Volume Title: Advances in the Economics of Aging

Volume Author/Editor: David A. Wise, editor

Volume Publisher: University of Chicago Press

Volume ISBN: 0-226-90302-8

Volume URL: http://www.nber.org/books/wise96-1

Conference Date: May 6-9, 1993

Publication Date: January 1996

Chapter Title: Living Arrangements: Health and Wealth Effects

Chapter Author: Axel Borsch-Supan, Daniel L. McFadden, Reinhold Schnabel

Chapter URL: http://www.nber.org/chapters/c7324

Chapter pages in book: (p. 193 - 216)

6 Living Arrangements: Health and Wealth Effects

Axel Börsch-Supan, Daniel L. McFadden, and
Reinhold Schnabel

6.1 Introduction

The choice of a living arrangement—as an independent household, with adult children or other related or unrelated persons, or in an institution—has many implications for the well-being of an elderly person. Changes in living arrangements are likely to be associated with changes in the level of care and assistance received by the elderly. Living with other family members eases situations of illness; living alone makes coping with illnesses harder. Thus, the choice of living arrangements has many external effects. Moreover, living arrangements commonly affect the elderly's eligibility for certain types of government assistance, such as food stamps and supplemental Social Security, and induces demand for social support services such as district nursing, meals-on-wheels, and so forth. Finally, the change of living arrangements frequently involves the sale of the home by the elderly and may therefore dramatically change the liquid wealth of the elderly. On the other hand, if the elderly tend to live longer independently, the balance of the housing market changes because housing becomes relatively more scarce due to the increased length of stay in the family home by the older generation. In short, it is important to understand the determinants of the living arrangement choice.

Axel Börsch-Supan is professor of economics at Mannheim University and a research associate of the National Bureau of Economic Research and of the Center for Economic Policy Research, London. Daniel L. McFadden is professor of economics at the University of California at Berkeley and a research associate of the National Bureau of Economic Research. Reinhold Schnabel is a research associate in the department of economics and statistics at Mannheim University.

The first author appreciated the hospitality at the University of California at Berkeley during his sabbatical. Financial assistance was provided by the National Institute on Aging, grant 3-PO-AG05842-01. The authors thank Ed Norton, who cleaned up the NBER Economic Supplement, and Angus Deaton, Steven Venti, and David Wise for their helpful comments. Any opinions expressed are those of the authors and not necessarily those of the National Bureau of Economic Research.

There is a long line of literature investigating the determinants of living arrangements of the aged. Schwartz, Danziger, and Smolensky (1984) employ the Retirement History Survey (RHS) to estimate a binary choice model between living independently and dependently. Their empirical results were mixed, and neither health nor income effects are very strong. Börsch-Supan (1989) estimates a multinomial logit model of living arrangements using data from the Annual Housing Survey (AHS). As in the paper by Schwartz, Danziger, and Smolensky, the data preclude an analysis of institutionalization. In contrast, Garber (1990) and Greene, Lovely, and Ondrich (1993) concentrate on the determinants of institutionalization and its duration, using the channeling demonstration, while Kotlikoff and Morris (1987, 1990) and Börsch-Supan, Gokhale, Kotlikoff, and Morris (1992) analyze the importance of family links in forming multigenerational households.

Papers by Ellwood and Kane (1990), Börsch-Supan (1990), and Börsch-Supan, Hajivassiliou, Kotlikoff, and Morris (1992) represent more comprehensive analyses of living arrangements that include both institutionalized and noninstitutionalized elderly. All three papers find an increasing proportion of elderly living alone and attribute this to the positive income elasticity of privacy.

These studies leave several questions unanswered. First, most studies of living arrangements suffer from a less than satisfactory description of health. This is partly due to lack of data, but the problem is deeper: even when health is measured by indicators such as activities of daily living (ADLs) and instrumental activities of daily living (IADLs), or by the presence of conditions such as cancer or Alzheimer's disease, or by simply asking the elderly how they feel, we do not really measure health but a concoction of subjective feelings and objective states that are correlated with health. In the language of econometrics, health is a latent, unmeasurable variable, for which we only observe a set of indicators. One goal of this paper is to develop an econometric framework in order to model this errors-in-variables problem in the discrete decision of living arrangements. We relate latent health to ADLs and IADLs by a nonlinear version of a multiple-indicator, multiple-cause (MIMIC) model, which explicitly considers the categorical measurement of the health indicators. We estimate this model using data from the Longitudinal Study on Aging (LSOA).

Another important question that has not been answered is the role of wealth. Does housing wealth tie the elderly to their homes? This question extends the lock-in discussion (Feinstein and McFadden 1989; Venti and Wise 1990) to household formation. What is the role of financial wealth in the demand for old-age institutions? Wealth data are rarely available in elderly surveys, and if so, their value may be questionable. We will explore in this respect the National Bureau of Economic Research (NBER) Economics Supplement of the LSOA, which contains information on income and assets of the LSOA sample persons in 1990.

The paper is set up as follows. Section 6.2 introduces the data sources and presents descriptive statistics of our working sample. Estimates based on a standard discrete choice model are briefly described in section 6.3. In section 6.4 we discuss the econometric model and address the issues of identification and estimation, while section 6.5 presents the results and section 6.6 concludes.

6.2 The Longitudinal Study on Aging and the NBER Economic Supplement

The LSOA is a panel survey based on the 1984 Supplement on Aging (SOA) to the National Health Interview Survey (NHIS). The NHISs are continuing surveys comprising each year about 100,000 noninstitutionalized persons of all ages in about 40,000 households (see Kovar and Poe 1985). Interviews are held every week throughout the year. The SOA was added to the NHIS during the 1984 interviews. The SOA included questions on

- family structure,
- community and social support,
- occupation and retirement,
- conditions and impairment, ADLs and IADLs,
- structural characteristics of housing,
- regular medical care and nursing home stay, and
- health opinions and behavior

to all NHIS sample persons aged 65 years and over.[1] The questions were similar to those in the 1984 National Nursing Home Survey (NNHS), so that when the two data sets are combined, estimates for the total elderly population are possible.

The SOA was explicitly designed to be the first wave of the LSOA. In 1986, 1988, and 1990, all persons aged 70 and above in the 1984 SOA were reinterviewed by computer-assisted telephone interviews with mail follow-ups (National Center for Health Statistics 1991).

Records for participants who gave permission were also matched with the National Death Index maintained by the National Center for Health Statistics and the Medicare files maintained by the Health Care Financing Administration. While the first wave does not include the institutionalized elderly, sample persons were interviewed in the later waves even when they entered a nursing home or another institution.

In 1990 the NBER added an Economics Supplement to the LSOA. This supplement included a detailed account of personal income sources for each sample person, an inventory of assets including financial and real wealth, and

1. See Fitti and Kovar (1987). The response rate to the SOA was 96.7%.

questions about structural housing characteristics. Response rates to these questions were smaller than to the standard LSOA questions, and particularly small to the wealth questions.[2]

As a working sample, we selected only single elderly because almost all married elderly are living independently. In the 1990 cross-section this working sample consists of 2,193 elderly between age 76 and 102. The average age in 1990 was almost 83 years.

Table 6.1 presents descriptive statistics of the most important variables. Even in this sample of the very old and nonmarried, 63% live by themselves; 28.7% live with their children, other relatives, or nonrelatives, and 8.2% live in institutions. Women make up 81.4% of the sample. The nonwhite population is underrepresented with only 9.2%. On average, the sample persons have two children still living.

The economic variables comprise income and wealth. Income is very low: the median is below $2,400, and 27.6% report no income at all. On the other hand, 63.4% have their own home, and except for less than 15% of the homeowners, this home is free and clear of mortgages. The median value of the home is $31,000, and the average value is about $50,000. The discrepancy between mean and median is much larger for financial assets. The median financial assets sum up to only $3,500, while the mean is ten times as large. These numbers are approximately in line with results from the Survey of Income and Program Participation (SIPP) and other surveys (Venti and Wise 1991).

Table 6.1 also reports on a set of health indicators. We restrict our attention to functional health measures such as the ADLs and the IADLs, which are measured in four categories (no, some, severe problems in doing xyz, and cannot do xyz at all). The variables are coded such that *higher* values for ADLs and IADLs indicate *less* capability. Functional health indicators have been found most appropriate in describing living arrangements, and superior to subjective health ratings or indicators for the presence and severity of diagnosed conditions (Börsch-Supan, Kotlikoff, and Morris 1991). Table 6.1 lists the percentages of sample persons who have no problems in performing a set of ten activities. IADLs were asked only for the noninstitutionalized, ADLs for all sample persons. The pattern is familiar: most problems occur with walking, and the fewest with eating.

6.3 The Standard Approach: Multinomial Logit Analysis

Tables 6.2 and 6.3 present results of a simple multinomial logit model, relating the choice of living arrangements to demographic, economic, and—in

2. The response rate to financial assets was 63.5%. Missing values were assigned by Edward Norton, using a hot-deck method.

Table 6.1 Description of Variables: Longitudinal Study on Aging 1990

Dependent variable (living arrangements) (%)			
LIVARG	Living independently	63.0	
	Living with others	28.7	
	Living in an institution	8.2	
Demographic exogenous variables			
AGE90	Age in 1990 (years)	82.6	
EDUC	Highest grade completed (years)	10.1	
RACE	Black and Hispanic = 1 (%)	9.2	
GENDER	Female = 1 (%)	81.4	
DAUGHTERS	Number of living daughters	1.07	
SONS	Number of living sons	1.01	
Economic exogenous variables			
OWN	Homeownership = 1 (%)	63.4	
MORTG	Home free and clear = 1	85.7[a]	
		Mean	Median
FIN	Financial assets ($)	36,012	3,500
	Stocks, bonds, mutual funds	16,517	
	Savings, other bank accounts	19,495	
INCPERS	Annual personal income ($)	7,748	2,394
HOME	House value, all ($)	38,113	20,000
	House value, owners ($)	49,684	31,000
Health indicators (%)			
Activities of daily living: sample person without difficulties			
BATH	Bathing	74.4	
DRESS	Dressing	82.5	
EAT	Eating	92.1	
GETUP	Getting up from bed/chair	76.6	
WALK	Walking	58.8	
OUTSD	Getting outside	75.9	
TOIL	Toiletting	86.4	
Instrumental activities of daily living: sample person without difficulties[b]			
HOUSEW	Doing light housework	77.9	
SHOP	Shopping	68.9	
MEALS	Preparing meals	75.0	

Source: Longitudinal Study on Aging 1990.

Note: Means and medians were computed on the working sample of 2,193 elderly.

[a]Percentage of owners.

[b]Asked only for elderly persons in households.

table 6.3—health indicators. Both versions of the discrete choice model show that educated persons are less likely to live with others or in nursing homes, and that the probability of living with others (mainly children) increases with the number of daughters but not significantly with the number of sons. Higher wealth increases the likelihood of living with children, while there is no significant wealth effect in institutionalization, except that ownership of a house reduces the probability of entering a nursing home.

The contribution of the health indicators in table 6.3 is highly significant—

Table 6.2 **Multinomial Logit Model: Estimation Results**

	Probability to . . . Rather Than to Live Independently			
	Live with Children or Others		Live in an Institution	
	Coefficient	*t*-Value	Coefficient	*t*-Value
CONSTANT	−3.51220	−3.98	−11.35623	−7.90
AGE90	0.04896	4.82	0.13259	8.24
EDUC	−0.09395	−6.07	−0.08393	−3.22
RACE	0.59230	3.61	−1.09008	−2.24
GENDER	−0.17913	−1.32	−0.09591	−0.39
DAUGHTERS	0.15276	3.74	0.06029	0.80
SONS	0.03730	0.88	−0.05156	−0.63
OWN	0.33773	3.02	−1.82145	−8.94
MORTG	−0.95982	−5.85	−0.25593	−0.75
FIN	0.00124	2.41	0.00100	1.04
HOME	0.00157	1.91	0.00249	1.69
INCPERS	0.00037	0.14	−0.00282	−0.53

Source: Longitudinal Study on Aging 1990.
Notes: Sample size = 2,193 elderly. Log likelihood = −1,657.1.

the log likelihood increases considerably, and the likelihood ratio test statistic is 718.2. However, the inclusion of so many indicators results in multicollinearity and low *t*-statistics among the individual ADLs. This is one reason to contemplate using factor analysis in describing the effect of the health indicators. Exploratory factor analysis, taking the health indicators as if they were continuous indicators, shows that more than three-quarters of the variance can be explained by only two factors.

The inclusion of the health indicators does not change the other parameters by a lot. The main exception is age, which becomes insignificant once the functional health measures are taken into account. In turn, personal income, which was insignificant when the health indicators were left out, increases in statistical importance, with a negative effect on institutionalization and living with others.

These results essentially reproduce the estimates of Börsch-Supan, Kotlikoff, and Morris (1991). This is helpful to know because the latter estimates were obtained from a geographically very restricted sample of Massachusetts elderly, the Hebrew Rehabilitation Center for the Aged (HRCA) sample. Knowing that the HRCA sample is representative at least in the respect of choosing living arrangements gives confidence in the other analyses that have been performed on the basis of this rich data set.[3]

3. Kotlikoff and Morris (1987, 1990); Börsch-Supan, Kotlikoff, and Morris (1991); Börsch-Supan, Gokhale, Kotlikoff, and Morris (1992); Börsch-Supan, Hajivassiliou, Kotlikoff, and Morris, (1992).

Table 6.3 **Multinomial Logit: Estimation Results with Activities of Daily Living and Instrumental Activities of Daily Living**

	Probability to . . . Rather Than to Live Independently			
	Live with Children or Others		Live in an Institution	
	Coefficient	*t*-Value	Coefficient	*t*-Value
CONSTANT	−1,97921	−2.10	−10.39988	−4.15
AGE90	0.01790	1.61	0.00993	0.39
EDUC	−0.07186	−4.42	−0.02114	−0.52
RACE	0.50494	2.91	−1.49199	−2.56
GENDER	−0.24538	−1.74	−0.33389	−0.85
DAUGHTERS	0.14204	3.34	0.07087	0.65
SONS	0.04433	1.00	−0.03871	−0.33
OWN	0.31200	2.68	−1.87982	−6.79
MORTG	−0.90636	−5.30	−0.18384	−0.38
FIN	0.00150	2.77	0.00249	1.87
HOME	0.00155	1.83	−0.00113	−0.50
INCPERS	−0.00176	−0.60	−0.01341	−2.06
BATH	−0.02732	−0.29	0.04103	0.24
DRESS	−0.09357	−0.74	−0.04878	−0.27
GETUP	−0.04733	−0.42	0.02812	0.14
WALK	−0.02884	−0.34	−0.09203	−0.49
OUTSD	0.00642	0.06	0.01751	0.09
HOUSW	0.22450	2.52	1.63224	5.49
MEALS	0.38729	4.52	0.95070	3.87
SHOP	0.13567	1.98	0.57994	1.76

Source: Longitudinal Study on Aging 1990.
Notes: Sample size = 2,193 elderly. Log likelihood = −1,298.0.

6.4 An Econometric Model of the Influence of Latent Health

6.4.1 Model Specification

Obviously, the contribution of the health indicators in table 6.3 is highly significant. However, one might doubt that these indicators directly affect the choice of living arrangements. Rather, one might argue that it is the underlying but unobservable health status that affects both, the choice of living arrangements *and* the set of indicators. The problem boils down to the question of causal links among four groups of variables:

- the choice among N_a living arrangements, denoted by u,
- the latent health status, denoted by h^*, N_h-dimensional,
- the health indicators (ADLs and IADLs), denoted by y_k, $k = 1, \ldots, N_y$, and

- the demographic and economic exogenous variables, denoted by z_j, $j = 1, \ldots, N_z$.

Figures 6.1 and 6.2 visualize the two approaches, using the above notation for the four variable groups, and distinguishing latent from observable variables by an asterisk. In addition to latent health, we have two more latent variables. First, the choice between the discrete alternatives u depends on the unobserved utility levels u_i^*, $i = 1, \ldots, N_a$. In our case N_a equals three (living independently, with others, or in an institution). A person chooses the living arrangement that yields the highest utility level u_i^*;

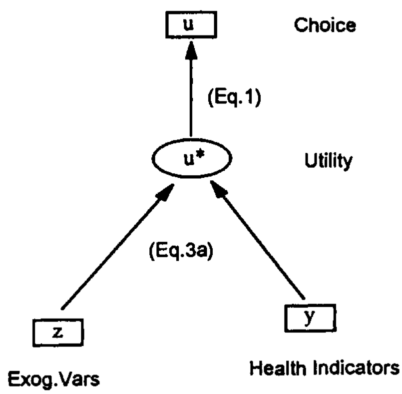

Fig. 6.1 Multinomial logit model

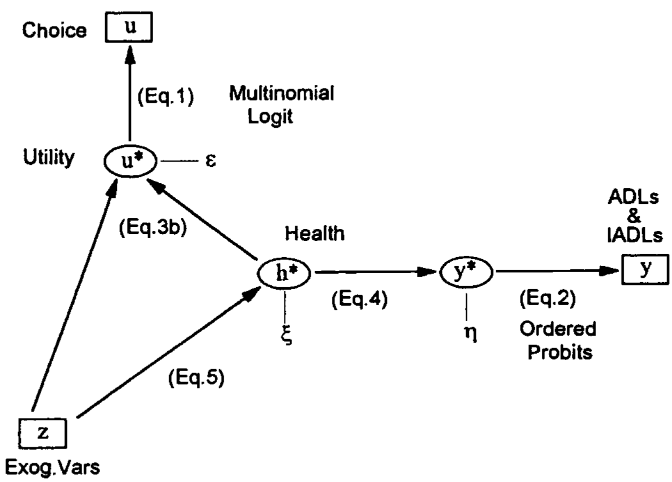

Fig. 6.2 Nonlinear MIMIC model

$$(1) \qquad u = i \quad \Leftrightarrow \quad u_i^* = \max(u_j^*, j = 1, \ldots, N_a).$$

This is the conventional random utility-maximization hypothesis underlying discrete choice. Second, we also do not precisely observe the health indicators because the sample persons are asked to report their performance in each activity using S_k ordinal categories (e.g., no, some, severe problems in walking, and cannot walk at all) rather than a continuous scale. The relation between the kth observed health indicator y_k and the underlying continuous y_k^* is described by thresholds $\mu_{k,j}$, which will be estimated:

$$(2) \quad y_k = j \quad \Leftrightarrow \quad \mu_{k,j-1} < y_k^* < \mu_{k,j}, \qquad k = 1, \ldots, N_y, j = 1, \ldots, S_k.$$

In the discrete choice model of the preceding section, the choice of living arrangements is directly linked to the ordinal health indicators and to the exogenous variables (fig. 6.1). Moreover, the transmission between ordinal measurement and continuous indicators (equation 2) is ignored. The unobserved utility levels u_i^* are therefore given by

$$(3a) \qquad u_i^* = \tilde{\beta}_i'z + \tilde{\gamma}_i'y + \tilde{\varepsilon}_i, \qquad i = 2, \ldots, N_a,$$

where $\tilde{\varepsilon}_i$ denotes an additive error term in the utility of alternative i. Alternative 1 (living independently) is taken as the reference alternative.

The MIMIC model endogenizes the indicators y_k. Latent health determines both indicators and living arrangement choice. The model also takes the categorical measurement of the health indicators and the choice decision into account. Moreover, our MIMIC model distinguishes between the direct influence of the exogenous variables on the living arrangement choice, and the indirect influence via the latent health status.

The unobserved utility levels u_i^* are now determined by

$$(3b) \qquad u_i^* = \beta_i'z + \gamma_i'h^* + \varepsilon_i, \qquad i = 2, \ldots, N_a.$$

Rather than taking the health indicators as given, we determine them now by the health status in a factor-analytic model:

$$(4) \qquad y_k^* = \lambda_k'h^* + \eta_k, \qquad k = 1, \ldots, N_y.$$

Finally, a set of equations expresses the influence of the exogenous variables on the latent health status:

$$(5) \qquad h_m^* = \delta_m'z + \xi_m, \qquad m = 1, \ldots, N_h,$$

or in stacked form,

$$h^* = \Delta'z + \xi.$$

One may interpret relation 5 as a production function of health. Due to progress in medical science, this function may change over time.

The three sets of equations 3b, 4, and 5 form a nonlinear version of a LISREL model.[4] It is nonlinear in two respects. First, the main dependent variable, the choice of living arrangements, is described by a nonlinear discrete choice model that links the observed choices u to the latent utilities u^* (equation 1). McFadden (1988) introduced this case of factor analysis in the presence of a discrete choice equation, and Morikawa, Ben-Akiva, and McFadden (1990) present an application to travel demand.

Our model introduces a second nonlinearity with the additional complication of categorical indicators. The measurement equations 4, which link the indicators y^* with the health status h^* via the factor loadings λ_k, are described by ordered probit models if we assume the η_k to be normally distributed.

By inserting equation 5 into 3b and 4, we eliminate the health production equation and obtain two sets of reduced-form equations on which our estimation will be based:

$$(6) \qquad u_i^* = \beta_i'z + \gamma_i'(\Delta'z + \xi) + \varepsilon_i, \qquad i = 2, \ldots, N_a$$

$$= \pi_i'z + \gamma_i'\xi + \varepsilon_i,$$

and similarly for the factor-analysis equations that determine the health indicators:

$$(7) \qquad y_k^* = \lambda_k'(\Delta'z + \xi) + \eta_k, \qquad k = 1, \ldots, N_y$$

$$= \psi_k'z + \lambda_k'\xi + \eta_k,$$

where the reduced-form parameters π_i and ψ_k are

$$(8) \qquad \pi_i' = \beta_i' + \gamma_i'\Delta' \quad \text{for } i = 2, 3$$

and

$$\psi_k' = \lambda_k'\,\Delta' \quad \text{for } k = 1, \ldots, N_y.$$

6.4.2 The Likelihood Function

We assume that the three groups of error terms ξ, ε, and η are mutually independent. Moreover, we assume that the ε are extreme-value distributed, resulting in a logit model for the choice equation 6. The η are assumed to be normal, resulting in N_y ordered probit models for the health indicators. The likelihood of an individual who has chosen alternative i and is characterized by the values of the health indicators j_k, $k = 1, \ldots, N_y$, conditional on ξ, the

4. See Jöreskog and Sörbom (1988) for a description of LISREL (analysis of linear structural relationships).

errors of the health equation, is therefore a product of the probabilities of a logit model and N_y ordered probit models:[5]

$$
\begin{aligned}
(9)\quad L(\beta, \gamma, \Delta, \lambda, \mu \mid \xi) &= \frac{\exp(\beta_i'z + \gamma_i'\Delta'z + \gamma_i'\xi)}{1 + \sum_{j=2}^{N_a} \exp(\beta_j'z + \gamma_j'\Delta'z + \gamma_j'\xi)} \\
&\quad \times \prod_{k=1}^{N_y} \Big(\Phi(\mu_{k,j_k} - \lambda_k'\Delta'z - \lambda_k'\xi) \\
&\quad - \Phi(\mu_{k,j_k-1} - \lambda_k'\Delta'z - \lambda_k'\xi) \Big) \\
&= LOGIT(i, z, \xi) \prod_{k=1}^{N_y} ORDPROBIT(j_k, z, \xi).
\end{aligned}
$$

We now have to eliminate the error terms ξ in equation 9, which represent the latent components of the health status. We accomplish this by integrating over the N_h-dimensional error term, assuming that the ξ are jointly standard normally distributed, possibly with correlations $\rho(\xi_m, \xi_m')$. The unconditional likelihood function is therefore

$$
\begin{aligned}
(10)\quad & L(\beta, \gamma, \Delta, \lambda, \mu, \rho) = \\
& \int_{-\infty}^{\infty} LOGIT(i, z, \xi) \prod_{k=1}^{N_y} ORDPROBIT(j_k, z, \xi)\, \phi(\xi, \rho)\, d\xi.
\end{aligned}
$$

We estimate the nonlinear MIMIC model by maximizing the sum of the individual log-likelihood contributions over the coefficients β, γ, Δ, and λ, over the thresholds $\mu_{k,j}$, and over the correlations ρ among the latent health components.

6.4.3 Identification and Estimation

In order to check the identification of the system, we start by inspecting the set of equations 7, which make up the ordered probit part of the likelihood function.[6] Maximizing equation 10 directly identifies the absolute value of the factor loadings λ_k attached to ξ through the term $\lambda_k'\xi$ in the case of orthogonal ξ. The signs are not identified because the thresholds $\mu_{j,k}$ of the ordered probit can be ordered either way. By counting the elements of δ_m, the coefficients of the exogenous variables in the health equations, and the elements of the reduced form parameters ψ_k in the ordered probit part

5. For notational convenience the index for individual observations is left out.

6. In the sequel we consider uncorrelated ξ. If the ξ are correlated, the ρ have to be estimated and additional identification restrictions are required.

$$(11)\qquad \begin{pmatrix} \psi_{1k} \\ \psi_{2k} \\ \cdot \\ \cdot \\ \cdot \\ \psi_{N_zk} \end{pmatrix} = \lambda_{1k} \begin{pmatrix} \delta_{11} \\ \delta_{21} \\ \cdot \\ \cdot \\ \cdot \\ \delta_{N_z1} \end{pmatrix} + \lambda_{2k} \begin{pmatrix} \delta_{12} \\ \delta_{22} \\ \cdot \\ \cdot \\ \cdot \\ \delta_{N_z2} \end{pmatrix} \quad \text{for } k = 1, \ldots, N_y,$$

it becomes clear that the structural coefficients δ_m are identified only if $N_y \geq N_h$. Hence, the number of indicators y_k has to be at least as large as the number of latent health dimensions h^*. Since in typical applications the number of indicators tends to be large compared to the number of underlying factors, identification of λ and δ is easily achieved.

In contrast to the factor loadings λ_k in equations 7, the coefficients of health in the choice of living arrangements, γ_i, are not identifiable through the term $\gamma_i' \xi$ because the scale in the discrete choice model is undetermined. Moreover, the coefficients of the exogenous variables in the choice of living arrangements, β_i, are also not directly identifiable even though δ_m is given:

$$(12)\qquad \begin{pmatrix} \pi_{1i} \\ \pi_{2i} \\ \cdot \\ \cdot \\ \cdot \\ \pi_{N_zi} \end{pmatrix} = \begin{pmatrix} \beta_{1i} \\ \beta_{2i} \\ \cdot \\ \cdot \\ \cdot \\ \beta_{N_zi} \end{pmatrix} + \gamma_{1i} \begin{pmatrix} \delta_{11} \\ \delta_{21} \\ \cdot \\ \cdot \\ \cdot \\ \delta_{N_z1} \end{pmatrix} + \gamma_{2i} \begin{pmatrix} \delta_{12} \\ \delta_{22} \\ \cdot \\ \cdot \\ \cdot \\ \delta_{N_z2} \end{pmatrix} \quad \text{for } i = 2, \ldots, N_a.$$

The number of elements in β_i equals the number of reduced-form parameters in π_i. Since γ_i is not identifiable, there is an excess number of structural parameters equal to the number of elements in γ_i, the number of health dimensions. Hence, β_i and γ_i can be identified only by imposing further restrictions.

We explore two possibilities of identifying β_i and γ_i:[7] identification in a cross-section with N_h parameter restrictions on each β_i, and identification in repeated cross-sections exploiting parameter differences in Δ over time.

In the first case we impose the assumption that at least N_h exogenous variables influence the choice of living arrangements only indirectly via their influence on health, but not directly. This pins down the parameters γ_i, the impact of health on choice. With γ_i given, the remaining β_i are just identified.[8]

In the second approach we impose the assumption that the coefficients of the main choice equation 3b do not change over time but that technical progress in medical science changes the health production function (equations 5). With two cross-sections t_1 and t_2, we first estimate the reduced form coefficients:

7. Other identification approaches are possible with panel data.

8. Identification of factor analytic models through linear parameter restrictions has been introduced by Jöreskog (1967).

(13)
$$\hat{\pi}'_{i(t_1)} = \beta'_i + \gamma'_i \hat{\Delta}'_{(t_1)};$$
$$\hat{\pi}'_{i(t_2)} = \beta'_i + \gamma'_i \hat{\Delta}'_{(t_2)}.$$

Then γ_i can be estimated from

(14)
$$\hat{\pi}'_{i(t_1)} - \hat{\pi}'_{i(t_2)} = \gamma'_i(\hat{\Delta}'_{(t_1)} - \hat{\Delta}'_{(t_2)}),$$

provided that $N_z \geq N_h$.

In either approach to identification, we first estimate the reduced form parameters by maximizing equation 10 using equations 8. In a second step we compute the structural parameters by a minimum-distance method (nonlinear generalized least squares) applied to equations 8.

Given the results from the exploratory factor analysis, we assume that two dimensions suffice to describe the latent health status. For simplicity we also impose $\rho(\xi_1, \xi_2) = 0$, although other factor structures can be thought of. Even with $\rho = 0$, the integral in equation 10 does not factor easily due to the functional form. In order to evaluate the integral we therefore employ two-dimensional Gauss-Hermite integration.

6.5 Estimation Results

Table 6.4 presents the reduced form estimates of the nonlinear MIMIC model. The first panel refers to the discrete choice submodel (equations 6) with parameters π, while the second panel represents estimates of the ordered probit submodel (equations 7) with parameters ψ_k, λ_k, and μ_k. In addition to the factor loadings γ_k for the two latent health status variables and the switch points μ,[9] some of the structural parameters β_{ik} in the living arrangement choice (equations 3b) can directly be identified because the corresponding δ_{nk} (equations 5) are zero. These are the coefficients of those exogenous variables that appear in the upper but not in the lower panel. The corresponding rows of coefficients are marked by $\beta = \pi$.

The results are encouraging. The large t-values of π and ψ show that the causal links in figure 6.2 are significant. The values of the "thresholds" μ_2^* and μ_3^* and the corresponding t-statistics have to be interpreted with care: large negative values and t-values indicate that the difference between adjacent thresholds is small, while t-values close to zero indicate that the null (i.e., $\exp(0) = 1$) cannot be rejected. We proceed in estimating the structural coefficients. We first pursue identification through parameter restrictions.

9. The proper ordering of the thresholds has been enforced by the parameterization: $\mu_2 = \mu_1 + \exp(\mu_2^*)$ and $\mu_3 = \mu_2 + \exp(\mu_3^*)$. This ensures $\mu_1 < \mu_2 < \mu_3$. In the tables we display μ_1, μ_2^* and μ_3^*.

Table 6.4 Multiple-Indicator, Multiple-Cause Model: Reduced Form 1990

Living Arrangement Choice (equations 6)

	Probability to . . . Rather Than to Live Independently				
	Live with Children or Others		Live in an Institution		
	Coefficient	*t*-Value	Coefficient	*t*-Value	
CONSTANT	−5.07076	−4.40	−12.87920	−6.68	
AGE90	0.07081	5.37	0.15511	7.28	
EDUC	−0.12157	−6.12	−0.12186	−3.65	
RACE	0.87069	3.74	−0.76198	−1.45	
GENDER	−0.28649	−1.60	−0.15910	−0.49	
DAUGHTERS	0.21032	3.82	0.12253	1.35	($\beta=\pi$)
SONS	0.02979	0.55	−0.04329	−0.42	
OWN	0.27072	1.91	−1.85104	−7.63	
MORTG	−1.18610	−5.13	−0.56230	−1.24	($\beta=\pi$)
FIN	0.00173	2.28	0.00119	1.11	($\beta=\pi$)
HOME	0.00197	2.00	0.00243	1.20	($\beta=\pi$)

Health Measurement (equations 7)[a]

	Bathing		Dressing		Getting Up		Walking	
AGE90	0.114	13.00	0.129	11.26	0.104	9.32	0.103	11.73
EDUC	−0.034	−2.55	−0.040	−2.74	−0.043	−2.92	−0.050	−4.26
RACE	0.968	5.49	1.193	6.21	0.799	4.65	0.652	4.90
GENDER	0.059	0.41	−0.208	−1.48	0.189	1.35	−0.007	−0.06
OWN	−0.324	−3.02	−0.517	−4.55	−0.479	−4.53	−0.406	−4.79
HEALTH1	−1.084	−13.10	−1.210	−13.74	−1.322	−13.67	−1.123	−14.27
HEALTH2	−1.717	−18.30	−1.702	−18.45	−1.493	−18.49	−1.260	−20.63
MU1	13.254	13.36	12.339	12.28	9.870	9.91	8.367	11.26
*MU2**[b]	−0.138	1.89	−0.050	−0.63	0.162	2.27	0.231	4.62
*MU3**[b]	−0.785	−6.63	−0.478	−3.58	−0.167	−1.43	−0.118	−1.68
	Going Outside		Light Housework		Preparing Meals		Shopping	
AGE90	0.186	13.92	0.199	11.28	0.208	12.40	0.223	14.97
EDUC	−0.077	−4.89	−0.102	−5.43	−0.135	−6.94	−0.127	−7.50
RACE	1.118	5.82	1.153	5.27	1.264	6.01	1.154	6.15
GENDER	0.163	1.04	−0.225	−1.39	−0.029	−0.17	0.420	2.51
OWN	−0.574	−4.69	−0.852	−5.95	−0.832	−5.84	−0.726	−5.85
HEALTH1	−1.376	−13.33	−0.761	−8.31	−0.625	−7.21	−0.718	−9.62
HEALTH2	−2.035	−17.06	−2.621	−14.88	−2.689	−15.55	−2.308	−16.68
MU1	16.645	14.16	17.485	11.51	17.852	12.44	18.791	14.80
*MU2**[b]	−0.272	−3.19	−0.749	−6.30	−0.496	−4.47	−0.867	−7.97
*MU3**[b]	−0.422	−3.94	−1.078	−6.48	−0.884	−5.99	−1.098	−8.49

Source: Longitudinal Study on Aging 1990.

Notes: Sample size = 2,193 elderly. Log likelihood = −8,122.

[a]Left-hand columns are coefficients, right-hand are *t*-values.

[b]μ_2^* and μ_3^* are defined by $\mu_2 = \mu_1 + \exp(\mu_2^*)$ and $\mu_3 = \mu_2 + \exp(\mu_3^*)$.

In selecting possible restrictions, the main question is which variables are most likely to influence the living arrangement decision only by their indirect impact on health without directly influencing the living arrangement choice. Of the variables included, age per se as well as education certainly does effect the health status but is less likely to directly affect living arrangement choices. This is also clear from the exploratory logit analysis, table 6.3, where age in both columns and education in the second column become insignificant after including the health indicators. The estimated coefficient of education, although still significant in the first column, decreases in magnitude and its significance level.

Table 6.5 presents the estimates. The upper panel displays the living arrangement choice equation. The demographic variables are weaker than in the multinomial logit estimation, table 6.3, except for the "daughters' effect." Living with children is strongly correlated with the number of daughters who can take care of the elderly. There is no corresponding "sons' effect."

Higher financial and housing wealth significantly increases the likelihood to live with children, while the ownership of a house reduces the probability of entering a nursing home. The positive correlation between wealth of the elderly and living together appears to be evidence in favor of the "bribery hypothesis" of Kotlikoff and Morris (1990)—wealthy elderly who like to be taken care of by their children are able to bribe the children, who would rather live by themselves, if it weren't for the shared wealth. Unfortunately, we do not know the wealth of the children to shed more light on this issue. Because the wealth of children is commonly highly correlated with the wealth of the parents, the coefficients may also express a supply effect: only wealthy children can take their parents in. As a caveat, we note that reported wealth may reflect household wealth including the younger generation's wealth, although the question in the survey instrument was intended to record the personal wealth of the elderly sample person.

The strong negative and significant coefficient on the *MORTG* variable tells us that the few elderly who still have mortgages on their home are unlikely to move to their children's home (or, though not significantly, into a nursing home). This is easily explained by the fact that almost all elderly with a mortgage are recent movers and unlikely to move again.

The main point of the MIMIC model was capturing the influence of health. Both health variables significantly affect the choice to live with children. While the first factor affects only the probability of living with children, a higher value of the second health factor, indicating a healthier elderly person, makes both dependent living arrangements less likely than living independently.

What are the two health factors? If we look at the next block of results—pertaining to the health measurement equations 4—we see that the second factor is strongly associated with the IADLs, while the first factor is more related to the first four ADLs. Looking at the health production function—lower panel of table 6.5, compare equations 5—we see that the second factor

Table 6.5 **Structural Parameters of the Multiple-Indicator, Multiple-Cause Model**

Living Arrangement Choice (equations 3b)

	Probability to . . . Rather Than to Live Independently			
	Live with Children or Others		Live in an Institution	
	Coefficient	*t*-Value	Coefficient	*t*-Value
CONSTANT	−5.21285	−4.60	−12.49175	−6.59
RACE	1.06272	3.38	−1.09591	−1.69
GENDER	−0.01280	−0.04	0.18139	0.47
DAUGHTERS	0.22783	4.18	0.14136	1.58
SONS	0.03278	0.62	−0.03544	−0.34
OWN	0.56104	2.33	−1.34210	−4.55
MORTG	−1.31190	−5.74	−0.52219	−1.17
FIN	0.00150	1.99	0.00094	0.88
HOME	0.00189	1.94	0.00190	0.95
HEALTH1	−2.72910	−2.16	−1.28417	−0.86
HEALTH2	−0.76748	−2.93	−1.67740	−5.43

Health Measurement (equations 4)[a]

	Bathing		Dressing		Getting Up		Walking	
HEALTH1	−1.057	−13.15	−1.179	−13.78	−1.333	−14.18	−1.154	−15.17
HEALTH2	−1.635	−19.07	−1.616	−19.30	−1.440	−18.52	−1.273	−21.38
MU1	12.390	16.28	13.005	16.85	11.284	14.75	8.976	14.86
MU2[*b]	−0.164	−2.28	−0.048	−0.63	0.169	2.41	0.270	5.54
MU3[*b]	−0.805	−6.94	−0.506	−3.87	−0.146	−1.27	−0.091	−1.31
	Going Outside		**Light Housework**		**Preparing Meals**		**Shopping**	
HEALTH1	−1.370	−13.66	−0.772	−8.55	−0.638	−7.54	−0.711	−9.66
HEALTH2	−2.039	−17.53	−2.490	−14.97	−2.654	−16.01	−2.369	−17.46
MU1	15.540	15.32	18.795	14.14	19.631	14.84	16.976	14.99
MU2[*b]	−0.242	−2.89	−0.763	−6.35	−0.479	−4.41	−0.895	−8.39
MU3[*b]	−0.461	−4.39	−1.118	−6.84	−0.899	−6.21	−1.160	−9.16

Health Production (equations 5)

	HEALTH1		*HEALTH2*	
AGE 90	−0.00216	−0.31	−0.08708	−20.15
EDUC	0.02881	2.97	0.05623	9.56
RACE	0.20709	1.85	−0.42710	−6.83
GENDER	0.04999	0.55	0.01938	0.34
OWN	0.02259	0.31	0.32748	7.24

Source: Longitudinal Study on Aging 1990.

Notes: Sample size = 2,193 elderly. Identification is by parameter restrictions.

[a]Left-hand columns are coefficients, right-hand are *t*-values.

[b]μ_2^* and μ_3^* are defined by $\mu_2 = \mu_1 + \exp(\mu_2^*)$ and $\mu_3 = \mu_2 + \exp(\mu_3^*)$.

is mainly determined by age, while the most important determinant for the first factor is education. The first health factor works more like a random effect, while the second factor carries the deterministic component associated with the exogenous variables.

The coefficients of the sociodemographic variables in table 6.5 have a pattern similar to the coefficients in table 6.3. However, some of the magnitudes change considerably. For example, the coefficients of the *RACE* and the *OWN* variables in the first column almost double in magnitude compared to table 6.3. In general, the changes are largest for those variables that appear in several equations of the system and not only in the choice equation. If we believe in the a priori assumptions underlying the MIMIC model, we must conclude that the multinomial logit model yields biased parameter results.

One may also be interested in seeing whether the nonlinear MIMIC model predicts better than the simple multinomial logit model. This is a weak test of the a priori assumptions underlying the MIMIC model. It is weak because the real strength of the structural model is the prediction of the effect of structural changes. However, the data do not provide such an experiment.

In order to test the out-of-sample performance, we used the 1986 and 1988 waves of the LSOA. We restricted attention to the unmarried elderly, so the 1986 and 1988 samples are smaller than the 1990 sample due to those elderly who were still married in 1986 or 1988. Table 6.6 shows the results.

In the in-sample prediction, the multinomial logit model fits the sample better than the nonlinear MIMIC model. It produces better estimates of the institutionalization probability, and it has an overall higher success rate. This might be expected from an atheoretical model designed to describe the data. The balance changes in the out-of-sample prediction. Now the nonlinear model has a better overall performance, and it is closer in predicting living with others. Again, this reversal is exactly what an econometrician wishes for a model that may mine the sample worse but capture the true structure better. The improvement, however, is rather modest. It would be helpful to have a holdout sample that consists of different elderly persons rather than of the same persons two years prior to the estimation period.

We also pursued the second method to identify the structural parameters in exploiting the variation in the health production function over time; see equation 14. We use the difference between the matrices Δ_{1988} and Δ_{1990}, estimated for the 1988 and 1990 waves, maintaining that the structural coefficients of the choice equation (β, γ) remain constant. It would be preferable to estimate the second set of coefficients from a cross-section as far away from 1990 as possible in order to capture a sufficient change in health technology, rather than using 1988. However, the 1986 wave has very few institutionalized persons, and the 1984 wave has none. The results are disappointing because the difference between Δ_{1988} and Δ_{1990} turns out to be virtually random: two years are too short to induce significant changes in health technology.

Table 6.6 **Prediction Performance of the Two Alternative Models (%)**

	Observed	Multinomial Logit	Nonlinear MIMIC Reduced Form	Nonlinear MIMIC Structural Form
In-sample 1990				
Alone	64.02	79.30	82.58	73.83
With others	28.45	13.41	15.18	23.16
Institution	7.52	7.30	2.33	3.01
% correct		74.15	69.08	63.61
Out-of-sample 1988				
Alone	67.50	87.32	86.70	76.97
With others	28.63	9.44	12.07	21.65
Institution	3.87	3.24	1.22	1.38
% correct		68.19	70.96	64.85
Out-of-sample 1986				
Alone	70.96	90.30	89.66	78.40
With others	27.62	8.50	10.12	21.18
Institution	1.42	1.20	0.2	0.42
% correct		74.86	72.8	67.07

Source: Longitudinal Study on Aging 1986, 1988, and 1990. Sample size is 1,412, 1,963, and 2,193 elderly, respectively.

6.6 Conclusions

Like the entire paper, the conclusions address econometric methodology as well as economic substance. We start with econometrics.

This paper is a classical exercise in what econometrics is supposed to do—and where the problems of sophisticated econometrics are. It uses a priori knowledge drawn from economics (and from common sense) in order to structure the inference we draw from the data. The multinomial logit model is atheoretical in the sense that it makes no usage of the causal links depicted in figure 6.1. In turn, the MIMIC model in figure 6.2 employs a rather involved superstructure to guide our inference.

The main problem with this model is of course identification. After all, the MIMIC model uses the same information as the simple multinomial logit model, and only introduces a potentially large number of latent variable constructs. In addition to postulating causal links as in figure 6.2, additional parameter restrictions were required. In the first case identification via exclusion restrictions is pretty much in the spirit of conventional simultaneous equation models. In the second case we assumed that some parameters change over time while others stay constant. Both identifying assumptions can easily be criticized. If the identifying assumptions are false, our estimates are inconsistent. If they are true, we have gained efficiency and have learned more about those structural coefficients that we have estimated.

Our panel data could identify the coefficients of the latent health variables much better than the cross-section models of section 6.5. The latent health variables have a function very similar to random effects. This is the reason they are so hard to identify in cross-sections. By exploiting the panel structure, we could identify, say, two latent health statuses in 1988 as well as in 1990, possibly correlated over time. The likelihood function would be similar to equation 10 but would require higher dimensional integration. In further research we will estimate this model by employing simulation methods for the computation of these integrals, such as the smooth simulated maximum-likelihood approach of Börsch-Supan and Hajivassiliou (1993).

As for economic substance, the coefficients of our main interest were health and wealth. While wealth is an important economic variable in the choice of living arrangements, income has proven to be of little relevance once wealth is included. Health is one of the main predictors of living arrangement choices. This is to be expected. Health is well captured by two factors, one associated with independent activities and strongly related to age, while the other, more person-specific factor is associated with more basic capabilities. Living with others, mainly children, is positively affected by financial and housing wealth, while homeowners are less likely to become institutionalized.

References

Börsch-Supan, A. 1989. Household Dissolution and the Choice of Alternative Living Arrangements among Elderly Americans. In *The Economics of Aging,* ed. David A. Wise. Chicago: University of Chicago Press.

———. 1990. A Dynamic Analysis of Household Dissolution and Living Arrangement Transitions by Elderly Americans. In *Issues in the Economics of Aging,* ed. David A. Wise. Chicago: University of Chicago Press.

Börsch-Supan, A., J. Gokhale, L. Kotlikoff, and J. Morris. 1992. The Provision of Time to the Elderly by Their Children. In *Topics in the Economics of Aging,* ed. David A. Wise. Chicago: University of Chicago Press.

Börsch-Supan, A., and V. Hajivassiliou. 1993. Smooth Unbiased Multivariate Probability Simulators for Maximum Likelihood Estimation of Limited Dependent Variable Models. *Journal of Econometrics* 58:347–68.

Börsch-Supan, A., V. Hajivassiliou, L. Kotlikoff, and J. Morris. 1992. Health, Children, and Elderly Living Arrangements: A Multiperiod-Multinomial Probit Model with Unobserved Heterogeneity and Autocorrelated Errors. In *Topics in the Economics of Aging,* ed. David A. Wise. Chicago: University of Chicago Press.

Börsch-Supan, A., L. Kotlikoff, and J. Morris. 1991. The Dynamics of Living Arrangements of the Elderly: Health and Family Support. In *The Economics of Care of the Elderly,* ed. J. Pacolet and C. Wilderom. London: Avebury Aldershot.

Ellwood, D. T., and T. J. Kane. 1990. The American Way of Aging: An Event History Analysis. In *Issues in the Economics of Aging,* ed. David A. Wise. Chicago: University of Chicago Press.

Feinstein, J., and D. McFadden, 1989. The Dynamics of Housing Demand by the El-

derly. In *The Economics of Aging,* ed. David A. Wise. Chicago: University of Chicago Press.
Fitti, J. E., and M. G. Kovar. 1987. The Supplement on Aging to the 1984 National Health Interview Survey. National Center for Health Statistics working paper. Washington, DC.
Garber, A. M. 1990. Predicting Nursing Home Utilization among the High-Risk Elderly. In *Issues in the Economics of Aging,* ed. David A. Wise. Chicago: University of Chicago Press.
Greene, V. L., M. E. Lovely, and J. I. Ondrich. 1993. Do Community-Based, Long-Term-Care Services Reduce Nursing Home Use? A Transition Probability Analysis. *Journal of Human Resources* 28 (2): 297–317.
Jöreskog, K. G. 1967. Some Contributions to Maximum Likelihood Factor Analysis. *Psychometrica* 32:443–82.
Jöreskog, K. G., and D. Sörbom. 1988. LISREL 7: A Guide to the Program and Applications. Chicago: SPSS Inc.
Kotlikoff, L. J., and J. Morris. 1987. How Much Care Do the Aged Receive from their Children? A Bimodal Picture of Contact and Assistance. NBER Working Paper no. 2391. Cambridge, MA: National Bureau of Economic Research.
———. 1990. Why Don't the Elderly Live with their Children? A New Look. In *Issues in the Economics of Aging,* ed. David A. Wise. Chicago: University of Chicago Press.
Kovar, M. G., and G. S. Poe. 1985. The National Health Interview Survey Design, 1973–1984, and Procedures, 1975–1983. National Center for Health Statistics working paper. Washington, DC.
McFadden, D. 1988. Discrete Response to Unobserved Variables for Which There Are Multiple Indicators. Massachusetts Institute of Technology. Mimeo.
Morikawa, T., M. Ben-Akiva, and D. McFadden. 1990. Incorporating Psychometric Data in Econometric Travel Demand Models. Massachusetts Institute of Technology. Mimeo.
National Center for Health Statistics. 1991. The Longitudinal Study on Aging. Version 4. Washington, DC. Mimeo.
Schwartz, S., S. Danziger, and E. Smolensky. 1984. The Choice of Living Arrangements by the Elderly. In *Retirement and Economic Behavior,* ed. H. J. Aaron and G. Burtless. Washington, DC: Brookings Institution.
Venti, Steven F., and David A. Wise. 1990. But They Don't Want to Reduce Equity. In *Issues in the Economics of Aging,* ed. David A. Wise. Chicago: University of Chicago Press.
———. 1991. The Saving Effect of Tax-Deferred Retirement Accounts: Evidence from SIPP. In *National Saving and Economic Performance,* ed. B. D. Bernheim and J. B. Shoven. Chicago: University of Chicago Press.

Comment Steven F. Venti

Axel Börsch-Supan, Daniel McFadden, and Reinhold Schnabel present and estimate a model of the effects of health and wealth on the living arrangements of the elderly. Most of my discussion will deal with wealth effects on living

Steven F. Venti is professor of economics at Dartmouth College and a research associate of the National Bureau of Economic Research.

arrangements. This is a bit unfair, since the principal objective of the paper is to obtain better estimates of the effect of health on living arrangements. Let me say at the outset that this objective has been met. I thus have little to add, either critically or constructively, to their comprehensive and thorough analysis of health effects. Instead I will focus on some other implications of their work I find interesting.

For the benefit of those who have not followed this area of research closely, let me briefly review some of the dramatic changes in living arrangements over the past two or three decades. If we concentrate attention on unmarried persons, age 75–79, we find that the percentage living independently has approximately doubled over the period 1960–90. Over the same period the percentage living with relatives has fallen by half, and the percentage living in nursing homes, although still small (about 7%), has doubled. The last few decades have also witnessed substantial growth of the wealth of the elderly. The explosion in house prices in the 1970s and early 1980s, the run-up in the stock market, the favorable "deal" received by the current retirement generation on their Social Security investment, and the increasing pension coverage of recent retirement cohorts have all contributed to this trend.

It seems natural to consider whether these two trends—rising wealth and an increase in the likelihood of independent living—are related. There is what I will call the "conventional view" (see the references in Schwartz, Danziger, and Smolensky 1984). This view suggests the trend toward independence is an indicator of increasing well-being of the elderly. The assumption, either implicit or explicit, is that the elderly clearly prefer living independently to either living with relatives or in an institution. Thus recent trends are a sign that the elderly today are more likely to be free of the health and wealth limitations that in the past "forced" them into alternative living arrangements. Independent living simply reflects a high income elasticity of privacy, according to this view. Empirical research, mostly based on cross-section studies, has generally been supportive. Wealth, good health, and income have all been found to be positively associated with the choice of an independent living arrangement.

There is, of course, an alternative view of the trend toward independent living (see, for example, Börsch-Supan 1990). For whatever reason—the entry of more women into the labor force is often cited—it may be that living with relatives is no longer a viable alternative for many of the elderly. The trend to independence is a trend to isolation, reflecting constraints rather than preferences, and the implications for the rising well-being of the elderly are ominous.

This study doesn't do great damage to the conventional view of living arrangements, but it is suggestive that some recent trends may be the result more of constraints than of preferences. The authors' work is the first on living arrangements to be based on the LSOA and the associated NBER Economics Supplement. These data are very recent (1990), which is important, given the pace of change. Much prior work was based on the Retirement History Survey, which spanned the period 1969–79 and thus predates some of the current trends. The LSOA data also have good information on health and wealth, probably superior to anything else available for this purpose. The one shortcoming of these data is the absence of information on the proximity and financial resources of kin, which would permit us to better ascertain the set of feasible alternative living arrangements for elderly persons in the sample.

The authors begin by estimating a conventional multinominal logit model of the choice between living independently, living with relatives or others, and living in an institution. Among the explanatory variables are five measured ADLs and three IADLs. As a group these variables provide a great deal of explanatory power, although the five ADLs are individually not significant, thus suggesting that the effect of health may be reasonably captured in fewer dimensions in the ensuing latent-variable model. Age, education, and the number of sons and daughters have the expected effects. There is surprisingly little effect of income, due perhaps to the presence of very good measures of wealth. It is these wealth effects that I find most intriguing. The three measures of wealth—homeownership, financial assets, and housing assets—are all associated with an increase in the likelihood of living with relatives or others.

To uncover the true effects of health, which cannot be directly measured, the authors adopt the MIMIC framework. Essentially they face an errors-in-variables problem because ADLs and IADLs only imperfectly measure true health. This gives rise to a two-factor latent-variable parameterization of health. Moreover, the observed health indicators are categorical. This requires an ordered probit model of the health indicators as functions of the latent health variables. Thus estimation of this model requires "integrating out" the two latent health variables from a likelihood function comprising the product of logit choice equations and probits. This is a formidable task that is successfully executed.

If the question is, "Why do some elderly live independently and others in alternative living arrangements?" then the structural MIMIC model clearly implicates health as the answer. Estimates of the two latent health factors are large and significant. One of these factors is clearly capturing the general deterioration of health associated with aging. The other is more of a puzzle, having an unexpected negative sign in the health indicator equations.

The wealth effects are similar to those estimated in the earlier specification and imply that the wealthier elderly are more likely to live with relatives or others. There are several possible explanations for this curious result. The authors suggest a "bribery" effect where wealthy parents are able to get their children, who would otherwise choose to live alone, to take them in. This explanation suggests wealthy parents are living in the homes of their children.

Alternatively, the children may be living in the homes of their parents. This "wealth attracts kids" phenomenon has been observed by others (Schwartz, Danziger, and Smolensky 1984) in the Retirement History Survey. In these data, we cannot distinguish this explanation from the bribery hypothesis. However, the fact that more elderly persons own homes than live independently in this sample suggests this explanation may be reasonable.

A final explanation focuses on the "others" in the choice category "living with relatives or others." A possibility here is what Feinstein (chap. 9 in this volume) calls transitional living arrangements. This form of housing—somewhere between independent and institutional—includes many varieties such as congregate housing, life-care communities, and other arrangements where the elderly generally do not own their housing unit, but are also not part of an institutional arrangement. Such facilities are typically characterized by the presence of on-site dining facilities, availability of nursing or personal care, and perhaps housekeeping or laundry services. It is difficult to assess how prevalent such arrangements are because, as a group, they are only vaguely defined. In particular, it is not clear how survey respondents in transitional arrangements would classify their own living arrangements. About the only data I have been able to uncover on these arrangements is a 1988 Congressional Budget Office report indicating that the percentage of elderly living with "unrelated others" approximately doubled between 1980 and 1984. The results of Börsch-Supan, McFadden, and Schnabel may suggest that, once health limitations set in, these transitional facilities are the *preferred* next step for wealthy families that are either unable to or prefer not to live with relatives. More disaggregated information on living arrangements would be useful to address this point.

I have one final comment on the econometric innovation at the core of this paper. I agree with the authors that, because health is not measurable, a latent-variable framework is important to deal with the errors-in-variables problem posed by using observed health indicators such as ADLs and IADLs. However, it may also be that, in some sense, the "errors" themselves may be of interest. For instance, given true health, the choice of living arrangements may depend on whether an elderly person perceives himself or herself to be limited in the ability to provide, say, meals (one of the IADLs). It is conceivable that two persons with the same health may differ in this ability. In this case, the measured ADLs and IADLs may provide useful additional information not captured by the true latent health variables. Thus it may make sense to include both measured and latent health in the choice specification.

In summary, the authors have made a significant methodological and substantive contribution to our understanding of the determinants of the living standards of the elderly. Their latent-variable characterization of health will help us better understand the complex relationship between health limitations and housing choice. And their results on wealth effects suggests great care should be exercised interpreting the trend to independent living as an indicator of the rising well-being of the elderly.

References

Börsch-Supan, Axel. 1990. A Dynamic Analysis of Household Dissolution and Living Arrangement Transitions by Elderly Americans. In *Issues in the Economics of Aging*, ed. David A. Wise. Chicago: University of Chicago Press.

Schwartz, Saul, Sheldon Danziger, and Eugene Smolensky. 1984. The Choice of Living Arrangements by the Elderly. In *Retirement and Economic Behavior*, ed. H. Aaron and G. Burtless. Washington, DC: Brookings Institution.