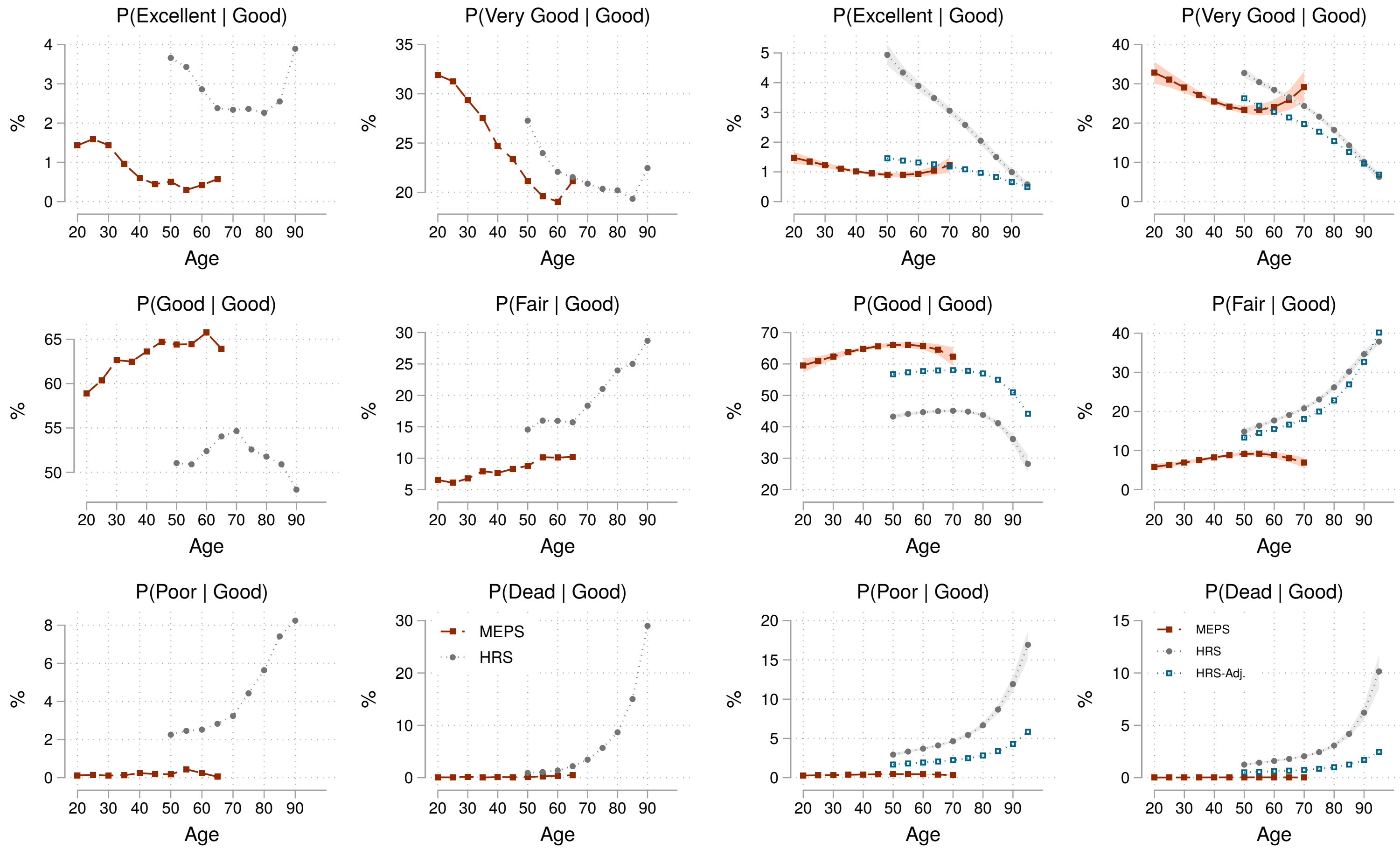
(a) Weighted Count

(b) Ordered Logit

Figure 2: **Transition Probabilities from Very Good Health State**

Note: **Panel** (a) reports relative frequencies of counts of **weighted** transitions from **very good** health states to one of six possible health states for individuals belonging to the following five-year age groups: 20–24, 25 ± 2, $30 \pm 2, \ldots$, 90 ± 2.

Panel (b) shows average predicted conditional probabilities based on separate **Ordered Logit** model estimates using **weighted** observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016. HRS estimates are controlled for initial health conditions. Since HRS estimates are based on two-year predictions, we transform the two-year predictions (gray lines with circle marker) into one-year predictions (blue lines with square marker). [back to page 8, 17]



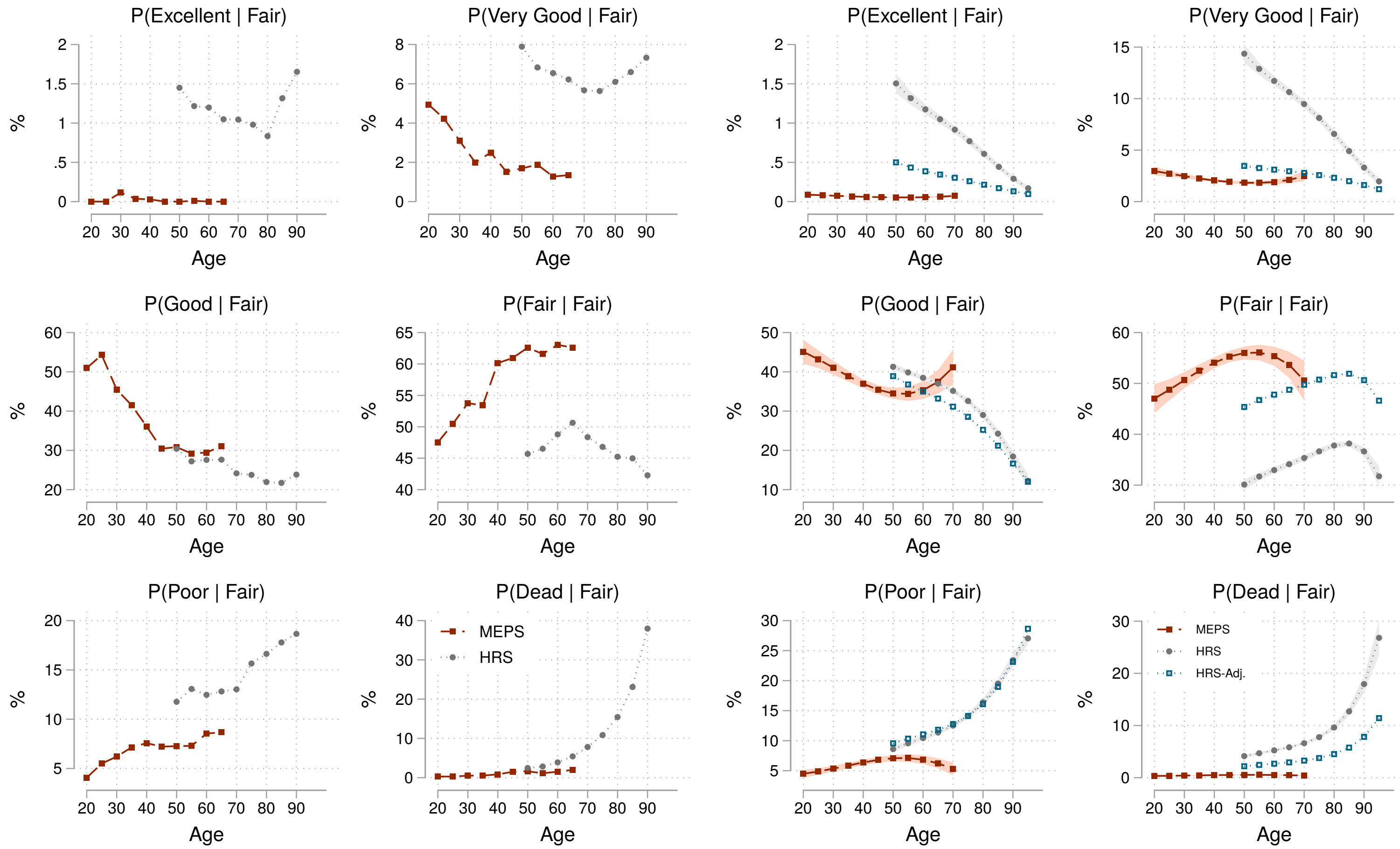
(a) Weighted Count

(b) Ordered Logit

Figure 3: **Transition Probabilities from Good Health State**

Note: **Panel** (a) reports relative frequencies of counts of **weighted** transitions from **good** health states to one of six possible health states for individuals belonging to the following five-year age groups: 20–24, 25 ± 2, $30 \pm 2, \ldots, 90 \pm 2$.

Panel (b) shows average predicted conditional probabilities based on separate **Ordered Logit** model estimates using **weighted** observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016. HRS estimates are controlled for initial health conditions. The predictions are shown with 95 percent confidence bounds. Since HRS estimates are based on two-year predictions, we transform the two-year predictions (gray lines with circle marker) into one-year predictions (blue lines with square marker). [back to page 8, 17]



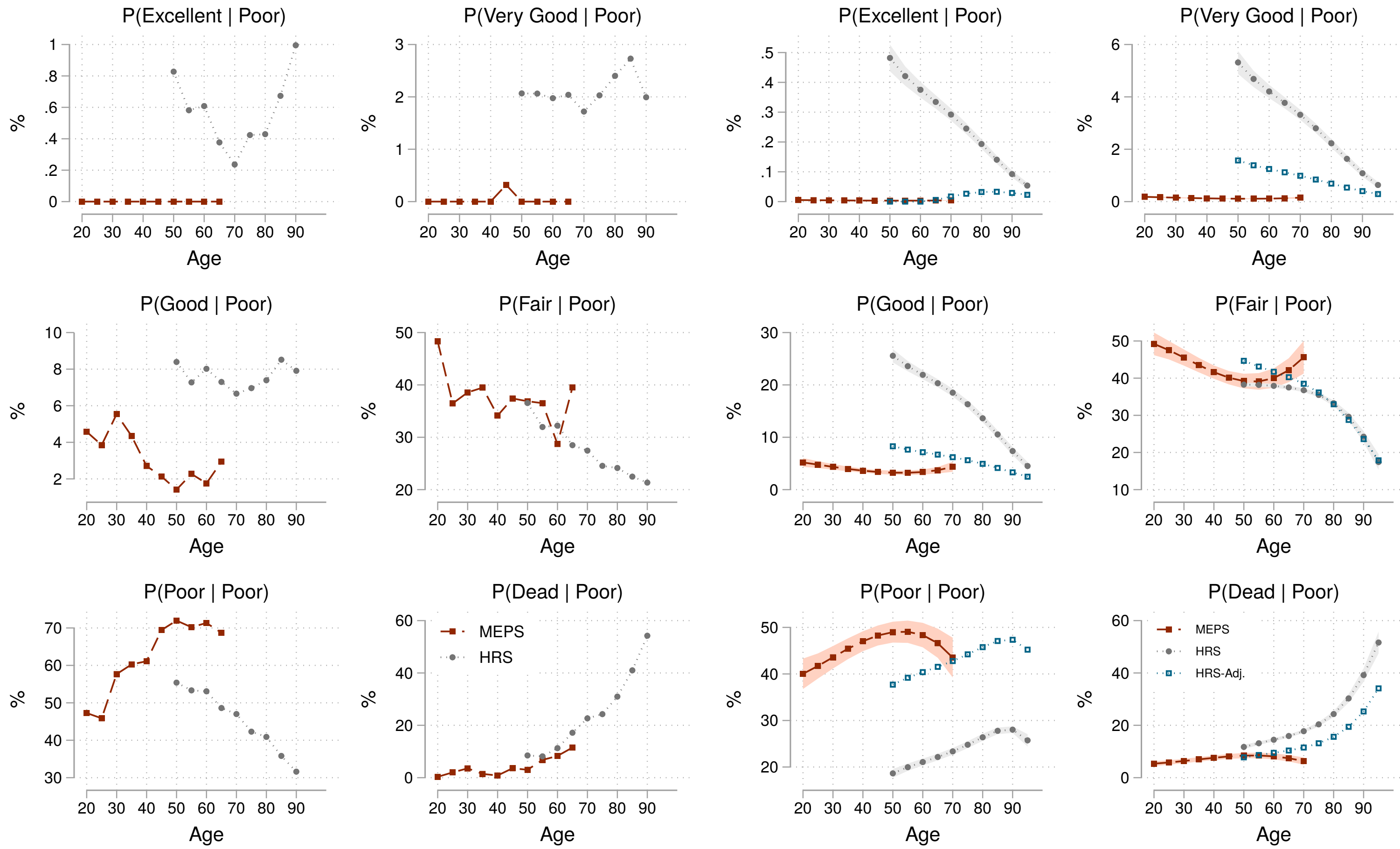
(a) Weighted Count

(b) Ordered Logit

Figure 4: **Transition Probabilities from Fair Health State**

Note: **Panel** (a) reports relative frequencies of counts of **weighted** transitions from **fair** health states to one of six possible health states for individuals belonging to the following five-year age groups: 20–24, 25 ± 2, $30 \pm 2, \ldots, 90 \pm 2$.

Panel (b) shows average predicted conditional probabilities based on separate **Ordered Logit** model estimates using **weighted** observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016. HRS estimates are controlled for initial health conditions. The predictions are shown with 95 percent confidence bounds. Since HRS estimates are based on two-year predictions, we transform the two-year predictions (gray lines with circle marker) into one-year predictions (blue lines with square marker). [back to page 8, 17]



(a) Weighted Count (b) Ordered Logit

Figure 5: **Transition Probabilities from Poor Health State**

Note: **Panel** (*a*) reports relative frequencies of counts of **weighted** transitions from **poor** health states to one of six possible health states for individuals belonging to the following five-year age groups: 20–24, 25 ± 2, $30 \pm 2, \ldots, 90 \pm 2$.

Panel (*b*) shows average predicted conditional probabilities based on separate **Ordered Logit** model estimates using **weighted** observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016. HRS estimates are controlled for initial health conditions. The predictions are shown with 95 percent confidence bounds. Since HRS estimates are based on two-year predictions, we transform the two-year predictions (gray lines with circle marker) into one-year predictions (blue lines with square marker). [back to page 8, 17]

Tables

Table 1: **Summary Statistics: Restricted Sample**

	MEPS			**HRS**		
	Nobs.	Freq.	Age	Nobs.	Freq.	Age
Year						
1992	0	0.0%		8,985	4.7%	55.6
1994	0	0.0%		15,044	7.9%	66.2
1996	0	0.0%		13,242	7.0%	67.5
1998	0	0.0%		18,751	9.9%	66.5
2000	5,227	3.8%	41.0	17,218	9.1%	67.7
2001	10,693	7.7%	41.3	0	0.0%	
2002	7,959	5.7%	40.9	15,905	8.4%	69.0
2003	8,035	5.8%	40.9	0	0.0%	
2004	8,070	5.8%	41.0	17,508	9.2%	67.3
2005	7,685	5.5%	41.6	0	0.0%	
2006	8,153	5.9%	42.0	16,174	8.5%	68.7
2007	6,200	4.5%	41.9	0	0.0%	
2008	9,440	6.8%	41.1	14,909	7.9%	69.9
2009	8,474	6.1%	41.9	0	0.0%	
2010	7,493	5.4%	41.6	18,984	10.0%	66.4
2011	9,705	7.0%	41.5	0	0.0%	
2012	9,639	6.9%	41.4	17,455	9.2%	67.6
2013	8,454	6.1%	41.5	0	0.0%	
2014	7,983	5.7%	41.7	15,474	8.2%	68.7
2015	8,382	6.0%	42.1	0	0.0%	
2016	7,657	5.5%	42.3	0	0.0%	
2017	16	0.0%	54.9	0	0.0%	
Total	139,265	100.0%	41.5	189,649	100.0%	67.2

Note: The restricted sample frequencies and the average age statistic are based on unweighted observations of individuals aged 20–65 in MEPS 2000–2017 and individuals aged 50–95 in RAND-HRS 1992–2016. In addition, the restricted sample contains individual/time observations with a complete set of control variables. The 16 observations for year 2017 in MEPS are individuals that entered MEPS at the beginning of the year, reported their base variables and subsequently died. We count them as transitions from their beginning of year health state to death. HRS data does not show 2016 observations because of the health state information from 2016 is counted as the h_{t+2} future health state for an individual in 2014. [back to page 7]

Table 2: **Summary Statistics II: Restricted Sample**

	(1) MEPS b	(2) MEPS-restr b	(3) HRS b	(4) HRS-restr b
Age	46.467	41.509	66.753	67.167
Female	0.538	0.540	0.579	0.570
Married/Partnered	0.538	0.548	0.646	0.647
Black	0.176	0.178	0.163	0.157
No high school degree	0.241	0.223	0.294	0.289
High school degree	0.530	0.542	0.514	0.518
College or higher degree	0.217	0.229	0.191	0.193
Labor income (in $1,000)	27.508	31.042	17.814	16.930
Labor income of HH (in $1,000)	56.907	61.750	31.274	28.812
Pre-government HH income (in $1,000)	68.441	69.416	71.720	71.316
Health Excellent	0.181	0.191	0.117	0.116
Health Very Good	0.384	0.396	0.279	0.283
Health Good	0.297	0.286	0.311	0.312
Health Fair	0.110	0.102	0.203	0.201
Health Poor	0.027	0.026	0.090	0.088
Initial Health Excellent	0.000	0.000	0.194	0.200
Initial Health Very Good	0.000	0.000	0.282	0.288
Initial Health Good	0.000	0.000	0.291	0.290
Initial Health Fair	0.000	0.000	0.161	0.154
Initial Health Poor	0.000	0.000	0.071	0.067
Dead/Diseased	0.005	0.003	0.051	0.000
Dead in t+k	0.005	0.003	0.052	0.058
Indicator for Healthy	0.863	0.873	0.707	0.710
Body Mass Index	26.679	27.245	27.656	27.590
Smoker	0.190	0.212	0.158	0.153
OOP health expenditure (in $1,000)	0.694	0.634	3.837	3.464
Total OOP expenditure HH ($1,000)	1.524	1.476	6.043	5.713
Insured	0.812	0.784	0.887	0.897
Public health insurance	0.207	0.153	0.428	0.438
Private health insurance	0.605	0.631	0.459	0.460
Head of HH/HIEU	0.573	0.596	0.697	0.699
Observations	433125	139265	259663	189649

Note: The restricted sample statistics are based on unweighted observations of individuals aged 20–65 in MEPS 2000–2017 and individuals aged 50–95 in RAND-HRS 1992–2016. In addition, the restricted sample contains individual time observations with a complete set of control variables. [back to page 7]

Table 4: **MEPS: Health Transitions using Counting Method**

	Health Status (t+1) incl. Death													
	Excellent		**Very Good**		**Good**		**Fair**		**Poor**		**Dead**		**Total**	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Health Status (t)														
Excellent	18,255	68.6%	7,983	30.0%	362	1.4%	8	0.0%	0	0.0%	7	0.0%	26,615	100.0%
Very Good	7,029	12.7%	37,638	68.3%	10,050	18.2%	366	0.7%	3	0.0%	47	0.1%	55,133	100.0%
Good	313	0.8%	9,668	24.3%	25,948	65.2%	3,710	9.3%	93	0.2%	71	0.2%	39,803	100.0%
Fair	3	0.0%	326	2.3%	4,486	31.7%	8,275	58.4%	934	6.6%	134	0.9%	14,158	100.0%
Poor	0	0.0%	1	0.0%	93	2.6%	1,188	33.4%	2,142	60.2%	132	3.7%	3,556	100.0%
Total	25,600	18.4%	55,616	39.9%	40,939	29.4%	13,547	9.7%	3,172	2.3%	391	0.3%	139,265	100.0%

Note: **Unweighted** sample counts of annual health transitions for age group 20–65. Data Source: MEPS 2000–2017. [back to page 3, 12]

Table 5: **MEPS: Health Transitions using Counting Method**

	Health Status (t+1) incl. Death						
	Excellent	**Very Good**	**Good**	**Fair**	**Poor**	**Dead**	**Total**
	%	%	%	%	%	%	%
Health Status (t)							
Excellent	70.7%	28.2%	1.1%	0.0%	0.0%	0.0%	100.0%
Very Good	12.7%	70.0%	16.6%	0.6%	0.0%	0.1%	100.0%
Good	0.8%	25.1%	65.2%	8.6%	0.2%	0.2%	100.0%
Fair	0.0%	2.0%	32.4%	57.5%	7.0%	1.1%	100.0%
Poor	0.0%	0.1%	2.3%	32.3%	60.6%	4.7%	100.0%
Total	20.9%	41.8%	27.0%	8.0%	2.0%	0.3%	100.0%

Note: **Weighted** sample counts of annual health transitions for age group 20–65. Data Source: MEPS 2000–2017. [back to page 3, 12]

Table 6: **HRS: Health Transitions using Counting Method**

	Health Status (t+2) incl. Death													
	Excellent		**Very Good**		**Good**		**Fair**		**Poor**		**Dead**		**Total**	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Health Status (t)														
Excellent	11,430	48.2%	8,243	34.7%	2,650	11.2%	721	3.0%	234	1.0%	450	1.9%	23,728	100.0%
Very Good	6,151	10.8%	29,990	52.7%	15,084	26.5%	3,388	6.0%	822	1.4%	1,457	2.6%	56,892	100.0%
Good	1,822	2.9%	12,855	20.5%	31,282	49.8%	11,551	18.4%	2,329	3.7%	2,992	4.8%	62,831	100.0%
Fair	501	1.2%	2,403	5.9%	9,614	23.4%	18,698	45.6%	5,691	13.9%	4,116	10.0%	41,023	100.0%
Poor	92	0.5%	363	1.9%	1,323	7.0%	4,737	25.0%	8,157	43.0%	4,284	22.6%	18,956	100.0%
Total	19,996	9.8%	53,854	26.5%	59,953	29.5%	39,095	19.2%	17,233	8.5%	13,299	6.5%	203,430	100.0%

Note: **Unweighted** sample counts of 2-year health transitions for age group 50–95. Data Source: RAND-HRS 1992–2016. [back to page 3, 12]

Table 7: **HRS: Health Transitions using Counting Method**

	Health Status (t+2) incl. Death						
	Excellent	**Very Good**	**Good**	**Fair**	**Poor**	**Dead**	**Total**
	%	%	%	%	%	%	%
Health Status (t)							
Excellent	50.5%	35.2%	9.7%	2.4%	0.8%	1.4%	100.0%
Very Good	11.0%	55.2%	25.5%	5.1%	1.1%	2.0%	100.0%
Good	2.7%	21.5%	50.9%	17.6%	3.4%	4.0%	100.0%
Fair	1.1%	6.1%	24.8%	46.0%	13.4%	8.6%	100.0%
Poor	0.5%	1.9%	7.3%	26.4%	44.6%	19.3%	100.0%
Total	10.8%	29.1%	29.7%	17.8%	7.5%	5.1%	100.0%

Note: **Weighted** sample counts of 2-year health transitions for age group 50–95. Data Source: RAND-HRS 1992–2016. [back to page 3, 12]

Table 8: **MEPS: Predicted Transition Probabilities from Ordered Logit Model**

(a) Age Only

	Health (t+1)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	69.9	28.8	1.2	0.0	0.0	0.0	100.0
(s.e.)	0.340	0.321	0.028	0.001	0.000	0.000	.
Very Good	12.4	70.3	16.6	0.7	0.0	0.0	100.0
(s.e.)	0.167	0.220	0.183	0.017	0.001	0.000	.
Good	1.0	25.2	64.9	8.4	0.4	0.0	100.0
(s.e.)	0.023	0.263	0.280	0.153	0.017	0.003	.
Fair	0.1	1.9	34.5	56.0	7.1	0.6	100.0
(s.e.)	0.002	0.056	0.481	0.497	0.230	0.048	.
Poor	0.0	0.1	3.1	37.9	50.0	8.9	100.0
(s.e.)	0.000	0.006	0.165	0.846	1.054	0.505	.

(b) Full Set of Controls

	Health (t+1)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	67.6	31.0	1.3	0.0	0.0	0.0	100.0
(s.e.)	0.355	0.334	0.031	0.001	0.000	0.000	.
Very Good	12.1	70.0	17.2	0.7	0.0	0.0	100.0
(s.e.)	0.164	0.221	0.186	0.017	0.001	0.000	.
Good	1.1	26.4	64.1	8.0	0.4	0.0	100.0
(s.e.)	0.024	0.275	0.287	0.147	0.016	0.003	.
Fair	0.1	2.2	38.0	53.1	6.2	0.5	100.0
(s.e.)	0.002	0.067	0.507	0.521	0.204	0.042	.
Poor	0.0	0.1	3.8	42.5	46.1	7.4	100.0
(s.e.)	0.000	0.008	0.209	0.859	1.058	0.429	.

Note: Standard errors are presented below the respective probabilities. All numbers are expressed in percent.
Panel (*a*) reports average predictions based on **Ordered Logit** estimates for age group 20–65 and age, age^2, and age^3 as sole control variables.
Panel (*b*) reports average predictions based on **Ordered Logit** estimates for age group 20–65 and a full set of control variables including age, cohort, partner status, smoking behavior, gender, race, education, income, and region. The average predicted probability to be in excellent health in the next period (**one year** from now) if an individual is in excellent health in the current period is 67.6 percent with a standard error of 0.355 percent. Due to the large sample size our predictions are very precise.
Data Source: MEPS 2000–2017. [back to page 12]

Table 9: **HRS: Predicted Transition Probabilities from Ordered Logit Model**

(a) Age Only

	Health (t+2)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	44.6	45.3	8.6	1.2	0.2	0.1	100.0
(s.e.)	0.591	0.406	0.212	0.038	0.007	0.003	.
Very Good	12.9	49.6	29.7	6.2	1.1	0.5	100.0
(s.e.)	0.168	0.277	0.218	0.094	0.024	0.012	.
Good	3.0	23.6	45.4	21.0	4.8	2.1	100.0
(s.e.)	0.058	0.199	0.234	0.178	0.077	0.046	.
Fair	0.7	6.7	29.3	38.2	16.0	9.1	100.0
(s.e.)	0.017	0.111	0.236	0.269	0.205	0.144	.
Poor	0.2	1.8	11.1	31.1	28.3	27.5	100.0
(s.e.)	0.005	0.044	0.197	0.273	0.360	0.300	.

(b) Full Controls

	Health (t+2)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	31.3	51.0	14.9	2.3	0.4	0.2	100.0
(s.e.)	0.500	0.277	0.325	0.072	0.013	0.006	.
Very Good	10.9	45.5	33.4	8.1	1.5	0.6	100.0
(s.e.)	0.147	0.277	0.213	0.122	0.032	0.016	.
Good	3.4	25.6	43.9	20.2	4.7	2.1	100.0
(s.e.)	0.068	0.212	0.235	0.171	0.076	0.046	.
Fair	1.0	10.4	35.6	34.0	12.3	6.7	100.0
(s.e.)	0.028	0.190	0.247	0.287	0.177	0.119	.
Poor	0.3	3.7	19.6	36.2	22.4	17.7	100.0
(s.e.)	0.011	0.106	0.357	0.250	0.347	0.306	.

Note: Standard errors are presented below the respective probabilities. All numbers are expressed in percent.
Panel (*a*) reports average predictions based on **Ordered Logit** estimates for age group 50–95 and age, age^2, and age^3 as sole control variables.
Panel (*b*) reports average predictions based on **Ordered Logit** estimates for age group 50–95 and a full set of control variables including age, cohort, partner status, smoking behavior, gender, race, education, income, initial health, and region. The average predicted probability to be in excellent health in the next period (**two years** from now) if an individual is in excellent health in the current period is 31.3 percent with a standard error of 0.500 percent. Due to the large sample size our predictions are very precise.
Data Source: RAND-HRS 1992–2016. [back to page 12]

Table 10: **MEPS - Marginal Effects from Ordered Logit on** $\Pr(\mathbf{Health}_{t+1})$

	Excellent	Very_Good	Good	Fair	Poor	Dead
Health_t:						
Very Good	-0.555***	0.390***	0.158***	0.006***	0.000***	0.000***
	(0.004)	(0.004)	(0.002)	(0.000)	(0.000)	(0.000)
Good	-0.665***	-0.046***	0.627***	0.080***	0.004***	0.000***
	(0.004)	(0.004)	(0.003)	(0.001)	(0.000)	(0.000)
Fair	-0.675***	-0.289***	0.367***	0.531***	0.062***	0.005***
	(0.004)	(0.003)	(0.005)	(0.005)	(0.002)	(0.000)
Poor	-0.676***	-0.309***	0.025***	0.425***	0.461***	0.074***
	(0.004)	(0.003)	(0.002)	(0.009)	(0.011)	(0.004)
Age	-0.001***	0.000	0.001***	0.000*	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married/Partnered	0.005**	0.001**	-0.003**	-0.002**	-0.001**	-0.000**
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Smoker	-0.018***	-0.004***	0.014***	0.006***	0.002***	0.001***
	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Female	-0.010***	-0.001*	0.007***	0.003***	0.001***	0.000***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Black	-0.007***	-0.002***	0.005***	0.003***	0.001***	0.000***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Hispanic	-0.005**	-0.001**	0.004**	0.002**	0.001**	0.000**
	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
High School Degree	0.012***	0.003***	-0.009***	-0.004***	-0.001***	-0.000***
	(0.002)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
College or Higher Degree	0.032***	0.006***	-0.023***	-0.010***	-0.003***	-0.001***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)
HH Gross Income (in $1,000)	0.000***	0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year $\leq$ 2001	-0.003	-0.001	0.002	0.001	0.000	0.000
	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)
Year $\geq$ 2012	-0.009***	-0.002***	0.007***	0.003***	0.001***	0.000***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)	(0.000)

Note: Nr. of individual/time observations NT = 139,265. We report average marginal effects based on **Ordered Logit** estimates for individuals between age 20–65 in the MEPS 2000–2017. Standard errors are clustered at the individual levels and estimates are based on weighted observations. The health states in the top line are future health states in $t+1$. [back to page 13]

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Table 11: **HRS - Marginal Effects from Ordered Logit on** $\Pr\left(\mathbf{Health}_{t+2}\right)$

	Excellent	Very_Good	Good	Fair	Poor	Dead
Health$_t$:						
Very Good	-0.203***	-0.055***	0.185***	0.058***	0.011***	0.005***
	(0.005)	(0.002)	(0.003)	(0.001)	(0.000)	(0.000)
Good	-0.278***	-0.254***	0.290***	0.179***	0.043***	0.020***
	(0.005)	(0.003)	(0.004)	(0.002)	(0.001)	(0.000)
Fair	-0.302***	-0.406***	0.206***	0.317***	0.119***	0.066***
	(0.005)	(0.003)	(0.004)	(0.003)	(0.002)	(0.001)
Poor	-0.309***	-0.473***	0.047***	0.339***	0.221***	0.175***
	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Initial Health$_{t=0}$:						
Very Good	-0.044***	-0.042***	0.023***	0.035***	0.017***	0.012***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
Good	-0.070***	-0.079***	0.031***	0.061***	0.032***	0.024***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Fair	-0.089***	-0.116***	0.032***	0.085***	0.049***	0.039***
	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)
Poor	-0.099***	-0.140***	0.029***	0.099***	0.060***	0.051***
	(0.002)	(0.004)	(0.001)	(0.003)	(0.002)	(0.001)
Age	-0.002***	-0.003***	0.000*	0.002***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married/Partnered	0.005***	0.006***	-0.001***	-0.004***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Smoker	-0.021***	-0.023***	0.004***	0.016***	0.011***	0.012***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Female	0.009***	0.012***	-0.000	-0.008***	-0.006***	-0.007***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Black	-0.006***	-0.005***	0.002***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Hispanic	-0.006***	-0.006***	0.001***	0.004***	0.003***	0.003***
	(0.002)	(0.002)	(0.000)	(0.001)	(0.001)	(0.001)
High School Degree	0.013***	0.013***	-0.003***	-0.009***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
College or Higher Degree	0.029***	0.028***	-0.008***	-0.021***	-0.014***	-0.013***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
HH Gross Income (in $1,000)	0.000***	0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year $\leq$ 2001	0.006***	0.005***	-0.002***	-0.004***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Year $\geq$ 2012	-0.006***	-0.006***	0.001***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)

Note: Nr. of individual/time observations NT = 189,649. We report average marginal effects based on **Ordered Logit** estimates of individuals between age 50–95 in the RAND-HRS 1992–2016. Standard errors are clustered at the individual levels and estimates are based on weighted observations. The health states in the top line are future health states in $t+2$. [back to page 13]

Table 12: **HRS: Predicted Transition Probabilities from Multinomial Logit Model**

	Health (t+2)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	33.8	37.7	16.9	6.1	2.3	3.2	100.0
Very Good	9.8	48.8	28.7	7.9	2.0	2.8	100.0
Good	3.6	23.4	47.8	17.5	3.7	3.9	100.0
Fair	2.6	11.1	29.6	38.6	10.7	7.4	100.0
Poor	1.9	6.0	13.7	27.7	32.1	18.6	100.0

Note: We report average predictions based on **Multinomial Logit** estimates for age group 50–95. Data Source: RAND-HRS 1992–2016. [back to page 18]

Table 13: **HRS: Predicted Transition Probabilities from Multinomial Probit Model**

	Health (t+2)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	36.5	35.7	16.1	6.1	2.5	3.1	100.0
Very Good	10.0	49.5	27.8	7.8	2.2	2.8	100.0
Good	3.8	23.2	48.0	17.3	3.8	3.8	100.0
Fair	3.1	11.5	28.2	39.0	10.8	7.4	100.0
Poor	2.4	6.9	13.1	25.6	33.5	18.6	100.0

Note: We report average predictions based on **Multinomial Probit** estimates for age group 50–95. Data Source: RAND-HRS 1992–2016. [back to page 18]

Table 14: **Attrition Rates**

	(1) MEPS b	(2) HRS b
Attrition due to recorded death	0.0019	0.0537
Attrition due to missing health info	0.0002	0.0000
Attrition excl. death	0.0869	0.0478
Attrition total	0.0888	0.1014
Observations	364514	250460

Note: Statistics are based on unweighted observations of individuals aged 20–65 in MEPS 2000–2017 and individuals aged 50–95 in RAND-HRS 1992–2016. [back to page 21]

A Summary Statistics

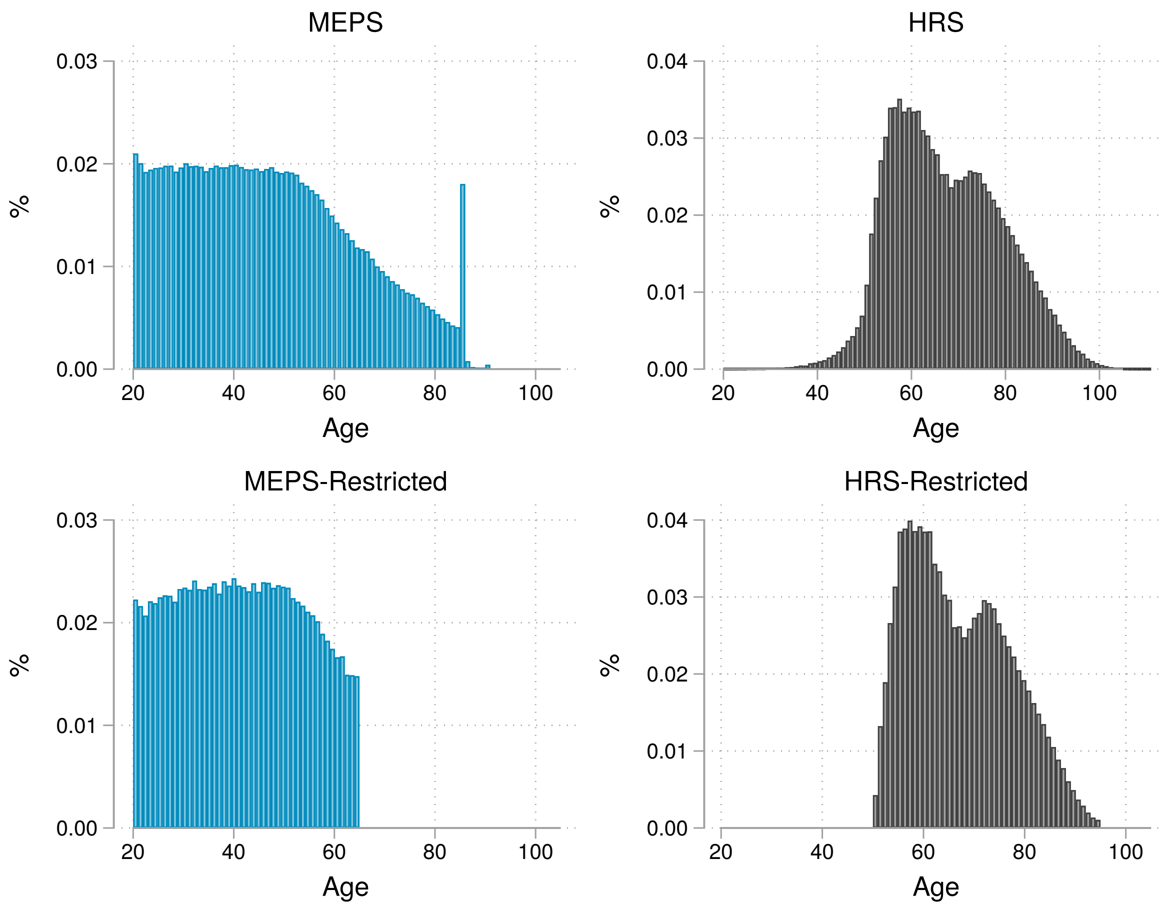


Figure A.1: **Histograms of Full and Restricted Samples**

Note: Histograms are based on unweighted observations of individuals aged 20–65 in MEPS 2000–2017 and individuals aged 50–95 in RAND-HRS 1992–2016. The restricted MEPS sample only includes information from 2000–2017 because the smoking information is only available from 2000 onward. [back to page 7]

Table A.1: **Summary Statistics: Full Sample**

	MEPS			**HRS**		
	Nobs.	Freq.	Age	Nobs.	Freq.	Age
Year						
1992	0	0.0%		12,651	4.8%	55.3
1994	0	0.0%		19,865	7.6%	65.1
1996	0	0.0%		19,052	7.3%	67.0
1998	0	0.0%		22,608	8.6%	66.7
1999	16,344	3.8%	46.0	0	0.0%	
2000	16,744	3.9%	46.1	20,901	8.0%	67.9
2001	22,574	5.2%	46.1	0	0.0%	
2002	26,021	6.0%	46.0	19,576	7.5%	69.1
2003	22,424	5.2%	45.8	0	0.0%	
2004	22,761	5.3%	45.9	21,300	8.1%	67.4
2005	22,444	5.2%	46.1	0	0.0%	
2006	22,685	5.2%	46.9	19,727	7.5%	68.8
2007	20,740	4.8%	46.9	0	0.0%	
2008	22,030	5.1%	45.9	18,422	7.0%	70.0
2009	24,846	5.7%	46.0	0	0.0%	
2010	22,372	5.2%	46.6	23,439	9.0%	66.6
2011	24,112	5.6%	46.4	0	0.0%	
2012	26,703	6.2%	46.1	21,635	8.3%	67.5
2013	25,157	5.8%	46.0	0	0.0%	
2014	23,870	5.5%	46.4	19,989	7.6%	68.7
2015	24,496	5.7%	47.1	0	0.0%	
2016	24,188	5.6%	47.7	22,249	8.5%	66.6
2017	22,614	5.2%	48.8	0	0.0%	
Total	433,125	100.0%	46.5	261,414	100.0%	67.0

Note: Statistics are based on unweighted observations of individuals aged 20–65 in MEPS 2000–2017 and individuals aged 50–95 in RAND-HRS 1992–2016. [back to page 7]

B Ordered Probit Model vs. Ordered Logit Model

Table B.1: **MEPS: Transition Probabilities Ordered Logit vs. Ordered Probit**

(a) Ordered Logit

	Health (t+1)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	67.6	31.0	1.3	0.0	0.0	0.0	100.0
(s.e.)	0.355	0.334	0.031	0.001	0.000	0.000	.
Very Good	12.1	70.0	17.2	0.7	0.0	0.0	100.0
(s.e.)	0.164	0.221	0.186	0.017	0.001	0.000	.
Good	1.1	26.4	64.1	8.0	0.4	0.0	100.0
(s.e.)	0.024	0.275	0.287	0.147	0.016	0.003	.
Fair	0.1	2.2	38.0	53.1	6.2	0.5	100.0
(s.e.)	0.002	0.067	0.507	0.521	0.204	0.042	.
Poor	0.0	0.1	3.8	42.5	46.1	7.4	100.0
(s.e.)	0.000	0.008	0.209	0.859	1.058	0.429	.

(b) Ordered Probit

	Health (t+1)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	67.1	32.2	0.7	0.0	0.0	0.0	100.0
(s.e.)	0.361	0.340	0.029	0.000	0.000	0.000	.
Very Good	12.9	67.9	18.9	0.3	0.0	0.0	100.0
(s.e.)	0.169	0.237	0.196	0.014	0.000	0.000	.
Good	0.5	28.6	61.2	9.5	0.2	0.0	100.0
(s.e.)	0.021	0.280	0.307	0.166	0.014	0.001	.
Fair	0.0	2.1	40.2	49.4	7.8	0.5	100.0
(s.e.)	0.000	0.093	0.478	0.545	0.230	0.069	.
Poor	0.0	0.0	6.0	45.0	37.7	11.3	100.0
(s.e.)	0.000	0.004	0.377	0.661	1.087	0.586	.

Note: Standard errors are presented below the respective probabilities. All numbers are expressed in percent.
Panel (*a*) reports average predictions based on **Ordered Logit** estimates for age group 20–65.
Panel (*b*) reports average predictions based on **Ordered Probit** estimates for age group 20–65.
Data Source: MEPS 2000–2017. [back to page 12]

Table B.2: **HRS: Transition Probabilities Ordered Logit vs. Ordered Probit**

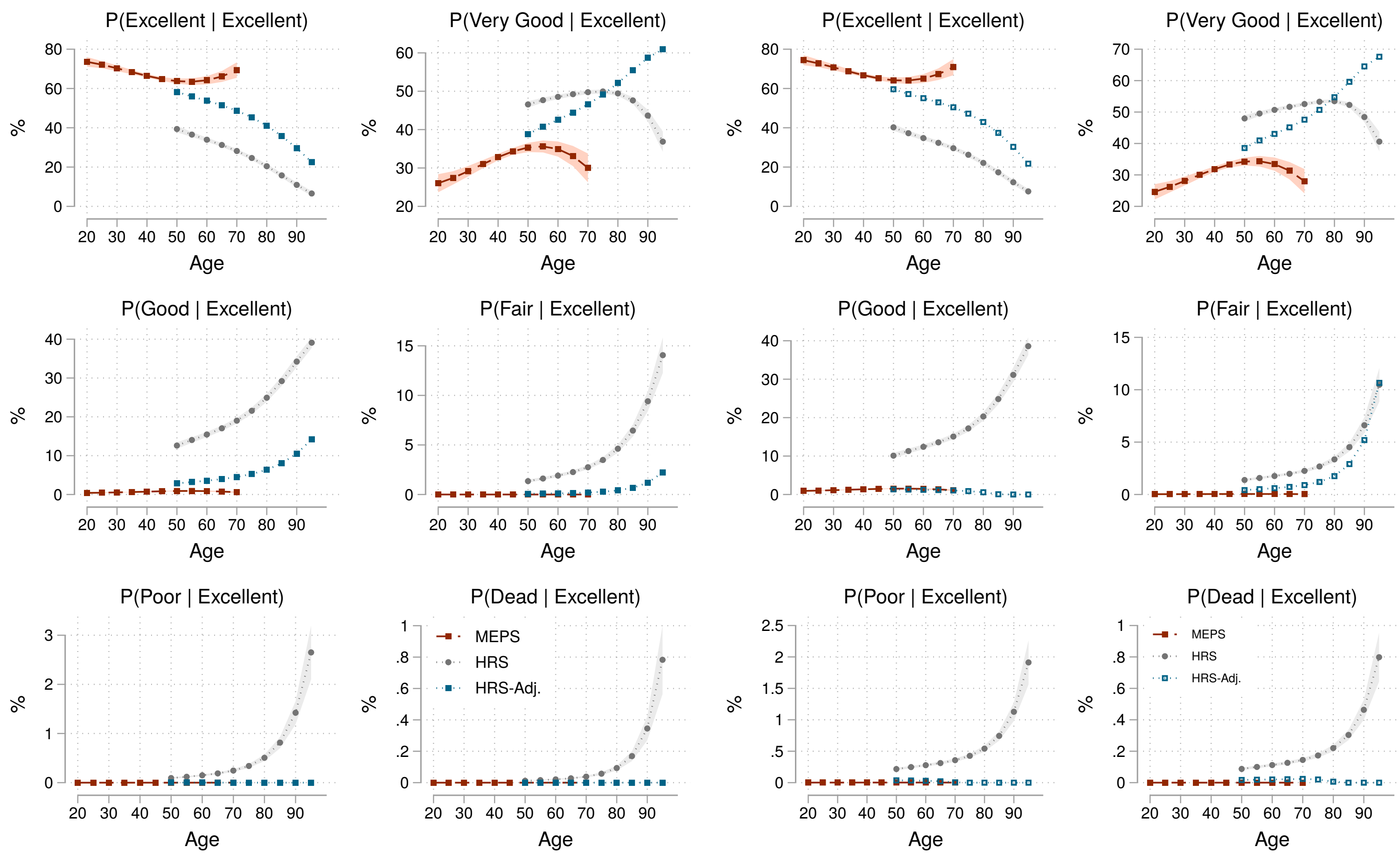
(a) Ordered Probit

	Health (t+2)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	31.3	51.0	14.9	2.3	0.4	0.2	100.0
(s.e.)	0.500	0.277	0.325	0.072	0.013	0.006	.
Very Good	10.9	45.5	33.4	8.1	1.5	0.6	100.0
(s.e.)	0.147	0.277	0.213	0.122	0.032	0.016	.
Good	3.4	25.6	43.9	20.2	4.7	2.1	100.0
(s.e.)	0.068	0.212	0.235	0.171	0.076	0.046	.
Fair	1.0	10.4	35.6	34.0	12.3	6.7	100.0
(s.e.)	0.028	0.190	0.247	0.287	0.177	0.119	.
Poor	0.3	3.7	19.6	36.2	22.4	17.7	100.0
(s.e.)	0.011	0.106	0.357	0.250	0.347	0.306	.

(b) Ordered Probit

	Health (t+2)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	30.1	48.4	18.3	2.8	0.3	0.0	100.0
(s.e.)	0.478	0.264	0.332	0.100	0.015	0.003	.
Very Good	11.5	43.1	33.7	9.7	1.6	0.4	100.0
(s.e.)	0.153	0.265	0.204	0.134	0.041	0.017	.
Good	3.4	27.1	40.9	20.9	5.4	2.2	100.0
(s.e.)	0.078	0.202	0.221	0.174	0.086	0.055	.
Fair	0.8	12.8	35.5	30.9	12.2	7.8	100.0
(s.e.)	0.030	0.212	0.218	0.254	0.179	0.135	.
Poor	0.1	4.6	23.0	33.1	19.5	19.6	100.0
(s.e.)	0.008	0.148	0.333	0.233	0.292	0.335	.

Note: Standard errors are presented below the respective probabilities. All numbers are expressed in percent.
Panel (*a*) reports average predictions based on **Ordered Logit** estimates for age group 50–95.
Panel (*b*) reports average predictions based on **Ordered Probit** estimates for age group 50–95 with smoking behavior as second dependent variable.
Data Source: RAND-HRS 1992–2016. [back to page 12]



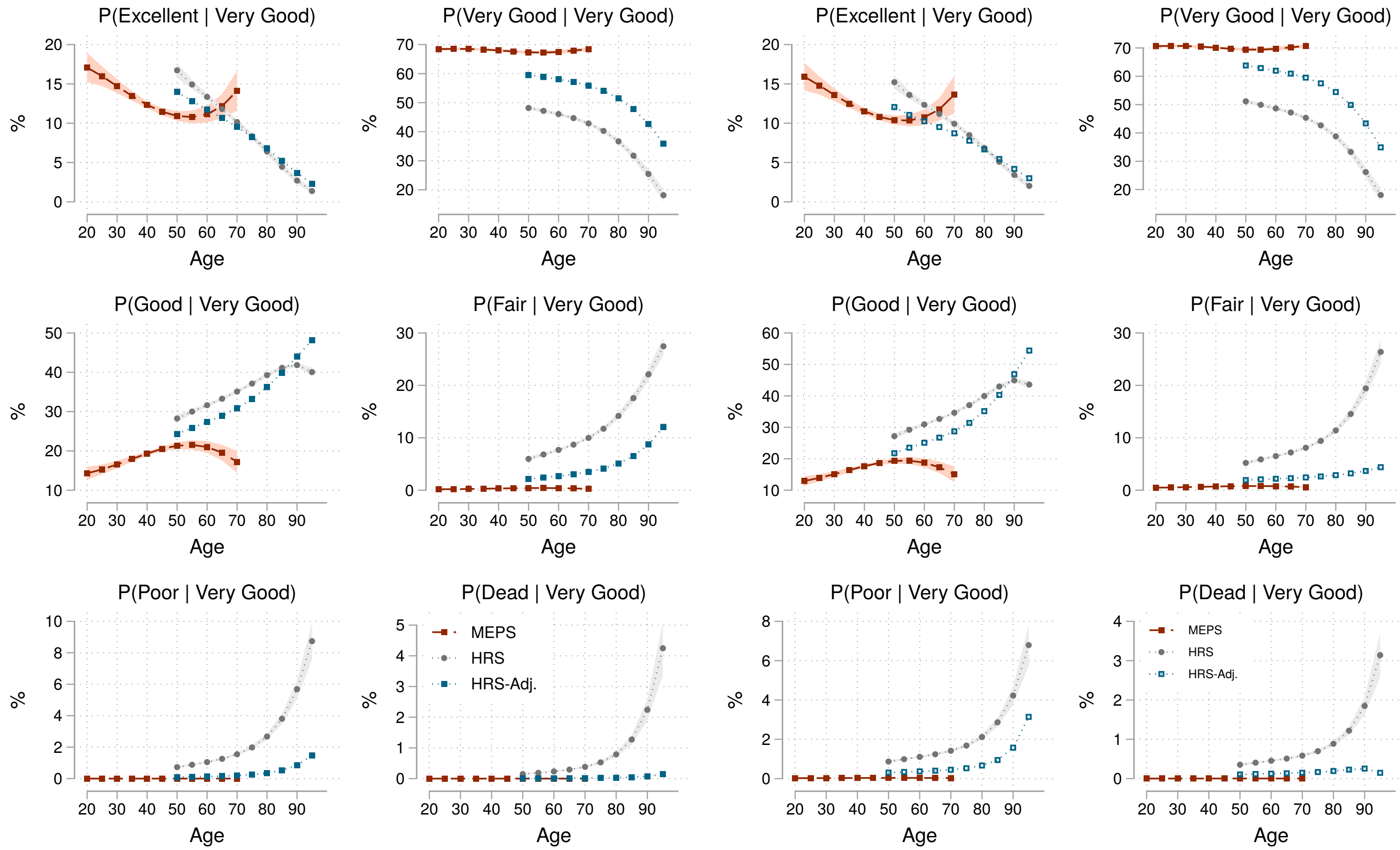
(a) Ordered Probit

(b) Ordered Logit

Figure B.1: **Ordered Probit vs. Ordered Logit: Transitions from Excellent Health**

Note: **Panel** (*a*) shows average predicted conditional probabilities based on separate **Ordered Probit** model estimates using weighted observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016.

Panel (*b*) shows average predicted conditional probabilities based on separate **Ordered Logit** model estimates using weighted observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016. In both panels the predictions are shown with 95 percent confidence bounds and one-year transitions (blue lines) are calculated from the two-year HRS estimates (gray lines). [back to page 18]



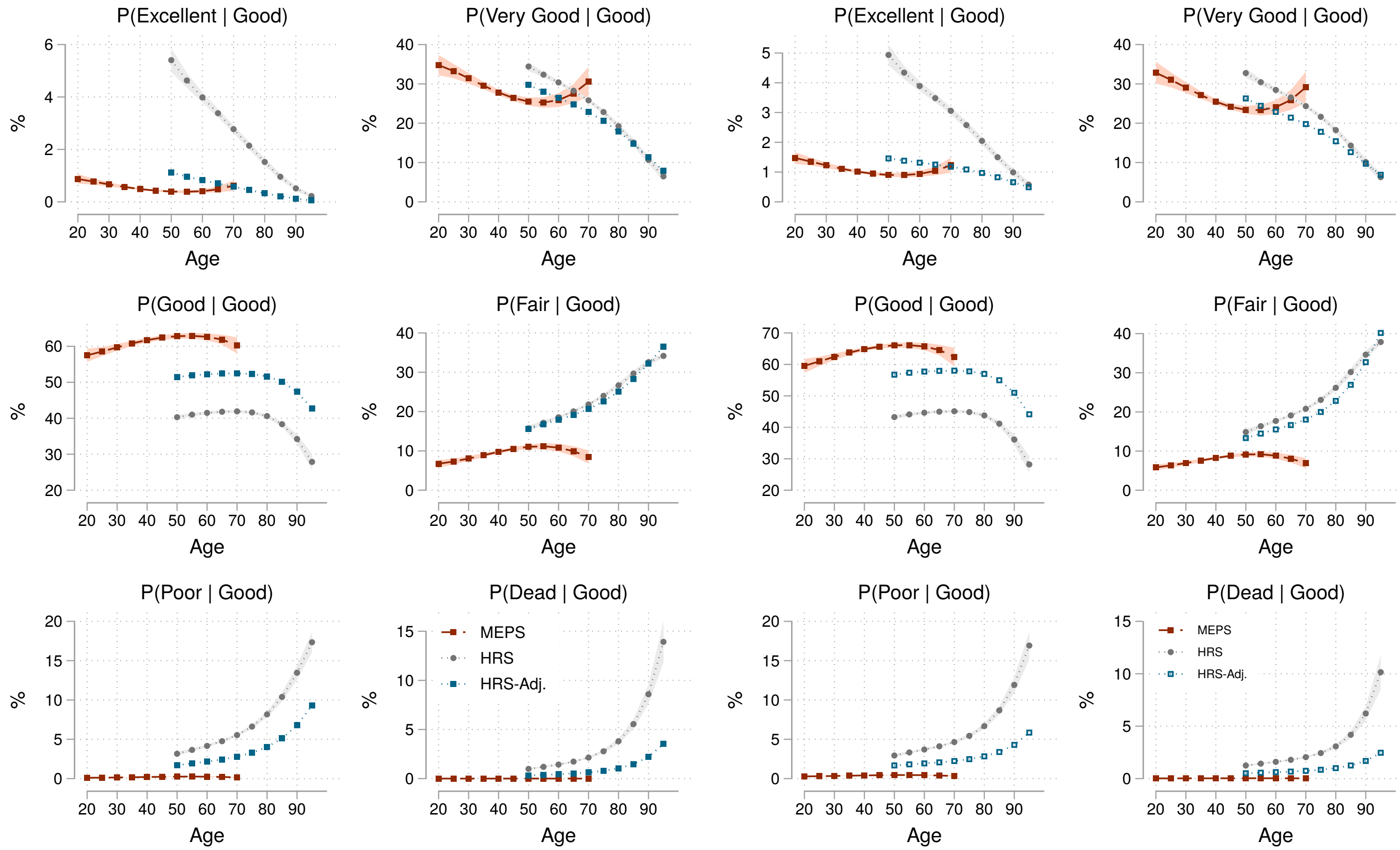
(a) Ordered Probit

(b) Ordered Logit

Figure B.2: **Ordered Probit vs. Ordered Logit: Transitions from Very Good Health**

Note: **Panel** (*a*) shows average predicted conditional probabilities based on separate Ordered Probit model estimates using weighted observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016.

Panel (*b*) shows average predicted conditional probabilities based on separate Ordered Logit model estimates using weighted observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016. In both panels the predictions are shown with 95 percent confidence bounds and one-year transitions (blue lines) are calculated from the two-year HRS estimates (gray lines). [back to page 18]



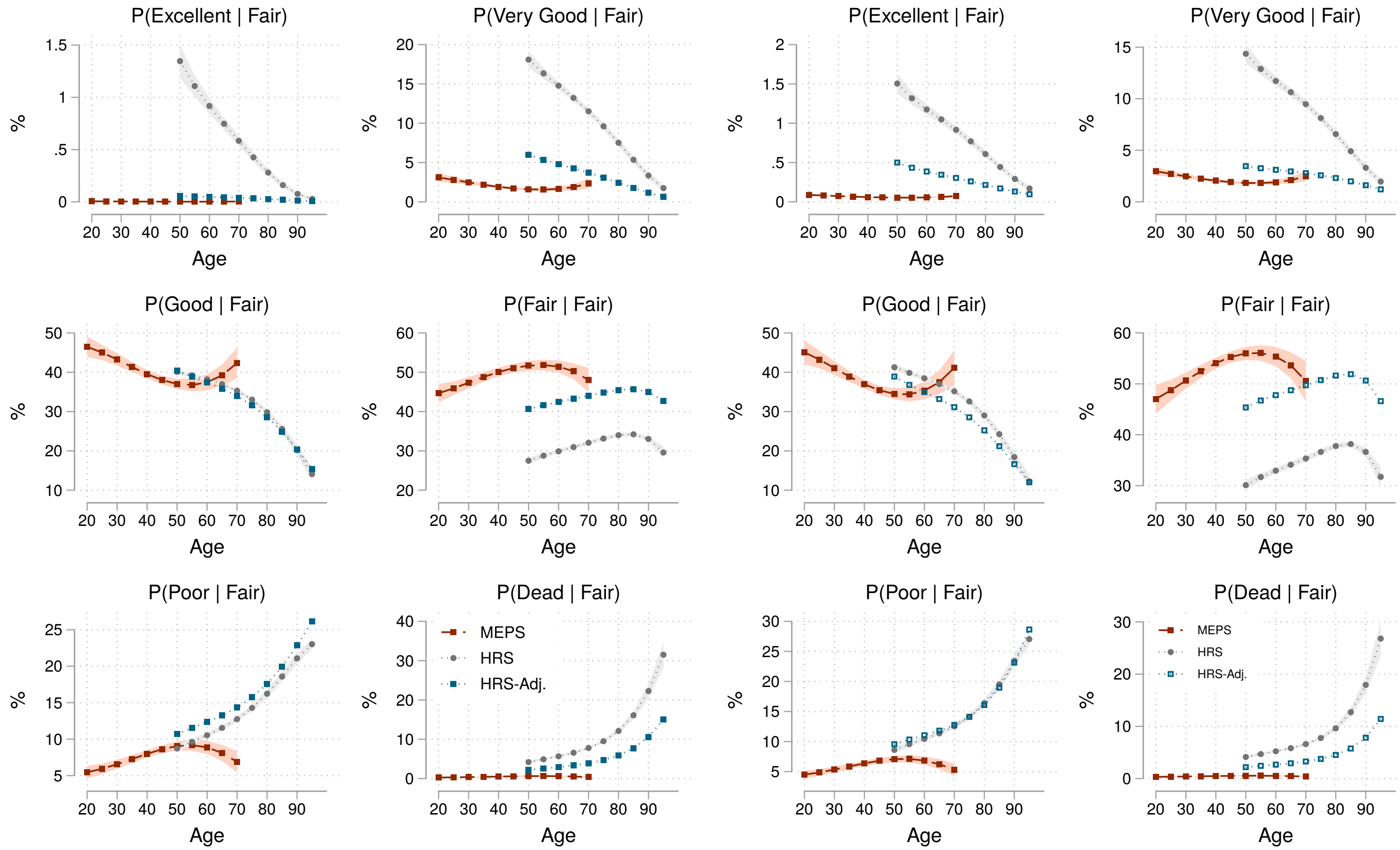
(a) Ordered Probit

(b) Ordered Logit

Figure B.3: **Ordered Probit vs. Ordered Logit: Transition Probabilities from Good Health**

Note: **Panel** (*a*) shows average predicted conditional probabilities based on separate Ordered Probit model estimates using weighted observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016.

Panel (*b*) shows average predicted conditional probabilities based on separate Ordered Logit model estimates using weighted observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016. In both panels the predictions are shown with 95 percent confidence bounds and one-year transitions (blue lines) are calculated from the two-year HRS estimates (gray lines). [back to page 18]



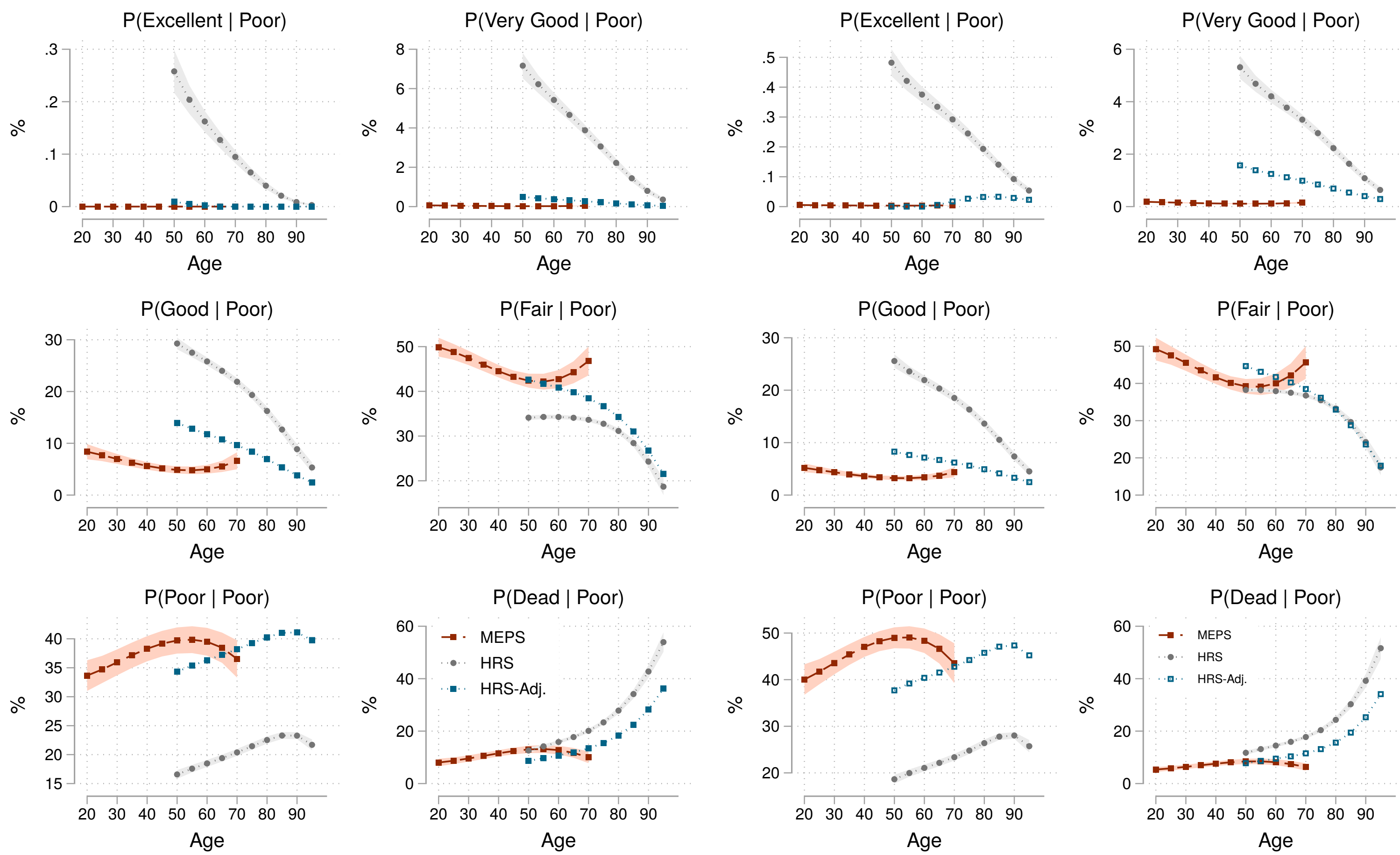
(a) Ordered Probit

(b) Ordered Logit

Figure B.4: **Ordered Probit vs. Ordered Logit: Transitions from Fair Health**

Note: **Panel** (*a*) shows average predicted conditional probabilities based on separate Ordered Probit model estimates using weighted observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016.

Panel (*b*) shows average predicted conditional probabilities based on separate Ordered Logit model estimates using weighted observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016. In both panels the predictions are shown with 95 percent confidence bounds and one-year transitions (blue lines) are calculated from the two-year HRS estimates (gray lines). [back to page 18]



(a) Ordered Probit

(b) Ordered Logit

Figure B.5: **Ordered Probit vs. Ordered Logit: Transitions from Poor Health**

Note: **Panel** (*a*) shows average predicted conditional probabilities based on separate Ordered Progit model estimates using weighted observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016.

Panel (*b*) shows average predicted conditional probabilities based on separate Ordered Logit model estimates using weighted observations of individuals aged 20–65 from MEPS 2000–2017 and weighted observations of individuals aged 50–95 from RAND-HRS 1992–2016. In both panels the predictions are shown with 95 percent confidence bounds and one-year transitions (blue lines) are calculated from the two-year HRS estimates (gray lines). [back to page 18]

C Marginal Effects Based on Multinomial Logit and Probit Models and HRS Data

Table C.1: **HRS - Marginal Effects from Multinomial Logit**

	Excellent	Very_Good	Good	Fair	Poor	Dead
Health$_t$:						
Very Good	-0.240***	0.110***	0.118***	0.018***	-0.003	-0.004
	(0.006)	(0.006)	(0.005)	(0.003)	(0.002)	(0.002)
Good	-0.302***	-0.143***	0.309***	0.115***	0.015***	0.007***
	(0.006)	(0.006)	(0.005)	(0.004)	(0.002)	(0.002)
Fair	-0.312***	-0.266***	0.127***	0.325***	0.084***	0.042***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.003)	(0.002)
Poor	-0.320***	-0.317***	-0.032***	0.217***	0.299***	0.154***
	(0.007)	(0.007)	(0.007)	(0.006)	(0.008)	(0.005)
Initial Health$_{t=0}$:						
Very Good	-0.078***	0.010*	0.058***	0.016***	0.002	-0.007***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Good	-0.099***	-0.071***	0.115***	0.053***	0.009***	-0.006**
	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)	(0.002)
Fair	-0.099***	-0.132***	0.073***	0.123***	0.034***	0.002
	(0.004)	(0.006)	(0.006)	(0.005)	(0.003)	(0.002)
Poor	-0.107***	-0.141***	0.019	0.118***	0.095***	0.017***
	(0.007)	(0.011)	(0.010)	(0.008)	(0.005)	(0.004)
Age	-0.002***	-0.001**	-0.000	0.000	-0.000	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married/Partnered	0.003	0.009**	0.001	-0.004	-0.001	-0.007***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)
	(.)	(.)	(.)	(.)	(.)	(.)
Smoker	-0.018***	-0.031***	-0.005	0.013***	0.014***	0.027***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)
Female	0.005*	0.014***	-0.001	0.003	0.003	-0.023***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
Black	-0.005	-0.016***	0.010*	0.017***	-0.006***	-0.000
	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.001)
Hispanic	0.013**	-0.053***	0.008	0.053***	-0.006*	-0.015***
	(0.004)	(0.006)	(0.006)	(0.004)	(0.002)	(0.002)
High School Degree	-0.000	0.021***	0.015***	-0.021***	-0.015***	0.000
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)
College or Higher Degree	0.016***	0.045***	-0.003	-0.040***	-0.016***	-0.001
	(0.003)	(0.005)	(0.005)	(0.004)	(0.003)	(0.002)
HH Gross Income (in \$1,000)	0.000***	0.000**	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year $\leq$ 2001	0.007*	0.003	0.003	-0.013***	-0.006*	0.006**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)
Year $\geq$ 2012	-0.010***	-0.006	0.009*	0.004	-0.003	0.006**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)

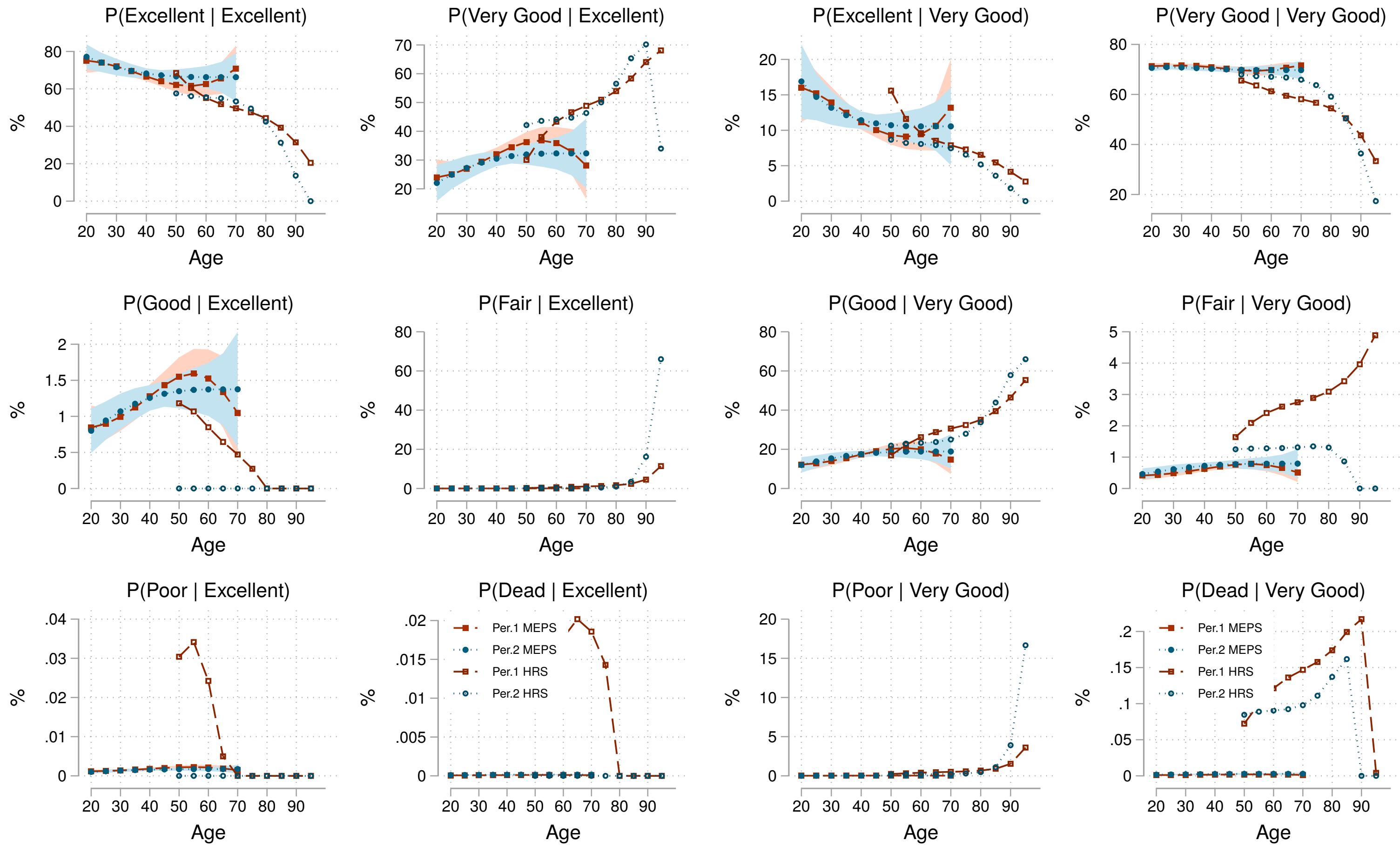
Note: We report average marginal effects based on **Multinomial Logit** estimates of individuals between age 50–95 in the RAND-HRS 1992–2016. Standard errors are clustered at the individual levels and estimates are based on weighted observations. The health states in the top line are future health states in $t + 2$.

Table C.2: **HRS - Marginal Effects from Multinomial Probit**

	Excellent	Very_Good	Good	Fair	Poor	Dead
Health$_t$:						
Very Good	-0.265***	0.138***	0.117***	0.017***	-0.003	-0.003
	(0.006)	(0.006)	(0.004)	(0.003)	(0.002)	(0.002)
Good	-0.327***	-0.125***	0.319***	0.112***	0.013***	0.007***
	(0.006)	(0.006)	(0.005)	(0.003)	(0.002)	(0.002)
Fair	-0.334***	-0.242***	0.121***	0.328***	0.084***	0.043***
	(0.006)	(0.006)	(0.006)	(0.005)	(0.003)	(0.002)
Poor	-0.341***	-0.288***	-0.031***	0.195***	0.311***	0.155***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.005)
Initial Health$_{t=0}$:						
Very Good	-0.084***	0.016***	0.059***	0.016***	0.000	-0.006**
	(0.003)	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)
Good	-0.102***	-0.069***	0.118***	0.051***	0.007**	-0.005*
	(0.003)	(0.005)	(0.005)	(0.004)	(0.002)	(0.002)
Fair	-0.098***	-0.123***	0.063***	0.125***	0.031***	0.001
	(0.004)	(0.006)	(0.006)	(0.005)	(0.003)	(0.002)
Poor	-0.106***	-0.127***	0.010	0.107***	0.105***	0.011***
	(0.006)	(0.009)	(0.009)	(0.007)	(0.005)	(0.003)
Age	-0.002***	-0.001*	-0.000	0.000	-0.000	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married/Partnered	0.003	0.009**	0.001	-0.005	-0.002	-0.007***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Smoker	-0.016***	-0.031***	-0.006	0.014***	0.014***	0.024***
	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)
Female	0.004*	0.014***	-0.001	0.002	0.003*	-0.022***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
Black	-0.001	-0.015***	0.007	0.016***	-0.007***	-0.000
	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.001)
Hispanic	0.016***	-0.053***	0.005	0.053***	-0.006*	-0.015***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.002)	(0.002)
High School Degree	-0.004	0.019***	0.019***	-0.021***	-0.015***	0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)
College or Higher Degree	0.013***	0.045***	-0.001	-0.041***	-0.016***	0.000
	(0.003)	(0.005)	(0.005)	(0.003)	(0.002)	(0.002)
HH Gross Income (in \$1,000)	0.000***	0.000**	0.000	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year $\leq$ 2001	0.007**	0.002	0.003	-0.013***	-0.005*	0.006**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)
Year $\geq$ 2012	-0.010***	-0.006	0.010*	0.004	-0.002	0.005*
	(0.003)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)

Note: We report average marginal effects based on **Multinomial Probit** estimates of individuals between age 50–95 in the RAND-HRS 1992–2016. Standard errors are clustered at the individual levels and estimates are based on weighted observations. The health states in the top line are future health states in $t + 2$.

D Transition Probabilities Across Different Time Periods

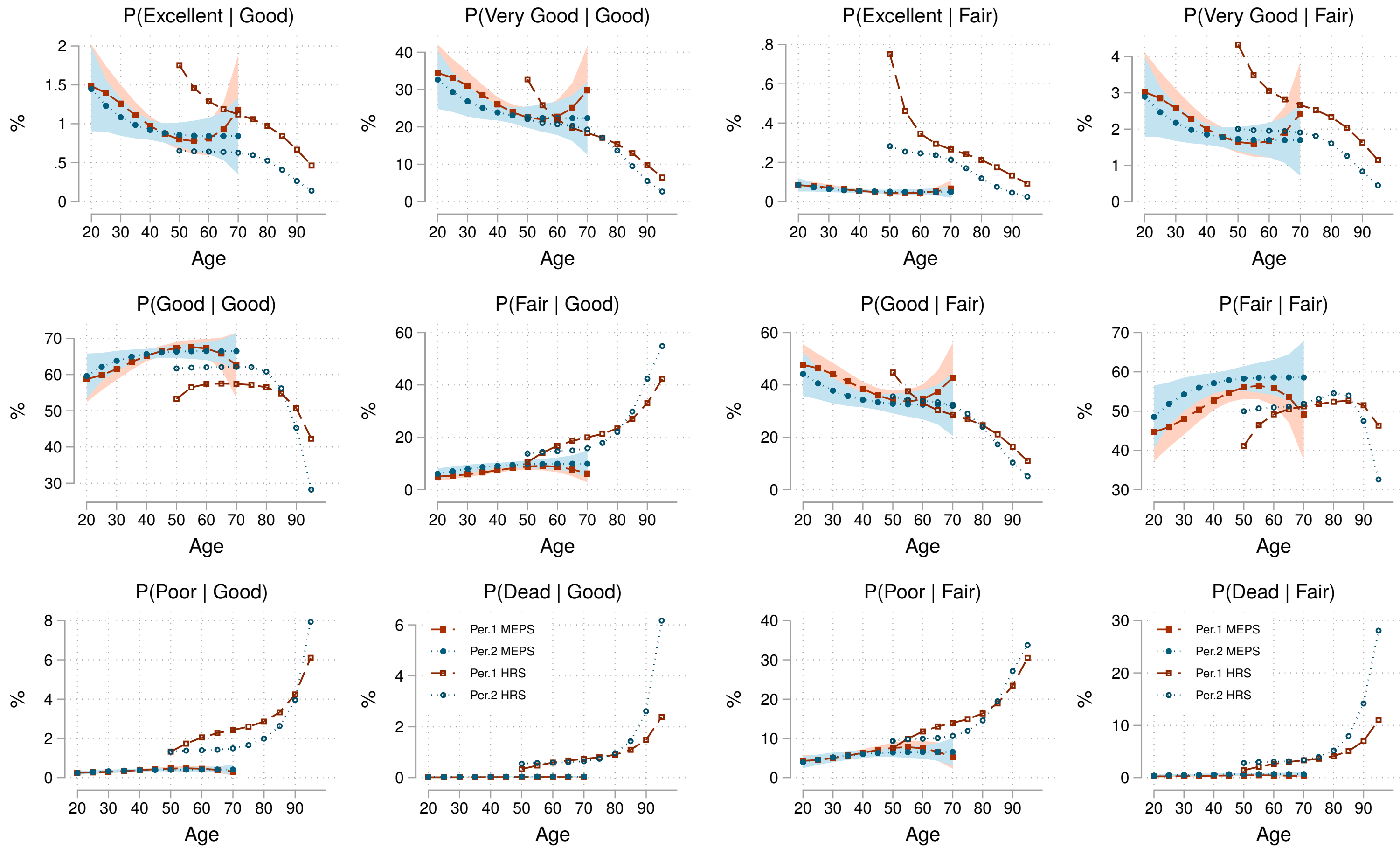


(a) From Excellent Health

(b) From Very Good Health

Figure D.1: **Ordered Logit: Health Transitions Period 1 (2002–2006) vs. Period 2 (2012–2016)**

Note: We report average predicted conditional probabilities based on **Ordered Logit** estimates. The estimates are based on weighted observations of individuals aged 20–65 in MEPS 2002–2006 and MEPS 2012-2016 as well as weighted observations of individuals aged 50–95 in the RAND-HRS 2002–2006 and RAND-HRS 2012–2016. The ordered logit models are estimated separately for the two samples. Since HRS predictions are two-year predictions, we transform them into one year predictions.



(a) From Good Health

(b) From Very Good Health

Figure D.2: **Ordered Logit: Health Transitions Period 1 (2002–2006) vs. Period 2 (2012–2016)**

Note: We report average predicted conditional probabilities based on **Ordered Logit** estimates. The estimates are based on weighted observations of individuals aged 20–65 in MEPS 2002–2006 and MEPS 2012–2016 as well as weighted observations of individuals aged 50–95 in the RAND-HRS 2002–2006 and RAND-HRS 2012–2016. The ordered logit models are estimated separately for the two samples. Since HRS predictions are two-year predictions, we transform them into one year predictions.

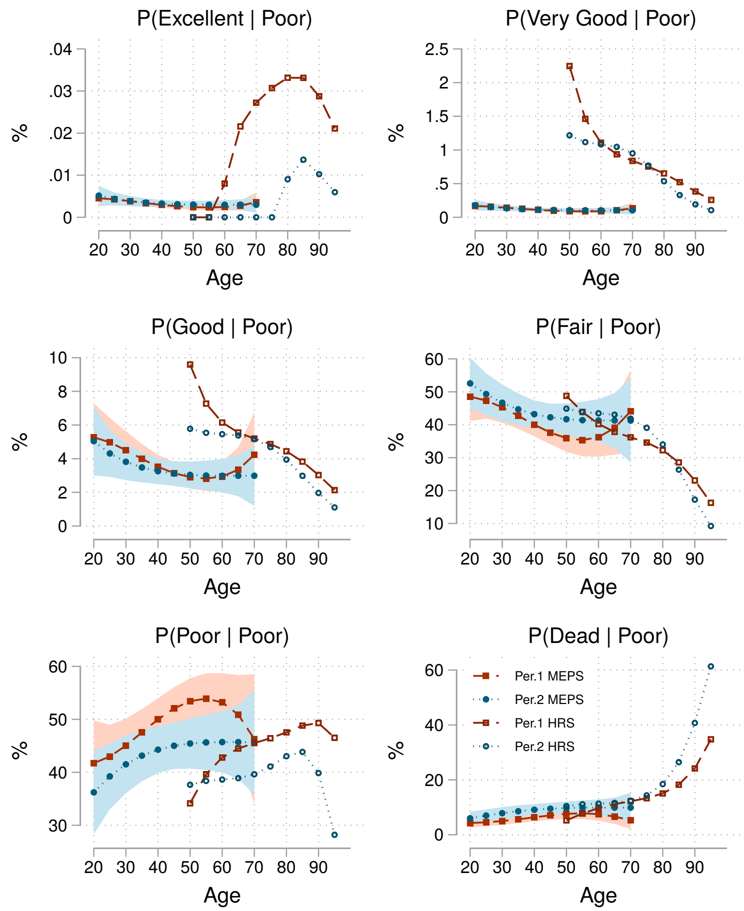


Figure D.3: **Ordered Logit: Health Transitions Period 1 (2002–2006) vs. Period 2 (2012–2016)**

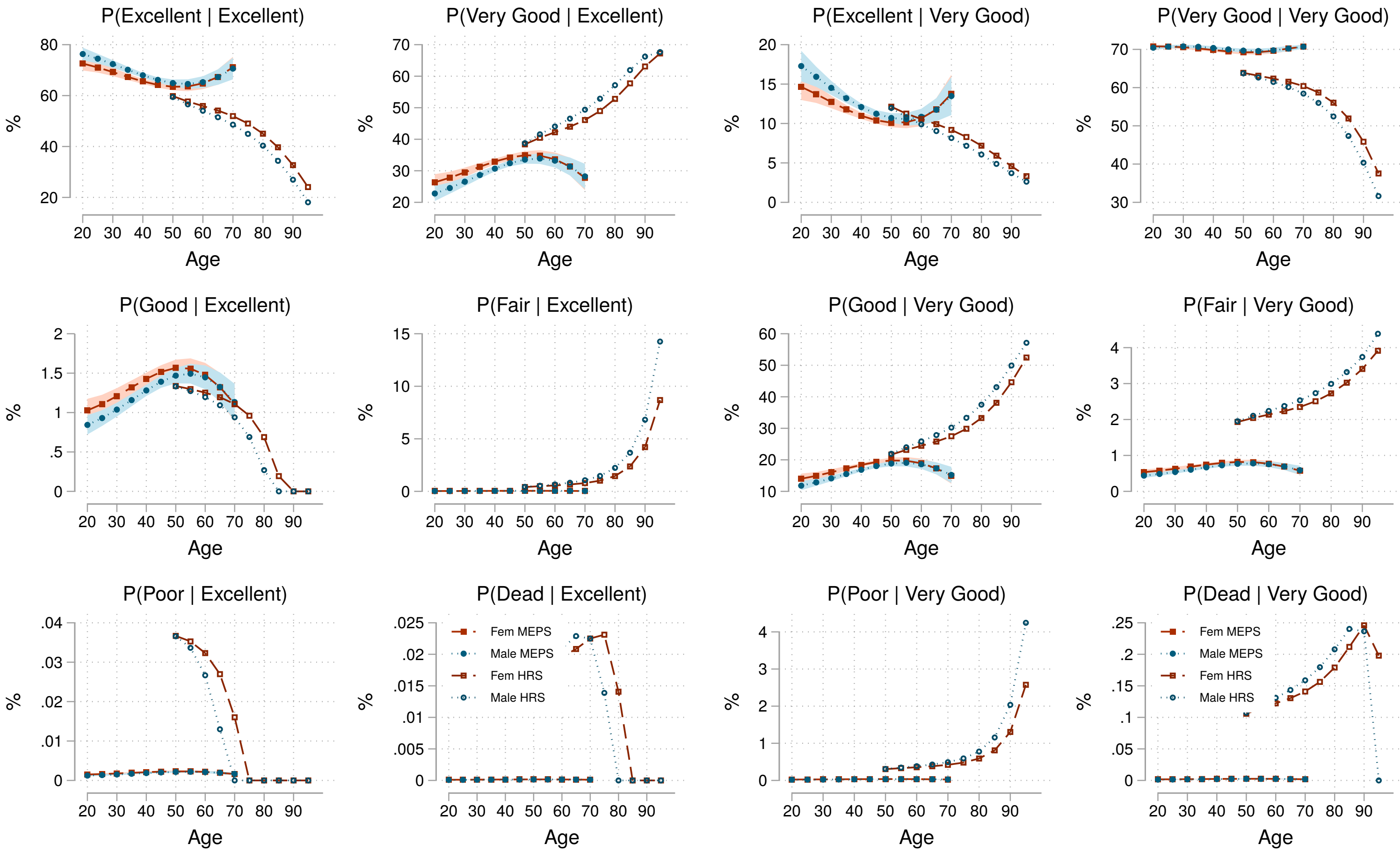
Note: We report average predicted conditional probabilities based on **Ordered Logit** estimates. The estimates are based on weighted observations of individuals aged 20–65 in MEPS 2002–2006 and MEPS 2012–2016 as well as weighted observations of individuals aged 50–95 in the RAND-HRS 2002–2006 and RAND-HRS 2012–2016. The ordered logit models are estimated separately for the two samples. Since HRS predictions are two-year predictions, we transform them into one year predictions.

Table D.1: **Summary Statistics: Comparing Samples from Period 1 (2002–2006) and Period 2 (2012–2016)**

	(1) MEPS: 2002–2016 b	(2) 2002–2006 b	(3) 2012–2016 b	(4) HRS: 2002–2016 b	(5) 2002–2006 b	(6) 2012–2016 b
Age	41.532	41.283	41.768	68.248	68.308	68.158
Female	0.541	0.544	0.539	0.574	0.574	0.575
Married/Partnered	0.538	0.583	0.496	0.636	0.649	0.615
Black	0.178	0.151	0.204	0.161	0.139	0.194
No high school degree	0.220	0.261	0.180	0.263	0.282	0.234
High school degree	0.547	0.522	0.571	0.527	0.520	0.538
College or higher degree	0.227	0.213	0.240	0.210	0.198	0.228
Labor income (in $1,000)	30.775	31.727	29.873	15.586	15.287	16.035
Labor income of HH (in $1,000)	61.067	62.326	59.873	26.696	26.407	27.131
Pre-government HH income (in $1,000)	68.734	70.440	67.119	71.050	72.899	68.264
Health Excellent	0.188	0.186	0.190	0.101	0.111	0.085
Health Very Good	0.392	0.392	0.392	0.286	0.282	0.293
Health Good	0.288	0.287	0.289	0.320	0.314	0.329
Health Fair	0.106	0.105	0.107	0.210	0.206	0.214
Health Poor	0.026	0.030	0.023	0.084	0.087	0.079
Initial Health Excellent	0.000	0.000	0.000	0.207	0.209	0.205
Initial Health Very Good	0.000	0.000	0.000	0.296	0.295	0.296
Initial Health Good	0.000	0.000	0.000	0.291	0.293	0.289
Initial Health Fair	0.000	0.000	0.000	0.148	0.145	0.152
Initial Health Poor	0.000	0.000	0.000	0.058	0.058	0.058
Dead/Diseased	0.003	0.003	0.003	0.000	0.000	0.000
Dead in t+k	0.003	0.003	0.003	0.059	0.058	0.062
Indicator for Healthy	0.868	0.865	0.870	0.707	0.707	0.707
Body Mass Index	27.346	26.927	27.743	27.967	27.543	28.605
Smoker	0.207	0.237	0.178	0.137	0.139	0.134
OOP health expenditure (in $1,000)	0.641	0.784	0.506	3.926	4.511	3.044
Total OOP expenditure HH ($1,000)	1.479	1.794	1.181	6.452	7.449	4.950
Insured	0.788	0.785	0.791	0.910	0.926	0.886
Public health insurance	0.169	0.141	0.196	0.465	0.442	0.500
Private health insurance	0.619	0.644	0.595	0.445	0.484	0.386
Head of HH/HIEU	0.600	0.600	0.600	0.702	0.693	0.715
Observations	82017	39902	42115	82516	49587	32929

Note: Statistics are based on unweighted observations of individuals aged 20–65 in MEPS 2002–2016 and individuals aged 50–95 in RAND-HRS 2002–2016.

E Transition Probabilities by Gender

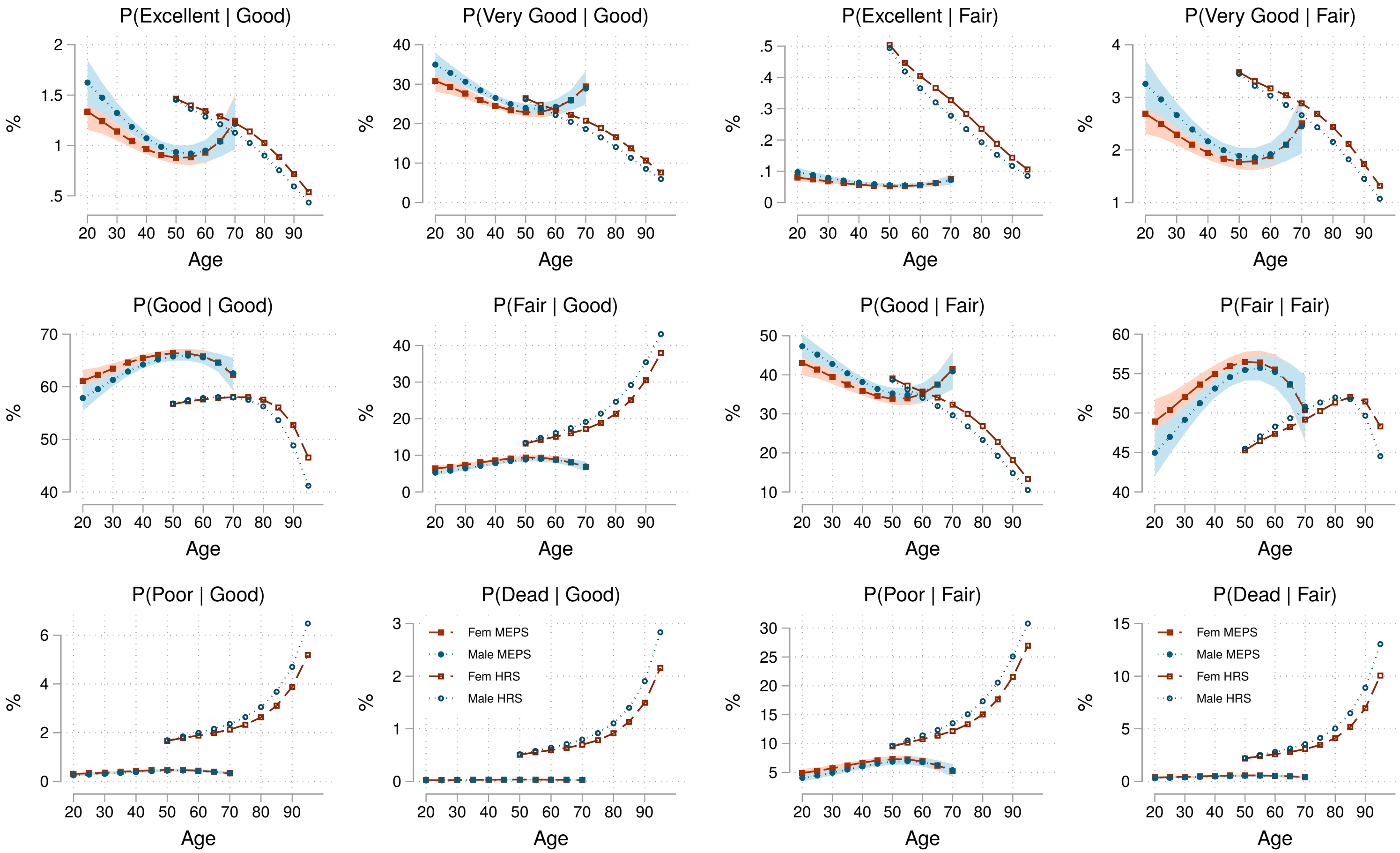


(a) From Excellent Health

(b) From Very Good Health

Figure E.1: **Ordered Logit: Health Transitions by Gender**

Note: We report average predicted conditional probabilities based on ordered Logit estimates. The estimates are based on weighted observations of individuals aged 20–65 in the MEPS 2000–2017 and weighted observations of individuals aged 50–95 in the RAND-HRS 1992–2016. The ordered logit models are estimated separately for the two samples. Since HRS predictions are two-year predictions, we transform them into one year predictions.



(a) From Good Health

(b) From Very Good Health

Figure E.2: **Ordered Logit: Health Transitions by Gender**

Note: We report average predicted conditional probabilities based on ordered Logit estimates. The estimates are based on weighted observations of individuals aged 20–65 in the MEPS 2000–2017 and weighted observations of individuals aged 50–95 in the RAND-HRS 1992–2016. The ordered logit models are estimated separately for the two samples. Since HRS predictions are two-year predictions, we transform them into one year predictions.

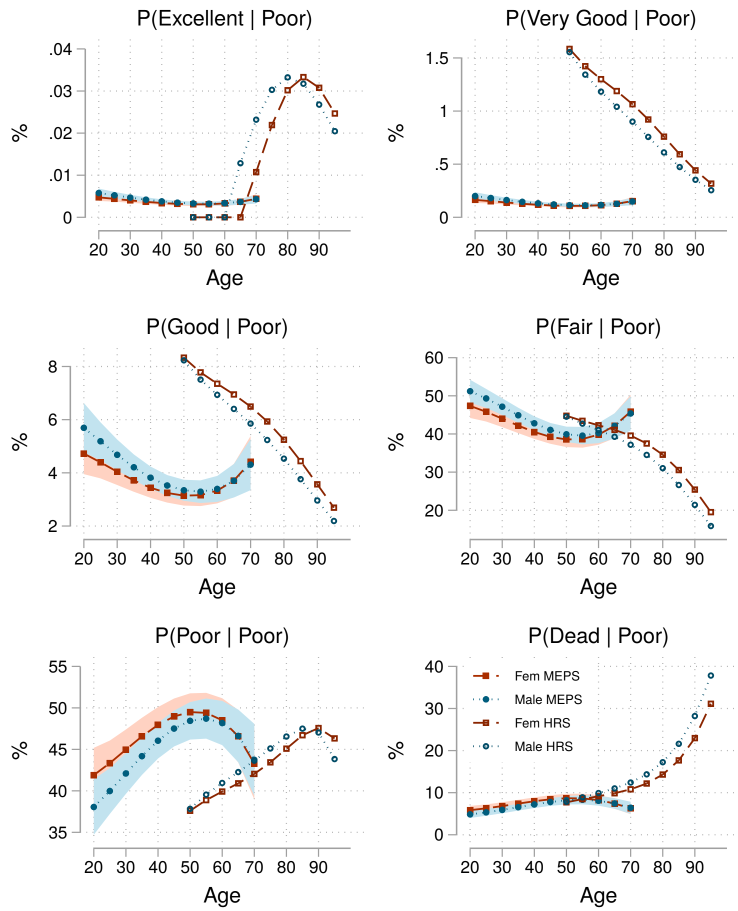


Figure E.3: **Ordered Logit: Health Transitions by Gender**

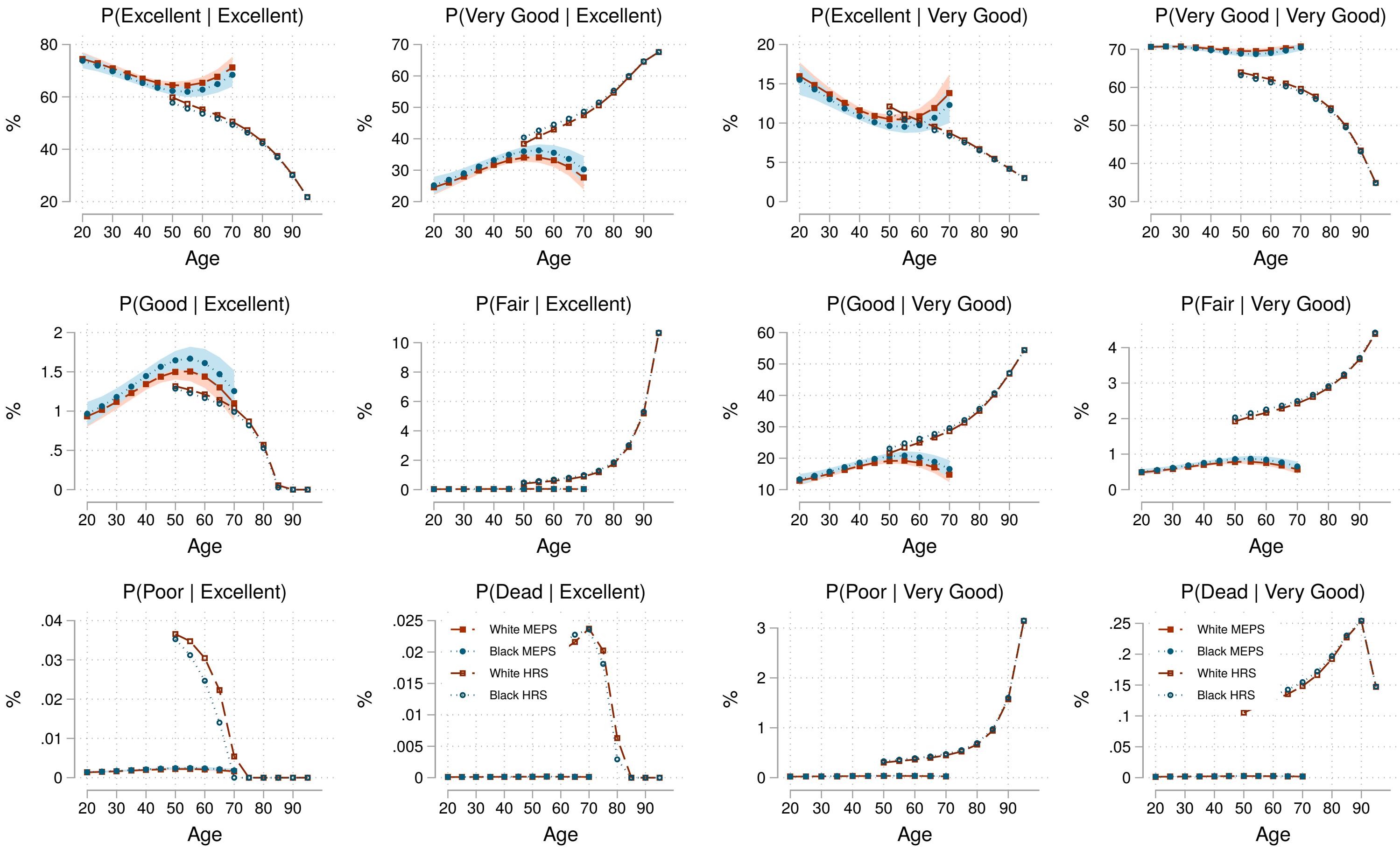
Note: We report average predicted conditional probabilities based on ordered Logit estimates. The estimates are based on weighted observations of individuals aged 20–65 in the MEPS 2000–2017 and weighted observations of individuals aged 50–95 in the RAND-HRS 1992–2016. The ordered logit models are estimated separately for the two samples. Since HRS predictions are two-year predictions, we transform them into one year predictions.

Table E.1: **Summary Statistics: Comparing Female Sample to Male Sample**

	(1) MEPS: 2000–2017 b	(2) Female b	(3) Male b	(4) HRS: 1992–2016 b	(5) Female b	(6) Male b
Age	41.509	41.546	41.466	67.167	67.419	66.832
Female	0.540	1.000	0.000	0.570	1.000	0.000
Married/Partnered	0.548	0.527	0.573	0.647	0.541	0.789
Black	0.178	0.196	0.157	0.157	0.171	0.139
No high school degree	0.223	0.219	0.228	0.289	0.287	0.291
High school degree	0.542	0.547	0.536	0.518	0.552	0.473
College or higher degree	0.229	0.229	0.228	0.193	0.161	0.236
Labor income (in $1,000)	31.042	25.197	37.910	16.930	11.497	24.135
Labor income of HH (in $1,000)	61.750	58.306	65.799	28.812	23.691	35.604
Pre-government HH income (in $1,000)	69.416	66.274	73.107	71.316	62.350	83.206
Health Excellent	0.191	0.174	0.211	0.116	0.111	0.123
Health Very Good	0.396	0.387	0.406	0.283	0.283	0.282
Health Good	0.286	0.298	0.271	0.312	0.309	0.314
Health Fair	0.102	0.112	0.089	0.201	0.206	0.195
Health Poor	0.026	0.028	0.023	0.088	0.091	0.085
Initial Health Excellent	0.000	0.000	0.000	0.200	0.192	0.212
Initial Health Very Good	0.000	0.000	0.000	0.288	0.289	0.287
Initial Health Good	0.000	0.000	0.000	0.290	0.287	0.295
Initial Health Fair	0.000	0.000	0.000	0.154	0.163	0.143
Initial Health Poor	0.000	0.000	0.000	0.067	0.069	0.064
Dead/Diseased	0.003	0.002	0.004	0.000	0.000	0.000
Dead in t+k	0.003	0.002	0.004	0.058	0.050	0.069
Indicator for Healthy	0.873	0.859	0.888	0.710	0.703	0.720
Body Mass Index	27.245	27.193	27.307	27.590	27.539	27.657
Smoker	0.212	0.185	0.245	0.153	0.141	0.168
OOP health expenditure (in $1,000)	0.634	0.733	0.517	3.464	3.646	3.218
Total OOP expenditure HH ($1,000)	1.476	1.495	1.453	5.713	5.429	6.096
Insured	0.784	0.807	0.756	0.897	0.893	0.903
Public health insurance	0.153	0.189	0.110	0.438	0.455	0.415
Private health insurance	0.631	0.618	0.647	0.460	0.438	0.489
Head of HH/HIEU	0.596	0.605	0.585	0.699	0.472	0.999
Observations	139265	75239	64026	189649	108116	81533

Note: Statistics are based on unweighted observations of individuals aged 20–65 in MEPS 2000–2017 and individuals aged 50–95 in RAND-HRS 1992–2016.

F Transition Probabilities by Race

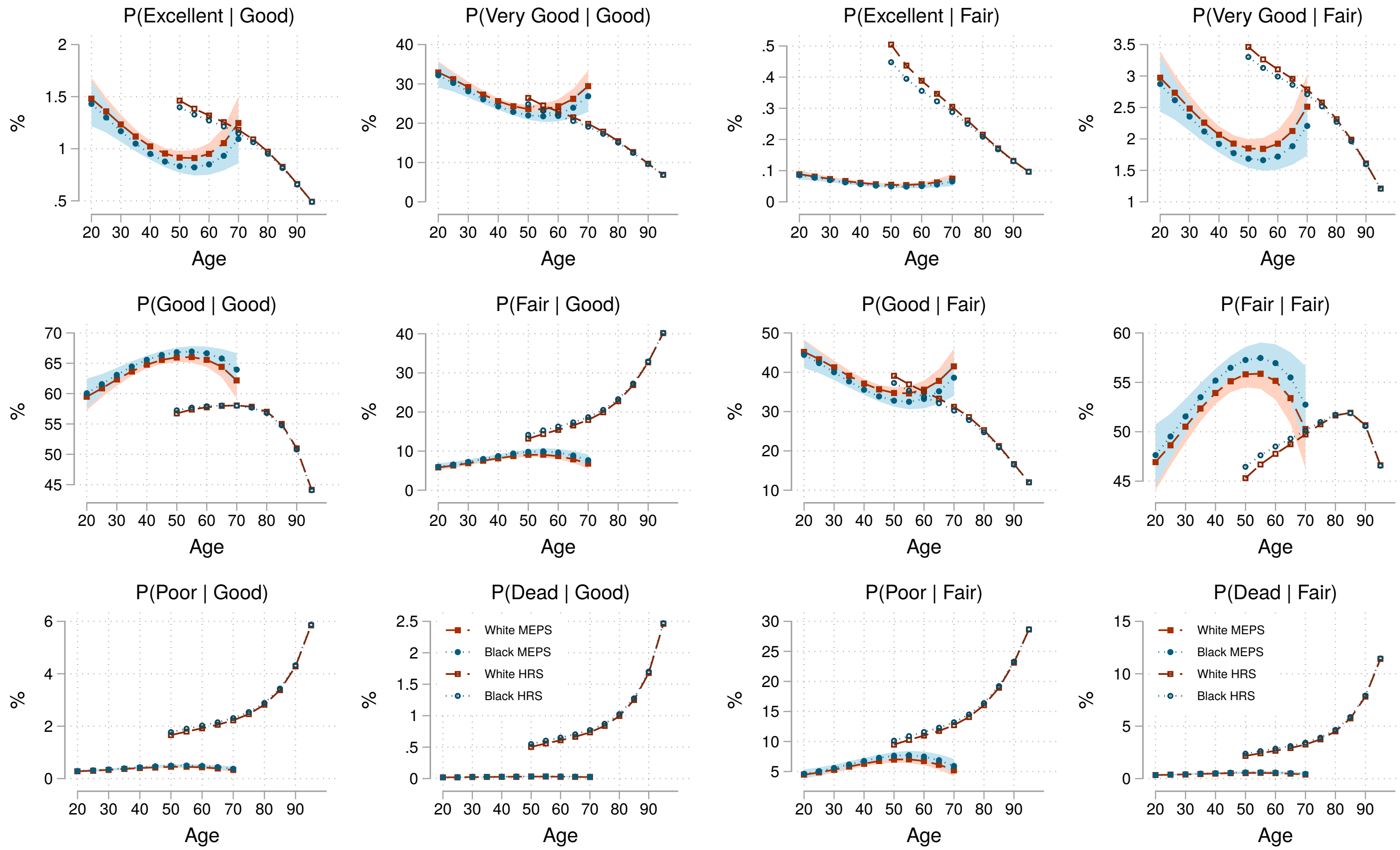


(a) From Excellent Health

(b) From Very Good Health

Figure F.1: **Ordered Logit: Health Transitions by Race**

Note: We report average predicted conditional probabilities based on **Ordered Logit** estimates. The estimates are based on weighted observations of individuals aged 20–65 in the MEPS 2000–2017 and weighted observations of individuals aged 50–95 in the RAND-HRS 1992–2016. The ordered logit models are estimated separately for the two samples. Since HRS predictions are two-year predictions, we transform them into one year predictions.



(a) From Good Health

(b) From Very Good Health

Figure F.2: **Ordered Logit: Health Transitions by Race**

Note: We report average predicted conditional probabilities based on **Ordered Logit** estimates. The estimates are based on weighted observations of individuals aged 20–65 in the MEPS 2000–2017 and weighted observations of individuals aged 50–95 in the RAND-HRS 1992–2016. The ordered logit models are estimated separately for the two samples. Since HRS predictions are two-year predictions, we transform them into one year predictions.

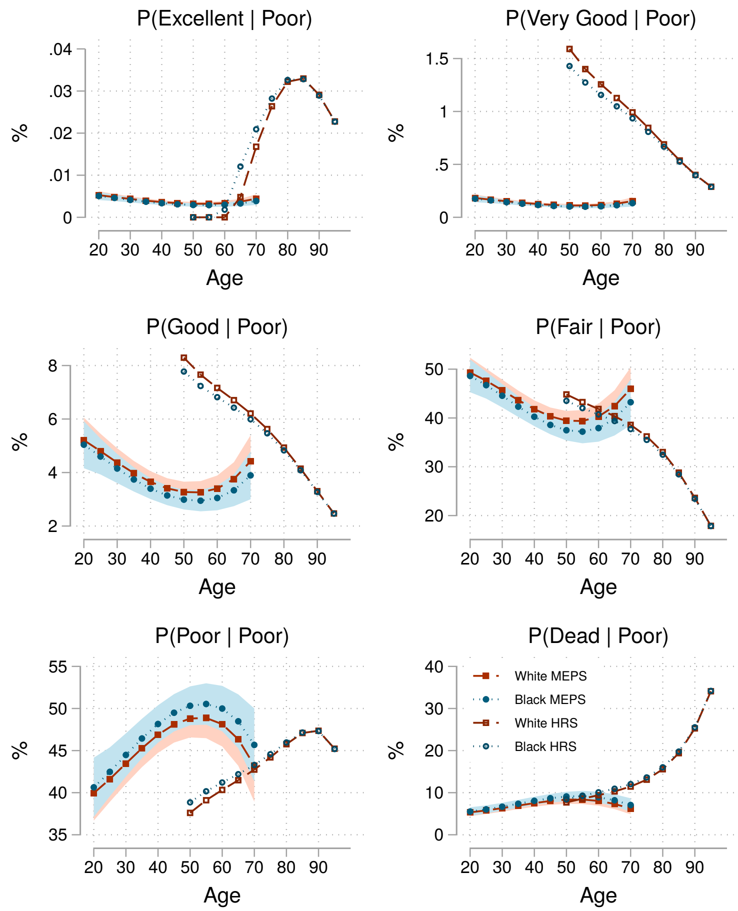


Figure F.3: **Ordered Logit: Health Transitions by Race**

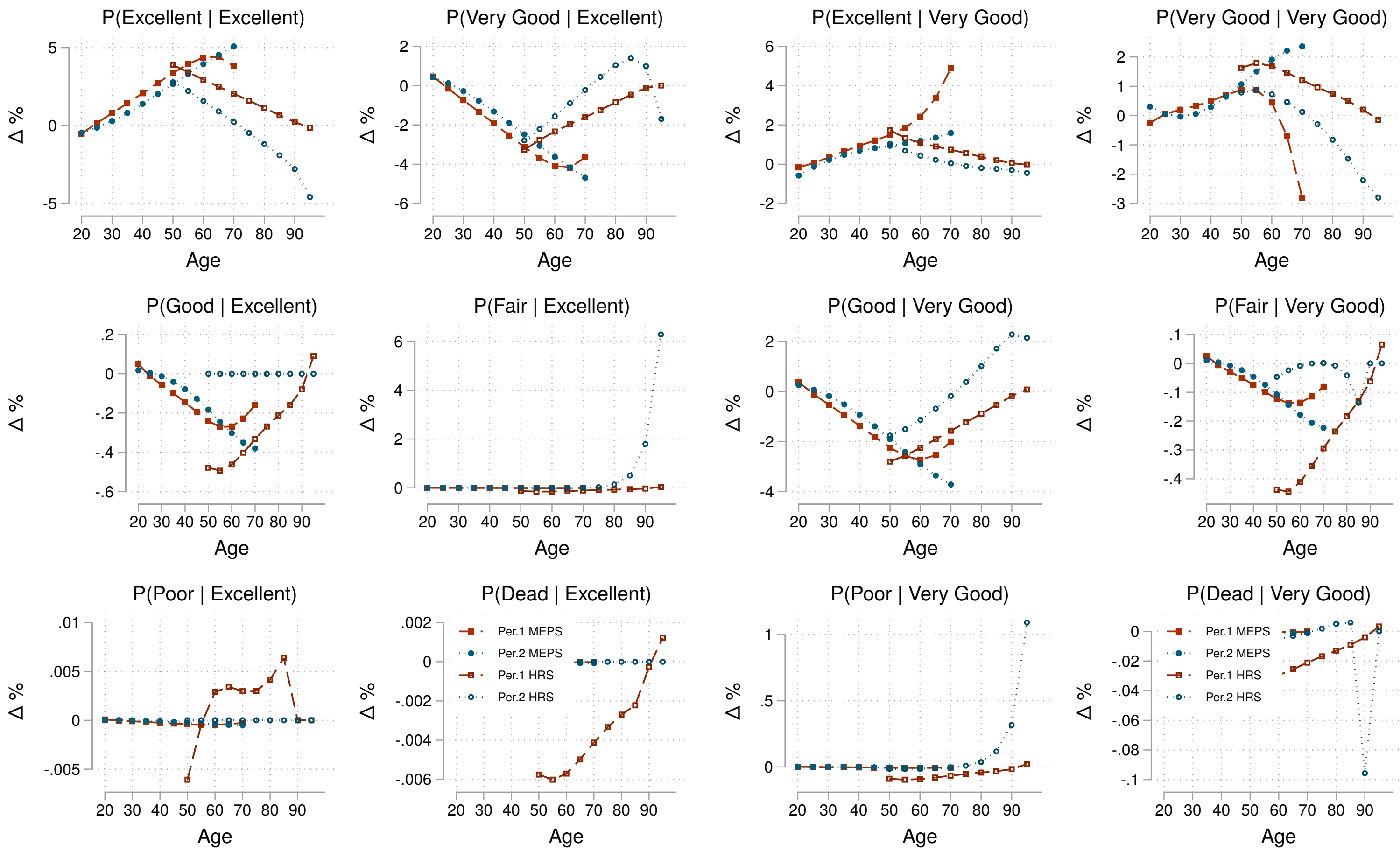
Note: We report average predicted conditional probabilities based on **Ordered Logit** estimates. The estimates are based on weighted observations of individuals aged 20–65 in the MEPS 2000–2017 and weighted observations of individuals aged 50–95 in the RAND-HRS 1992–2016. The ordered logit models are estimated separately for the two samples. Since HRS predictions are two-year predictions, we transform them into one year predictions.

Table F.1: **Summary Statistics: Comparing Black Sample to Non-Black Sample**

	(1) MEPS: 2000–2017 b	(2) Black b	(3) Non-Black b	(4) HRS: 1992–2016 b	(5) Black b	(6) Non-Black b
Age	41.509	41.380	41.538	67.167	65.358	67.504
Female	0.540	0.596	0.528	0.570	0.621	0.561
Married/Partnered	0.548	0.338	0.594	0.647	0.467	0.681
Black	0.178	1.000	0.000	0.157	1.000	0.000
No high school degree	0.223	0.201	0.228	0.289	0.425	0.263
High school degree	0.542	0.644	0.519	0.518	0.458	0.529
College or higher degree	0.229	0.148	0.246	0.193	0.116	0.208
Labor income (in $1,000)	31.042	23.724	32.629	16.930	14.584	17.368
Labor income of HH (in $1,000)	61.750	43.628	65.678	28.812	22.435	30.003
Pre-government HH income (in $1,000)	69.416	50.403	73.535	71.316	44.577	76.307
Health Excellent	0.191	0.165	0.197	0.116	0.064	0.126
Health Very Good	0.396	0.371	0.401	0.283	0.208	0.297
Health Good	0.286	0.305	0.282	0.312	0.331	0.308
Health Fair	0.102	0.130	0.096	0.201	0.273	0.188
Health Poor	0.026	0.030	0.025	0.088	0.123	0.082
Initial Health Excellent	0.000	0.000	0.000	0.200	0.103	0.219
Initial Health Very Good	0.000	0.000	0.000	0.288	0.221	0.301
Initial Health Good	0.000	0.000	0.000	0.290	0.331	0.283
Initial Health Fair	0.000	0.000	0.000	0.154	0.238	0.139
Initial Health Poor	0.000	0.000	0.000	0.067	0.108	0.059
Dead/Diseased	0.003	0.005	0.002	0.000	0.000	0.000
Dead in t+k	0.003	0.005	0.002	0.058	0.063	0.057
Indicator for Healthy	0.873	0.841	0.880	0.710	0.604	0.730
Body Mass Index	27.245	29.013	26.859	27.590	29.298	27.272
Smoker	0.212	0.251	0.204	0.153	0.196	0.144
OOP health expenditure (in $1,000)	0.634	0.462	0.671	3.464	2.815	3.584
Total OOP expenditure HH ($1,000)	1.476	0.967	1.586	5.713	4.199	5.993
Insured	0.784	0.798	0.780	0.897	0.873	0.902
Public health insurance	0.153	0.247	0.132	0.438	0.478	0.430
Private health insurance	0.631	0.551	0.648	0.460	0.396	0.472
Head of HH/HIEU	0.596	0.667	0.581	0.699	0.792	0.681
Observations	139265	24799	114466	189649	29829	159820

Note: Statistics are based on unweighted observations of individuals aged 20–65 in MEPS 2000–2017 and individuals aged 50–95 in RAND-HRS 1992–2016.

G Transition Probabilities by Race and Time



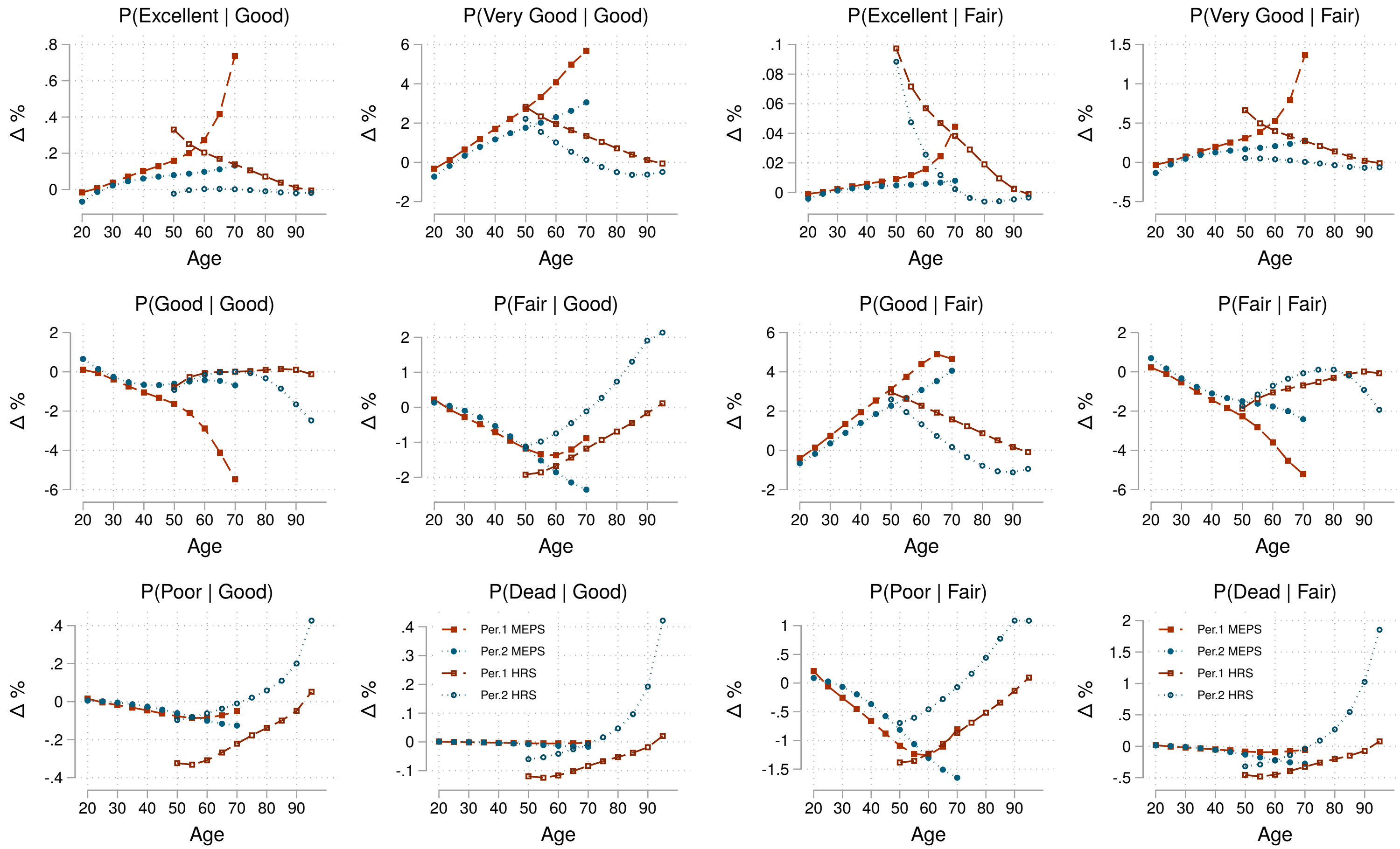
(a) From Excellent Health

(b) From Very Good Health

Figure G.1: **Ordered Logit: Differences in Conditional Health Transition Probabilities**

Note: We report **differences by race** of average predicted conditional probabilities based on **Ordered Logit** estimates. More specifically, we report $\Delta\% = \hat{\Pr}(h_{t+1}|h_t, \text{age}_t, \text{non-black}) - \hat{\Pr}(h_{t+1}|h_t, \text{age}_t, \text{black})$ for two separate time periods, 1996–2000 (red lines) and the second from 2013–2017 (blue lines). Predictions are calculated as average predictions over the remaining variables in the control vector X_t. The estimates are based on weighted observations of individuals aged 20–65 in the MEPS samples and weighted observations of individuals aged 50–95 in the RAND-HRS samples. The ordered logit models are estimated separately for the four samples. Since HRS predictions are two-year predictions, we transform them into one year predictions.

If the blue line is closer to the origin, then the difference in conditional health transition probabilities between black and non-black population has decreased over time. If the blue line is further from the origin, the gap between black and non-black conditional health transition probabilities has increased from period 1996–2000 to period 2013–2017.



(a) From Good Health

(b) From Very Good Health

Figure G.2: **Ordered Logit: Health Transitions by Race and Time**

Note: We report **differences by race** of average predicted conditional probabilities based on **Ordered Logit** estimates. More specifically, we report $\Delta\%=\hat{\Pr}\left(h_{t+1}|h_t, \text{age}_t, \text{non-black}\right) - \hat{\Pr}\left(h_{t+1}|h_t, \text{age}_t, \text{black}\right)$ for two separate time periods, 1996–2000 (red lines) and the second from 2013–2017 (blue lines). Predictions are calculated as average predictions over the remaining variables in the control vector X_t. The estimates are based on weighted observations of individuals aged 20–65 in the MEPS samples and weighted observations of individuals aged 50–95 in the RAND-HRS samples. The ordered logit models are estimated separately for the four samples. Since HRS predictions are two-year predictions, we transform them into one year predictions.

If the blue line is closer to the origin, then the difference in conditional health transition probabilities between black and non-black population has decreased over time. If the blue line is further from the origin, the gap between black and non-black conditional health transition probabilities has increased from period 1996–2000 to period 2013–2017.

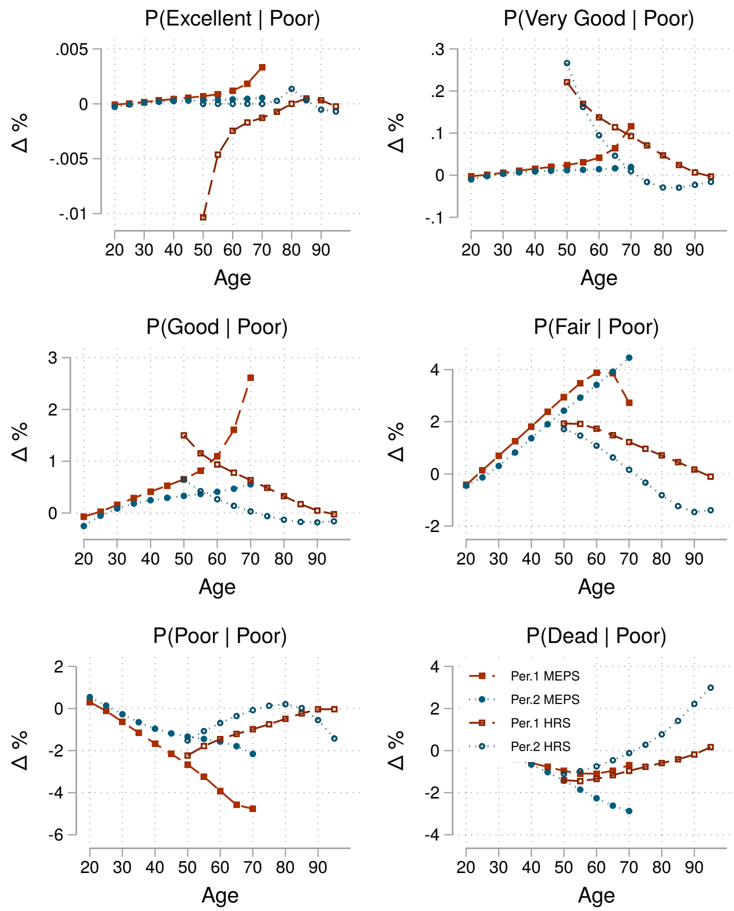


Figure G.3: **Ordered Logit: Health Transitions by Race and Time**

Note: We report **differences by race** of average predicted conditional probabilities based on **Ordered Logit** estimates. More specifically, we report $\Delta\%{=}\hat{\Pr}\left(h_{t+1}|h_t, \text{age}_t, \text{non-black}\right) - \hat{\Pr}\left(h_{t+1}|h_t, \text{age}_t, \text{black}\right)$ for two separate time periods, 1996–2000 (red lines) and the second from 2013–2017 (blue lines). Predictions are calculated as average predictions over the remaining variables in the control vector X_t. The estimates are based on weighted observations of individuals aged 20–65 in the MEPS samples and weighted observations of individuals aged 50–95 in the RAND-HRS samples. The ordered logit models are estimated separately for the four samples. Since HRS predictions are two-year predictions, we transform them into one year predictions.

If the blue line is closer to the origin, then the difference in conditional health transition probabilities between black and non-black population has decreased over time. If the blue line is further from the origin, the gap between black and non-black conditional health transition probabilities has increased from period 1996–2000 to period 2013–2017.

Table G.1: **Summary Statistics: Comparing Black Sample to Non-Black Sample**

	(1) MEPS:2000–2001 Black b	(2) Non-Black b	(3) 2013–17:Blk b	(4) N.Blk b	(5) HRS:1996–2001 Blk b	(6) N.Blk b	(7) 2013–17: Blk b	(8) N.Blk b
Age	40.297	41.343	41.989	41.859	66.397	67.357	65.707	69.473
Female	0.599	0.524	0.583	0.530	0.622	0.559	0.623	0.566
Married/Partnered	0.391	0.655	0.304	0.540	0.478	0.690	0.433	0.649
Black	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
No high school degree	0.254	0.235	0.144	0.188	0.523	0.298	0.303	0.214
High school degree	0.615	0.533	0.694	0.536	0.386	0.522	0.549	0.534
College or higher degree	0.125	0.229	0.157	0.269	0.091	0.181	0.148	0.252
Labor income (in $1,000)	26.883	35.734	22.593	32.186	13.208	16.214	13.583	15.917
Labor income of HH (in $1,000)	49.317	70.825	41.715	65.001	20.585	28.125	20.641	27.487
Pre-government HH income (in $1,000)	55.542	79.509	48.783	72.395	44.835	77.603	42.576	75.194
Health Excellent	0.181	0.201	0.181	0.194	0.070	0.139	0.047	0.084
Health Very Good	0.377	0.425	0.363	0.394	0.201	0.288	0.209	0.305
Health Good	0.289	0.271	0.298	0.286	0.314	0.302	0.373	0.327
Health Fair	0.121	0.079	0.133	0.103	0.271	0.184	0.274	0.211
Health Poor	0.033	0.024	0.025	0.023	0.145	0.088	0.097	0.073
Initial Health Excellent	0.000	0.000	0.000	0.000	0.094	0.204	0.114	0.231
Initial Health Very Good	0.000	0.000	0.000	0.000	0.214	0.290	0.234	0.311
Initial Health Good	0.000	0.000	0.000	0.000	0.317	0.289	0.334	0.278
Initial Health Fair	0.000	0.000	0.000	0.000	0.252	0.151	0.227	0.133
Initial Health Poor	0.000	0.000	0.000	0.000	0.123	0.065	0.091	0.048
Dead/Diseased	0.005	0.002	0.005	0.003	0.000	0.000	0.000	0.000
Dead in t+k	0.005	0.002	0.005	0.003	0.077	0.061	0.057	0.070
Indicator for Healthy	0.846	0.897	0.843	0.874	0.584	0.729	0.629	0.716
Body Mass Index	28.001	26.485	29.573	27.358	28.473	26.600	30.194	28.278
Smoker	0.267	0.245	0.230	0.159	0.187	0.153	0.193	0.110
OOP health expenditure (in $1,000)	0.457	0.693	0.347	0.556	2.728	3.160	2.299	2.987
Total OOP expenditure HH ($1,000)	1.019	1.683	0.695	1.308	4.082	5.341	3.394	4.869
Insured	0.815	0.822	0.832	0.804	0.885	0.899	0.867	0.903
Public health insurance	0.172	0.079	0.295	0.183	0.471	0.399	0.536	0.523
Private health insurance	0.643	0.742	0.537	0.622	0.414	0.500	0.331	0.379
Head of HH/HIEU	0.651	0.573	0.669	0.588	0.787	0.678	0.804	0.700
Observations	2232	13688	6601	25891	6912	42299	3037	12437

Note: Statistics are based on unweighted observations of individuals aged 20–65 in MEPS 2000–2017 and individuals aged 50–95 in RAND-HRS 1992–2016.

H Finite Mixture Models

Unobserved heterogeneity, such as an unobserved health risk type or an unobserved health preference type, can lead to endogeneity issues and biased estimates. We therefore implement a finite mixture model that allows for two such unobserved types or classes. In general, in finite mixture models the responses to the SAH question are allowed to come from a number of distinct and unobserved classes. These latent classes are modeled according to a multinomial logit model (McLachlan and Basford, 1988; Deb and Trivedi, 1997).

In the following tables we present predicted transition probabilities based on the ordered logit model with age as the only control variable from Section 5.1 and an ordered logit model based on a finite mixture model with two latent classes to allow for unobserved heterogeneity.[36]

[36] Convergence issues prevent us from estimating finite mixture models with a full control vector as well as for any of the models using the MEPS sample.

Table H.1: **HRS: Predicted Transition Probabilities from Ordered Logit Model**

(a) Ordered Logit: Only Age Controls

	Health (t+2)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	44.6	45.3	8.6	1.2	0.2	0.1	100.0
(s.e.)	0.591	0.406	0.212	0.038	0.007	0.003	.
Very Good	12.9	49.6	29.7	6.2	1.1	0.5	100.0
(s.e.)	0.168	0.277	0.218	0.094	0.024	0.012	.
Good	3.0	23.6	45.4	21.0	4.8	2.1	100.0
(s.e.)	0.058	0.199	0.234	0.178	0.077	0.046	.
Fair	0.7	6.7	29.3	38.2	16.0	9.1	100.0
(s.e.)	0.017	0.111	0.236	0.269	0.205	0.144	.
Poor	0.2	1.8	11.1	31.1	28.3	27.5	100.0
(s.e.)	0.005	0.044	0.197	0.273	0.360	0.300	.

(b) Finit Mixture Order Logit: Only Age Controls

	Health (t+1)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	49.6	34.6	10.5	3.1	0.9	1.3	100.0
(s.e.)	0.545	0.455	0.226	0.104	0.038	0.065	.
Very Good	11.1	54.5	25.8	5.4	1.3	1.9	100.0
(s.e.)	0.175	0.301	0.254	0.098	0.039	0.052	.
Good	2.8	22.2	49.8	17.8	3.3	4.0	100.0
(s.e.)	0.071	0.231	0.290	0.209	0.065	0.073	.
Fair	1.0	6.3	26.5	44.9	13.6	7.7	100.0
(s.e.)	0.044	0.149	0.311	0.347	0.231	0.136	.
Poor	0.3	1.7	7.8	28.5	45.3	16.5	100.0
(s.e.)	0.016	0.084	0.194	0.473	0.551	0.324	.

Note: Standard errors are presented below the respective probabilities. All numbers are expressed in percent.
Panel (*a*) reports average predictions based on **Ordered Logit** estimates for age group 50–95 and age, age^2, and age^3 as sole control variables.
Panel (*b*) reports average predictions based on **Finite Mixture Ordered Logit** estimates for age group 50–95 and age, age^2, and age^3 as sole control variables.
Data Source: RAND-HRS 1992–2016. [back to page 12]

I Mixed Process Estimation

In this section we estimate health outcomes as an ordered probit model but also allow for a separate outcome variable measuring health behavior (i.e., smoking) in a systems equation similar to Balia and Jones (2008) and Balia (2014). More specifically the model can be expressed as

$$\begin{aligned} h_{i,t+1} &= H\left(h_{i,t}, \text{smoking}_{i,t}, x_{i,t}, \epsilon^{h}_{i,t}\right), \\ \text{smoking}_{i,t} &= S\left(h_{i,t}, x_{i,t}, \epsilon^{s}_{i,t}\right), \end{aligned}$$

where the first equation is estimated using an ordered probit specification and the second equation is a probit with the two error terms following a joint normal distribution that allows for correlation. Exclusion restrictions are difficult to find. Number of children is sometimes used in the health behavior equation as number of children seems to affect smoking but not one's assessment of health. However, exclusion restriction are not necessary for identification according to Wilde (2000).

Table I.1: **MEPS: Predicted Transition Probabilities from Mixed Process Ordered Probit Model**

(a) Ordered Probit

	Health (t+1)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	67.1	32.2	0.7	0.0	0.0	0.0	100.0
(s.e.)	0.361	0.340	0.029	0.000	0.000	0.000	.
Very Good	12.9	67.9	18.9	0.3	0.0	0.0	100.0
(s.e.)	0.169	0.237	0.196	0.014	0.000	0.000	.
Good	0.5	28.6	61.2	9.5	0.2	0.0	100.0
(s.e.)	0.021	0.280	0.307	0.166	0.014	0.001	.
Fair	0.0	2.1	40.2	49.4	7.8	0.5	100.0
(s.e.)	0.000	0.093	0.478	0.545	0.230	0.069	.
Poor	0.0	0.0	6.0	45.0	37.7	11.3	100.0
(s.e.)	0.000	0.004	0.377	0.661	1.087	0.586	.

(b) Mixed Process Model: Ordered Probit & Probit

	Health (t+1)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	63.9	35.0	1.1	0.0	0.0	0.0	100.0
(s.e.)	0.333	0.299	0.046	0.000	0.000	0.000	.
Very Good	12.9	65.7	21.0	0.5	0.0	0.0	100.0
(s.e.)	0.147	0.244	0.183	0.020	0.000	0.000	.
Good	0.6	27.8	60.9	10.4	0.2	0.0	100.0
(s.e.)	0.023	0.234	0.281	0.144	0.012	0.000	.
Fair	0.0	2.2	40.2	49.9	7.3	0.4	100.0
(s.e.)	0.000	0.085	0.373	0.421	0.181	0.027	.
Poor	0.0	0.0	6.0	46.6	37.9	9.5	100.0
(s.e.)	0.000	0.004	0.292	0.580	0.678	0.395	.

Note: Standard errors are presented below the respective probabilities. All numbers are expressed in percent.
Panel (*a*) reports average predictions based on **Ordered Probit** estimates for age group 20–65.
Panel (*b*) reports average predictions based on **Multi Process Ordered Probit + Probit** estimates for age group 20–65 with smoking behavior as second dependent variable.
Data Source: MEPS 2000–2017. [back to page 12]

Table I.2: **HRS: Predicted Transition Probabilities from Mixed Process Ordered Probit Model**

(a) Ordered Probit

	Health (t+2)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	30.1	48.4	18.3	2.8	0.3	0.0	100.0
(s.e.)	0.478	0.264	0.332	0.100	0.015	0.003	.
Very Good	11.5	43.1	33.7	9.7	1.6	0.4	100.0
(s.e.)	0.153	0.265	0.204	0.134	0.041	0.017	.
Good	3.4	27.1	40.9	20.9	5.4	2.2	100.0
(s.e.)	0.078	0.202	0.221	0.174	0.086	0.055	.
Fair	0.8	12.8	35.5	30.9	12.2	7.8	100.0
(s.e.)	0.030	0.212	0.218	0.254	0.179	0.135	.
Poor	0.1	4.6	23.0	33.1	19.5	19.6	100.0
(s.e.)	0.008	0.148	0.333	0.233	0.292	0.335	.

(b) Mixed Process Model: Ordered Probit & Probit

	Health (t+2)						
	Excellent	Very Good	Good	Fair	Poor	Dead	Sum
Health (t)	.	.	.	.	.	.	.
Excellent	29.3	44.5	21.0	4.4	0.6	0.1	100.0
(s.e.)	0.280	0.197	0.187	0.083	0.018	0.006	.
Very Good	12.5	38.8	33.4	11.9	2.5	0.9	100.0
(s.e.)	0.141	0.173	0.146	0.100	0.042	0.024	.
Good	4.3	25.4	38.0	22.1	6.7	3.5	100.0
(s.e.)	0.079	0.127	0.177	0.113	0.072	0.067	.
Fair	1.1	12.6	32.3	30.1	13.3	10.6	100.0
(s.e.)	0.034	0.133	0.161	0.164	0.109	0.144	.
Poor	0.2	4.9	21.0	30.7	19.4	23.9	100.0
(s.e.)	0.011	0.107	0.203	0.178	0.158	0.285	.

Note: Standard errors are presented below the respective probabilities. All numbers are expressed in percent.
Panel (*a*) reports average predictions based on **Ordered Probit** estimates for age group 50–95.
Panel (*b*) reports average predictions based on **Multi Process Ordered Logit + Probit** estimates for age group 50–95 with smoking behavior as second dependent variable.
Data Source: RAND-HRS 1992–2016. [back to page 12]