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5

Dimensions of Health in the Elderly Population

David M. Cutler and Mary Beth Landrum

Understanding changes in the health of the elderly is a central policy issue. A healthier elderly population is able to work to later ages, spends less on medical care each year, and requires less informal care from family and friends. Efforts to promote population health are therefore central to many health reform proposals (Pardes et al. 1999).

By many metrics, the health of the elderly has improved over time. For example, the share of elderly people with basic physical impairments such as difficulty walking around the home or bathing has declined markedly over the past two decades. By other metrics, however, the health of the elderly is worsening. Problems with more advanced functional measures such as stooping and walking moderate distances have increased over time, and obesity among the elderly has soared along with weight in the nonelderly population.

Researchers have attempted to combine indicators of the health of the elderly into a single summary measure, but these summaries are generally ad hoc and lacking in nuance. The most common single measure of disability is whether the person has any impairments in Activities of Daily Living (ADLs, such as bathing or dressing) or Instrumental Activities of Daily Living (IADLs, such as doing light housework or managing money). In the Medicare Current Beneficiary Survey, which we analyze in this chapter,

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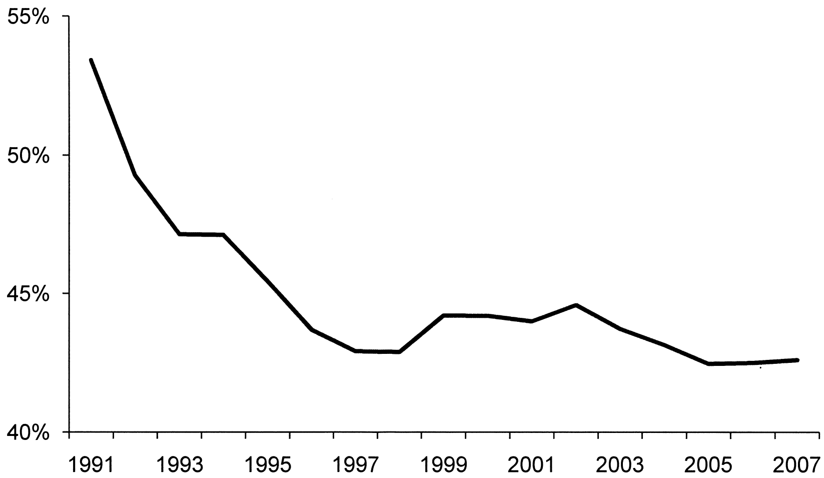

Fig. 5.1 Disability among the elderly

Notes: Disability is measured as the share of people reporting at least one impairment in ADLs and IADLs. Data are from the MCBS Access to Care sample. Tabulations use sample weights and are adjusted to the age/sex composition of the elderly population in 2000.

the share of the elderly population that is disabled by this definition has declined from 53 percent in 1991 to 42 percent in 2007 (figure 5.1). This summary measure exhibits somewhat different trends in different surveys and for different measures of health (Schoeni, Freedman, and Wallace 2001; Manton and Gu 2001), however, and ignores measures of functional impairment (e.g., can the person walk a reasonable distance), cognitive problems such as memory loss, and sensory impairments such as difficulty seeing and hearing.

At the same time, there is a history of more theoretically grounded measures of disability—as with the Grade of Membership (GOM) model proposed by Ken Manton and colleagues (Lamb 1996; Manton, Stallard, and Corder 1998; Woodbury, Clive, and Garson 1978; Manton, Woodbury, and Tolley 1994). But these models met resistance because of their complexity. Perhaps as a result, they have not been widely pursued.

In this chapter, we characterize the multifaceted health of the elderly and understand how health along multiple dimensions has changed over time. Our data are from the Medicare Current Beneficiary Survey (MCBS), a rotating panel of nearly 12,000 elderly people annually. The survey started in 1991; we employ data through 2007. The MCBS has the virtue that it is a person-based sample, not a housing-unit based sample. Thus, it samples and follows people when they move into nursing homes and records death.

We first consider how to optimally combine different measures of health into a smaller number of summary measures. Of course, the best way to summarize multiple measures of health depends on the question being asked. The optimal measure to predict medical spending may be somewhat different than the optimal measure to predict health transitions, for example. We use a somewhat ad hoc approach and estimate factor models for nineteen indicators of health in the community-based population. These measures include specific ADL impairments, IADL impairments, functional impairments, and sensory impairments.

We show that these nineteen dimensions can be compressed into three broad summary measures. The dominant factor is impairment in very basic physical and social tasks such as dressing, eating, transferring in and out of bed, preparing meals, doing light housework, and managing money. This encompasses many of the ADLs and IADLs, but not all. The second factor loads heavily on functional limitations and includes measures such as walking moderate distances, stooping, and reaching. The third dimension is sensory impairments—trouble seeing and hearing.

After determining these factors, we analyze the evolution of these health dimensions over time. We show that the set of physical and social limitations and sensory impairments have declined rapidly over time. Functional ability was flat or increasing, after declining early in the time period.

These results suggest many possible patterns. One possibility is that the community-dwelling population is increasingly concentrated among the less severely ill, with more severely ill individuals in nursing homes or having died. We show, however, that composition changes—both people leaving the sample and new people entering the sample—cannot explain a change in the health of the community-dwelling population. In a second scenario, it may be that people are recovering from severe disability more frequently in later years in the sample, thanks to better medical care or other environmental changes.

We investigate the evolution of health states in the final part of the chapter. In particular, we estimate models explaining within-person health trends over time, controlling for demographic characteristics and year dummy variables. We examine health trends in the early years in the sample (1991–1996), middle years in the sample (1997–2001), and later years in the sample (2002–2007). We show that health deteriorates less rapidly in later years of the sample than in earlier years. This sets up an exploration of what shocks to health are occurring less rapidly, which is the subject of ongoing research.

This chapter is structured as follows. The first section describes the data we employ. The second section presents information on trends in elderly health and reports the results of factor analyses for the 1991 to 2007 period. The third section shows the evolution of summary health measures of health over time, and the fourth section examines within-person changes. The last section concludes.

5.1 The Data

Our primary data source is the Medicare Current Beneficiary Survey (MCBS). The MCBS, sponsored by the Centers for Medicare and Medicaid Services (CMS), is a nationally representative survey of aged, disabled, and institutionalized Medicare beneficiaries that oversamples the very old (aged eighty-five or older) and disabled Medicare beneficiaries. Since we are interested in disability among the elderly, we restrict our sample to the population aged sixty-five and older.

While a number of surveys have measures of disability in the elderly population (Freedman, Martin, and Schoeni 2002), including the National Health Interview Study and the Health and Retirement Study, the MCBS has a number of advantages. First, the sample size is large, about 10,000 to 18,000 people annually. In addition, the MCBS samples people regardless of whether they live in a household or a long-term care facility, or switch between the two during the course of the survey period. Finally, the set of health questions are very broad, encompassing health in many domains.

The MCBS started as a longitudinal survey in 1991. In 1992 and 1993, the only supplemental individuals added were to replace people lost to attrition and to account for newly enrolled beneficiaries. Beginning in 1994, the MCBS began a transition to a rotating panel design, with a four-year sample inclusion. About one-third of the sample was rotated out in 1994, and new members were included in the sample. The remainder of the original sample was rotated out in subsequent years. We use all interviews that are available for each person from the start of the survey in 1991 through the 2007 survey.

The MCBS has two samples: a set of people who were enrolled for the entire year (the Access to Care sample) and a set of ever enrolled beneficiaries (the Cost and Use sample). The latter differs from the former in including people who die during the year and new additions to the Medicare population. The primary data that we use are from the health status questionnaire administered in the fall survey, which defines the Access to Care sample. We thus use the Access to Care data. We supplement this with information about death in the year following the fall interview, taken from the Cost and Use data. Because the Cost and Use data are only available through 2006, our analysis of deaths, nursing home transitions, and loss to follow-up go only through that year. Other data go through 2007.

Table 5.1 shows the number of individuals in the sample by year or interview and wave (number of interviews for that person). The sample of new beneficiaries is low in 1992 and 1993, rises throughout the 1990s, and then declines in the early 2000s. The difference between the number of people in one wave in year t and the next wave in year $t + 1$ is an approximate death and attrition rate across years.

The health questions asked about in the MCBS are shown in table 5.2. The questions are generally the same for the community population and the institutional population, with the exception that the institutionalized are not asked about three IADLs limitations—light housework, preparing meals, and heavy lifting. The tabulations in table 5.1 are for people interviewed in 1991 to 2007. On average, 5 percent of people are in a nursing home.

Table 5.1 **Sample size for MCBS**

	Wave						
Year	1	2	3	4	5	6	Total
1991	10,495						10,495
1992	1,685	8,495					10,180
1993	1,795	1,516	7,391				10,702
1994	4,011	1,510	1,408	6,472			13,401
1995	4,250	3,270	1,244	809	3,411		12,984
1996	6,494	3,443	2,803	1,037	277	1,046	15,100
1997	6,274	3,764	3,036	2,450	—	—	15,524
1998	8,069	3,698	3,370	2,678	—	—	17,815
1999	5,341	3,545	3,289	2,958	—	—	15,133
2000	4,274	3,572	3,115	2,861	—	—	13,822
2001	4,279	3,563	3,172	2,709	—	—	13,723
2002	4,207	3,479	3,142	2,770	—	—	13,598
2003	4,160	3,437	2,996	2,741	—	—	13,334
2004	4,055	3,292	2,961	2,556	—	—	12,864
2005	4,195	3,302	2,916	2,617	—	—	13,030
2006	4,317	3,308	2,838	2,523	—	—	12,986
2007	4,203	3,411	2,910	2,485	—	—	13,009

Note: The sample is the elderly population in the Access to Care survey. Dashed cells indicate no observations.

Functional limitations are most common. Sixty-nine percent of the community-dwelling population report difficulty stooping, crouching, or kneeling, along with 93 percent of the institutionalized. For other questions, positive responses are reported by a quarter to a half of the population. Very severe physical impairments, such as help needed bathing or toileting, are very common for the institutionalized, but rare in the community. The same is true about social indicators such as managing money and shopping, with the exception that there is significant difficulty doing heavy housework among people living in the community. About one-third of both groups report difficulties seeing or hearing.

Figure 5.2 shows the trend in health for each of the dimensions identified in table 5.2, along with the share of people living in a nursing home. For each dimension, we determine the share of people who report having being impaired in at least one specific item, in each year of the data. For example, our ADL trend is the share of people in each year who report at least one ADL impairment. In this analysis, we do not distinguish between one or more than one impairment. Our models in the next section will do so.

There are very different patterns for the different dimensions of health. The share of people who are in a nursing home, who have an ADL or IADL impairment, or who have a sensory impairment has declined over time. The decline in nursing home residence is about 30 percent. The reduction in ADL impairment is also about 30 percent, while the reduction in IADL

Table 5.2 **Health questions in MCBS**

Num	Question	Prevalence: Community (95%)	Prevalence: Institutionalized (5%)
	Functional limitations: Difficulty		
1	Stooping/crouching/kneeling	69	93
2	Lifting/carrying 10 pounds	37	92
3	Extending arms above shoulder	27	68
4	Writing/handling object	26	63
5	Walking 1/4 mile or 2–3 blocks	44	90
	Activities of Daily Living: Says difficulty doing by himself/herself because of a health or physical problem		
6	Bathing or showering	11	91
7	Going in or out of bed or chairs	7	80
8	Eating	3	48
9	Dressing	13	65
10	Walking	24	66
11	Using the toilet	5	70
	Instrumental Activities of Daily Living: Difficulty doing the following activities by yourself because of a health or physical problem		
12	Using the telephone	7	61
13	Doing light housework (like washing dishes, straightening up, or light cleaning)	12	—
14	Doing heavy housework (like scrubbing floors or washing windows)	31	—
15	Preparing own meals	9	—
16	Shopping for personal items	14	85
17	Managing money (like keeping track of expenses or paying bills)	7	85
	Sensory problems		
18	Trouble seeing	35	44
19	Trouble hearing	40	39

Note: Tabulations are from the MCBS Access to Care sample for 1991–2007 and use sample weights. Dashed cells indicate that questions were not asked of those individuals.

impairment is about 20 percent. Sensory impairments declined by 24 percent. The share of the population with functional limitations, in contrast, was relatively flat.

The appendix shows the specific items that contribute to the trends for each dimension. There is surprisingly little variation within the specific items in each domain. Almost all of the ADL and IADL impairments have declined, as have both of the sensory impairments. Most of the functional limitations have been relatively flat, as have the two cognitive measures. This suggests that the grouping shown in figure 5.1 may be relatively accurate as a true description of elderly health. We turn to this next.

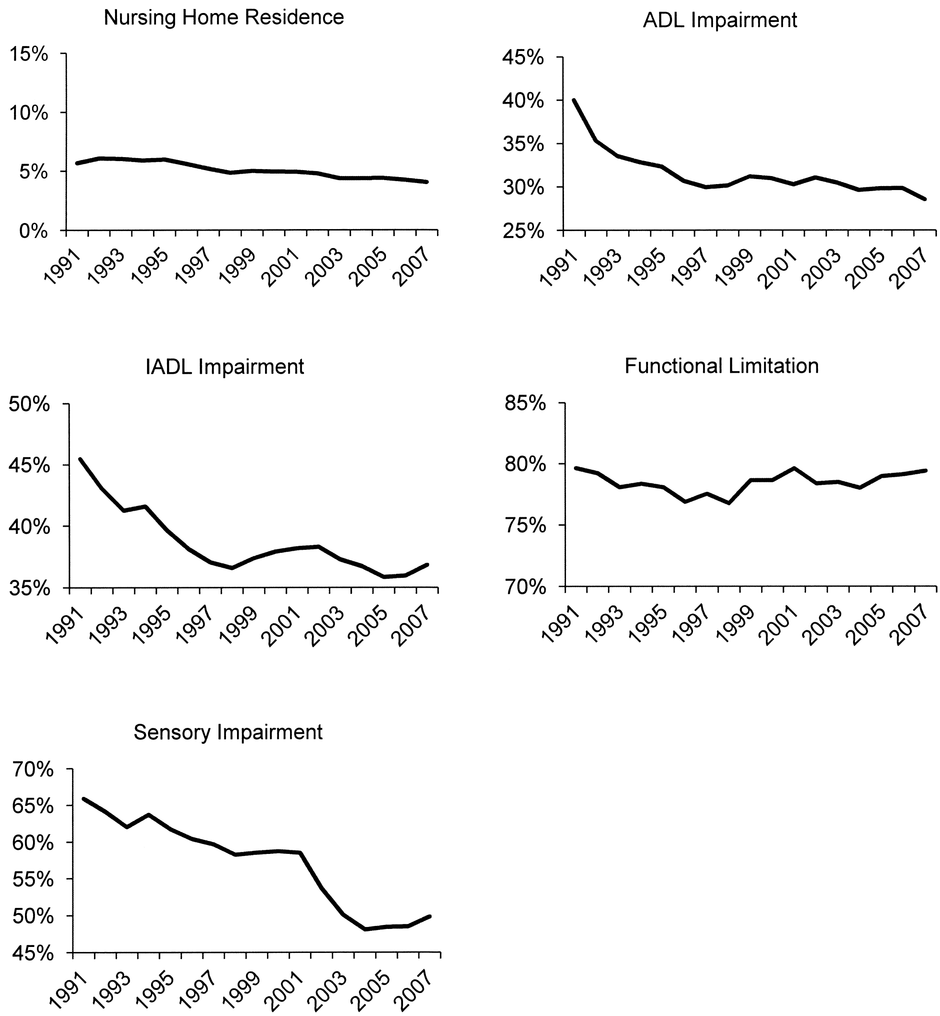

Fig. 5.2 Summary health measures by domain

Notes: Data are from the MCBS Cost and Use sample. Percentages use sample weights and are adjusted to the age/sex composition of the population in 2000.

5.2 The Dimensions of Elderly Health

As noted before, most research defines disability as a binary variable based on the self-report of any ADL or IADL impairment. While simple to implement, this measure lacks a theoretically rigorous foundation. Moreover, a binary measure does not capture heterogeneity in the population. For many purposes, we care about the distribution of health in addition to the proportion with any specific limitation. At the same time, there is a literature (e.g., Verbrugge and Jette 1994) arguing for a distinction between functional status (measures of specific physical functioning) and disability (the ability to engage in the activities typically expected of a person). Within this latter spirit, we examine the different dimensions of health among the elderly.

The optimal way to combine the different measures depends on the purpose for which the data are being used. If one were interested in forecasting medical spending, for example, one would weight the questions by how much they are associated with medical service use. We propose a less structural version and simply ask the question: How many domains summarize the health impairments that people have? Those domains can then be used to assess the health status of the elderly. To do this, we will use factor analysis to characterize responses into different domains of functioning.

Formally, denote y_{ij} as the response to question j for individual i. Suppose there are J questions total ($J = 19$ in our setting). We imagine that these health states are a linear function of K different unobserved or latent factors, denoted F_{ik}. We fit a latent variable model of the form (e.g., Bartholomew 1987; Knol and Berger 1991):

$$(1) \qquad y_{ij} = \gamma_{0j} + \gamma_{1j}F_{i1} + \gamma_{2j}F_{i2} + \gamma_{3j}F_{i3} + \ldots + \gamma_{Kj}F_{iK},$$

where y_{ij} is a 0 or 1 outcome variable, γ_{0j} is a threshold parameter that accounts for varying prevalence of limitations in the population (for example, limitations climbing stairs are more common than limitations in bathing), and the γ_{kj}'s are factor loadings that describe the relationship between unobserved factor k and question j. Unobserved factors are assumed to follow a Multivariate Normal distribution. The latent variable model described by (1) is similar to the factor analyses and Grade of Membership models that have been previously used to describe dimensions of disability (Lamb 1996; Manton, Stallard, and Corder 1998; Woodbury, Clive, and Garson 1978; Manton, Woodbury, and Tolley 1994).

We can fit this model provided $K < J$. Empirically, because the data tend to be highly correlated and we have nineteen dimensions of health, a small number of factors is associated with a wide range of variation in the data.

Table 5.3 shows the results of the factor analysis on community-dwelling elderly over the 1991 to 2007 time period. By the usual criterion of eigenvalues greater than 1, there are three significant factors. These three also have natural economic and demographic interpretations. We thus work with those three.

To aid in interpretation, we consider rotations of the factors that maximize the loading of individual measures into single factors while also allowing correlation between latent factors. Specifically, we use an oblique rotation of the three factor scores (promax = 3). The predicted factor scores are positively correlated. The correlation between factors 1 and 2 is .428, between 1 and 3 is .251, and between 2 and 3 is .242.

Figure 5.3 shows plots of the (rotated) first factor against factors 2 and 3. These plots are primarily useful to see the individual items that are loading most highly on each dimension. The first factor encompasses largely ADL and IADL limitations, with heavy loading on all of the ADLs and IADLs such as shopping, light housework, and preparing meals. The second factor is largely associated with functional limitations and related IADLs, including difficulty walking, lifting, stooping, reading, and doing heavy housework. The third factor is concentrated in sensory impairments, including both vision and hearing.

For each individual, we predict their score on each of the three dimensions. Figure 5.4 shows trends in factor scores over the 1991 to 2006 time period. By definition, the factor scores are normalized to mean 0 and standard deviation 1. Thus, a decline of .1 is a reduction of .1 standard deviation. Corresponding to figure 5.2, there are large declines in factor 1 (ADL and IADL limitations) and factor 3 (sensory impairment) over time. Factor 2 declines in the early years of the sample, picking up the reduction in IADLs and ADLs that enter factor 2.

Table 5.3 **Factor analysis for MCBS data**

	Eigenvalue	Proportion	Cumulative
1	6.90	.363	.363
2	1.75	.092	.455
3	1.17	.062	.517
4	0.98	.051	.568
5	0.89	.047	.615
6	0.82	.043	.658

Note: The results are from factor analyses using the MCBS community-dwelling sample from 1991–2007. The sample includes 211,952 observations.

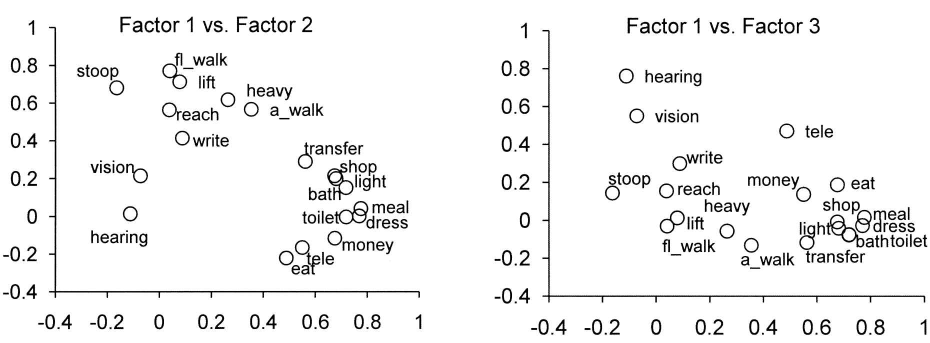

Fig. 5.3 Factor loadings

Notes: Data are from the MCBS Access to Care sample. The factor analysis is for people surveyed in 1991–2007. Table 5.3 has details.

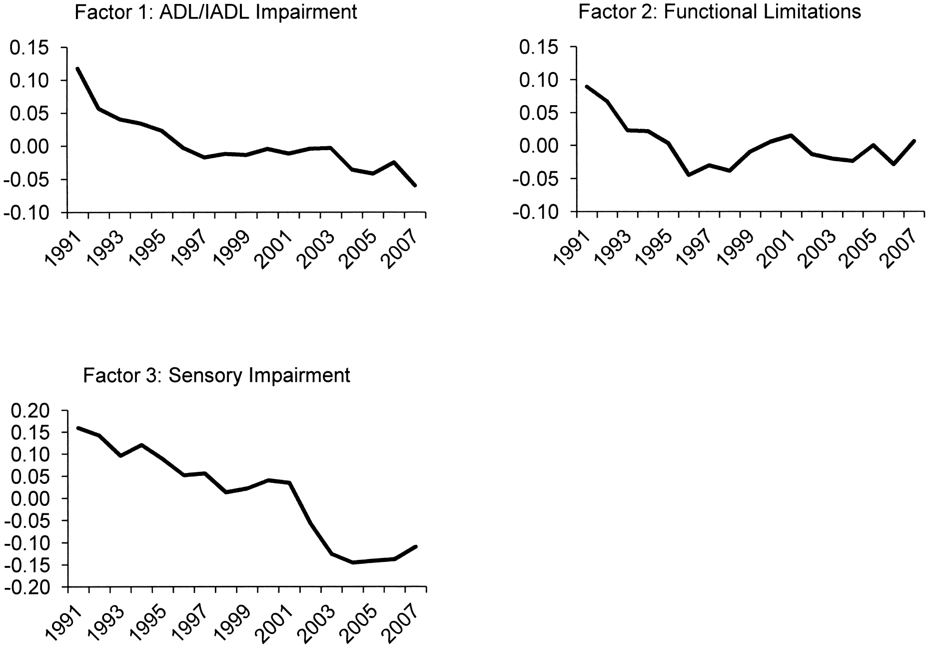

Fig. 5.4 Trends in factor scores

Notes: Data are from the MCBS Access to Care sample. The factor analysis is for people surveyed in 1991–2007. Table 5.3 has details.

We next plot the factor scores by age. If all of the health improvement were at younger elderly ages, the explanation would likely fall in the medical and environmental factors that influence health of the working age population. Conversely, improvements in health at older ages raise the possibility that conditions at those older ages are the driving factor (though they do not prove it, as the literature on the impact of in utero conditions shows; Barker 1992).

Figure 5.5 shows the trend in each of the three factor scores by age. Health improvements in factors 1 and 3 are prevalent at all ages. For example, the reduction in factor 1 is 0.1 (.1 standard deviation) for people aged sixty-five to sixty-nine and 0.38 for people aged eighty-five and over.

Since there are more young elderly than old elderly, the contribution of the older elderly to the reduction in total disability is perhaps overstated. Another metric is to evaluate the share of the total improvement in the health of the elderly that is accounted for by improvements in the health of each age group. At any time period t, $F(t) = \Sigma_a pct(a,t) * F(a,t)$, where $pct(a,t)$ is the percent of the population at time t that is in age group a. The contribution of age group a to the total change in health between two time

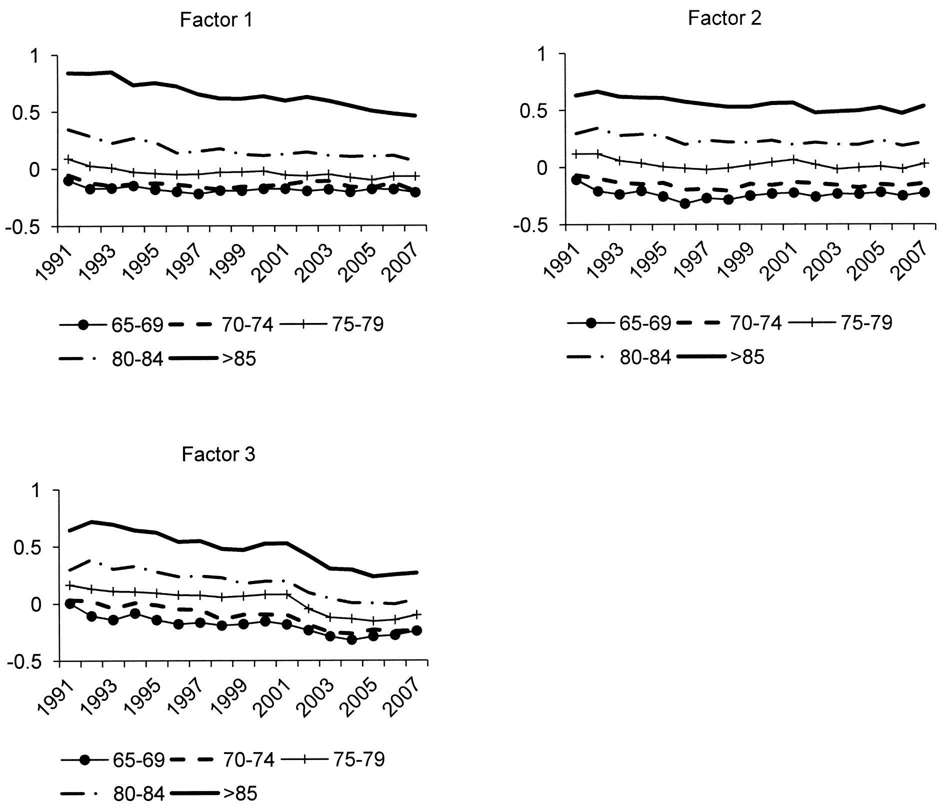

Fig. 5.5 Factor scores by age

Notes: Data are from the MCBS Access to Care sample. The factor analysis is for people surveyed in 1991–2007. Table 5.3 has details.

periods is then $pct(a,0) * \Delta F(a)$, and the total change in the population is $\Sigma_a pct(a,0) * \Delta F(a)$. The ratio of those two, $pct(a,0) * \Delta F(a) / \Sigma_a pct(a,0) * \Delta F(a)$, is the contribution of health improvements at age group a to the total change in population health.

Figure 5.6 shows these contribution shares for factors 1 and 3, the dimensions on which health is improving most significantly, along with the population distribution by age. For both factors 1 and 3, the oldest old contribute disproportionately to health improvements. People aged eighty-five and older are 14 percent of the population in 1991 but account for 30 to 50 percent of the health improvement. This suggests that late life health and social conditions may be important contributors to population health. At minimum, any theory of health improvement will have to account for this age differential.

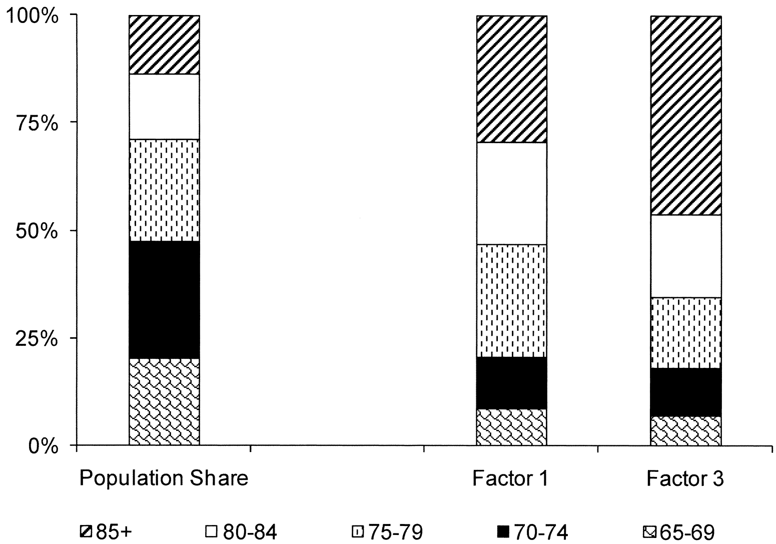

Fig. 5.6 Contribution of different ages to health improvement

Note: Calculations are based on the trends shown in figure 5.5.

5.3 Explaining the Improvement in Health

The central economic challenge is to understand why health improves in so many dimensions. We consider two explanations for improved health. The first explanation is composition change: people with severe health impairments may be more likely to die or transition into a nursing home over time. Alternatively, new entrants to the survey may be healthier than the people they replace. Either of these situations would improve the health of the community-dwelling population because of selection. Second, people may be impaired along the same dimensions, but impairment may not progress to more severe stages as frequently as it did formerly, either because of person-specific aging trends (e.g., richer people can manage their chronic conditions better), or because of population-wide shocks (a new treatment for vision impairment).

Figure 5.7 shows a schematic of the model that we estimate. We start off with the community-dwelling population in year t. Between t and $t + 1$, two things happen. First, the sample changes. Some people leave the sample, either through death, loss to follow-up, or nursing home entry, and others enter. The combination of these two transitions is the composition effect. Second, new health shocks occur (for example, a heart attack or diagnosis of cancer) and old health conditions exert an effect on health. An example of the latter is a continued deterioration that might occur from untreated arthritis. The combination of composition changes and health changes among the existing population yields the new population health at $t + 1$.

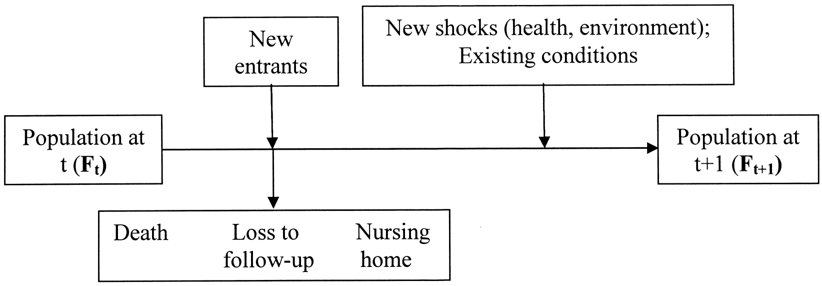

Fig. 5.7 Schematic of estimation model

5.3.1 Composition Change

We now show the equations that we model, starting with the composition change. Denote F_{kit} as the factor score in dimension k for person i in year t; $\mathbf{F}_{\mathbf{it}}$ is the vector of factor scores for person i in year t. The equations for nursing home entry (NH), death (Die), and loss to follow-up (Loss) are given by:

(2) $$\mathrm{NH}_{it+1} = \mathbf{F}_{\mathbf{it}}\boldsymbol{\alpha}^{\mathbf{NH}} + \mathbf{X}_{\mathbf{it+1}}\boldsymbol{\theta}^{\mathbf{NH}} + \mu^{\mathbf{NH}}{}_{\mathbf{it+1}}$$

(3) $$\mathrm{Die}_{it+1} = \mathbf{F}_{\mathbf{it}}\boldsymbol{\alpha}^{\mathbf{Die}} + \mathbf{X}_{\mathbf{it+1}}\boldsymbol{\theta}^{\mathbf{Die}} + \mu^{\mathbf{Die}}{}_{\mathbf{it+1}}$$

(4) $$\mathrm{Loss}_{it+1} = \mathbf{F}_{\mathbf{it}}\boldsymbol{\alpha}^{\mathbf{Loss}} + \mathbf{X}_{\mathbf{it+1}}\boldsymbol{\theta}^{\mathbf{Loss}} + \mu^{\mathbf{Loss}}{}_{\mathbf{it+1}}$$

where i denotes individuals and t is year. In a general specification, the μ_{it} error terms might be correlated. For simplicity, we assume they are not.

For new entrants, the issue is whether people who are new to the survey are healthier than those who continue. We estimate this as follows:

(5) $$F_{kit} = \mathbf{X}_{\mathbf{it}}\boldsymbol{\theta}^{\mathbf{k}} + \pi_1^k \mathrm{Wave1} + \mu_{it}^k$$

where Wave1 is a dummy for the first year in the survey. To the extent that new entrants at any age are more or less healthy than people of the same age but who are continuing in the survey, the coefficient π_1 will be different from zero.

5.3.2 Health Trends within Individuals

We then consider the model for health of the continuing population. We describe the evolution of health for the surviving, community-dwelling population as:

(6) $$F_{kit} = \alpha_{0ik} + \alpha_{1ik}t + \alpha_{2ik}h_{it} + \mathrm{Year}_{\mathrm{t}}\,\gamma_k + \varepsilon_{kit}.$$

The factor score for an individual depends on their demographics (α_{0ik}), aging (t), new and ongoing health shocks (h_{it}), and year dummy variables (γ_k).

It is natural for α_{0ik} to vary in the population, for both measurable reasons (older people are sicker than younger people) and unmeasurable reasons (random differences across individuals). Similarly, aging and health shocks may affect people differently. Generally, we parameterize α_{jik} ($j = 0$, 1, and 2—corresponding to the three α terms in equation [6]) as follows:

$$(7) \qquad \alpha_{jik} = \beta_{j0k} + X_{it}\,\beta_{j1k} + \text{Period}_{it}\,\beta_{j2k} + \xi_{jik}.$$

Equation (7) relates the level and trend in health to a constant, person-specific factors, and the time period.

In principle, the ε_{kit} errors may be correlated (factor scores in different domains), as might the ξ_{jik} errors (coefficients on different control variables). A general formulation would model these as $\varepsilon \sim N(0, \Sigma)$ and $\xi \sim N(0, \Psi)$. For this analysis, we assume that the ε's are independent, as are the ξ's. Also for simplicity, we assume that the only coefficients that vary over people are α_{0ik} and α_{1ik}—the constant term and the coefficient on the time trend. We parameterize α_{0ik} as depending on demographics and an error term (i.e., $\alpha_{0ik} = \beta_{00k} + X_{it}\,\beta_{01k} + \xi_{0ik}$) and the β_{12k} as differing in three time periods: 1991–1996; 1997–2001; and 2002–2007 (i.e., $\alpha_{1ik} = \beta_{10k} + \text{Period}_{it}\,\beta_{12k} + \xi_{1ik}$). Finally, for this analysis, we leave out the health measures h_{it}. We do this not because they are unimportant, but because we wish to focus on the aging effect α_{1ik}. We therefore estimate β_{00k}, β_{01k}, β_{10k}, β_{12k}, var(ξ_{0ik}), and var(ξ_{1ik}).

Our **X** vector consists of basic demographics. We include dummy variables for age and gender (a dummy for aged sixty-five to sixty-nine, seventy to seventy-four, seventy-five to seventy-nine, eighty to eighty-four, and eighty-five and older interacted with gender), and a dummy for nonwhites. We also include year dummy variables. Future work could naturally incorporate a richer array of variables, including health shocks to the individual and other family members, changes in socioeconomic status such as reductions in income or wealth, and environmental conditions.

5.4 Composition Change

All three exits from the community sample are common. About 1.5 percent of the elderly population transitions into a nursing home in any year. This is smaller than the share of people who are living in a nursing home at a point in time (around 5 to 6 percent) because of the long-stayers. We also exclude from this analysis people who died between one survey wave and the next, since we do not know about nursing home utilization for them. About 4 percent of the population dies in any year (this is among the community-dwelling sample; a larger share of the institutionalized population dies). Finally, about 12 percent of the population is lost to follow-up each year. This share is particularly high early in the sample, when the initial population was purposely phased out. Outside of those years, the average loss to follow-up is about 10 percent.

The primary question we explore is whether people who are sicker (that is, score higher on the factor score) depart the sample more frequently, and whether this is particularly likely to occur over time. Thus, we interact the factor scores in equations (2) through (4) with the period dummies noted before: 1991 to 1996, 1997 to 2001, 2002 to 2006. We then test whether being sick has a greater effect on sample exit in later years of the sample.

Table 5.4 shows the estimates of death, transitions to a nursing home, or loss to follow-up. Since we have repeat observations on the same individual, we cluster the standard errors by individual—as we do in table 5.5 as well. In the first column, factor 1 is particularly predictive of mortality. An increase of 1 standard deviation raises mortality rates by 3 percent. Factor 1 is mildly more predictive of death in the later years of the sample than

Table 5.4 Transitions out of the community sample

Independent variable	Die	Enter a nursing home	Loss to follow-up
Factor 1			
1991–1996	.028**	.021**	.006**
	(.001)	(.001)	(.002)
1997–2001	.031**	.020**	.007**
	(.002)	(.001)	(.002)
2002–2006	.032**	.016**	.011**
	(.002)	(.001)	(.002)
Factor 2			
1991–1996	.009**	–.001	.000
	(.001)	(.001)	(.002)
1997–2001	.010**	.000	.002
	(.001)	(.001)	(.002)
2002–2006	.010**	.000	.003
	(.001)	(.001)	(.002)
Factor 3			
1991–1996	.000	.003**	–.008**
	(.001)	(.001)	(.002)
1997–2001	.001	.002**	–.009**
	(.001)	(.001)	(.002)
2002–2006	.001	.002*	–.006*
	(.001)	(.001)	(.002)
Demographics	Yes	Yes	Yes
Wave dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
N	153,214	123,270	153,214
R^2	.053	.045	.032
Dependent variable mean	.035	.013	.125

Notes: Data are from the MCBS. Demographic controls include age-sex dummies (ages sixty-five to sixty-nine, seventy to seventy-four, seventy-five to seventy-nine, eighty to eighty-four, eighty-five and over, by gender), and a dummy for nonwhite. Standard errors are clustered by individual.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

the earlier years. An *F*-test rejects that that the coefficients in later years are the same as in earlier years. But the quantitative difference is not large at .4 percentage points.

We determine the quantitative impact of this change on the health of survivors using a simulation model. Specifically, we simulate for each person death under the coefficients in the early time period, and then again using the coefficients in the later time period, but keeping the X's the same as in the early time period. We then average health of the survival group in each case. We estimate that the average score on factor 1 would decline by .004 because of the increased propensity of the sick to die. Given an overall decline in factor 1 of .072 between the early and late time periods, mortality selection can explain only 5 percent of the decline in factor 1 over time.

In the models for nursing home entry, shown in the second column, factor 1 is particularly predictive of transitions into a nursing home. This corresponds to severe physical or social impairment. Factors 2 and 3 (functional limitations and sensory impairment), in contrast, have relatively little impact on nursing home transitions. The coefficient on factor 1 declines a bit, implying that sicker people are more likely to be in the community in later years of the sample.

The third column shows the model for loss to follow-up. If appropriate effort is put into follow-up, loss to follow-up should be approximately random. Somewhat surprisingly, this is not true in the data. Higher scores on factor 1 (that is, worse health) predicts loss to follow-up, while those with sensory impairments are somewhat less likely to be lost to follow-up. These coefficients are relatively small, however, and do not vary much over time.

We evaluate the combined impact of these three sources of sample attrition using the simulation noted earlier. We draw random variables to predict death, nursing home entry, and loss to follow-up and then simulate the community-dwelling population under the coefficients in the early years of the sample and the later years of the sample. The simulation shows that factor 1 for the community-dwelling population would decline by .006 as a result of selection, or 8 percent of the total decline. For factor 3, the predicted change is only 1 percent of the total improvement.

The regressions in table 5.4 have year dummies included, and these year dummies are graphed in figure 5.8. Generally, the year dummies are relatively flat—death and nursing home entry are no more or less likely over time, conditional on health status and demographics. As noted before, loss to follow-up is high in two years of the sample (1991 and 1994) and constant in other years.

The final component of composition change is the changing health of new enrollees to the survey. We estimate equation (5) interacting the wave 1 dummy variable with dummy variables for early, middle, and late periods of the sample. We then examine whether people in the first wave of the survey are increasingly healthy over time.

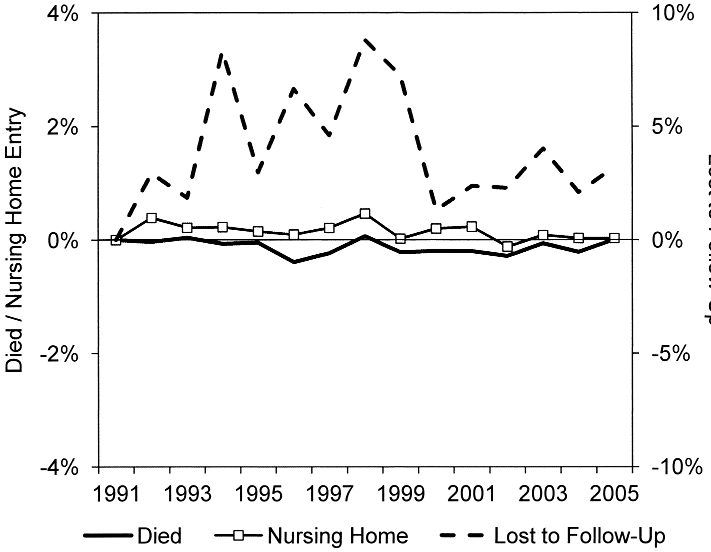

Fig. 5.8 Year effects for leaving the sample

Notes: Figure shows the year dummy variables for models of death, nursing home entry, and loss to follow-up. Data are from the MCBS Cost and Use sample. Table 5.4 describes the model.

Table 5.5 The health of new entrants

Independent variable	Factor 1	Factor 2	Factor 3
Coefficient on Wave 1 dummy			
1991–1996	.013	–.009**	–.008
	(.009)	(.012)	(.009)
1997–2001	.029**	–.021**	.006
	(.007)	(.008)	(.008)
2002–2007	.021**	–.021**	.060**
	(.007)	(.007)	(.007)
Demographics	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
N	211,952	211,952	211,952
R^2	.072	.085	.062

Notes: Data are from the MCBS. Demographic controls include age-sex dummies (ages sixty-five to sixty-nine, seventy to seventy-four, seventy-five to seventy-nine, eighty to eighty-four, eighty-five and over, by gender), year dummies, and a dummy for nonwhite. Standard errors are clustered by individual.

**Significant at the 5 percent level.

Table 5.5 shows the results. The three columns show averages for factors 1, 2, and 3, respectively. New entrants to the survey are less healthy than existing members along factor 1, but healthier in the second dimension. In both cases, the coefficients are relatively small. Furthermore, the factor 1 and 3 coefficients are somewhat increasing over time. That is, health of new entrants is on average deteriorating relative to the health of existing members across the years.

The implication of these transition models is therefore that the improving health of the community-based population is not attributable to changes in the sample of people living in the community, or picked up by the MCBS. By residual, then, it must be the case that the same population is increasingly healthy over time.

5.5 The Evolution of Health among Community Dwellers

In this section, we turn to the evolution of health among the community-dwelling population. Specifically, we estimate the model given by equations (6) and (7). Given the aforementioned results, our primary focus is on the time trend, and how that varies in the early, middle, and later years of the sample.

Table 5.6 shows the models' health trends. The three columns correspond to models for the three different factors. Within each model, we present the

Table 5.6 The evolution of health

Independent variable	Factor 1	Factor 2	Factor 3
Average effects			
t*(1991–1996)	.065**	.041**	.019**
	(.004)	(.003)	(.004)
t*(1997–2001)	.035**	.037**	.010**
	(.003)	(.003)	(.003)
t*(2002–2007)	.034**	.031**	–.016**
	(.003)	(.002)	(.003)
Standard deviation of average			
t*(1991–1996)	.192	.087	.101
t*(1997–2001)	.137	.076	.089
t*(2002–2007)	.128	.063	.092
Demographics	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes
N	211,952	211,952	211,952

Notes: Data are from the MCBS. Demographic controls include age-sex dummies (ages sixty-five to sixty-nine, seventy to seventy-four, seventy-five to seventy-nine, eighty to eighty-four, eighty-five and older, by gender) and a dummy for nonwhite. Standard errors are clustered by individual.

**Significant at the 5 percent level.

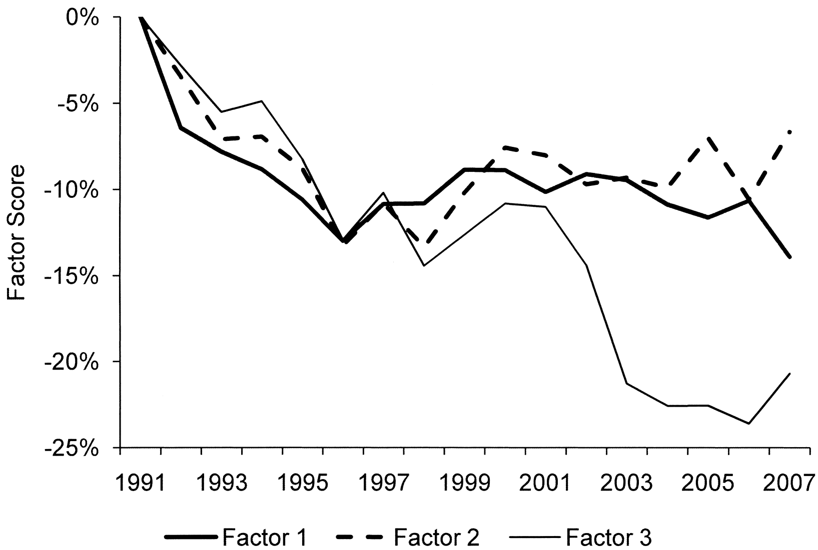

Fig. 5.9 Year effects in factor scores

average aging effect (β_{10k}) and the standard deviation of that coefficient. There are also year dummies in the model, and these are shown in figure 5.9.

The averages show considerable decline in health as a person ages. For example, factor 1 increases by .065 each year (.065 standard deviations) during the early phase of the sample, and factor 3 increases by .019 each year.

The rate of decline in health has slowed over time. Relative to the increase in factor 1 of .065 each year, as shown in the first time period, the increase is only .034 in the more recent time period. This reduction, which occurs after 1997, accounts for a large change in health over time. Had the decrement to health stayed the same after 1996 as before 1996, health in 2007 would have been one-third of a standard deviation worse. Another way to show the impact of this change is to consider the year effects in figure 5.9. While there are strong year trends in factors 1 and 2 up through 1996, there are no consistent year trends afterwards.

Health in the third dimension also deteriorates less rapidly over time, with roughly the same pattern. Factor 3 increases by 0.019 per year in the early time period, and then declines by .016 per year in the later time period. There is an unexplained year trend in the early time period and again between 2001 and 2003. Other than those time periods, there is little aggregate drift.

Not only does the rate of decline in health slow, but health is actually estimated to improve for many people. The standard deviations of health trends, shown in the middle rows of table 5.6, are large. The standard deviation of .19 for factor 1 in the early time period implies that the 95 percent interval for the impact of aging is –.32 to +.44. There are clearly many people whose health is improving, even while health is deteriorating on average.

5.6 Conclusions and Next Steps

Our results provide important evidence on the well-noted decline in disability in the elderly population. We show that health has several dimensions: one that is largely severe physical and social impairment; a second that is less severe physical limitations; and a third that encompasses sensory impairments. The first and third of these dimensions are improving over time, while the second is not.

The reason for the improvement in health is complex. On the one hand, the health improvement is not a result of sample or demographic changes. Younger people are healthier than younger people used to be, but the same is true of older people. Rather, health is improving because individual health deteriorates less rapidly now than in the past. We do not know exactly why this occurs, but we show that the average trend masks significant heterogeneity. Even as health deteriorates overall as people age, health is improving for a significant minority of people.

The next step is to develop a richer model of the change in health over time. To what extent is the improvement in health a result of fewer new conditions developing, existing problems being cared for better, or changes in the social and environmental circumstances that the elderly face? Considering these questions is a fruitful area for further study.

Appendix

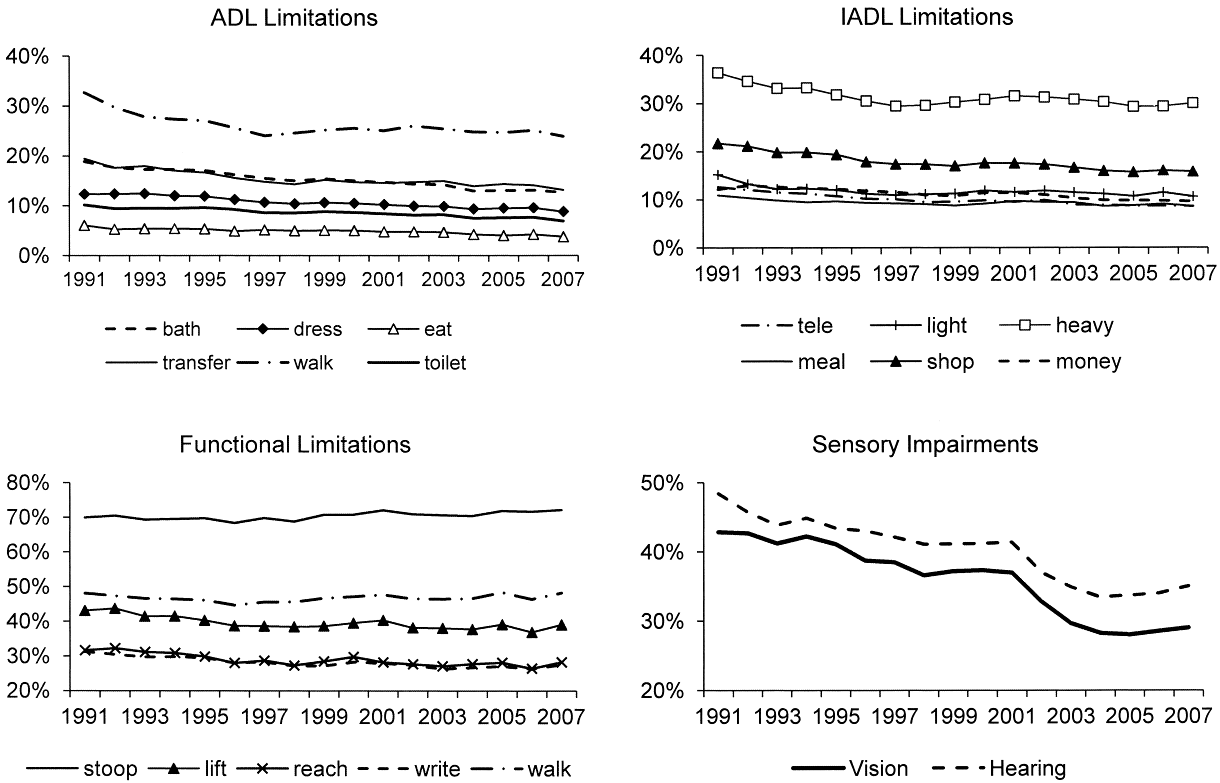

Fig. 5A.1 Plots of individual health measures

Notes: See table 5.2 for the specific items graphed. All tabulations use weighted data, with the population adjusted for changes in the age/sex mix of the population over time.

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Comment David R. Weir

The chapter by Cutler and Landrum is concerned with trends in the health of the elderly population over the past twenty years. Health here is physical functioning and limitations; the chapter does not examine trends in disease prevalence or severity. It is rather an examination of the trend toward declining disability first identified by Kenneth Manton and colleagues using the National LongTerm Care Survey, and subsequently confirmed in a number

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