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Florian Heiss, Axel Börsch-Supan, Michael Hurd and David Wise

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L13, 17_D-68131 Mannheim_Phone +49 621 181-2773/1862_Fax +49 621 181-1863_www.mea.uni-mannheim.de

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Pathways to Disability: Predicting Health Trajectories

Florian Heiss
Mannheim Research Institute for the Economics of Aging (MEA), Mannheim, Germany

Axel Börsch-Supan
MEA, Mannheim, Germany, and NBER

Michael Hurd
RAND Corporation, Santa Monica, California, and NBER

David Wise
John F. Kennedy School, Harvard University, Cambridge, Massachusetts, and NBER

Corresponding author:
Axel Börsch-Supan
MEA, University of Mannheim
L13, 17
D-68131 Mannheim, Germany
Email: Axel@Boersch-Supan.de

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ABSTRACT

The paper considers transitions in the health and disability status of persons as they age. In particular, we explore the relationship between health and disability at younger ages (say 50) and health and disability in future ages. We consider for example, the future health path of persons who are in good health at age 50 compared to the future health path of persons who are in poor health at age 50.

To do this, we develop a model that jointly considers health and mortality. The key feature of the model is the assumption of underlying "latent" health that determines both mortality and self-reported responses to categorical health and disability questions. Latent health allows for heterogeneity among individuals and allows for correlation of health status over time, thus allowing for state dependence as well as heterogeneity. The model also allows for classification errors in self-reported response to categorical health and disability questions. All of these are important features of health and disability data, as we show with descriptive data. The model accommodates the strong relationship between self-reported health status and mortality, which is critical to an understanding of the paths of health and disability of the survivors who are observed in panel data files.

Our empirical analysis is based on all four cohorts of the Health and Retirement Study (HRS) -- the HRS, AHEAD, CODA and WB cohorts). We find that self-reported health and self-reported disability correspond very closely to one another in the HRS. We find that both self-reported health and disability are strong predictors of mortality. Health and disability at younger ages are strongly related to future health and disability paths of persons as they age. There are important differences in health and disability paths by education level, race, and gender.

1. Introduction

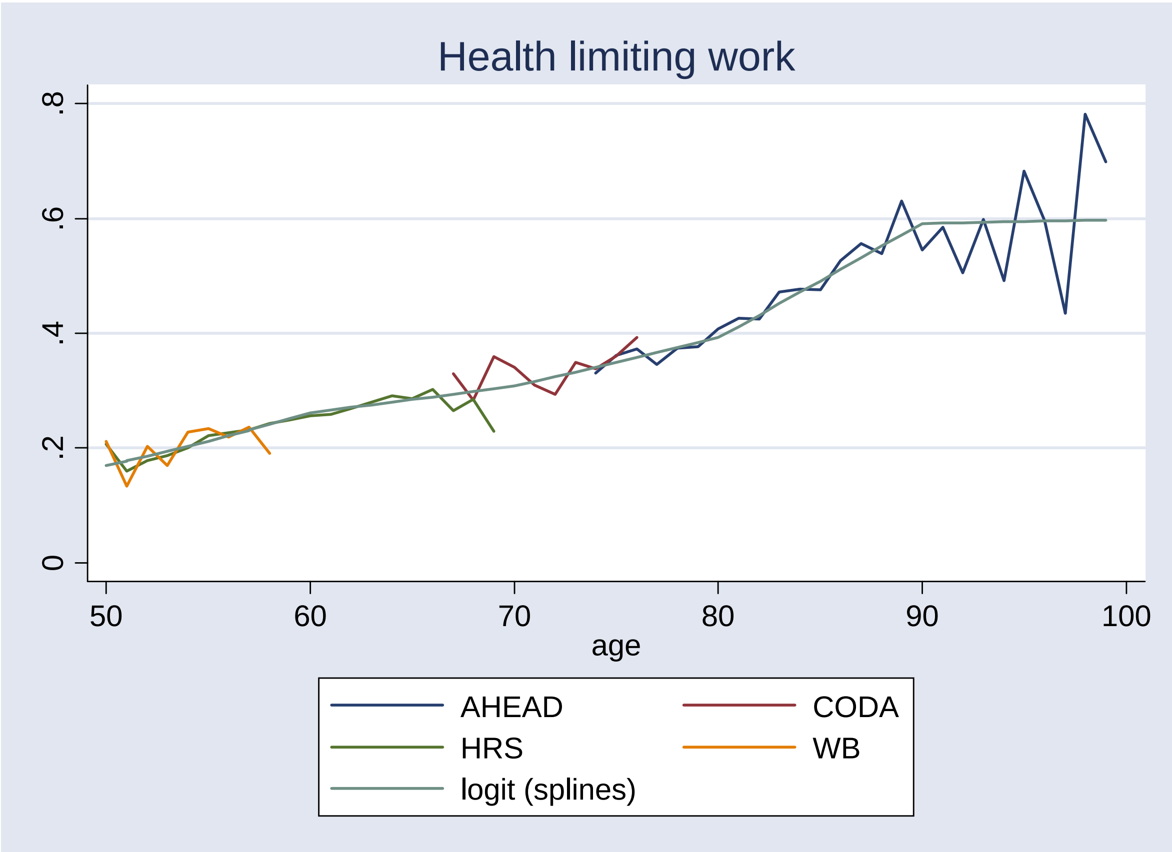
The aging of populations and the prospect of a rising number of disabled persons has generated an increasing interest in understanding the causes and the precursors of disability. A perhaps countervailing motivation to understand disability has been the finding by some analysts of declining age-specific disability rates over the past two or three decades, in the United States in particular. Declining age-specific disability rates could moderate the projected increase in the incidence of disability due to aging populations.

In contrast to the finding of declining health disability, there has been an increase in participation in the Disability Insurance program in the United States (see Duggan et al., in this volume). The participation rate in disability insurance programs has also increased in some European countries. Moreover, DI participation rates vary dramatically across the industrial countries (Aarts et al. 1996; Börsch-Supan, 2005). The differences across countries, however, are almost surely explained in large part by differences in the provisions of disability insurance programs (Gruber and Wise, 1999 and 2004).

In this paper, we explore the pathways to disability in the United States. Our analysis is based on data in the Health and Retirement Study (HRS). We exploit the rich information in the HRS to shed light on transitions into and out of disability and on the relationship of disability to self-reported health. We consider health precursors of disability and consider how disability is related to education and other socioeconomic circumstances of individuals. Our hope is that by advancing our understanding of the precursors and the correlates of disability we will be in a better position to project future disability rates and to perhaps even to understand how the incidence of disability might be reduced.

By way of introduction to the HRS data, we show the responses to two questions, one pertaining to disability and the other the health status. Figure 1.1 shows responses to this question: ”Do you have any impairment or health problem that limits the kind or amount of paid work you can do?". The figure shows the steady increase in work-related disability from about 20 percent at age 50 to about 60 percent at age 85 and above.

Figure 1-1: Work-Related Disability in the Health and Retirement Study

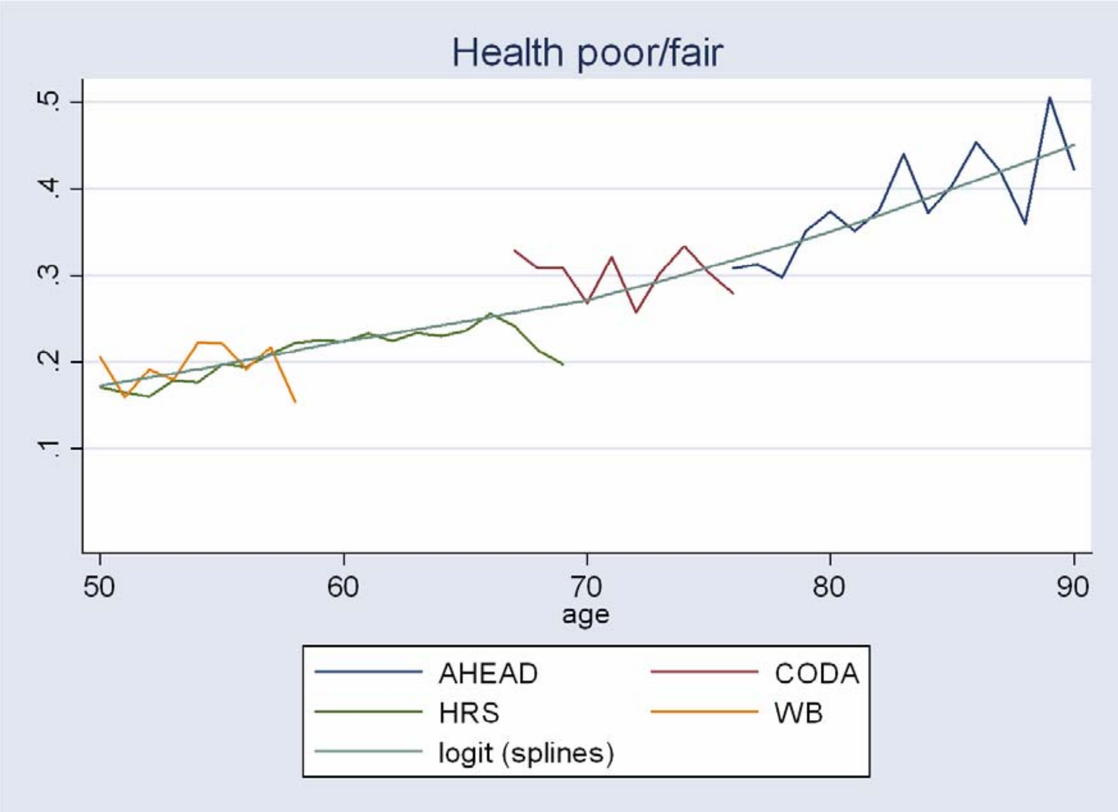


Note: Share of respondents who report a disability which limits their ability to work. Source: Authors' calculations based on the Health and Retirement Study, merged data of AHEAD, CODA, HRS, and WB cohorts. For cohort and variable definition, see Section 2.

Figure 1-2 shows the proportion of persons who say they are in poor or fair health (as distinct from good, very good, or excellent health). By comparing Figures 1-1 and 1-2, it can be seen that the HRS data show a close correspondence between work-related disability and self-reported health. (The HRS data for the United States differ from European data that show a divergence between trends in self-reported disability and trends in self-reported health.[1]

[1] See Börsch-Supan (2004)

Figure 1-2: Prevalence of Poor and Fair Health in the Health and Retirement Study



Note: Share of respondents who self-assess their health as fair or poor. Source: Authors' calculations based on the Health and Retirement Study, merged data of AHEAD, CODA, HRS, and WB cohorts. For cohort and variable definition, see Section 2.

To understand health and disability transitions, of course, panel data like those in the HRS are required. Several avenues of prior work help to inform our analysis. The most widely used measure of health has been self-rated health because of its predictive power for the onset of disease and mortality (Idler and Kasl, 1995; Burstrom and Fredlund, 2001; Borg and Kristensen, 2000; Hurd, McFadden and Merrill, 2001; Power, Mathews and Manor, 1998), and because of its wide availability in social science surveys such as the HRS.

Models of health dynamics typically begin with estimation of a first-order Markov transition equation

$$P(H_t \mid H_{t-1}, X_{t-1})$$

Where H_t is health status at time t and X_{t-1} are covariates that are thought to influence the rate of transition of health between $t-1$ and t. This relationship can be estimated on panel data. Separate estimates by age can reveal whether the effect of X on the transition probability varies with age. In prior research, the determinants X of the relationship between SES and health have included income, wealth, education, occupation, and social class.[2]

However, unobserved heterogeneity which has an influence both on X and on H_t conditional on H_{t-1} will cause biased estimation of the casual relationship between H and X. For example, unobserved heterogeneity may be traced to differences in early childhood circumstances. Such differences appear to affect the rate of onset of disease later in life (Richards and Wadsworth, 2004; Ravelli et al., 1998; Barker, 1997). Childhood circumstances are also likely a determinant of SES status later in life.

In models of health transitions, accounting for unobserved heterogeneity often produces substantially different results from models that do not account for heterogeneity. For example, Halliday (2005) used the waves of the PSID from 1984-1997 to study the evolution of self-rated health. He distinguished healthy and unhealthy persons and considered their transition probabilities between the states of "ill" (self-rated health fair or poor) and "well" (self-rated health excellent, very good or good.) He found that the transition rates varied substantially between the two groups and that the change in the transition rates with age also varied between the two groups. These differences led Halliday to conclude that investments in childhood health would have substantial health payoffs later in life. Models that do not permit heterogeneity could not have come to this conclusion.

Contoyannis and Jones (2004) allow unobserved heterogeneity to influence the choice of healthy and unhealthy behaviours, as well as health status itself. They find that in a model that allows for heterogeneity and controls for the correlation between behaviors and unobserved health characteristics the effect of behaviors on health is substantially increased. They conclude that "…over 75% of the total effect of lifestyle on

[2] Meer, Miller and Rosen, 2003; Smith, 2004; Adams *et al*., 2003; Hurd and Kapteyn, 2003; Wadsworth and Kuh, 1997; Marmot, 1999; Adda, Chandola and Marmot, 2003; Michaud and van Soest, 2004.

the social class gradient [in health] is masked when unobserved heterogeneity is ignored." [3]

On the other hand, Michaud and van Soest (2004) consider whether SES causes health or whether health causes SES, as Adams et al. (2003) had done. They find that controlling for heterogeneity does not substantially alter their results. But whereas Adams et al. conditioned health and wealth changes on as many as 19 health conditions and behaviors, Michaud and van Soest used a first-order Markov model and summarized health by the first principle component of a large number of health conditions. In estimation there is some similarity between first-order Markov models that control for a number of health states and first-order Markov models with unobserved heterogeneity. Unobserved health heterogeneity can be at least partially observed. Indeed, the results of Michaud and van Soest are similar to those of Adams et al. with respect to the causal flows between SES and health.

The method used by Halliday (2005) is similar in spirit to the method we propose in this paper. Our estimations model, however, sets out a more complex error structure than his and includes a heterogeneity specification that allows for more extreme levels of health and disability. In addition, we study an older age group and use data from a different time period. We consider higher order Markov processes and use simulation methods to explore the implications of heterogeneity.

The remainder of this paper is organized as follows: In section 2 we describe the data and variables that we use. In section 3 we present descriptive data on changes in self-reported health and self-reported work-related disability during the 8 years between the first wave of the HRS in 1992 and the fifth wave in 2000. In section 4 we use data on sequences of self-reported health status to demonstrate that to correctly model health transitions, it is critical to account for state dependence, heterogeneity, and classification errors in self-reported categorical assessment of health. In section 5 we present a model of health transitions based on a latent ("hidden") continuous measure of health. The model allows for unobserved heterogeneity, state dependence, and classification error in self-reported health and disability. In section 6 we present results, through simulations

[3] Page 986.

based on the model. Section 7 provides a summary of results and suggests further analysis based on the model developed in this paper.

2. Data and Variable Definition

This paper is based on all four cohort components of the Health and Retirement Study (HRS):

(1) The original HRS cohort, comprising “age eligibles” persons between 51 and 60 years of age at the time of the first HRS wave in 1992, plus their (potentially younger or older) spouses. The age-eligibles therefore represent the birth cohorts born between 1931 and 1941.

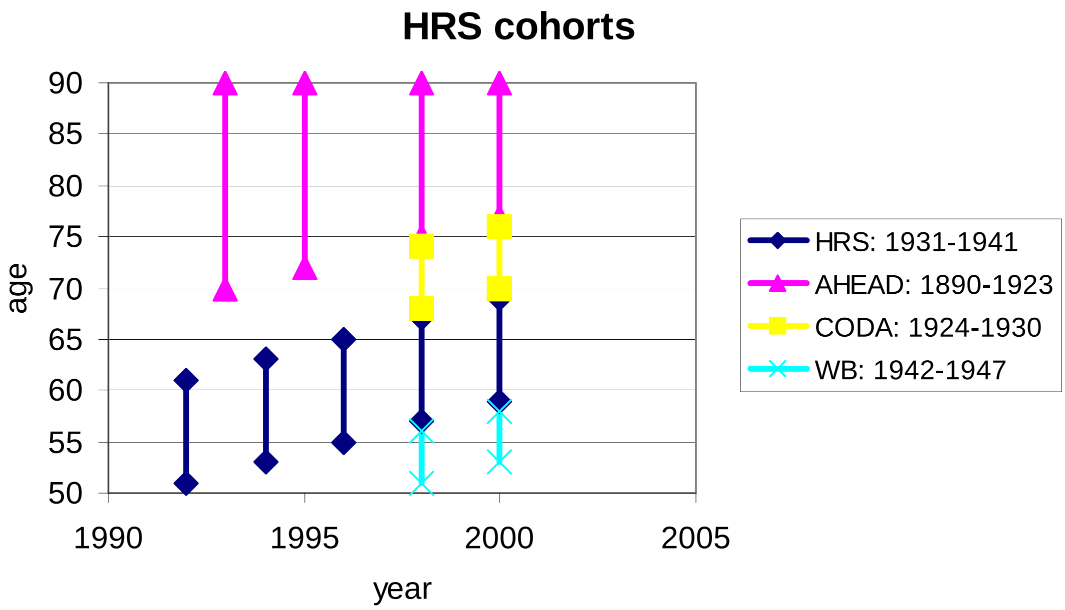
(2) The AHEAD cohort (Survey of Asset and Health Dynamics of the Oldest Old), comprising all persons age 70 or older in 1994, at the time of the first AHEAD wave (birth cohorts born before 1923), plus their spouses.

(3) The cohort comprising “children of the depression age” (CODA), born between 1924 and 1930--and their spouses--filling the gap between the HRS and the AHEAD birth cohorts.

(4) The cohort of “war babies” (WB) was added in 1998 and included persons who became age eligible since the beginning of the HRS in 1992. The WB cohorts comprise the birth cohorts born between 1942 and 1947.

Respondents were re-interviewed every two years. Attrition due to various reasons and death were recorded separately, deaths were ascertained with the help of the National Death Index. Figure 2-1 shows the age coverage of the longitudinal data in each of the HRS cohorts

Figure 2-1: Longitudinal data



Work-related disability and self-reported health are the key outcome variables in our analysis. Work-related disability is available in all waves for all cohorts, except for the first two waves of the AHEAD cohort (1994 and 1996). Work-related disability is constructed from the question: "Do you have any impairment or health problem that limits the kind or amount of paid work you can do?" (See Figure 1-1.)

Self-reported health is available in all waves for all cohorts. It is constructed from the question: "Would you say your health is excellent, very good, good, fair, or poor?". Although five categorical choices are allowed--"excellent", "very good," "good," "fair," and "poor"—in most of our analyses, we group "excellent," "very good." and "good" in one category, and "fair" and "poor" in a second category, as in Figure 1-2 above.

Work-related disability and self-reported heath are very closely related in our data. A simple cross-sectional logit regression of work-related disability on various health measures shows strong associations between disability and health. Table 2.2 shows the odds of having a work-related disability compared to persons who say their health is very good or excellent for the pooled data of wave 1 through 5. For example, persons who say they are in poor or fair health are 4.53 times as likely to have a work-related disability as persons who say they are in very good or excellent health. Persons who have an additional_IADL are 1.813 time more likely to have a work-related disability. And so forth.

Table 2-2: Work-Related Disability as Function of Self-Reported Health

	Odds ratio	p-value
Age (splines)	---	0.000
Female	0.771	0.000
# health conditions	1.264	0.000
# fine motor skills	1.159	0.008
# gross motor skills	0.791	0.000
# mobility problems	1.598	0.000
# large muscle activities	1.513	0.000
# ADLs	1.235	0.000
# IADLs	1.813	0.000
health very good or excellent.	1.000	---
health good	1.944	0.000
health poor/fair	4.530	0.000

Source: Authors' calculations based on the HRS

In addition, a similar logit regression of mortality on lagged disability and health shows that even after controlling for other health measures, work-related disability is a strong predictor of mortality, as shown in Table 2-3. The table shows that persons who say they have a work-related disability are 1.76 more likely to die before the interview for the next wave than people who say they are in very good or excellent health, even after controlling for the other measures of health in the regression.

Table 2-3: Work-Related Disability as Predictor of Mortality

	Odds ratio	p-value
Age (splines)	---	0.000
female	0.524	0.000
disabled	**1.760**	**0.000**
# health conditions	1.254	0.000
# fine motor skills	1.011	0.874
# gross motor skills	1.024	0.754
# mobility problems	1.210	0.000
# large muscle act.	0.813	0.000
# ADLs	1.014	0.842
# IADLs	1.220	0.000
health very good or excellent.	1.000	---
health good	1.310	0.005
health poor/fair	2.146	0.000

Source: HRS cohort

In summary, self-reported work disability as measured in the Health and Retirement Study is strongly related to future longevity. This relationship is unlikely to hold in all countries, in particular in countries where the underlying health of the population is close to that in the United States but a much larger fraction of older people are receiving benefits from a disability program. For example there is a very limited correlation between work-related disability and self-reported health as reported in the German Socio-Economic Panel.[4]

3. Health Transitions in the HRS: From 1992 to 2000

In this section, we present descriptive data on health and disability transitions. These descriptive data, as well as the data in the next section are intended to inform the more formal analysis in sections 4 through 6 and to motivate the econometric specification that underlies that analysis.

Respondents in the first wave of the HRS in 1992 were between 51 and 61 years of age. Table 3-1 shows transitions by self-reported health status. About 78 percent of respondents reported that they were in good health or better (excellent, very good, good) and 22 percent were in fair or poor health. Eight years later, their health had deteriorated,

[4] Börsch-Supan (2001).

with only 68 percent of the respondents reporting that they were in good or better health and 22 percent reporting that they were in fair or poor health; and 10 percent had died (excluding persons who were not longer in the sample—"attrition.") The table also shows that the transition to poor or fair health and the transition to death vary enormously by health status in 1992. For example, of those who were in good or better health in 1992, only 11 percent were in poor or fair health in 2000 and only 5 percent had died. Of those who were in poor or fair health in 1992, over 43 percent stayed in poor or fair health in 2000 and almost 21 percent had died.

Table 2 shows transitions by self-reported disability status. The transitions between 1992 and 2000 are very similar to the self-reported health transitions. That is, the transitions for those who report a work disability are very similar to those who report that they are in fair or poor health, and the transitions for those who report no work disability are very similar to those who say that they are in good or better health. In addition, the share reporting work-related disabilities in 1992 is almost identical to the share reporting poor or fair health in 1992 (78.73 percent compared to 78.17 percent). (Attrition rates show little correlation with initial health status or with initial work disability status.)

Table 3-1: 8-Year Transitions for Self-Reported Health in the HRS

Status In 1992	Status in 2000 health good or better	health poor or fair	dead	attrition	total
Health good or better	6,052	1,037	465	1,506	9,060
	66.8	*11.45*	*5.13*	*16.62*	*100*
Health poor or fair	511	1,090	526	403	2,530
	20.2	*43.08*	*20.79*	*15.93*	*100*
Total	6,563	2,127	991	1,909	11,590
	56.63	*18.35*	*8.55*	*16.47*	*100*

Source: Authors' calculations from HRS.

Table 3-2: 8-Year Transitions for Work-Related Disability in the HRS

Status in 1992	Status in 2000 not disabled	disabled	dead	attrition	total
Not disabled	5,735	1,295	500	1,551	9,081
	63.15	*14.26*	*5.51*	*17.08*	*100*
Disabled	517	1,094	490	352	2,453
	21.08	*44.60*	*19.98*	*14.35*	*100*
Total	6,252	2,389	990	1,903	11,534
	54.2	*20.71*	*8.58*	*16.5*	*100*

Source: Authors' calculations from the HRS.

Tables 3-3 and 3-4 show transition rates by health status, by age in 1992, and by gender. Transition rates by health status are in Table 3-3 and by disability status in Table 3-4. These tables show, as expected, that death rates are substantially higher for men than for women. For example, of men who report that they are disabled in 1992, over 23 percent have died by 2000, whereas of women who report they are disabled in 1992 only about 16 percent have died by 2000. Again, these detailed data show a striking relationship between health status and death rates at all ages, and between disability status and death rates at all ages. For example, for men age 61 who reported that they were disabled in 1992, over 38 percent had died by 2000; for those who reported that they were not disabled, only about 8 percent had died by 2000.

Table 3-3: 8-Year health transitions in the HRS, by age and sex.

Age at wave1	obs.	health good+	poor/ fair	dead	Attri-tion	Age at wave 1	obs.	health good+	poor/ fair	dead	Attri-tion
Men, health in wave 1 = good or better						**Women, health in wave 1 = good or better**					
50	86	66.28	12.79	3.49	17.44	50	117	72.65	11.97	3.42	11.97
51	340	67.35	10.88	2.94	18.82	51	390	73.33	11.28	2.82	12.56
52	336	63.99	9.82	6.25	19.94	52	364	75.00	11.54	1.10	12.36
53	359	60.45	15.04	5.29	19.22	53	340	70.59	11.76	4.41	13.24
54	302	64.90	10.26	5.30	19.54	54	352	69.89	11.65	4.55	13.92
55	301	65.78	11.30	5.32	17.61	55	350	73.14	11.14	4.57	11.14
56	314	64.01	13.06	3.50	19.43	56	344	77.03	7.85	4.65	10.47
57	311	64.95	11.58	5.14	18.33	57	307	71.99	12.70	4.23	11.07
58	267	66.29	10.11	8.61	14.98	58	310	75.81	10.97	3.55	9.68
59	252	61.90	13.49	9.92	14.68	59	292	73.29	13.36	4.11	9.25
60	297	64.31	9.43	9.76	16.50	60	294	67.01	14.63	5.78	12.59
61	179	63.69	12.29	7.26	16.76	61	219	73.52	8.22	7.31	10.96
All	**3,344**	**64.38**	**11.60**	**6.04**	**17.97**	**Total**	**3,679**	**72.82**	**11.42**	**4.10**	**11.66**
Men, health in wave 1 = poor/fair						**Women, health in wave 1 = poor/fair**					
50	18	22.22	44.44	16.67	16.67	50	33	15.15	63.64	15.15	6.06
51	73	17.81	36.99	30.14	15.07	51	92	25.00	57.61	8.70	8.70
52	66	22.73	37.88	19.70	19.70	52	99	16.16	57.58	13.13	13.13
53	79	16.46	44.30	13.92	25.32	53	98	24.49	41.84	16.33	17.35
54	72	18.06	37.50	25.00	19.44	54	103	16.50	57.28	13.59	12.62
55	82	19.51	39.02	28.05	13.41	55	109	24.77	57.80	9.17	8.26
56	76	19.74	40.79	21.05	18.42	56	95	25.26	44.21	18.95	11.58
57	87	25.29	39.08	24.14	11.49	57	109	23.85	43.12	22.94	10.09
58	94	14.89	46.81	24.47	13.83	58	108	22.22	60.19	12.96	4.63
59	84	22.62	32.14	27.38	17.86	59	105	24.76	46.67	18.10	10.48
60	77	23.38	35.06	31.17	10.39	60	117	23.93	42.74	23.08	10.26
61	67	13.43	29.85	40.30	16.42	61	62	20.97	45.16	20.97	12.90
All	**875**	**19.54**	**38.51**	**25.60**	**16.34**	**Total**	**1,130**	**22.39**	**50.88**	**16.11**	**10.62**

Source: Authors' calculations based on the HRS cohort

Table 3-4: 8-Year disability transitions in the HRS, by age and sex.

age (w1)	obs.	not disab.	disabled	dead	attrition	age (w1)	obs.	not disab.	disabled	dead	attrition
Men, not disabled in wave 1						**Women, not disabled in wave 1**					
50	85	64.71	14.12	3.53	17.65	50	114	67.54	11.40	4.39	16.67
51	341	66.28	10.26	5.28	18.18	51	406	64.04	17.24	2.22	16.50
52	329	57.75	15.81	5.47	20.97	52	374	66.58	14.97	1.60	16.84
53	360	62.50	11.94	5.28	20.28	53	356	61.52	13.48	3.93	21.07
54	309	61.49	12.94	5.18	20.39	54	350	60.57	14.00	4.29	21.14
55	304	62.50	12.83	8.22	16.45	55	362	63.81	16.85	4.70	14.64
56	305	63.61	13.77	2.95	19.67	56	340	62.94	16.76	3.82	16.47
57	314	60.51	16.24	6.05	17.20	57	298	66.11	13.42	3.02	17.45
58	270	61.85	12.96	11.11	14.07	58	320	66.25	16.56	3.75	13.44
59	238	62.61	13.03	10.08	14.29	59	304	63.49	18.09	3.62	14.80
60	290	65.86	8.28	9.31	16.55	60	306	62.09	16.01	7.19	14.71
61	181	62.98	13.81	8.29	14.92	61	210	62.86	15.24	5.71	16.19
Total	3,326	62.57	12.90	6.70	17.83	Total	3,740	63.80	15.59	3.88	16.74
Men, disabled in wave 1						**Women, disabled in wave 1**					
50	18	33.33	33.33	16.67	16.67	50	36	25.00	55.56	8.33	11.11
51	72	20.83	41.67	19.44	18.06	51	74	18.92	55.41	13.51	12.16
52	72	22.22	40.28	22.22	15.28	52	83	9.64	62.65	10.84	16.87
53	74	13.51	50.00	14.86	21.62	53	82	18.29	45.12	15.85	20.73
54	64	15.63	40.63	28.13	15.63	54	104	24.04	51.92	13.46	10.58
55	78	17.95	46.15	17.95	17.95	55	96	29.17	46.88	9.38	14.58
56	83	8.43	51.81	21.69	18.07	56	92	26.09	43.48	22.83	7.61
57	83	21.69	40.96	21.69	15.66	57	111	21.62	45.05	22.52	10.81
58	90	26.67	38.89	17.78	16.67	58	95	25.26	55.79	8.42	10.53
59	97	17.53	39.18	24.74	18.56	59	89	24.72	47.19	20.22	7.87
60	84	19.05	39.29	30.95	10.71	60	101	17.82	49.50	18.81	13.86
61	65	12.31	27.69	38.46	21.54	61	68	25.00	39.71	23.53	11.76
Total	880	18.30	41.48	23.07	17.16	Total	1,031	22.11	49.56	16.00	12.32

Source: Authors' calculations based on the HRS cohort

Tables 3-5 and 3-6 show the progression of health status and disability status over the first five waves of the HRS. Each table has three panels: one for persons who were age 51 in 1992, one for persons age 61, and one panel for all ages in 1992. Each panel shows data for men and for women separately. Table 3-5 shows progression of health status, by health status in 1992; Table 3-6 shows progression of disability, by disability status in 1992. For each combination of age in 1992, health or disability status in1992, gender, and health or disability status in 2000, there are four values. The four values are for health or disability status in wave 2, wave 3, and wave 4, and wave 5 of the HRS.

The wave 5 values correspond to the 8-years transitions between 1992 and 2000, that are shown above.

For example, consider the progression of health in Table 3-5 for men who were age 61 in 1992 and in good or better health. The progression of the proportion that reported they were in good or better health over the next four waves of the HRS are shown in the top row of numbers for men. The proportion in good or better health was .87 in the second wave, .82 in the third wave, .70 in the fourth, and .67 in the fifth wave.

In almost all cases, there is a consistent decline in the proportion in good or better health. And there is a consistent increase in the proportion that has died. On the other hand, the proportion in fair or poor health does not follow a consistent pattern. The reason is the relationship between death and health status. For example, consider men of all ages who were in fair or poor health in 1992—the bottom panel of Table 3-5. The proportion that had died increased from .08 to .15 to .19 to .26, but the proportion in fair or poor health *declined* from .64 to .50 to .48 to .39. The implication is that those in poor health were more likely to die, so that of those remaining fewer and fewer were in fair or poor health. This relationship highlights the strong selection effect that disproportionately leaves healthier persons in the sample as age increases. Similar relationships can be seen for the progression of disability as shown in Table 3-6.

Table 3-5: Progression of health status by 1992 status, by age and sex.

Initial age = 51

health 1992	status	male, wave: 2	3	4	5	female, wave: 2	3	4	5
good+	good+	0.874	0.824	0.700	0.674	0.854	0.795	0.695	0.703
	fair-	0.056	0.065	0.126	0.109	0.100	0.105	0.156	0.103
	dead	0.003	0.012	0.018	0.029	0.000	0.010	0.021	0.028
	attrition	0.068	0.100	0.156	0.188	0.046	0.090	0.128	0.167
fair-	good+	0.356	0.315	0.192	0.178	0.293	0.337	0.174	0.239
	fair-	0.507	0.397	0.438	0.370	0.674	0.543	0.652	0.543
	dead	0.096	0.178	0.219	0.301	0.011	0.043	0.054	0.087
	attrition	0.041	0.110	0.151	0.151	0.022	0.076	0.120	0.130

Initial age = 61

health 1992	status	male, wave: 2	3	4	5	female, wave: 2	3	4	5
good+	good+	0.832	0.782	0.659	0.637	0.831	0.772	0.685	0.694
	fair-	0.123	0.117	0.173	0.123	0.119	0.132	0.142	0.082
	dead	0.006	0.028	0.050	0.073	0.005	0.009	0.050	0.068
	attrition	0.039	0.073	0.117	0.168	0.046	0.087	0.123	0.155
fair-	good+	0.194	0.149	0.179	0.134	0.274	0.226	0.210	0.210
	fair-	0.612	0.507	0.418	0.299	0.597	0.613	0.532	0.452
	dead	0.119	0.224	0.269	0.403	0.081	0.113	0.145	0.210
	attrition	0.075	0.119	0.134	0.164	0.048	0.048	0.113	0.129

Averaged over all ages:

health 1992	status	male, wave: 2	3	4	5	female, wave: 2	3	4	5
good+	good+	0.840	0.764	0.676	0.644	0.850	0.795	0.708	0.696
	fair-	0.086	0.097	0.131	0.116	0.095	0.099	0.137	0.107
	dead	0.009	0.026	0.042	0.060	0.006	0.014	0.026	0.037
	attrition	0.064	0.113	0.151	0.180	0.049	0.092	0.129	0.160
fair-	good+	0.221	0.246	0.181	0.195	0.255	0.284	0.204	0.212
	fair-	0.643	0.502	0.480	0.385	0.655	0.565	0.566	0.482
	dead	0.077	0.145	0.192	0.256	0.041	0.073	0.112	0.154
	attrition	0.059	0.107	0.147	0.163	0.050	0.077	0.118	0.151

Source: Authors’ calculations based on the HRS cohort

Table 3-6: Progression of disability status by 1992 status, by age and sex.

Initial age = 51

status 1992	status	male, wave: 2	3	4	5	female, wave: 2	3	4	5
not disab.	not disab.	0.848	0.767	0.696	0.663	0.860	0.748	0.705	0.640
	disabled	0.082	0.118	0.115	0.103	0.101	0.156	0.149	0.172
	dead	0.009	0.024	0.035	0.053	0.000	0.007	0.017	0.022
	attrition	0.062	0.091	0.153	0.182	0.039	0.089	0.129	0.165
disabled	not disab.	0.208	0.181	0.208	0.208	0.253	0.176	0.189	0.189
	disabled	0.653	0.542	0.486	0.417	0.680	0.676	0.608	0.554
	dead	0.069	0.125	0.139	0.194	0.013	0.068	0.081	0.135
	attrition	0.069	0.153	0.167	0.181	0.053	0.081	0.122	0.122

Initial age = 61

health 1992	status	male, wave: 2	3	4	5	female, wave: 2	3	4	5
not disab.	not disab.	0.840	0.718	0.669	0.630	0.826	0.741	0.676	0.629
	disabled	0.122	0.188	0.177	0.138	0.122	0.165	0.162	0.152
	dead	0.006	0.033	0.055	0.083	0.000	0.009	0.043	0.057
	attrition	0.033	0.061	0.099	0.149	0.052	0.085	0.119	0.162
disabled	not disab.	0.092	0.108	0.138	0.123	0.206	0.209	0.209	0.250
	disabled	0.692	0.523	0.415	0.277	0.676	0.627	0.522	0.397
	dead	0.123	0.215	0.262	0.385	0.088	0.104	0.149	0.235
	attrition	0.092	0.154	0.185	0.215	0.029	0.060	0.119	0.118

Averaged over all ages:

health 1992	status	male, wave: 2	3	4	5	female, wave: 2	3	4	5
not disab.	not disab.	0.836	0.743	0.683	0.626	0.831	0.756	0.690	0.638
	disabled	0.092	0.117	0.122	0.129	0.113	0.135	0.146	0.156
	dead	0.011	0.030	0.047	0.067	0.006	0.015	0.029	0.039
	attrition	0.061	0.109	0.148	0.178	0.051	0.094	0.135	0.167
disabled	not disab.	0.175	0.185	0.181	0.183	0.183	0.187	0.224	0.221
	disabled	0.684	0.564	0.490	0.415	0.729	0.669	0.570	0.496
	dead	0.069	0.128	0.173	0.231	0.044	0.073	0.109	0.160
	attrition	0.073	0.123	0.155	0.172	0.043	0.071	0.097	0.123

Source: Authors' calculations based on the HRS cohort

4. Modelling Health Transitions: What are the Difficulties?

The tables in section 3 show transition probabilities over an eight-year period and from wave to wave in the HRS. Can these transition probabilities be used to project health and disability status into the future? The apparent relationship between health (or disability) and death revealed in Tables 3-5 and 3-6 suggests that the answer is no. Those who remain in the sample are likely to be healthier than those who die. This section demonstrates this and additional features of the data that must be accounted for to adequately specify transitions models of self-reported health and work-related disability. Since most of this section serves to demonstrate the key issues, most of the presentation pertains to our binary indicator of self-reported health (good or better versus fair or worse) and to men only.

The transition probabilities from wave to wave in the HRS are shown in Table 4-1, for men who were in good or better health in the first wave. The entries in the table represent the average transition probabilities over all waves, by initial age. There are 308 observations of men initially aged 50 in good or better health in waves 1 through 4. Overall, 83.6 percent of them remain in good health in the subsequent wave, while for 11.2 percent health deteriorates, 0.3 percent die, and 4.9 percent cannot be interviewed in the following wave.

Table 4-1: Average 2-year transition probabilities

Age (w1)	Obs.	health good+	poor/fair	dead	attrition
Men, lagged health = good or better					
50	308	83.55	11.18	0.33	4.93
51	1,237	85.55	8.13	0.99	5.34
52	1,181	83.79	8.94	1.58	5.70
53	1,226	82.16	11.47	0.84	5.53
54	1,072	84.91	8.08	1.17	5.84
55	1,058	84.18	9.59	1.34	4.89
56	1,110	83.04	10.51	0.83	5.62
57	1,115	84.19	9.47	1.19	5.15
58	941	82.99	11.12	1.64	4.25
59	887	82.26	12.33	1.61	3.80
60	1,051	84.65	8.65	1.85	4.86
61	627	82.77	11.76	1.61	3.86

Total	11,813	83.75	9.91	1.27	5.07

Source: Authors' calculations from the HRS

An important question is whether these 2-year transitions can be used to predict the evolution of heath in the longer run. A simple estimate of an 8-year transition probability is the 2-year transition probability raised to the power four. Using this procedure to estimate health status in 2000, given health status in 1992 does not work well, however. The results are shown in Table 4-2. The actual proportion of respondents in good health is substantially greater than the predicted probability at all ages. The actual proportion in poor or fair health is substantially less than the simulated probability at all ages.

Table 4-2: Projection of 1992-2000 health changes based on 2-year average transition probabilities—men in good or better health in wave 1

	Actual probabilities				Predicted probability			
age (w1)	good+	poor/fair	dead	attrition	good+	poor/fair	dead	attrition
50	0.663	0.128	0.035	0.174	0.617	0.165	0.041	0.178
51	0.674	0.109	0.029	0.188	0.624	0.130	0.058	0.189
52	0.640	0.098	0.063	0.199	0.583	0.142	0.072	0.203
53	0.604	0.150	0.053	0.192	0.553	0.189	0.053	0.205
54	0.649	0.103	0.053	0.195	0.586	0.143	0.065	0.205
55	0.658	0.113	0.053	0.176	0.588	0.163	0.075	0.174
56	0.640	0.131	0.035	0.194	0.580	0.170	0.052	0.199
57	0.650	0.116	0.051	0.183	0.591	0.162	0.067	0.179
58	0.663	0.101	0.086	0.150	0.565	0.189	0.093	0.153
59	0.619	0.135	0.099	0.147	0.561	0.185	0.104	0.150
60	0.643	0.094	0.098	0.165	0.591	0.140	0.103	0.166
61	0.637	0.123	0.073	0.168	0.554	0.183	0.109	0.155

Source: Authors' calculations from the HRS cohort

There are several potential reasons why this procedure predicts actual probabilities poorly. One reason is the simplistic first-order Markov assumption that underlies the predictions. State dependence may be more complicated; the value in wave t may depend on the value not only in wave t-1, but on prior waves as well. A second reason is heterogeneity. If there are two populations, for instance, one intrinsically healthier than the other, the transition probability averaged over both subpopulations will underestimate the proportion in good health after eight years and will overestimate the proportion in fair or poor health after 8 years. Below, we show descriptive evidence of both state dependence and heterogeneity. A third reason is measurement error, in this case misclassification of a respondent into the wrong categorical health status. We will also show descriptive evidence of this problem below.

To demonstrate that that health outcomes in wave 3 depend on health in wave 1 as well as wave 2, we show in Table 4-3 a complete "tree" of health status probabilities in waves 1, 2, and 3. These probabilities are based on 513 men who were aged 51 in wave 1. The first column (wave 1) simply shows the proportions in good and poor health at wave 1. Column 2 (wave 2) shows the distribution of health status in wave 2, given health status in wave 1. The third column (wave 3) shows the evidence on state dependence. Health in wave 3 depends not only on health in wave 2, but also on health in wave 1. For example, 91.25 percent of men who are in good health in wave 2 *and* in wave 1 are in good health in wave 3. But only 61.54 percent of men who are in good health in wave 2 *and* in fair health in wave 1 are in good health in wave 3. Also, 36.84 percent of men who are in good health in wave 1 and in fair health in wave 2 are in fair health in wave 3. On the other hand, 59.46 percent of men who are in fair health in *both* wave 1 and in wave 2 have a fair health in wave 3. That is, health status in wave 3 depends not only on health in the preceding wave 2, but also on health in the prior wave 3. Thus a second-order Markov process would describe these transitions much better than a first-order Markov process.

Table 4-3: Health transitions in the first three waves of the HRS cohort, for men age 51 in wave 1

wave 1		wave 2		wave 3	
Good +	82.32	Good +	87.35	Good +	91.25
				Poor/Fair	5.05
				Dead	0.67
				Attrition	3.03
		Poor/Fair	5.59	Good +	47.37
				Poor/Fair	36.84
				Dead	5.26
				Attrition	10.53
		Dead	0.29		
		Attrition	6.76		

Poor/Fair	17.68	Good +	35.62	Good +	61.54
				Poor/Fair	26.92
				Dead	3.85
				Attrition	7.69
		Poor/Fair	50.68	Good +	18.92
				Poor/Fair	59.46
				Dead	13.51
				Attrition	8.11
		Dead	9.59		
		Attrition	4.11		

Source: Authors' calculations based on the HRS cohort

The underlying reason for such state dependence may, however, be population heterogeneity. Indeed Table 4-4 shows the results of a regression of change of health status between each pair of successive waves on a host of individual characteristics in the first of the two waves. The table shows that the individual characteristics of a substantial effect on the transition. Thus substantial heterogeneity is attributable to observed individual characteristics, suggesting substantial heterogeneity over unobserved characteristics as well. The marital status is interacted with gender; the reference group is married males. Particularly striking are the estimated coefficients on the upper and lower wealth and income quartiles. They indicate a significantly lower probability of remaining in poor health if a person is in the top wealth quartile or in the top income quartile.

Table 4-4: Regression of health in second of two waves based on observable characteristics in first wave

Attribute in the first of the two waves	Wave 1=>2			Wave 2=>3			Wave 3=>4			Wave 4=>5		
	Health poor/fair	dead	attrition	Health poor/fair	dead	attrition	Health poor/fair	dead	attrition	Health poor/fair	dead	attrition
Fair or poor health	2.894**	2.948**	1.029**	2.865**	2.917**	1.194**	2.933**	2.982**	0.557**	2.728**	2.672**	-0.483**
	(41.23)	(16.26)	(8.40)	(39.94)	(16.68)	(9.10)	(39.20)	(17.68)	(4.02)	(37.95)	(16.39)	(3.48)
Age	0.026*	0.099**	-0.020	0.009	0.042+	-0.040*	-0.009	0.074**	-0.016	0.009	0.076**	-0.032*
	(2.47)	(3.67)	(1.35)	(0.86)	(1.67)	(2.39)	(0.89)	(2.92)	(1.15)	(0.84)	(3.19)	(2.48)
Single male	-0.047	0.030	-0.059	-0.083	0.607*	-0.184	-0.056	-0.278	-0.168	-0.068	0.187	-0.063
	(0.35)	(0.10)	(0.32)	(0.57)	(2.43)	(0.81)	(0.39)	(0.85)	(0.89)	(0.45)	(0.71)	(0.37)
Single female	-0.235*	-0.644**	-0.574**	-0.195+	-0.564*	-0.799**	-0.066	-0.334	-0.357*	-0.330**	-0.729**	-0.403**
	(2.33)	(2.71)	(3.71)	(1.86)	(2.36)	(4.16)	(0.64)	(1.42)	(2.51)	(3.02)	(3.17)	(3.08)
Married female	-0.133+	-0.932**	-0.268*	-0.086	-0.962**	-0.196+	-0.077	-0.462*	-0.151	-0.156+	-0.670**	-0.189*
	(1.71)	(4.22)	(2.45)	(1.09)	(4.46)	(1.68)	(1.01)	(2.43)	(1.53)	(1.91)	(3.58)	(2.06)
1 child	0.139	0.813+	-0.346	0.229	0.099	0.044	0.102	0.240	-0.007	0.195	-0.327	0.039
	(0.84)	(1.88)	(1.64)	(1.33)	(0.26)	(0.17)	(0.60)	(0.61)	(0.03)	(1.06)	(0.92)	(0.20)
2 children	-0.176	0.246	-0.525**	0.017	0.160	-0.149	0.008	-0.215	-0.238	0.161	-0.276	-0.217
	(1.23)	(0.61)	(3.04)	(0.12)	(0.50)	(0.67)	(0.06)	(0.60)	(1.32)	(1.01)	(0.95)	(1.32)
3 or more children	0.114	0.651+	-0.631**	0.046	0.103	-0.197	0.125	0.164	-0.224	0.245+	-0.238	-0.196
	(0.86)	(1.76)	(3.95)	(0.33)	(0.35)	(0.93)	(0.92)	(0.52)	(1.33)	(1.66)	(0.91)	(1.27)
1st wealth quartile	0.524**	0.748**	0.471**	0.442**	0.179	0.064	0.450**	0.481*	0.540**	0.417**	0.208	0.652**
	(6.57)	(3.70)	(3.91)	(5.29)	(0.92)	(0.44)	(5.46)	(2.54)	(4.85)	(4.80)	(1.14)	(6.30)
4th wealth quartile	-0.448**	0.144	0.106	-0.308**	-0.005	0.091	-0.359**	-0.500+	-0.101	-0.449**	-0.512*	-0.046
	(4.49)	(0.57)	(0.86)	(3.08)	(0.02)	(0.69)	(3.86)	(1.95)	(0.88)	(4.38)	(2.18)	(0.44)
1st income quartile	0.601**	0.708**	0.508**	0.481**	0.474*	0.414**	0.525**	0.300	0.128	0.582**	0.794**	0.463**
	(7.43)	(3.48)	(4.20)	(5.65)	(2.43)	(2.95)	(6.26)	(1.53)	(1.09)	(6.58)	(4.29)	(4.35)
4th income quartile	-0.474**	-0.203	-0.242+	-0.305**	-0.318	-0.255+	-0.343**	-0.348	-0.408**	-0.395**	0.005	-0.188+
	(4.53)	(0.72)	(1.86)	(2.98)	(1.22)	(1.83)	(3.64)	(1.38)	(3.47)	(3.81)	(0.02)	(1.77)
Constant	-3.691**	-10.749**	-1.068	-2.846**	-6.757**	-0.407	-1.445*	-8.253**	-1.037	-2.897**	-8.102**	-0.033
	(6.13)	(6.84)	(1.26)	(4.59)	(4.64)	(0.43)	(2.40)	(5.58)	(1.32)	(4.53)	(5.89)	(0.05)
Observations	9024			8355			8044			7724		
Log Likelihood	-5588.88			-5146.94			-5814.33			-5702.05		
Pseudo-R^2	0.23			0.22			0.20			0.20		

Absolute value of z statistics in parentheses

+ significant at 10%; * significant at 5%; ** significant at 1%

Source: Authors' calculations based on the HRS cohort

To see whether these covariates improve the long-run predictive power of the 2-year transitions, we use the predicted transition probabilities to project health status in 2000, beginning with health status in 1992. One such specification is shown in Table 4-4. We again compare the predicted probabilities of the outcomes in 2000 with the actual probabilities. We are interested in how much closer the predicted probabilities are to the actual probabilities when a more individual attributes in the first wave are controlled for, in addition to health status in the first of the two waves. We used three specifications:

- Specification (1) includes only age and gender,
- Specification (2) is the one shown in Table 4-4,
- Specification (3) refines the description of health by adding to specification (2) the RAND summary indices for the number of conditions, and indices of gross and fine motor activities and mobility which significantly correlate with disability as shown in Table 2-2.

Table 4-5: Prediction of 1992-2000 health changes, controlling for observable characteristics

			Wave 5 health							
			Actual				Simulated			
Specification	"fit"	initial health	good+	poor/ fair	dead	attrition	good+	poor/ fair	dead	attrition
(1)	0.413	good+	**67.12**	11.13	4.83	16.92	**60.47**	16.77	5.88	16.89
		poor/fair	**20.50**	43.99	19.85	15.66	**43.81**	24.26	16.16	15.76
(2)	0.436	good+	**67.12**	11.14	4.83	16.91	**61.88**	15.58	5.64	16.91
		poor/fair	**20.51**	44.01	19.86	15.62	**38.89**	28.48	17.01	15.62
(3)	0.469	good+	**67.17**	11.10	4.82	16.91	**64.95**	13.07	4.89	17.09
		poor/fair	**20.56**	44.07	19.71	15.66	**29.06**	36.67	19.28	15.00

Source: Authors' calculations base on the HRS cohort. Note: The slight differences in the actual distributions are due to missing values for some of the covariates.

Controlling for initial values of covariates improves the predictions substantially. Still, even specification (3) understates the proportion of persons who were in poor of fair health in 1992 who are in poor or fair health in 2000. While 44.07 percent of these persons are in poor or fair health in 2000, the predicted percent is only 36.67 percent.

However, specification (3) does much better than specification (1) or specification (2), that control for fewer individual attributes. Specification (3) also predicts much better than specification (1) or (2) the percent of persons who were in good or better health in 1992 who are in good or better health in 2000. The improvement in "fit", displayed in the second column of Table 4-5, is measured by the average simulated probability of the observed outcome. Thus better control for individual heterogeneity improves the transition predictions substantially.

Finally, we consider misclassification error. We assume that underlying health (or disability) is continuous, ranging from persons with the worst health to those with the best health. The measure of health status reported in the HRS, however, is discrete, allowing for 5 self-reported categories (which we often condense even further into only two categories). Measured disability allows for only two categories. These categories are not precisely defined. Respondents may therefore "misclassify" their health or disability status because they report a different category than others who have the same underlying health status.

Misclassifications are likely to be particularly frequent in situations in which true underlying health status is on the borderline between categories. This may explain sequences which exhibit a frequent back and forth movement from one category to the other (such as 01010 in the binary disability categories). Another type of misclassification is simple error. Sequences which show a single deviation from an otherwise constant pattern (such as 00100) may reflect such errors, although they may also indicate a temporary illness, for example.

Table 4-6 shows the frequencies of each sequence of self-reported health in the HRS data. In each of the five waves between 1992 and 2000, "0" represents good or better health, "1" fair or poor health, and "x" either death or attrition. The sequences are ordered in descending frequency. The most striking feature of the data is the stability of self-reported health status. Almost 45 percent of all respondents reported that their health was good or better in all five waves. Another 6.4 percent reported that their health was fair or poor in all five waves. Including incomplete histories (noted by x), 71.3 percent of respondents never changed their self-reported health status. Another 13.7 percent changed their self-reported health status only once, mostly from good or better to fair or poor.

Self-reported health sequences with changes from good or better to fair or poor, or the reverse, are relatively rare. Thus these data provide *prima facie* evidence suggesting that misclassification cannot dominate self-reported health categorization. Self-reported sequences with three or four changes make up only 3.7 percent of all sequences. Single-change sequences are more frequent, accounting for 6.6 percent of all sequences. And it is not clear how many of these reflect true one-spell illnesses. Thus we should perhaps be less concerned about errors in the data than about the reduction in information inherent in the discrete coding of an underlying continuous variable.

Table 4-6: Sequences of health status, 1992-2000

Sequence	Freq.	Percent	Cum.	Sequence	Freq.	Percent	Cum.	Sequence	Freq.	Percent	Cum.
00000	4048	44.84	44.8	**11110**	67	0.74	88.2	**10xxx**	27	0.30	97.3
11111	578	6.40	51.2	**10111**	61	0.68	88.9	**010xx**	25	0.28	97.6
0xxxx	449	4.97	56.2	**11000**	56	0.62	89.5	**10100**	23	0.25	97.8
00xxx	327	3.62	59.8	**01011**	51	0.56	90.1	**10110**	23	0.25	98.1
000xx	267	2.96	62.8	**11010**	51	0.56	90.7	**0111x**	21	0.23	98.3
00010	257	2.85	65.6	**01110**	48	0.53	91.2	**101xx**	20	0.22	98.5
00001	243	2.69	68.3	**10011**	48	0.53	91.7	**0011x**	18	0.20	98.7
1xxxx	221	2.45	70.8	**11101**	45	0.50	92.2	**110xx**	17	0.19	98.9
0000x	211	2.34	73.1	**01010**	41	0.45	92.7	**1001x**	16	0.18	99.1
00011	144	1.60	74.7	**00101**	40	0.44	93.1	**10101**	16	0.18	99.3
11xxx	143	1.58	76.3	**001xx**	39	0.43	93.5	**1000x**	13	0.14	99.4
10000	128	1.42	77.7	**0001x**	38	0.42	94.0	**1011x**	10	0.11	99.5
01111	126	1.40	79.1	**10010**	33	0.37	94.3	**0110x**	8	0.09	99.6
00111	120	1.33	80.5	**11001**	33	0.37	94.7	**1101x**	8	0.09	99.7
01000	113	1.25	81.7	**10001**	32	0.35	95.1	**0100x**	7	0.08	99.8
00100	103	1.14	82.8	**01001**	31	0.34	95.4	**0010x**	5	0.06	99.8
111xx	101	1.12	84.0	**11100**	30	0.33	95.7	**1110x**	5	0.06	99.9
1111x	96	1.06	85.0	**01100**	29	0.32	96.0	**1100x**	4	0.04	99.9
01xxx	80	0.89	85.9	**011xx**	29	0.32	96.4	**0101x**	3	0.03	100.0
00110	75	0.83	86.7	**01101**	27	0.30	97.0	**1010x**	3	0.03	100.0
11011	69	0.76	87.5								
Total									9028	100	

Source: Authors' calculations from the HRS cohort

The sequences also provide some information that helps to distinguish true state dependence from unobserved heterogeneity. We calculate the probability of a bad health state in wave 5, conditional on a sequence in the first four waves of the HRS. The data are reported in Table 4-7. In this representation, we assume that heterogeneity is held constant by conditioning on the total number of past bad health states, regardless of order. State dependence in this representation is suggested if the sequence of past health states determines health status in wave 5, but the number of past bad health states does determine health status in wave 5.

Thus we order the entries in the table first by the number of bad health states, and then by the number of waves over which the most recent health state was observed without change. Not surprisingly, the probability of being in bad health in wave 5 increases with the number of prior bad states. In addition, there is also a distinct time lag effect: the more recent a bad health status the higher the probability of being in bad health in wave 5.

Table 4-7: Probability of bad health in wave 5, conditional on sequence of health states in waves 1 through 4

Number	Initial sequence in waves 1 through 4	Frequency of initial sequence	Number of past bad health states	Lag since last bad health state	Probability of bad health in wave 5
1	0000	5,572	0	-	0.06
2	1000	209	1	4	0.19
3	0100	185	1	3	0.21
4	0010	183	1	2	0.28
5	0001	538	1	1	0.38
6	1100	110	2	3	0.38
7	1010	46	2	2	0.39
8	0110	75	2	2	0.51
9	0101	125	2	1	0.55
10	1001	108	2	1	0.61
11	0011	249	2	1	0.61
12	1110	93	3	2	0.58
13	1101	157	3	1	0.61
14	0111	216	3	1	0.73
15	1011	106	3	1	0.73
16	1111	799	4	1	0.90
	Total	8,771			0.25

Source: Authors' calculations from HRS cohort

Comparing sequence 1 to sequence 2, we see clearly that even health status fives waves earlier affects health status in wave 5. With no prior bad health states, the probability of bad health in wave 5 is 0.06; if the only change is that health status 5 waves earlier is bad (but good in the subsequent 3 waves), the probability of bad health in wave 5 is increased from 0.06 to 0.19. This change suggests heterogeneity. The comparison of sequences 3 with 6 tells the same story. So does the comparison of sequences 4 and 7.

Comparison of sequences 2, 3, and 4 shows that, holding the number of past bad health states constant, the more recent the bad health state the greater the probability that health status in wave 5 will be bad. This suggests state dependence. Obviously, there is more going on than simple heterogeneity. State dependence may overlay differences in self-reported health status due to heterogeneity. Similar conclusions follow from comparing sequence 6 to sequence 7, and sequence 7 to sequence 8. In each sequence, there are two bad health states. But the more recent the last of these bad health states, the greater the probability that health status in wave 5 will be bad. One explanation for this "state dependence" is a drift in the underlying continuous health variable that underlies our coarse binary health indicator. We will return to this issue in our more refined model in Section 5.

The number of bad health states (as a measure of heterogeneity) and the number of waves since the last bad health state (as a measure of state dependence) are close to a sufficient statistic for the initial sequences. The probability of bad health in wave 5 is very closely approximated by these two measures. Table 4-8 shows logit regression estimates of health status in wave five regressed on these two measures (based on the first 4 waves). This specification cannot be rejected versus a specification with a full set of dummies for the 16 sequences in Table 4-7 (p=0.5409).

Table 4-8: Probability of bad health in wave 5 based on summary measures of health status in the prior 4 waves

Logit estimates	Odds Ratio	Std. Err.	Z	P>|z|
# bad states=0	1.00	(reference)		
# bad states=1	4.06	0.50	11.29	0.00
# bad states=2	8.40	1.61	11.11	0.00
# bad states=3	11.92	3.17	9.33	0.00
# bad states=4	39.24	13.18	10.93	0.00
status w1 = bad	1.00	(reference)		
status w2 = bad	1.06	0.15	0.43	0.67
status w3 = bad	1.44	0.17	2.99	0.00
status w4 = bad	2.24	0.26	6.85	0.00

Number of obs	Log likelihood	LR chi2(7)	Pseudo R2	Prob > chi2
8771	-3049.0437	3698.25	0.3775	0.00

Source: Authors' calculation based on the HRS cohort

Table 4-9 shows the "fitted" probabilities of bad health in wave 5 based on the regression above, together with the actual probabilities, for each of the sequences in Table 4-7. It is clear that the fitted values are close to the actual values.

Table 4-9: Predicted versus actual probability of health status in wave 5

Sequence In waves 1-4	Actual	Predicted
0000	0.061	0.061
0001	0.385	0.372
0010	0.279	0.276
0011	0.606	0.638
0100	0.205	0.219
0101	0.552	0.565
0110	0.507	0.455
0111	0.731	0.727
1000	0.187	0.209
1001	0.611	0.551
1010	0.391	0.441
1011	0.726	0.715
1100	0.382	0.367
1101	0.611	0.649
1110	0.581	0.542
1111	0.897	0.897
Total	0.246	0.246

Source: Authors’ calculations based on HRS cohort

5. An econometric model based on continuous latent ("hidden") health status

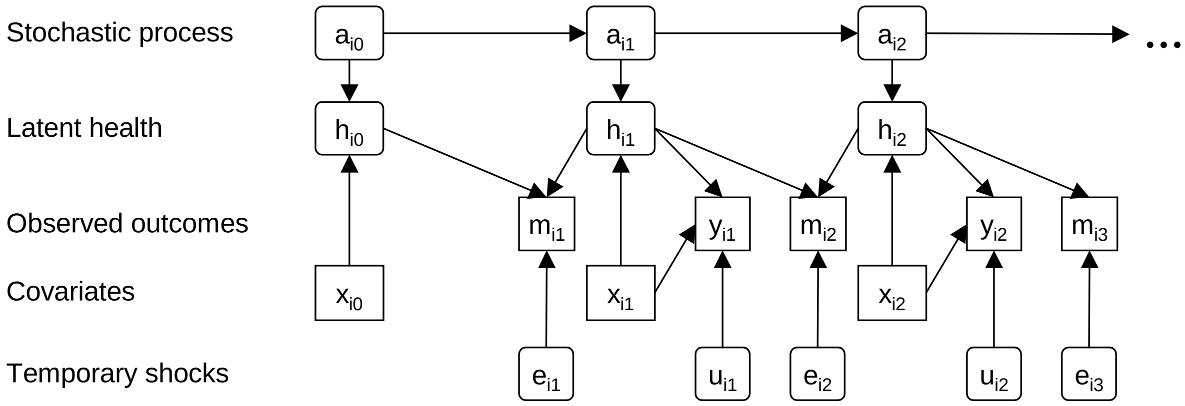
The descriptive analysis presented in section 4 suggests that self-reported health status in all waves prior to wave 5, contains information about wave 5 health status. That is health status in wave 5 depends on health status in all prior waves. There are at least three explanations for this:

- State dependence: past health states directly affect the risk of a current (good or bad) state.
- Heterogeneity: past states contain information on individual-specific risk that is correlated over time.
- Misclassification: categorical coding induces error in self-reported health status.

Thus to predict future health status, we use an econometric model that accounts for each of these features of the data.[5] The key idea is to model "true" underlying health status as a continuous "latent" variable. The categorical self-assessed indicators of health (or work disability) are determined by this latent health. The underlying continuous latent health variable is correlated over time and thus induces correlation over time in the observed responses to the categorical self-assessment of health status and disability. In addition, the probability of death is assumed to depend on the "hidden" health measure, thus allowing for correlation between health status and selection into the group of persons who survive from one period to the next. The key features of the specification are illustrated in Figure 5-1. It relates a categorical self-assessed health indicator y to "true" latent health h and a set of observed covariates x.

[5] Details can be found in Heiss (2005, Ch. 3).

Figure 5-1: Modeling a hidden health process



The diagram describes the evolution of latent heath, the measured health indicators y, and mortality m over time—in periods $0, 1, 2,$ and so forth. Latent health h depends on observed individual covariates x and on unobserved individual attributes a, which are correlated over time. In addition to the random unobserved variable a, which directly influences h, self-reported health or disability y, and mortality, depend on two additional stochastic shocks. One shock u represents classification error in self reported health as well as unmeasured variables that affect self-reported health. Another shock e reflects unobserved determinants of mortality.

More precisely, the model used to describe health (or disability) transitions and mortality is represented by the following equations:

(1) Latent "hidden" health:

$$h_{iw} = x_{iw}\gamma + a_{iw}$$

(2) Unobserved determinants of latent health (heterogeneity):

$$a_{iw} \sim N\left(0, \sigma_a^2\right)$$
$$a_{iw} \mid a_{iw-1} \sim N\left(\rho^{t(w)-t(w-1)} a_{iw-1}, \sigma_a^2\left(1-\rho^{2(t(w)-t(w-1))}\right)\right)$$

(3) Categorical self-reported health measure y:

$$
\begin{aligned}
\Pr\left(y_{iw}=y \mid x_{iw},h_{iw}\right) &= \Lambda\left(\alpha_y-h_{iw}-x_{iw}\beta\right)-\Lambda\left(\alpha_{y-1}-h_{iw}-x_{iw}\beta\right)\\
&= \Lambda\left(\alpha_y-\left(x_{iw}\gamma+a_{iw}\right)-x_{iw}\beta\right)-\Lambda\left(\alpha_{y-1}-\left(x_{iw}\gamma+a_{iw}\right)-x_{iw}\beta\right)
\end{aligned}
$$

(4) Mortality hazard rate:

$$
\begin{aligned}
\lambda_{it(w)} &= \exp\left(\alpha+\delta h_{iw}\right)\\
&= \exp\left(\alpha+\delta\left(x_{iw}\gamma+a_{iw}\right)\right)
\end{aligned}
$$

(5) Survival probability from HRS wave $w-1$ to wave w:

$$
S_i\left(t(w) \mid t(w-1)\right)=\exp\left(-\left(t(w)-t(w-1)\right)\frac{\lambda_{it(w)}-\lambda_{it(w-1)}}{\delta\left(h_{iw}-h_{iw-1}\right)}\right)
$$

Equation 1 describes the key latent health variable. Latent health of individual *i* in wave *w* is determined by two components: a deterministic part that is a function of the explanatory variables x_{iw}, and an unobserved component a_{iw} which persists from period to period and provides for heterogeneity among respondents. The persistence of the unobserved determinant of latent health is described in equation 2. The a_{iw} follow a first-order autoregressive process defined in continuous time.[6] The marginal distribution of a_{iw} is normal with zero mean and variance σ^2. Conditional on a previous realization *d* time units ago, where *d* may be continuous, its distribution is normal with mean $\rho^d a_{iw-d}$ and variance $\sigma^2(1-\rho^{2d})$. (Simpler specifications (such as independent realizations or random effects) can be specified as special cases of equation 2.)

The observed categorical self-reported health or work disability responses are determined by the ordered logit functional form described in equation 3. The logit probabilities depend on the covariates x_{iw} and by the latent health measure h--which in turn is also a function of the measured covariates x_{iw} and the unobserved determinant a_{iw} of latent health (equation 1)--and by transitory shocks u_{iw} which are independent and follow a logistic distribution. $\Lambda(\cdot)$ is the cumulative distribution function (c.d.f.) of the logistic distribution, with $\alpha_0 = -\infty$ and $\alpha_5 = \infty$. The threshold parameters α_1 through α_4 are "cut-off" values of latent health that indicate the switch

[6] An "Ornstein-Uhlenbeck process."

points from one categorical response y to another. They are estimated in the model. In the case of a binary specification, equation 3 reduces to a simple logit model. Notice that from equation 3 alone, both of the parameters γ and β cannot be identified. But mortality depends only on the covariates x through latent health and thus allows separate identification of γ, as described next.

Equations 4 and 5 describe the mortality process that induces sample selection, distinguishing persons who remain in the sample from those who die and leave the sample. We start with a straightforward formulation of the mortality hazard rate (equation 4) which depends only on latent health h_{iw}. We then use an approximation formula to integrate this expression over time to obtain the survival function (equation 5). The parameters α and δ are estimated.

The underlying health process and the selection process due to mortality are obviously related. The health change of a typical respondent between two waves is confounded by the fact that this comparison is possible only for the relatively healthy who survive from one wave to the next. A similar problem arises for example when back-casting the health at age 50 of a respondent who was interviewed at age 80. The fact that a person survived until 80 tells us that he was probably healthier that the average respondent at age 50.

In our model, the correlation between health and mortality is generated through latent health h, which in turn depends on observed covariates x as well as the unobserved component of latent health a. So conditional on the covariates x, mortality risk and health are allowed to be correlated through a. In order to identify the model, we assume that conditional on the covariates and the unobserved determinants of latent health, the self-reported health measures and mortality are independent. Hence, once we know the covariates x and latent health h, there is no additional information in the self-reported health measures of an individual that we could use to make a better prediction of the individual's life expectancy. Our core identifying assumption is that all such information is contained in the latent health variable.

The model is estimated by simulated maximum likelihood. Conditional on the sequence of unobserved persistent health shocks a_{iw}, all calculations are straightforward – the probabilities of self-reported health are given in equation (3) and the survival/mortality probabilities are given in equations (4) and (5). We then integrate over the sequence of health shocks a_{iw} using Monte-Carlo simulation. Their joint distribution is given by equation (2). We account for the fact that selectivity through mortality has gone on before the first wave by integrating not over the unconditional distribution of a_{iw} but over the distribution conditional on survival up to the first interview – see Figure 6-3 below.

This method results in asymptotically efficient parameter estimates if certain regularity conditions hold and the number of replications rises fast enough with the number of individuals. For details on these simulation methods see Hajivassiliou and Ruud (1994). Alternative simulation schemes for this and similar models such as nonlinear filtering are discussed by Heiss (2006).

6. Results

We have estimated the different joint model of the health status and mortality on the first six waves (1992-2002) of the HRS (using all four cohorts). As discussed above, the health outcomes we consider are the five categories of self-reported health (SRH) and the two categories of work disability (WD).

In a first model, the only covariates included are age splines. They enter the latent health equation and the SRH/WD outcome equations. The parameters in the latent health equation are identified by the fact that age does not separately enter the mortality equation and that latent health enters the outcome equations with a normalized weight of 1.

Table 6-1 presents the estimation results for the SRH and WD outcomes. The unobserved heterogeneity (the standard deviation of a) is substantial. The standard deviation of a is estimated to be 3.2 in the SRH model and 4.7 in the WD model. The correlation of a over time is close to 1 in both models, although significantly less than 1.

The estimated correlation over one year translates into a correlation between values 20 years apart of 0.7 in the SRH model and 0.5 in the WD model. Consequently, the hypothesis of no heterogeneity ($\sigma = 0$) and the random effects hypothesis ($\rho = 1$) are rejected. Results from these models can be requested from the authors.[7]

Table 6-1: Estimation results with age only

	Self-reported health		Work disability	
	Estimate	Std.err.	Estimate	Std.err.
Latent Health (h):				
Std. dev. of a (σ)	3.2411	0.0153	4.6886	0.0429
1-year correlation of a (ρ)	0.9817	0.0006	0.9663	0.0005
Covariates (γ): Age	-0.5908	0.0425	-0.4644	0.0141
Age spline 60+	0.3012	0.0573	0.1424	0.0303
Age spline 70+	-0.0128	0.0443	-0.0436	0.0394
Age spline 80+	-0.2429	0.0390	-0.2841	0.0382
Age spline 90+	-0.0974	0.0501	-0.0771	0.0539
Health measure (y):				
Latent health	(enters with weight normalized to 1)			
Covariates (β): Age	0.4610	0.0434	-0.2421	0.0162
Age spline 60+	-0.2504	0.0573	0.0627	0.0299
Age spline 70+	-0.0694	0.0431	0.0631	0.0383
Age spline 80+	0.1837	0.0374	-0.0701	0.0381
Age spline 90+	0.0325	0.0496	0.0202	0.0580
other	4 ordered logit cut points		constant	
Mortality (m):				
Baseline (α)	-6.8642	0.0846	-8.0584	0.0905
Latent health (δ)	-1.0721	0.0163	-0.4387	0.0055
\# individuals	25,497		25,050	
\# observations (health)	103,250		88,798	
\# parameters	18		15	
Log-Likelihood	-150,438.0		-60,269.9	

6.1 Simulations with age only

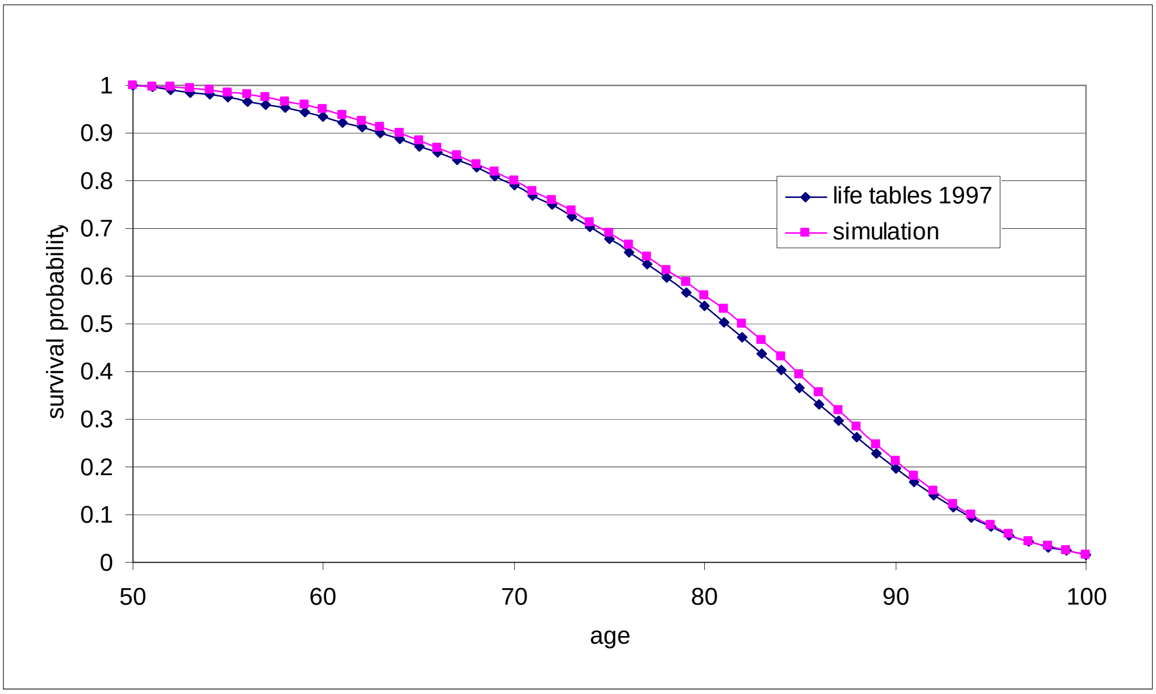
Given the parameter estimates for self-reported health (SRH) and work disability (WD) shown in Table 6-1, we can simulate future paths of survival and health (and

[7] The transitory shocks u in the categorical health equations are normalized to $\frac{\pi}{\sqrt{3}} \approx 1.8$, as is implicit in the logit model.

disability) conditional on health earlier in life. This is done by simulating not over the unconditional distribution of latent health shocks *a* but over the distributions conditional on survival or observed health outcomes. Figure 6-3 below presents such conditional distributions for survival up to different ages.

The simulated survival rates conditional on survival up to age 50 for the whole population is shown and compared with the life tables for 1997 (National Center for Health Statistics: National Vital Statistics Report, Vol. 47, No. 28) in Figure 6-1. Our simulated survival probabilities tend to be slightly higher than the numbers from the life tables. This might be because the HRS samples only individuals who are initially non-institutionalized.

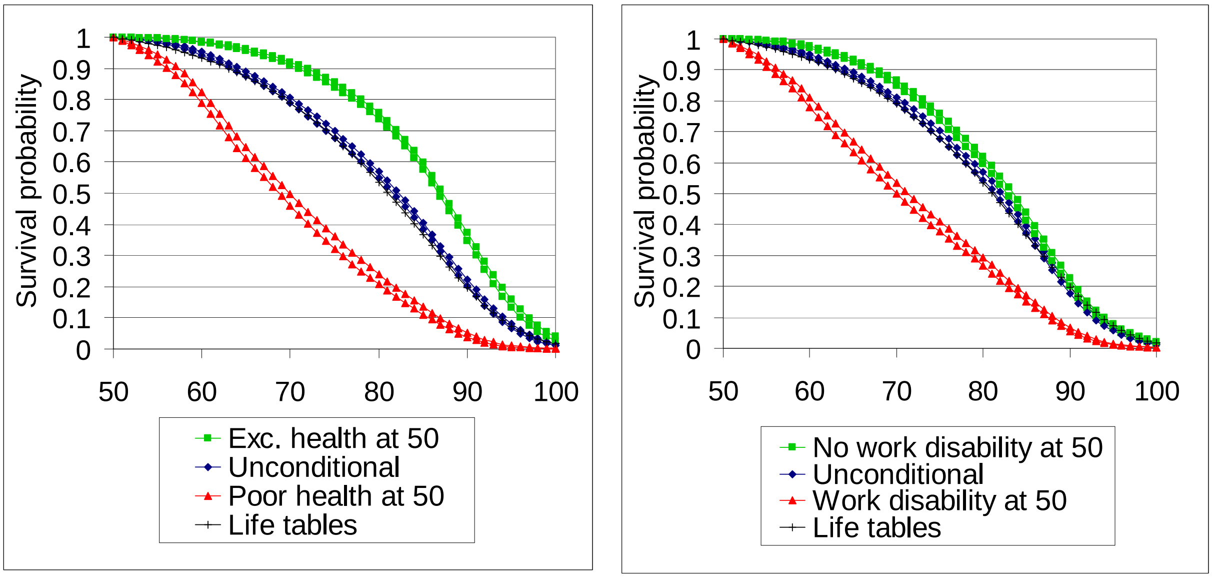
Figure 6-1: Survival probabilities – simulation vs. life tables



Both health and disability are strongly related to mortality, as shown in Figure 6-2. The figure shows this relationship by comparing future survival probabilities conditional on self-reported health (or disability) at age of 50. The differences are striking. For example, only 48.5 percent of respondents who report poor health at age 50 survive until age 70, whereas 91.6 percent of those reporting excellent health at age 50 survive until age 70. A similar pattern is revealed with respect to work disability.

Figure 6-2: Survival probabilities

(a) SRH poor/fair (b) Work disability



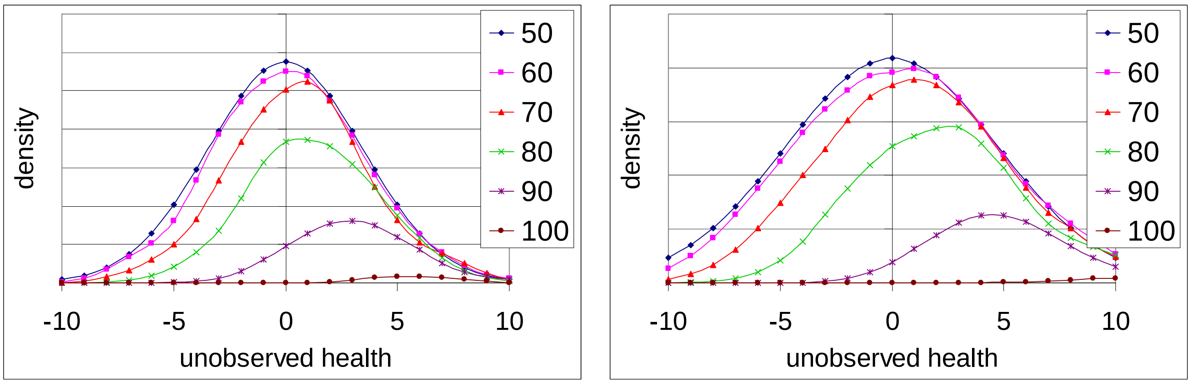
The two lines for each series represent the inner and outer 95% confidence bands.

Two technical aspects of Figure 6-2 are worth mentioning. First, the inner and outer 95% confidence bands represented by the two lines for each of the three simulations are very close to each other, indicating a rather precise fit. We therefore will not show confidence bands in the sequel of this paper. Second and as shown in Figure 6-1, the unconditional simulation is not significantly different from the actual life tables.

Figure 6-3 illustrates the selection effect induced by differential mortality. The figure shows the distribution of the unobserved component *a* of latent health given survival to selected ages. (These are weighted kernel density estimates and are scaled by survival probabilities, so that the curves integrate to the share of surviving population at the respective ages.) Those who are in the left part of the distributions with relatively poor latent health are more likely to be selected out, so the distribution shifts to the right with the survival age.

Figure 6-3: Distribution of unobserved health given survival to selected ages

(a) SRH model (b) Work disability model

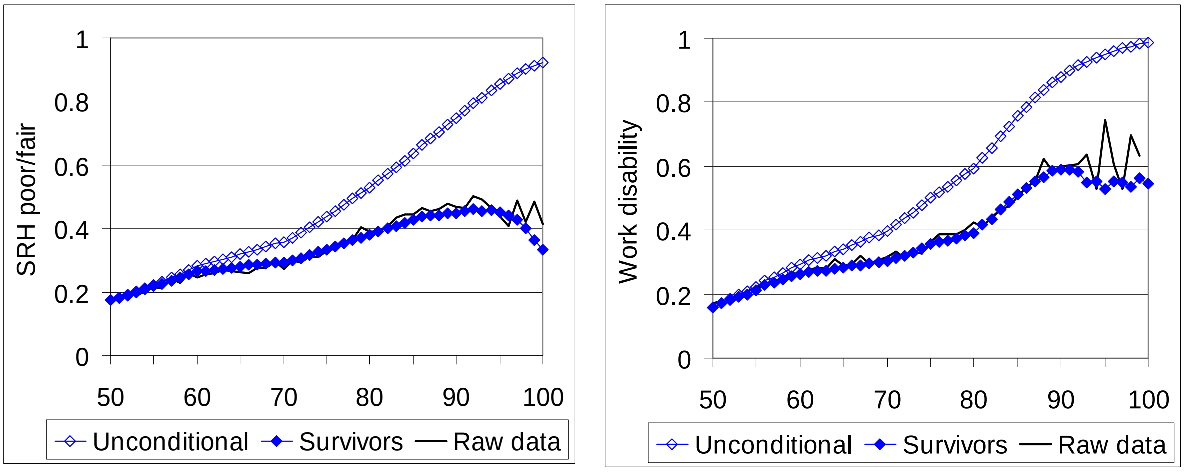


To simplify the presentation of simulated paths of health (or disability) we collapse the 5-point scale of self-reported health into two groups—good or better and fair or poor. Figure 6-4 shows three different health or disability paths. Figure 6-4a pertains to the proportion of the population in fair or poor health, from age 50 to age 100. Figure 6-4b pertains to the proportion of the population that reports a work disability. The path labelled "unconditional path" shows the hypothetical path of fair or poor health (or work disability) if there were no deaths, or perhaps more meaningful, it shows the path of poor health in the surviving population if poor health and mortality were independent. Because persons in poor health have a much higher mortality rate than persons in good health, health of the surviving population is much better than the hypothetical health shown by the "unconditional path." The path labelled "survivors" shows poor health among persons who survive to a given age. The difference between the unconditional path and the survivor path represents the selection effect—persons in poor health are more likely to die and thus are less likely to be in the sample at older ages.

Figure 6-4 also shows the actual proportion of persons in poor health (or disabled), based on self-reported health (or disability) responses among persons of a given age in the HRS. The survey of course can only interview survivors. The path determined by the actual response at each age is also shown in the figure. If the model represents an appropriate description of poor health and mortality, and their dependence, the simulated poor health path for the surviving population should correspond closely to the actual self-reported poor health levels of persons who survived to a given age. Figure 6-4 shows that the two paths correspond very closely for both poor health and for work disability. Only at very old ages do the two paths diverge noticeably. The actual data at these older ages is very sparse, however.

Figure 6-4: Paths of health measures and the selection effect

(a) SRH poor/fair (b) Work disability



Because of the mortality selection, the survival of a respondent provides information about the person's health at younger ages. The model can be used to simulate the health status at earlier ages of persons who survive to a given age. Figure 6-5 shows the simulated evolution of health (or disability), conditional on survival to at least age 80, or to at least age 90. Because of the strong relationship between health and mortality and the large inter-temporal correlation of health, the two conditional paths differ substantially. To understand the relationship, consider the four poor health paths shown in Figure 6-5. The unconditional path and the survivor path are the same as those shown in Figure 6-4. The proportion of all persons that is in poor or fair health at age 50 is about 0.18, as shown by the "survivors" path. The proportion of persons who are in poor health at age 50 among those who will survive until age 80 is about 0.09. Of those who survive until age 90, the proportion in bad health at age 50 is only about 0.06. The proportions with respect to disability are similar to those for health--about 0.16, 0.08, and 0.05 respectively.

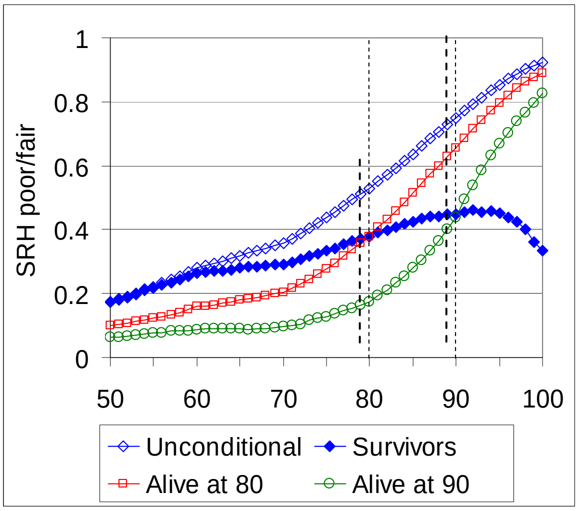
Perhaps more striking is the comparison of health at age 80 of persons who survive until at least 80 with the health at age 80 of those who survive until at least 90.

At age 80, about 40 percent of persons who survive until at least 80 are in poor health. On the other hand, only about 20 percent of persons who survive until at least age 90 are in poor health at age 80. A comparable comparison for disability shows similar values.

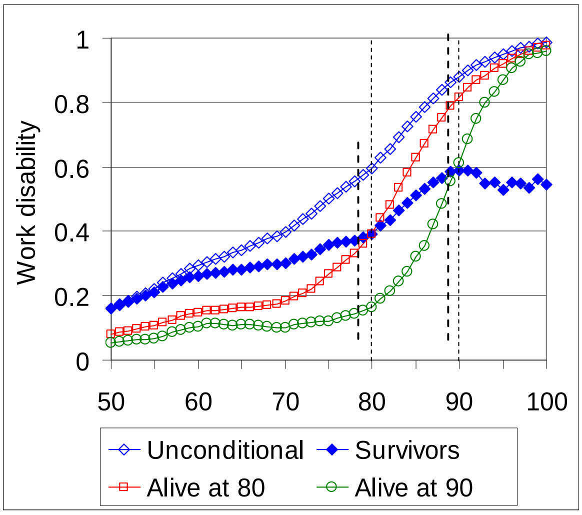
The model could also be used to simulate more detailed information about the health status at younger ages of persons who survive to a given age, like the distribution over all health states at age 50.

Figure 6-5: Health paths conditional on survival to age 80 and 90

(a) SRH poor/fair



(b) Work disability



What does self-reported health status tell us about underlying latent health? Figure 6-6 shows the distribution of latent health at age 50, given self reported health at age 50. The distribution of latent health is very different, depending on self reported health status. Figure 6-6a shows the distribution of latent health for persons who reported they were in poor health and for persons who reported they were in excellent health. These distributions hardly overlap. The different distributions, together with the high persistence of latent health over time, generate substantial persistence of health outcomes.

The distributions conditional on disability are somewhat different. The distribution of latent health for persons who report a work disability at age 50 is clearly over the left tail of the distribution of latent health for all persons at age 50. But knowing that a person reports no disability at age 50, provides only limited information to distinguish this group from all persons at age 50. The distribution of latent health for the no-disability group is only slightly to the right of the distribution of latent health for all persons. The reason is that at age 50 most respondents classify themselves in the no-disability group, and thus there can be little difference between the no-disability group and all respondents.

Figure 6-6: Distribution of latent health at age 50

(a) SRH (b) Work disability

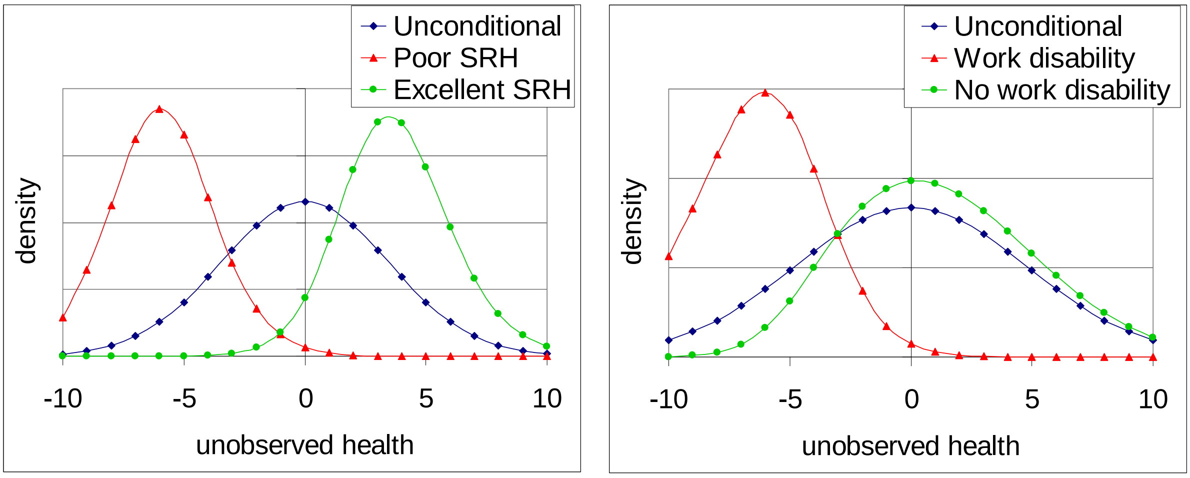


Figure 6-7 shows future health (and disability) conditional on self reported health at age 50. Conditional on self-reported health, two paths are shown—one for all persons that does not account for selection due to mortality, and one for survivors. Figure 6-7a shows the proportion in poor or fair health. Figure 6-7b shows the proportion with a work disability. Note that because of self-reported classification errors, the health path for those who report they are in poor health at age 50 does not start at zero. And the path for those who say they are in excellent health does not start at 1. Similar explanation pertains to the work disability paths.

Self-reported health is highly persistent—the two paths converge only slowly. Consider the two survivor paths. Until the age 70 or 80 the two paths remain far apart. The paths only start to converge rapidly after age 90. For persons surviving until age 100 the mortality selection effect leaves survivors with approximately the same health status at age 100, no matter what there reported health status at age 50. (The selection effect is much less pronounced for persons with excellent initial health. The paths of the total and the surviving population diverge more slowly for this group than for the group with poor reported health at age 50.) For work disability, the results are similar. Persistence with respect to disability, however, is not as strong as persistence with respect to poor versus excellent health. This is because poor and excellent health at age 50 are very distinct outcomes, which contain significant information about latent health, as shown in Figure 6-6. Work disability versus no work disability contains less information, also shown in Figure 6-6.

Figure 6-7: Health paths by initial health at age 50

(a) SRH poor/fair (b) Work disability

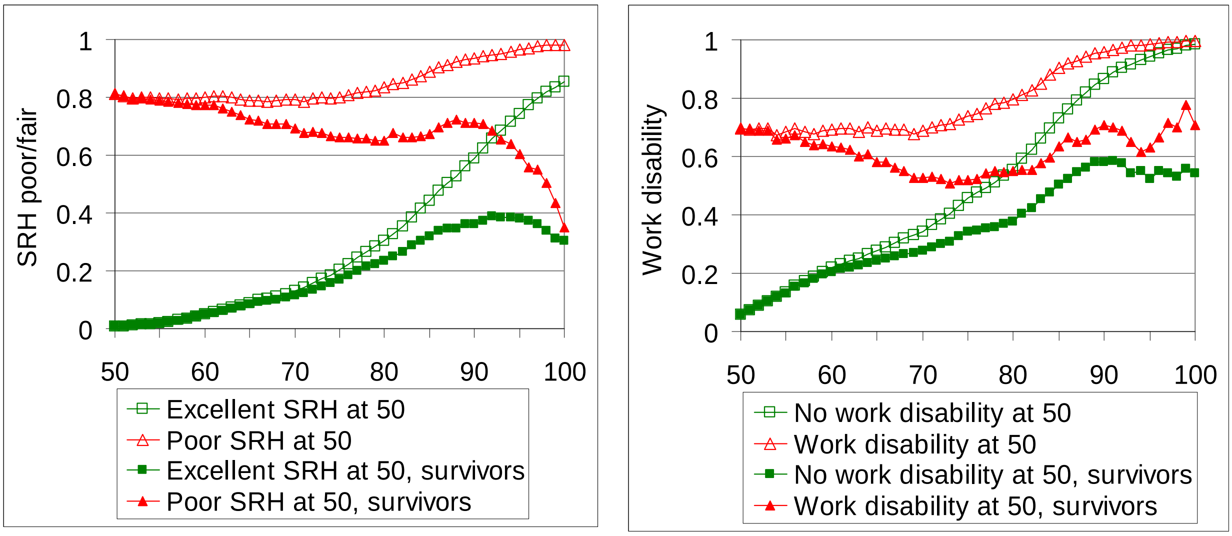
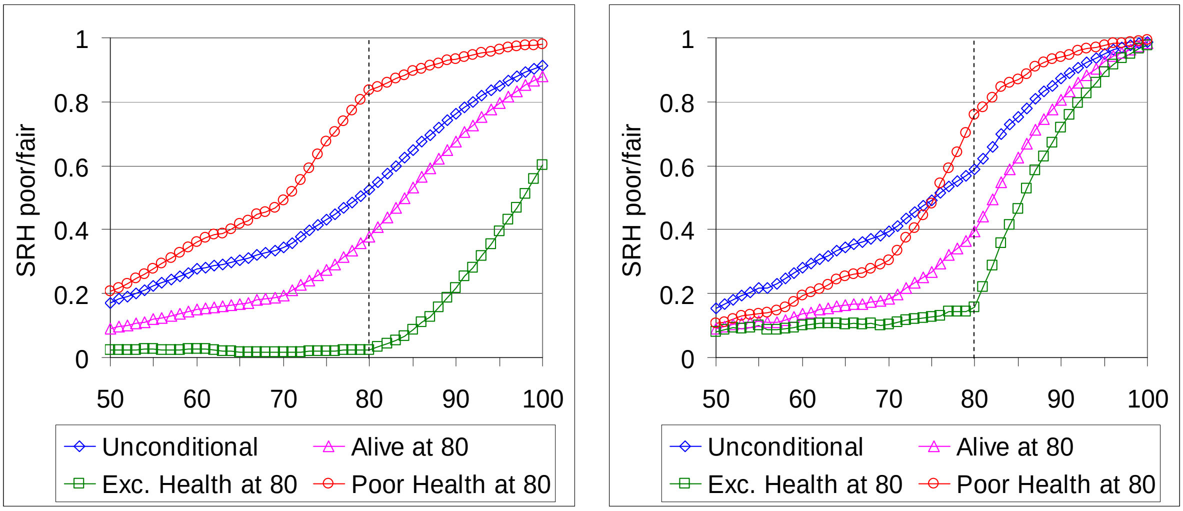


Figure 6-8, instead of showing the future path of persons conditional on reported health at age 50 (as in Figure 6-7), shows the reverse paths for persons who survive until at least age 80 and report their health status at age 80. The pure information about health provided by survival through age 80 is shown in Figure 6-5 above. Conditioning on reported health at age 80 obviously also conditions on survival to at least age 80. Survival to age 80 and health status at age 80 may provide countervailing information, however. Survival is good news; bad health is bad news. Bad self-reported poor health at age 80 outweighs the good information on survival through age 80. “Back-casting” SRH from age 80 to age 50, the unconditional poor health risk at 50 is 17.8 percent. Conditional on survival to age 80, the likelihood of poor health decreases to 10.0 percent. Of those who survive until age 80 and report poor health at age 80, 20.3 percent are simulated to be in poor or fair health at age 50. Of those who survive to age 80 and report excellent health at age 80, only 2.1 percent are predicted to be in poor or fair health at age 50.

On the other hand, information about work disability at age 80, given survival to at least age 80, provides little information about disability status at age 50, as suggested by Figure 6-6 above.

Figure 6-8: Health paths by initial health at age 80

(a) SRH poor/fair (b) Work disability



7.2 Simulations: Conditioning on Socio-Demographic Characteristics

In addition to the model in which we only conditioned on age, we estimate a model for SRH with additional covariates--gender, race, and education and interactions of these variables with age--in the latent health and the self-reported health outcome equations. Table 6-2 shows the parameter estimates. Remember that the covariates enter the latent health and the SRH equation. Therefore, the former capture the effects on mortality, the latter the additional effects on SRH. Females have a higher latent health (a lower mortality risk) at age 50 and this effect increases at higher ages.[8] On the other hand, given latent health (mortality risk), their SRH response is much worse. This might

[8] The variable “age” is actual age minus 50.

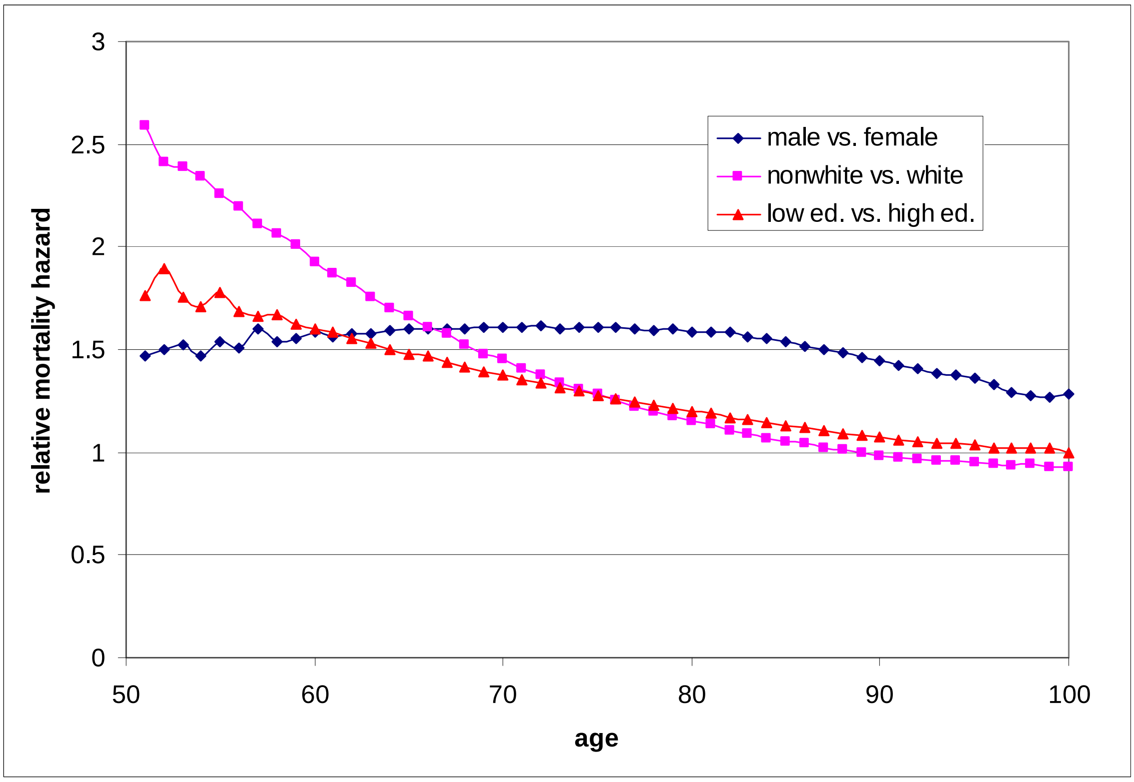
be due to different response scales or different health conditions that affect subjective health more than mortality such as arthritis. Respondents have a higher latent health and report better SRH given latent health.

Table 6-2: Estimation results with age and sociodemographics

	Latent health (h)		*SRH*	
	Estimate	Std.err.	Estimate	Std.err.
Latent Health (h):				
Std. dev. of a (σ)	2.9894	0.0386		
1-year correlation of a (ρ)	0.9787	0.0006		
Covariates (γ): Age	-0.4844	0.0319	0.4130	0.0299
Age spline 60+	0.2228	0.0422	-0.1717	0.0413
Age spline 70+	-0.0164	0.0415	-0.0589	0.0402
Age spline 80+	-0.2369	0.0368	0.1713	0.0351
Age spline 90+	-0.1028	0.0464	0.0549	0.0470
Female	1.0897	0.2388	-1.3104	0.2282
Education	0.2128	0.0385	0.1883	0.0358
Nonwhite	-2.6672	0.2768	1.1884	0.2626
Hispanic	0.0114	0.4468	-0.5425	0.4222
Female*age	0.0277	0.0083	-0.0027	0.0080
Education*age	-0.0033	0.0012	-0.0023	0.0012
Nonwhite*age	0.0586	0.0104	-0.0377	0.0099
Hispanic*age	0.0118	0.0167	0.0064	0.0155
Other			4 ordered logit cut points	
	Mortality (m):			
Baseline (α)	-5.8253	0.1904		
Latent health (δ)	-0.3541	0.0039		
\# individuals	25,497			
\# observations (health)	103,250			
\# parameters	34			
Log-Likelihood	-148,652.8			

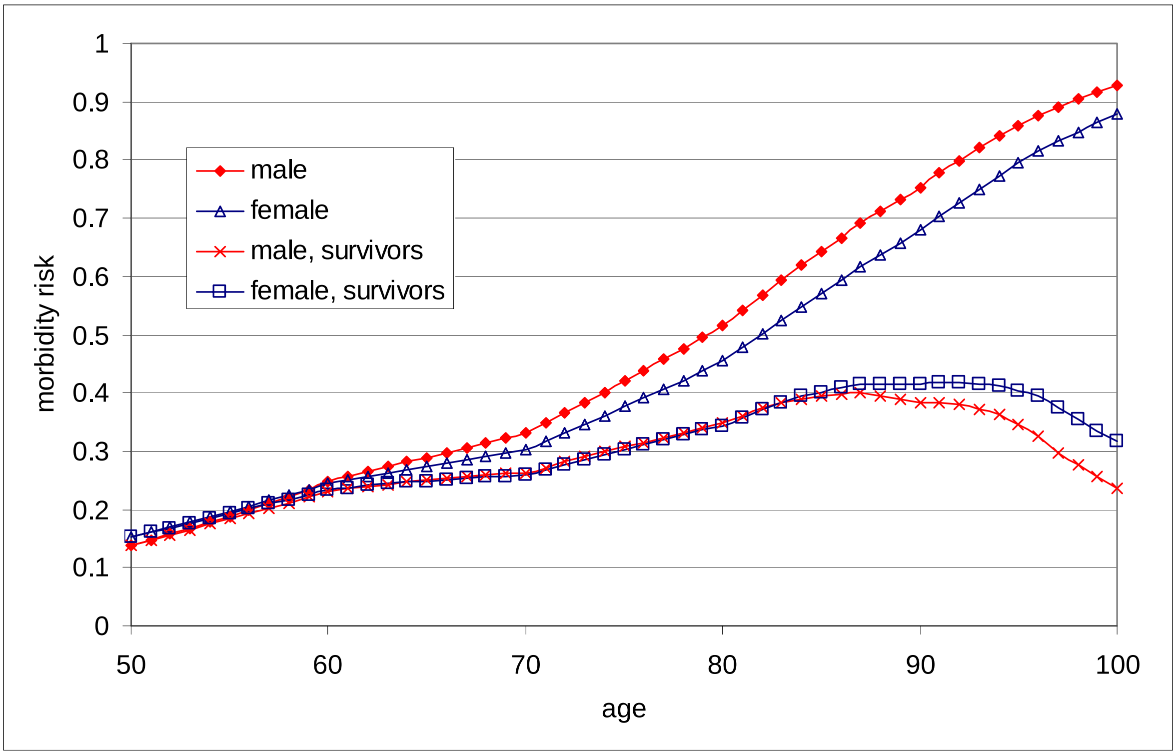
Figure 6-9 shows the relative mortality hazards for males versus females, nonwhite versus white respondents, and low- versus high-education respondents. While the mortality risk of males relative to females is more or less constant over all ages, mortality differences by race and education diminish at older ages. This apparently results from the mortality selection effect, with those in better health more likely to survive until older ages no matter what their race or education.

Figure 6-9: Relative mortality hazards



The next three figures show the likelihood of fair or poor SRH (sometimes referred to as "poor health") by gender, race, and education respectively. Figure 6-10 shows health paths by gender. The paths labelled "male" and "female" show unconditional health paths of men and women. The paths labelled "male survivors" and "female survivors" show the health of the survivors and account for the strong relationship between poor health and mortality (as seen in the figure above). At age 50, both men and women report about the same level of poor health – as discussed above, latent health is better for women, but SRH conditional on latent health is worse. It total, both effects roughly cancel out. Poor health increases more rapidly for men than for women, as shown by the "male" and "female" paths. On the other hand, selection due to mortality is greater for men than for women, and more men than women reporting poor health leave the sample. Thus the self-reported health of men and women survivors is about the same through age 85. After age 85, the health of women is worse than the health of men. This results entirely from differential mortality.

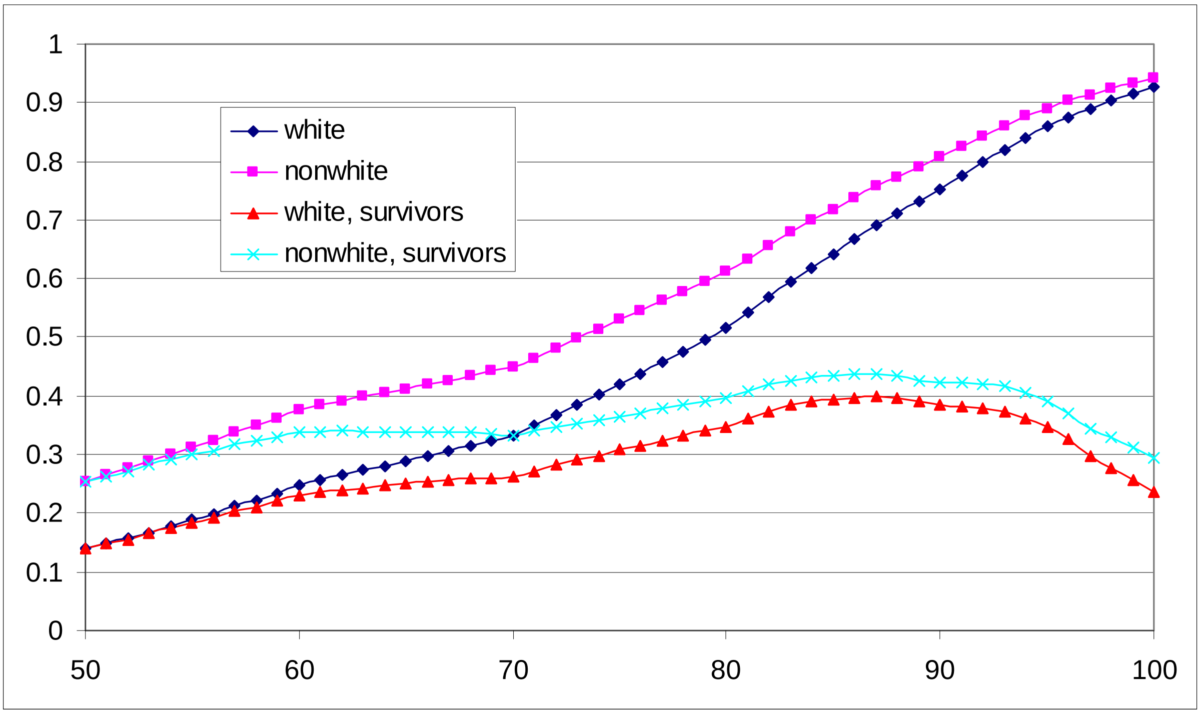
Figure 6-10: Poor health by gender



Note: All simulations for white respondents with 12 years of education

Figure 6-11 shows poor health by race. The figure shows poor health paths for white and African American men with 12 years of education. At age 50, African Americans have much more likely than whites to be in poor health. Through age 70, the slopes of the poor health paths (not accounting for mortality) for African American and for white respondents are about the same, but mortality is much higher for African Americans. Thus the paths for African American and white survivors converge. As shown in Figure 6-9 above, the mortality differences between African Americans and whites diminish at older ages. On the other hand, the "true" poor health paths start to converge after age 70. Thus the poor health paths of survivors remain roughly parallel at older ages, with poor health more likely for African Americans than for whites.

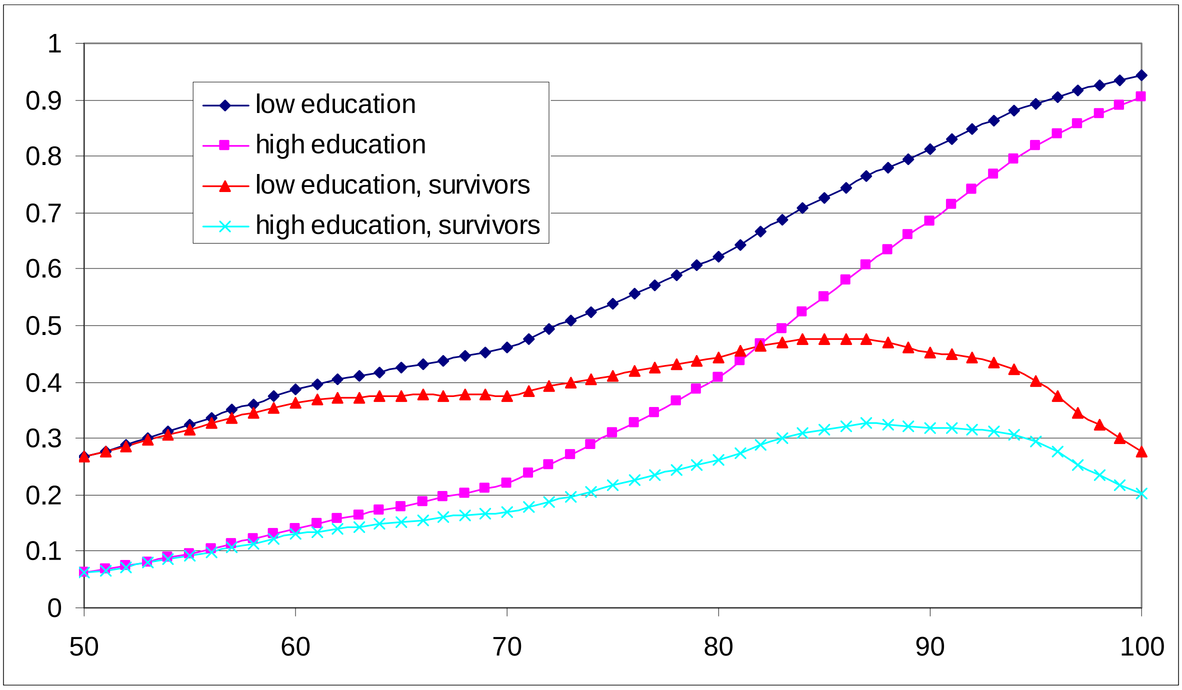
Figure 6-11: Poor health by race



Note: All simulations are for male respondents with 12 years of education

Figure 6-12 shows poor health paths by education level—8 years of schooling (low education) and 16 years (high education). At age 50, the likelihood of poor health for the low-education group is about four times as high as for the high-education group. The "true" poor health levels of the two groups increase in parallel to about age 70 and thereafter the "true" poor health levels of the two groups start to converge. In addition, as shown in Figure 6-9 above, the difference between the mortality rates of the two groups declines at older ages. Thus the difference in the poor health levels of low- and high-education survivors starts to converge after age 70, although the poor health level of the low-education group remains substantially higher than for the high-education group.

Figure 6-12: Poor health by education



Note: All simulations are for white male respondents

7: Conclusions

To help understand pathways to disability, we have explored the relationship between health (and disability) at younger ages and health (and disability) at older ages. In particular, we developed an econometric model designed to take account of three key features of the data that characterize the health and disability of persons as they age:

- State dependence: all past states directly affect the risk of a current bad state,
- Heterogeneity: past states contain information on the individual risk that is correlated over time,
- Misclassification: categorical coding of self-reported health and disability induces classification errors.

The key idea of the model is to consider "true" underlying health status, specified as a continuous "latent" variable. The categorical self-assessed indicators of health (or work disability) are determined by this latent health. The underlying continuous latent health variable is correlated over time and thus induces correlation over time in the observed responses to the categorical self-assessment of health status and disability. In addition, the probability of death is assumed to depend on the "hidden" latent health measure, thus allowing for correlation between health status and selection to the group of persons who survive from one period to the next.

The analysis is based on the four cohorts of the Health and Retirement Study (HRS, AHEAD, CODA and WB). We used the econometric model to simulate future mortality and the future health and disability paths of survivors, conditional on health or disability at younger ages (age 50).

We find that health and work disability correspond very closely (in the HRS data). We find a very strong relationship between health and disability and mortality. We find that future paths of health and disability are very strongly related to health and disability at age 50. Reversing the process, we find that survival to older ages (80 or 90) provides substantial information about health and disability status at younger ages.

In addition, the interplay between health and mortality of persons as they age can be studied in detail using simulations based on the econometric model. For example: At age 50, the poor health level of persons with 8 or fewer years of education is about four times as high as the poor health level of those with 16 or more years of education. The "true" poor health levels of the two groups increase in parallel to about age 70 and thereafter the "true" poor health levels of the two groups start to converge. But the difference between the mortality rates of the two groups declines at older ages. Thus the difference in the poor health levels of low- and high-education survivors starts to converge after age 70, although the poor health level for the low-education group remains substantially higher than the level for the high-education group. Similar "decomposition" of mortality and poor health is presented by race and by gender.

To date, we have used only a few individual socio-economic attributes in the model. Many more attributes, such as specific medical conditions, could be incorporated in the model. The onset of particular medical conditions could held to explain, for example, the differences between the health and disability paths of low-education and high-education groups or the differences between the health and disability paths by race or ethnic group. Such analysis may also help to understand how future medical technology, the coverage and extent of health insurance, and the frequency of prevention may change the prevalence of disability.

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