Mannheim Research Institute for the Economics of Aging

Subjective Health Assessments and Active Labor Market Participation of Older Men:

Evidence from a Semiparametric Binary Choice Model with Nonadditive Correlated Individual-specific Effects

Jürgen Maurer, Roger Klein and Fancis Vella

169-2008

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

Subjective Health Assessments and Active Labor Market Participation of Older Men: Evidence from a Semiparametric Binary Choice Model with Nonadditive Correlated Individual-specific Effects

Jürgen Maurer[*], Roger Klein[†] and Francis Vella[‡]

December 2007

Abstract

We use panel data from the US Health and Retirement Study 1992-2002 to estimate the effect of self-assessed health limitations on active labor market participation of men around retirement age. Self-assessments of health and functioning typically introduce an endogeneity bias when studying the effects of health on labor market participation. This results from justification bias, reflecting an individual's tendency to provide answers which "justify" his labor market activity, and individual-specific heterogeneity in providing subjective evaluations. We address both concerns. We propose a semiparametric binary choice procedure which incorporates potentially nonadditive correlated individual-specific effects. Our estimation strategy identifies and estimates the average partial effects of health and functioning on labor market participation. The results indicate that poor health and functioning play a major role in the labor market exit decisions of older men.

JEL classification: I10, J10, J26, C14, C30

Keywords: Health, Retirement, Nonadditive Correlated Effects, Semiparametric Estimation

---

[*]Mannheim Research Institute for the Economics of Aging (MEA), University of Mannheim, L13, 17, 68131 Mannheim, Germany. Parts of the paper were written while Maurer was visiting the Institute for Fiscal Studies, London, United Kingdom. He gratefully acknowledges financial support provided by the European Community's Human Potential Programme through contract HPRN-CT-2002-00235, [AGE]. Address for correspondence: Jürgen Maurer, Mannheim Research Institute for the Economics of Aging (MEA), University of Mannheim, L13, 17, 68131 Mannheim, Germany. Email: maurer@mea.uni-mannheim.de.

[†]Department of Economics, Rutgers University.

[‡]Department of Economics, Georgetown University, Washington DC.

1 Introduction

The ratio of individuals aged 65 years and older to those aged under 65 years in the United States (US) is projected to increase from 0.14 in 2005 to approximately 0.26 in 2050.[1] This increase in the dependency ratio is likely to produce severe budgetary pressure as the economy endeavors to cover the cost of an aging population, which has a substantially lower propensity to be in formal employment. Figure 1 presents the age profile of active labor market participation rates and age-specific prevalence rates of major and minor health conditions for male respondents from the US Health and Retirement Study (HRS) 1992-2002.[2] This figure indicates that although approximately 85% of 51-55 year olds actively participate in the labor market, this rate declines sharply as individuals age through their fifties and sixties. In fact, the participation rate falls below 40% for those aged 66-70 years. The figure also reveals that morbidity increases over mid-life. The fraction of respondents reporting to have been diagnosed with a major health condition increases from 13% to 53 % over the age range 51-70 years. Similarly, prevalence rates for minor health conditions increase from 50% to over 80% over the same period.

Empirical evidence has established that financial incentives associated with the Social Security system are important determinants of the labor market exit decisions of middle-aged workers (see e.g. Stock and Wise (1990), Rust and Phelan (1997), French (2005)). However, as health is a component of individual human capital, a decline in health and functioning is likely to reduce productivity with implications for labor supply. Labor market exit thus not only reflects an individual's response to pecuniary considerations, but may also result from his capacity to be gainfully employed (see e.g. Currie and Madrian (1999) for an overview).

While health considerations are clearly relevant for labor supply, evaluating their impact is not straightforward. This partially reflects the difficulty in adequately measuring individual health and functioning. While a comprehensive set of biomarkers combined with objective physical assessments are ideal, their collection is costly and difficult to implement. Accordingly, most empirical work employs survey data, in which health measures are based on self-reports. In

[1] See Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat (2005).

[2] Following Smith (2003), the prevalence of any major condition is measured by a binary variable indicating the presence of lung disease, cancer (but not skin cancer), heart attack or stroke while having a minor condition indicates the prevalence of hypertension, diabetes, psychological problems or arthritis.

such a setting, both the endogeneity and the self-assessed nature of the responses are potential problems due to justification bias and the subjective nature of the response scales used to evaluate health.

Justification bias arises when an individual's propensity to report a work-limiting health condition depends on his actual labor market status. For example, healthy individuals may inappropriately self-report work disability to "justify" their labor market inactivity. This bias can be reduced through the use of more objective self-reported assessments of health and functioning on specific domains, which also capture the multidimensional nature of functioning and disability (Fonda and Herzog 2004). Although not entirely noncontroversial (Baker et al.2004), their use has become common in the absence of biomarkers, objective medical records or reliable health assessments by health care professionals (see Currie and Madrian 1999 for an overview). These measures are often employed as instruments for broader measures of health and disability or directly included, in some form, in econometric models, as they are widely believed to be more objective than direct questions on work-related functioning and disability (Bound et al. (1999), Dwyer and Mitchell (1999), Smith (2003), Coile (2004) or Disney et al. (2006)).

While the use of these self-reported domain-specific measures may account for justification bias, there are concerns about individual-specific response heterogeneity inherent in such self-assessments (Kerkhofs and Lindeboom (1995), Lindeboom and Kerkhofs (2002), Lindeboom and van Doorslaer (2004), Jürges (2007)). Subjective response scales reflect heterogeneity in individuals' self-assessments of their health and functional status. One strategy to restore the comparability of these self-assessments is the use of vignettes (see e.g. Tandon et al. (2001) or Kapteyn et al. (2007)). Vignettes portray the same hypothetical health states to all respondents, which can be used to translate subjective health assessments to a common scale. Their administration, however, is costly and their use is restricted, as many existing surveys do not elicit the appropriate information. An alternative approach to controlling for the subjective nature of the responses is to include in the conditioning set some variable(s), which summarizes the "average" responses of each individual. Identification of the health effects is then based on changes in within individual responses. That is, we exploit the time-variation in individual assessments conditional on the respondents' respective response scales.

In this paper, we evaluate the impact of health on labor force participation, while accounting for justification bias and subjective response scales. We do so by employing self-reported domain-specific measures of health and functioning, modelling subjective response scales as nonseparable multidimensional individual-specific effects. We exploit repeated observations for each individual to construct a semiparametric control function, which accounts for the dependence between the self-reported health assessments and any subjective responses scales by capturing the individual-specific variability in self-reported health and functioning measures. We state assumptions under which the average partial effects of health on labor market participation can be identified and estimated.

The remainder of the paper is organized as follows. Section 2 describes our econometric strategy. Section 3 introduces the data and provides the model specification. Section 4 presents the estimation results and Section 5 concludes.

2 Econometric Strategy

2.1 Model

We focus on the extensive margin of the labor supply decision of individual i at time t. We model active labor market participation as:

$$Y_{it} = g\left(D_{it}, H_{it}, \alpha_i, \varepsilon_{it}\right) \tag{1}$$

where Y_{it} is an indicator function denoting whether the individual is employed or not; D_{it} denotes a set of demographic variables; H_{it} a vector of self-reported health controls; α_i represents a vector of time-invariant unobservable individual-specific effects; and ε_{it} denotes a time-varying, possibly multidimensional unobservable error term. The unknown function $g\left(\cdot,\cdot,\cdot,\cdot\right)$ maps the respondent's observable and unobservable characteristics $\left(D_{it}, H_{it}, \alpha_i, \varepsilon_{it}\right)$ into his observed employment status Y_{it}. Our main interest is how individual health assessments H_{it} affect active labor market participation Y_{it}.

The structure of (1) permits a flexible relationship between H_{it} and Y_{it}. In addition, it allows for subjective response scales in the measurement of H_{it} by including a set of individual-specific effects α_i. The model also allows interactions between the self-assessments of health and functioning H_{it} with the unobserved individual response scales α_i, as reflected in the potential nonseparability of $g(\cdot,\cdot,\cdot,\cdot)$.

We consider *iid* data on individual units i, each observed for T periods. We group all observable and unobservable terms respectively by defining $X_{it} = (D_{it}, H_{it})$ and $\eta_{it} = (\alpha_i, \varepsilon_{it})$ and make the following main assumptions:

Assumption 1 (Exclusion Restriction). Y_{it} depends on $X_i = [X_{i1}, ...X_{iT}]$ and $\eta_i = [\eta_{i1}, ...\eta_{iT}]$ only through their contemporaneous components. That is:

$$(Y_{it} \perp X_i, \eta_i) \, | X_{it}, \eta_{it}. \tag{2}$$

Assumption 2 (One-dimensional Control Function). There exists a control function $\overline{Z_i}\gamma$, such that η_{it} and X_i are conditionally independent given $\overline{Z_i}\gamma$, i.e.

$$(\eta_{it} \perp X_i) \, |\overline{Z_i}\gamma \tag{3}$$

with $\overline{Z_i}$ known.

Assumption 3 (Structural Index Restriction). There exits a single index $X_{it}\theta$, such that Y_{it} and X_{it} are conditionally independent given $X_{it}\theta$ and η_{it}. That is:

$$(Y_{it} \perp X_{it}) \, | X_{it}\theta, \eta_{it}. \tag{4}$$

Assumption 1 states that X_i and η_i contain no information regarding Y_{it} beyond X_{it} and η_{it}. That is, conditional on the respondent's current demographic and health characteristics, neither their past nor their future realizations directly affect contemporaneous labor supply decisions.

Assumption 2 is the control function assumption.[3] It postulates conditional independence between the explanatory variables X_i and the composite error term η_{it} given an appropriately specified one-dimensional control function $\overline{Z_i}\gamma$, where $\overline{Z_i}$ represents a vector of known transformations of X_i and γ denotes an unknown parameter vector to be estimated. Assumption 2 implies

[3] Similar control function approaches have been frequently suggested to deal with endogeneity issues in various semi and nonparametric settings. Examples include Newey, Powell and Vella (1999), Imbens and Newey (2007), and Blundell and Powell (2003, 2004).

that the potential dependence between η_{it} and X_i can be controlled for by additional conditioning on specific features of the within-unit distribution of X_i. In our context, $\overline{Z_i}\gamma$ is assumed to control the dependence between the subjective response scales α_i and the corresponding self-assessments of health and functioning H_{it}. Reflecting the time-invariant nature of the individual-specific effects in α_i, $\overline{Z_i}$ will consist of location and spread measures for the within-unit distribution of the components of X_i, such as their within-unit means and variances.

This approach is similar to Altonji and Matzkin (2005), who motivate the use of external controls for endogeneity based on an exchangeability assumption on the regressors. Exchangeability implies that symmetric functions of the explanatory variables can be used as external controls for endogeneity.[4] Constructing a control function based on means as simple within-unit location measures is also familiar from previous parametric modelling approaches. Most notable are Mundlak (1978) and Chamberlain (1984).[5]

Assumption 3 imposes that the effects of the model's explanatory variables X_{it} on the outcome Y_{it} operate through a single index $X_{it}\theta$. This restriction makes estimation feasible with a nontrivial number of explanatory variables.

Using these assumptions, we can write the conditional probability of Y_{it} given X_i as:

$$\begin{aligned}
\Pr(Y_{it}=1|X_i) &= E[Y_{it}|X_i] \\
&= E[g(X_{it},\eta_{it})|X_i] \\
&= E[g^*(X_{it}\theta,\eta_{it})|X_i] \\
&= \int g^*(X_{it}\theta,\eta_{it})\,dF_{\eta_{it}|X_i} \\
&= \int g^*(X_{it}\theta,\eta_{it})\,dF_{\eta_{it}|\overline{Z_i}\gamma} \\
&\equiv H^*\left(X_{it}\theta,\overline{Z_i}\gamma\right) \qquad (5)
\end{aligned}$$

where $g^*(\cdot,\cdot)$ denotes an adapted version of the unknown function $g(\cdot,\cdot,\cdot,\cdot)$, which incorporates

[4] In fact, Altonji and Matzkin (2005) conjecture that "in actual panel data applications with exchangeability, conditioning on one or two z_i functions to capturing the location of x_i (such as the average of the elements of x_i) and the dispersion of the elements of x_i (such as the variance) will be sufficient to eliminate most of the relationship between the unobservable terms and x_{ik}" (Altonji and Matzkin (2005), p. 1079).

[5] Semykina and Wooldridge (2005) adopt a similar approach in the estimation of sample selection models with correlated random effects.

the index restrictions of Assumption 3. $H^*(\cdot,\cdot)$, in turn denotes an unknown function that only depends on the two indices $X_{it}\theta$ and $\overline{Z_i}\gamma$, and $F_{\eta_{it}|\overline{Z_i}\gamma}$ denotes the distribution of η_{it} conditional on $\overline{Z_i}\gamma$.

2.2 Object of Interest

Equation (5) implies that the structural relationship between the index $X_{it}\theta$ and the dependent variable Y_{it} depends on the control function $\overline{Z_i}\gamma$. Thus, the effects of a self-assessed functional limitation, for example, will generally depend on the response scales. This issue does not arise from our modelling strategy, but occurs because subjective assessments in themselves define events of interest. We define an "effect" of a self-assessed health or functional limitation as the mean effect of such a response, with the mean taken with respect to the *marginal* distribution of response scales in the population. We hence define the "effect" of a self-assessed limitation as its expected impact on labor force participation for an individual randomly drawn from the population. This definition is related to existing approaches to evaluating partial effects in the presence of unobserved heterogeneity (see, for example, Chamberlain 1984). It is also similar to the concept of the "average structural function" (ASF) suggested by Blundell and Powell (2003, 2004). Accordingly, we employ the term "average structural function", which is also based on integration with respect to the marginal distribution of the control function, to describe the effect which we estimate here.

More formally, we define the ASF for a specific realization of the demographic and health controls x^0 as:

$$\begin{aligned} \mu\left(x^0\right) &= \int g^*\left(X_{it}\theta,\eta_{it}\right) dF_{\eta_{it}} && (6)\\ &= \int\int g^*\left(X_{it}\theta,\eta_{it}\right) dF_{\eta_{it}|\overline{Z_i}\gamma} dF_{\overline{Z_i}\gamma} && (7)\\ &= \int H^*\left(x^0\theta,\overline{Z_i}\gamma\right) dF_{\overline{Z_i}\gamma} && (8) \end{aligned}$$

where $F_{\cdot}$ denotes cumulative distribution functions. The ASF corresponds to the expected probability of observing $\{Y_{it}=1\}$ given x^0, but replacing the conditional distribution of the error term η_{it} given x^0 by the marginal distribution of η_{it} when taking expectations. The ASF thus summarizes the average structural relationship between x^0 and Y, with the average taken with respect to the (marginal) population distribution of response scales.[6] Knowledge of the ASF is sufficient to compute average partial effects for structural changes in X, which are again based on averaging over the *marginal* distribution of response scales in the population. Specifically, the average partial effect (APE) of assigning $X = x'$ versus $X = x''$ corresponds to the difference between two ASF values and is therefore given by:

$$\begin{aligned} APE(x', x'') &= \mu\left(x''\right) - \mu\left(x'\right) && (9) \\ &= \int H^*\left(x''\theta, \overline{Z_i}\gamma\right) dF_{\overline{Z_i}\gamma} - \int H^*\left(x'\theta, \overline{Z_i}\gamma\right) dF_{\overline{Z_i}\gamma}. && (10) \end{aligned}$$

While our modelling approach is similar to Altonji and Matzkin (2005), the ASF is conceptually distinct from their main parameter of interest, the "local average response" (LAR). The LAR represents the average derivative of the dependent variable with respect to the explanatory variables at a given value x^0, keeping any correlated unobservables fixed by means of conditioning on a suitably chosen control function. Specifically, after taking the derivative of $H^*\left(x^0\theta, \overline{Z_i}\gamma\right)$ at x^0 conditional on the control function $\overline{Z_i}\gamma$, Altonji and Matzkin (2005) construct an average of these derivatives by integrating over the conditional distribution of the control function $\overline{Z_i}\gamma$ given x^0, i.e. by integrating over $dF_{\overline{Z_i}\gamma|x^0}$. Integration in the LAR therefore incorporates the dependence between the explanatory variables x^0 and the control function $\overline{Z_i}\gamma$, reflecting the local response of changing x at x^0, where the control function features the conditional distribution $dF_{\overline{Z_i}\gamma|x^0}$. The LAR thus constitutes an analog to the average effect of treatment on the treated (ATT), whereas changes in the ASF, like the APE's in (10), resemble average treatment effects (ATE's).

The ASF is an interesting object in our application, as it represents the average effect of self-assessed limitations of health and functioning on active labor market participation for the entire population rather than for a specific subpopulation defined by actually reporting a particular realization x^0. In addition, the ASF is convenient in that it only requires integration with respect to the marginal distribution of the control function. It thus avoids the more demanding estimation

[6] Note though, that identification of this "average effect" also requires that $H^*\left(x^0\theta, \overline{Z_i}\gamma\right)$ is identified for all $\overline{Z_i}\gamma$ irrespectively of the chosen x^0. We therefore need an additional common support condition, i.e. that the support of $\overline{Z_i}\gamma$ given x^0 does not depend on x^0.

of the conditional density of the control function, given the high-dimension of the regressors, which would be required to obtain the LAR. Also, the ASF has the advantage that it accommodates the nonlinear and nonseparable structure of $H^*\left(x^0\theta, \overline{Z_i}\gamma\right)$.[7] The issue here is similar to the familiar use of average partial effects rather than partial effects at the average as summary measures for heterogeneous effects of specific explanatory variables in any nonlinear and/or nonseparable model.

2.3 Estimation

Estimation of the ASF requires estimates for θ, γ and $H^*(\cdot,\cdot)$. By using (5), we a obtain double index binary choice model, which we can estimate by the semiparametric ML estimator proposed in Klein and Vella (2006).

Defining $P_{it}(\theta,\gamma) \equiv \Pr(Y_{it}=1|X_i) \equiv H^*\left(X_{it}\theta, \overline{Z_i}\gamma\right)$, the semiparametric likelihood function can be written:

$$L(\theta,\gamma) \equiv \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} l_{it}(\theta,\gamma) \tag{11}$$

where:

$$l_{it}(\theta,\gamma) \equiv \tau_{it}\left(\ Y_{it}Ln\left[P_{it}(\theta,\gamma)\right] + \left[1-Y_{it}\right]Ln\left[1-P_{it}(\theta,\gamma)\right]\ \right) \tag{12}$$

and τ_{it} denotes a trimming function. Following Klein and Vella (2006), we represent $P_{it}(\theta,\gamma)$ as:

$$P_{it}(\theta,\gamma) \equiv H^*\left(X_{it}\theta, \overline{Z_i}\gamma\right) \tag{13}$$

$$= \frac{f_1\left(X_{it}\theta, \overline{X_i}\gamma\right)}{\left(f_0\left(X_{it}\theta, \overline{X_i}\gamma\right) + f_1\left(X_{it}\theta, \overline{X_i}\gamma\right)\right)} \tag{14}$$

where $f_k(\cdot,\cdot)$ denotes the joint density of $\left(X_{it}\theta, \overline{Z_i}\gamma\right)$ and $Y_{it}=k$ with $k\in\{0,1\}$, respectively. A quasi-likelihood function can be constructed by replacing the true densities in (14) by corresponding estimates. Estimates for the index parameters (θ,γ) are then obtained by maximizing this quasi-likelihood. That is:

$$\left(\widehat{\theta},\widehat{\gamma}\right) = \underset{(\theta,\gamma)}{\arg\max}\widehat{L}(\theta,\gamma) \equiv \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{l}_{it}(\theta,\gamma) \tag{15}$$

[7] An alternative would be to simply use the average value of the control function without performing any integration, though such an object would not have an obvious interpretation in terms of treatment effects.

with

$$\widehat{l}_{it}(\theta,\gamma) = \widehat{\tau}_{it}\left(\; Y_{it}Ln\left[\widehat{P}_{it}(\theta,\gamma)\right] + [1-Y_{it}]\,Ln\left[1-\widehat{P}_{it}(\theta,\gamma)\right] \; \right) \tag{16}$$

and

$$\begin{aligned}\widehat{P}_{it}(\theta,\gamma) &= \widehat{H^*}\left(X_{it}\theta,\overline{Z}_i\gamma\right) &(17)\\ &= \frac{\widehat{f}_1\left(X_{it}\theta,\overline{Z}_i\gamma\right)}{\left(\widehat{f}_0\left(X_{it}\theta,\overline{Z}_i\gamma\right)+\widehat{f}_1\left(X_{it}\theta,\overline{Z}_i\gamma\right)\right)} &(18)\end{aligned}$$

where the hats denote estimates. A detailed discussion of the estimator is provided in Klein and Vella (2006).[8]

Given our estimated index coefficients $\left(\widehat{\theta},\widehat{\gamma}\right)$, we can compute an estimate of the ASF at a particular value x^0 as:

$$\widehat{\mu}\left(x^0\right) = \frac{1}{N}\sum_{i=1}^{N}\widehat{H^*}\left(x^0\widehat{\theta},\overline{Z}_i\widehat{\gamma}\right) \tag{19}$$

where the average is taken with respect to the marginal distribution of the estimated control function $\overline{Z}_i\widehat{\gamma}$.

3 Data and Model Specification

Our empirical analysis employs data from the 1992-2002 waves of the US Health and Retirement Study (HRS) as compiled by the RAND Corporation (RAND (2004)). The HRS consists of a nationally representative sample of around 7,600 households (12,654 individuals) with at least one household member born in the years 1931-1941. It is a longitudinal data set that started in 1992 and comprises information from biannual follow-ups. It contains extensive demographic information and many measures of health, financial position, and labor market status. Here, we only focus on patterns of labor market participation of older men and thus select all men from the original sample of reference persons. We only use age-eligible individuals with no missing observations on any variable included in the model over all six waves, except those for which the RAND files already provided imputations. This sample selection produces a balanced panel consisting of 1809 men, each observed 6 times.

[8] Closley related papers are Ichimura and Lee (1991), Ichimura (1993) and Klein and Spady (1993).

3.1 Outcome of Interest

While the underlying economic concept of active labor market participation appears straightforward, different institutional definitions and arrangements make its measurement more difficult in practice. Distinct definitions of labor market exit or retirement are often not compatible with less institutional definitions of labor supply, such as hours worked or direct questions focussing on participation.[9] To avoid issues related to particular institutional arrangements or definitions of "retirement", we follow some earlier literature (see for example, Disney et al. (2006)) and concentrate on whether the respondent is currently working for pay. This measure is not contaminated by specific institutional arrangements, such as the claiming of Social Security benefits, and is easy to understand. Moreover, its use has the additional advantage that our model can incorporate "unretirement". This aspect may be quite important, as recent evidence for the US indicates that reentry into the labor force is quantitatively important for workers of older ages (see, for example, Maestas (2005)). In addition, this choice of outcome circumvents other definitional issues that arise from different institutional arrangements, such as a detailed distinction between disability, retirement and unemployment, which often reflect differences in program eligibility rather than effective labor supply decisions (Bound and Burkhauser (1999)).

3.2 Explanatory Variables

Our empirical approach employs two indices to capture the structural effects and the correlated unobserved heterogeneity, respectively. We construct the structural index with contemporaneous variables capturing the individual's current health status and other demographic characteristics. The control index consists of within-unit location measures for the subset of subjective assessments, which feature in the structural index.

3.2.1 Structural Index

As our primary focus is the impact of health on labor market participation, the explanatory variables of most interest are contemporaneous measures of health status and functional limitations. We use multiple quasi-objective health measures to account for the multidimensional character of

[9] See e.g. Gustman and Steinmeier (2000) for a more detailed exploration of the notion of retirement based on the HRS.

personal health. That is, we use the prevalence of doctor-diagnosed major and minor conditions as a first set of quasi-objective health measures. To directly capture potential heterogeneity in the functional associations of these health conditions, we use three additional indicator variables representing the presence of any mobility limitation (walking one block, walking several blocks, walking across a room, climbing one flight of stairs, and climbing several flights of stairs), any limitation in large muscle functioning (sitting for 2 hrs, getting up from a chair, stooping, kneeling or crouching, and pushing or pulling large objects) and any limitation in activities of daily living (ADL) (bathing, dressing, eating, getting out of the bed or walking across a room), respectively. We also include an indicator for the current prevalence of depression based on the respondent's scoring on the Centre for Epidemiological Studies Depression Scale (CES-D). Specifically, we classify a respondent as suffering from depression if he scores four or more items on the abbreviated eight-item CES-D administered in the HRS.

Our choice of health controls, and the questions on which they are based, is guided by four considerations. Namely; i) no reference to the labor market; ii) quasi-objectivity; iii) differentiation of severity; and iv) inclusion of both physical and mental health. Accordingly, our chosen measures do not refer to labor supply issues, but focus on well-defined domains of health and functioning. This choice is likely to restrict the presence of justification biases. Our different measures of health and functioning also provide a reasonable degree of differentiation in severity. Finally, our model also explicitly incorporates mental health as a potentially important determinant of early labor force withdrawal (Conti et al. (2006)).

Our depression measure illustrates our approach to modelling function and mental health. We measure disability due to depression via the respondent's scores on the abbreviated CES-D rather than a question directly asking whether any form of depression limits the amount or type of work that the respondent can do. By omitting a direct reference to the respondent's labor market status in the administration of the eight CES-D items, we reduce justification bias. However, using responses on rather subjective survey items like those constituting the CES-D renders our measure vulnerable to subjective response scales. We thus use the overall individual-specific average CES-D score over the entire sample period in our construction of a semiparametric control function to account for such individual-specific propensities to score on the CES-D items.

To capture any effects of economic or family-related incentives for retirement, we also include age, race and marital status controls in our model. In addition, we include measures of educational attainment and occupational status. Finally, the model also contains a measure of the labor supply and self-rated health of the spouse. The age controls capture the potentially confounding Social Security incentives associated with labor force withdrawal at ages 62 and 65 years. At those ages, the number labor force exits tends to feature peaks beyond flexibly specified age trends, which seem largely due to inherent incentives in the Social Security system, such as pension eligibility age, the tax treatment of pensions, discontinuities in pension accrual, actuarial considerations or the illiquidity of pension wealth.[10] Similarly, our controls for marital status, spouse's labor supply and self-rated health should capture potentially confounding (nonmonetary) incentives for joint retirement and/or differences in "need of care" of the partner.[11] The latter is thereby proxied by the overall self-rated health of the partner measured on a (potentially subjective) scale ranging from 1 (excellent) to 5 (poor).

Table 1 provides summary statistics for the dependent variable and the explanatory variables in the structural index for all six waves. Our sample covers the age range between 50 and 70 years. Blacks and Hispanics comprise 13% and 7% respectively of our sample. Furthermore, there is variation in the level of attained education and approximately half of the sample report their longest occupation as manual. The table also indicates substantial prevalence rates of various health conditions and functional limitations among middle-aged men. Around two thirds of the respondents have experienced a minor health condition, and more than a quarter report a major health event. Also, around a quarter of the respondents report at least one mobility limitation, 41% some functional limitations regarding large muscle activities, while 6% report to be severely disabled, i.e. being limited in at least one ADL. The table also reveals that minor health conditions are relatively common among middle-aged men (66%), whereas major health conditions are somewhat less so (26%). Finally, around 5% of the respondents appear to suffer from serious depressive symptoms, as captured by the abbreviated CES-D.

[10] For a more detailed discussion of possible explanation for these stylized facts see e.g. Stock and Wise (1990), Rust and Phelan (1997), French (2005) and the references therein.

[11] See e.g. Gustman and Steinmeier (2004) for a fully structural model highlighting some of these issues.

3.2.2 Control Function

The role of the control function is to account for any potentially confounding effects of individual-specific response scales through the inclusion of within-unit location measures of potentially affected survey items. Specifically, we include the individual-specific means of whether the respondent is suffering any limitation in mobility, large muscle functioning or ADL, as well as whether the respondent suffers from depressive symptoms as indicated by a CES-D score higher than 4. Finally, we also include the within-unit average of the spouse's self-rated health in the control function.

Similar specifications of control functions are not uncommon in the literature. The Chamberlain-Mundlak correlated random effects probit model is arguably the most prominent example. For our application, a control function specification that solely consists of within-unit means of the controls can also be motivated by the fact that most of our explanatory variables are only binary. For Bernoulli random variables, the underlying within-unit distribution is fully characterized by its respective mean. Accordingly, focussing on within-unit location measures to construct a control function seems reasonable.

4 Results

We discuss our results in three sections. First, we present the estimates for the parameters in the structural and the control function indices, $\widehat{\theta}$ and $\widehat{\gamma}$. We then describe the estimated nonparametric link function $\widehat{H^*}(\cdot,\cdot)$, which maps these two indices into the conditional probability of active labor market participation. Finally, we present estimates for the ASF $\widehat{\mu}(\cdot)$, which summarizes the " average structural dependence" between active labor market participation and our explanatory variables, while integrating out any potentially confounding heterogeneity as captured by the control function.

Table 2 presents the coefficient estimates and their respective standard errors for both indices, noting that each index is only identified up to location and scale. For normalization, we excluded intercepts from the two indices and set the coefficients of age/10 (structural index) and average self-rated health of the spouse (control function) equal to one. As the function that maps the estimated indices into the outcome probabilities is not parametrically specified, we cannot infer the size, or even direction, of any estimated effects by simple inspection. We can, however, compare the relative contribution of the variables to each index. Doing so reveals whether or not the obtained parameter estimates appear consistent with our expectations. Higher age, both types of doctor-diagnosed health conditions and all self-reported functional limitations enter the structural index with the same sign. Furthermore, while being married or partnered shifts the structural index in the same direction as higher age or worse health, having a working spouse affects the index in the opposite way. The spouse's self-reported overall health appears to have no impact on whether the partner works for pay.

The relative sizes of the coefficients also appear reasonable. Of the physical health measures, reporting a major health condition diagnosed by a doctor has the largest effect on the structural index. Its estimated coefficient of .1 is more than three times larger than the coefficient for reporting a minor health condition (.03), and of approximately the same magnitude as that associated with reporting any mobility limitation (.08). The estimated effect of suffering from any large muscle activity limitation is smaller with an estimated coefficient of .03. Beyond the effect of suffering from restricted mobility or large muscle activity, more severe disability as measured by limitations in basic ADL's adds .03 to the structural index.

Among the health controls, a prevailing depressive episode implies the largest shift in the structural index. With a point estimate of .14, the independent effect of depression on active labor market activity is larger than the combined effect of suffering from a major and minor health condition and almost twice as large as that of a self-reported mobility limitation.

Apart from the effects of poor health, the family circumstances of the respondents also appear important for explaining labor market activity during mid-life. Having a partner who is not working increases the structural index by .11, in the same direction as age or poor health whereas having a partner who has a job reduces the index by the same amount.

So far we have only discussed the point estimates for the structural index coefficients without considering their associated statistical significance. Although our semiparametric procedure is very conservative, we nonetheless obtain reasonably precise estimates. Apart from the age controls, which are well-known to have strong effects on active labor market participation, we also find statistically significant effects for some of our health controls. Particularly, having ever been diagnosed with a major condition has a statistically significant effect. Among the physical functioning measures, self-reported mobility limitations have a statistically significant effect, despite the inclusion of its respective within-unit averages in the control function. Similarly, the structural index parameter of poor mental health is also statistically different from zero, even after controlling for the average prevalence of depression for each respondent. Finally, marital status and the respective spouse's own labor market participation behavior (if present) also enter the structural index statistically significantly.

Turning to the properties of the estimated control function index, we find that the within-unit means of any mobility and ADL limitations have a statistically significant negative effect on the control function. In contrast the within-unit mean of reporting depressive symptoms enters the model significantly with a positive sign. Thus, controlling for the within-unit location of the self-assessments of health and functioning seems nonnegligible.

As our estimation procedure does not permit any off-support prediction, it is useful to clarify the relevant support of the data, before presenting a graphical representation of the link between the indices and the probability of active labor market participation. Figure 2 presents nonparametric estimates for the joint density of the structural and control index by means of corresponding surface and contour plots. The joint density of the two indices has a peak at values of around 3.85 for the structural index and 1.75 for the control index, with most of the data falling into the rectangle given by index values of $[3.4, 4.5]$ for the structural index and $[-2; 4]$ for the control index. We should therefore focus on this region when interpreting our estimation results, as it approximately marks the support of the data.

Figure 3 presents the mapping between the two estimated indices and the probability of active labor market participation in the sample. Given the age normalization and the estimated positive index coefficients of our health limitation variables for the structural index, we would expect the probability of active labor market participation to generally decline with increasing structural index values. This is consistent with Figure 3. The slope of the estimated link function with respect to the structural index is negative throughout, irrespective of the particular value of the control index. Our estimates thus indicate that higher age as well as poorer contemporaneous health are always associated with lower probabilities of active labor market participation, regardless of the control function values. Similarly, being married to a non-working spouse also decreases the probability of labor market participation, whereas having a working partner increases the chances of active labor market participation. Overall, the estimated probabilities display fairly substantial variation over the support of the data, ranging from values larger than .9 to values smaller than .3. This is true even if we only focus on the aforementioned rectangle spanned by the structural and control indices.

The estimated control function does not appear to have a large effect on the slope of the estimated probability surface with respect to the structural index - at least up to the tails of the distribution. It does, however, have some nontrivial effect on its level, with lower values of the control function generally leading to lower levels of active labor market participation. Hence, whereas respondents who persistently report mobility and/or ADL limitations typically feature a lower probability of working for pay ceteris paribus, the reverse is true for people showing more persistently signs of depression.

Figure 4 presents our estimates for the ASF over the support of the structural index, as highlighted by its marginal density. Similar to the double index probability plots, the ASF is downward sloping in the structural index, decreasing from a value of around .9 for a structural index value of 3.5 to a value of just over .3 for a structural index of 4.5. To illustrate the average structural dependence between active labor market participation and the individual explanatory variables, Tables 3-5 present estimates of the ASF for different configurations of the explanatory variables entering the structural index. Comparing different cells of the tables hence reveals the expected structural effect of changing health and demographic characteristics of a randomly selected respondent, reflecting the analogy between changes in the ASF and ATEs, which are common parameters of interest in the treatment effects literature.

Age varies across the three tables between 58 (Table 3), 63 (Table 4), and 68 (Table 5). Each table considers respondents of different ethnical background, with varying spousal variables as well as varying physical and mental health status. Regarding the latter, we label physical health as "perfect" if the respondent does not suffer from any health condition or functional limitation, as "good", if he suffers from a minor health condition only, as "fair" if he has both a major and a minor health condition and as "poor" if he suffers from a major and a minor health condition as well as functional limitations with respect to both mobility and large muscle activities. Moreover, we also consider the case of mental health problems, both for respondents suffering from depression only as well as for respondents in "poor health" who suffer from depression as an additional comorbidity.

Reflecting our coefficient estimates and the shape of the ASF in the structural index, the tables indicate that the probability of active labor market participation varies considerably by marital status and strongly declines with age, physical and mental health. Particularly, the effects of comorbidities appear almost additive, reflecting the estimated ASF is roughly linear over most of the support of the structural index. Regarding physical health, for example, we find that when moving from "perfect" to "poor" health, around one half of the effects of poor physical health on labor market participation can be attributed to the presence of a major and minor health condition, with the other half reflecting changes in functioning (mobility and large muscle activity limitations). Similarly, we estimate a large effect of depression on labor supply, irrespective of whether it occurs on its own or as a comorbidity. Marital status and the spouses labor market status feature the expected effects, revealing incentives for "joint retirement". Finally, our estimates of the ASF are quite similar for Blacks, Hispanics, and Whites, reflecting the small coefficients of our ethnic background controls in the structural index.

5 Conclusion

We estimated the effects of health and functioning on active labor market participation using US panel data from the HRS. We address two issues that plague any empirical assessment of the health-labor supply nexus, namely justification bias and subjective response scales. To address the former, we follow a common practice in the literature and use self-reported quasi-objective health indicators. To account for the latter, we propose a semiparametric modelling framework that accommodates individual specific heterogeneity in subjective responses. We also produce estimates of "average structural effects" of self-assessed health and functioning in the presence of such reporting heterogeneity. Our results indicate that health assessments play an important role in explaining labor market exits among middle-aged men in the US. Poor physical and mental health as well as functional limitations significantly reduce the probability of active labor market participation.

We highlight that our estimation strategy does not rely on tight parameterizations and imposes relatively little structure on the model. It is applicable under fairly general conditions and does not rely on a correct specification of the parametric error distribution. Moreover, the inclusion of a nonadditive control function to capture potentially important individual specific heterogeneity reduces the variation in the explanatory variables which our estimation method can exploit. This flexibility is associated with some loss of precision in estimation. Nevertheless, we find statistically significant effects of health and functioning on the extensive margin of labor supply. Thus, previous findings appear largely robust to deviations from simple parametric modelling approaches and a more explicit consideration of potentially confounding subjective response scales.

We conclude that both physical and mental health and its associated functional limitations are important determinants of labor market exits among older American men. Thus, while financial incentives to delay retirement may be very effective among those in good health, we expect early labor market exit by individuals for whom "early retirement" represents a constraint rather than a choice.

References

Altonji, J. and R. Matzkin (2005): Cross Section and Panel Data Estimators for Nonseparable Models with Endogenous Regressors, Econometrica, 73, 1053-1102.

Baker, M., M. Stabile and C. Deri (2004): What Do Self-reported Objective Measures of Health Measure? Journal of Human Resources 39, 1067-1093.

Blundell, R. and J. Powell (2003): Endogeneity in Nonparametric and Semiparametric Regression Models, in: M. Dewatripont, L. Hansen,and S. Turnovsky (eds.): Advances in Economics and Econometrics: Theory and Applications, Eighth World Congress, Vol. II, .312-357.

Blundell, R. and J. Powell (2004): Endogeneity in Semiparametric Binary Response Models, Review of Economic Studies, 71, 655-679.

Bound, J. and R. Burkhauser (1999): Economic Analysis of Transfer Programs for People with Disability, , in: D. Card and O. Ashenfelter (eds.): Handbook of Labor Economics, Volume 3c, 3417-3528.

Bound, J. M. Schoenbaum, T. Stinebrickner and M. Waidman (1999): The Dynamic Effects of Labor Force Transitions of Older Workers, Labor Economics 6, 176-202.

Chamberlain, G. (1984): Panel Data, in: Griliches and Intrilligator (eds.): Handbook of Econometrics, Vol. 2, Chapter 22, 1247-1320.

Coile, C. (2004): Health Shocks and Couples' Labor Supply Decisions, NBER Working Paper 10810.

Conti, R., E. Berndt and R. Frank (2006): Early Retirement and Public Disability Insurance Applications: Exploring the Impact of Depression, NBER Working Paper 12237.

Currie, J. and B. Madrian (1999): Health, Health Insurance and the Labor Market, in: D. Card and O. Ashenfelter (eds.): Handbook of Labor Economics, Volume 3c, 3309-3416.

Disney, R., C. Emmerson and M. Wakefield (2006): Ill Health and Retirement in Britain: A Panel Data-based Analysis, Journal of Health Economics 25, 621-649.

Dwyer, D. and O. Mitchell (1999): Health Problems as Determinants of Retirement: Are Self-rated Measures Endogenous? Journal of Health Economics 18, 173-193.

Fonda, S. and R. Herzog (2004): Documentation of Physical Functioning Measured in the Health and Retirement Study and the Asset and Health Dynamics among the Oldest Old Study, HRS/AHEAD Documentation Report, University of Michigan, mimeo.

French, E. (2005): The Effects of Health, Wealth, and Wages on Labour Supply and Retirement Behaviour, Review of Economic Studies, 72, 395-427.

Gustman, A. and T. Steinmeier (2000): Retirement Outcomes in the Health and Retirement Study, NBER Working Paper 7588.

Gustman, A. and T. Steinmeier (2004): Social Security, Pension and Retirement Behaviour within the Family, Journal of Applied Econometrics, 19, 723-737.

Ichimura, H, (1993): "Semiparametric least squares (SLS) and weighted SLS estimation of single index models" Journal of Econometrics, 58, 71-120.

Ichimura, H. and L.F. Lee (1991): "Semiparametric least squares (SLS) and weighted SLS estimation of multiple index models: Single equation estimation", in Nonparametric and Semiparametric Methods in Econometrics and Statistics, ed. W. Barnett, J. Powell and G. Tauchen, Cambridge University Press.

Imbens, G. W. and W. K. Newey (2007), Identification and Estimation of Triangular Simultaneous Equations Models Without Additivity, MIT, mimeo.

Jürges, H. (2007): True Health vs. Response Styles: Exploring Cross-country Differences in Self-reported Health, Health Economics, 16, 163-178.

Kapteyn, A., J. Smith and A. van Soest (2007), Vignettes and Self-reported Work Disability in the US and the Netherlands, American Economic Review, 97, 461-473.

Kerkhofs, M. and M. Lindeboom (1995): Subjective Health Measures and State-dependent Reporting Errors, Health Economics 4, 221-235.

Klein, R. and R. Spady (1993): An Efficient Semiparametric Estimator for the Binary Response Model, Econometrica, 61, 387-421.

Klein, R. and F. Vella (2006): A Semiparametric Model for Binary Response and Continuous Outcomes Under Index Heteroscedasticity, IZA Working Paper 2383.

Lindeboom, M. and E. van Doorslaer (2004): Cut-point Shift and Index Shift in Self-reported Health, Journal of Health Economics, 23, 1083-1099.

Maestas, N. (2005): Back to Work: Expectations and Realizations of Work after Retirement, RAND, mimeo.

Mundlak, Y. (1978); On the Pooling of Time Series and Cross Section Data, Econometrica, 46, 69-85.

RAND (2004): RAND HRS Data, Version D. Produced by the RAND Center for the Study of Aging, with funding from the National Institute on Aging and the Social Security Administration. Santa Monica, CA.

Rust, J. and C. Phelan (1997): How Social Security and Medicare Affect Retirement Behavior in a World of Incomplete Markets, Econometrica, 65, 781-831.

Semykina, A. and J. Wooldridge (2005): Estimating Panel Data Models in the Presence of Endogeneity and Selection: Theory and Application, Michigan State University, mimeo.

Smith, J. (2003): Consequences and Predictors of New Health Events, IFS Working Paper WP03/22.

Stock, J. and D. Wise (1990): An Option Value Model of Retirement, Econometrica, 58, 1151-1180.

Tandon, A. C. Murray, J. Salomon and G. King (2001): Statistical Models for Enhancing Cross-Population Comparability, Harvard University, mimeo.

Appendix: Tables and Figures

Table 1: Summary Statistics for the Pooled HRS Data, 1992-2002

Variable	Mean	Std. dev.	Min.	Max.
Currently working for pay	0.66	0.47	0	1
Age	60.30	4.62	50	71
Age ≥62	0.40	0.49	0	1
Age ≥65	0.20	0.40	0	1
Black	0.13	0.33	0	1
Hispanic	0.07	0.25	0	1
Years of education	12.75	3.18	0	17
Longest occupation manual	0.50	0.50	0	1
Any major health condition	0.26	0.44	0	1
Any minor health condition	0.66	0.47	0	1
Any mobility limitation	0.25	0.43	0	1
Any large muscle activity limitation	0.41	0.49	0	1
Any ADL limitation	0.06	0.24	0	1
Depression (CES-D score > 4)	0.05	0.22	0	1
Respondent married or partnered	0.84	0.37	0	1
Respondent's partner working	0.47	0.50	0	1
Respondent's partner's self-rated health	2.06	1.33	0	5
Number of respondents	1809			
Number of time periods	6			

Table 2: Parameter Estimates

Variable	Parameter estimate		Standard error
Structural index			
Age/10	1.00		-------
(Age/10) squared	-0.06	***	0.011
Age ≥ 62	0.09	**	0.038
Age ≥ 65	0.02		0.025
Black	0.02		0.022
Hispanic	-0.08		0.049
Years of education	0.01		0.148
Years of Education squared	-0.04		0.057
Longest occupation manual	0.03		0.021
Any major health condition	0.10	**	0.043
Any minor health condition	0.03		0.017
Any mobility limitation	0.08	**	0.042
Any large muscle activity limitation	0.03		0.021
Any ADL limitation	0.03		0.045
Depression (CES-D score > 4)	0.14	**	0.071
Respondent married or partnered	0.11	**	0.050
Respondent's partner working	-0.22	**	0.089
Respondent's partner's self-rated health	0.00		0.008
Control function			
Average: Respondent's partner's self-rated health	1.00		-------
Average: Any mobility limitation	-3.42	***	0.427
Average: Any large muscle activity limitation	-0.07		0.463
Average: Any ADL limitation	-3.60	***	0.562
Average: Depression (CES-D score > 4)	1.14	**	0.534

*, ** and *** indicate variables that appear statistically significant at the 10%, 5% and 1% level respectively.

Table 3: Average Structural Function for Selected Health States and Demographic Characteristics at Age 58*

Black	**Physical health**				**Mental health**	**Poor physical and mental health**
Partnership status	Perfect	Good	Fair	Poor	Depression	
Single	0.77	0.75	0.68	0.58	0.66	0.46
Partner not working	0.83	0.82	0.76	0.67	0.75	0.55
Partner working	0.69	0.67	0.58	0.48	0.57	0.38
Partner not working and poor health	0.68	0.66	0.58	0.48	0.56	0.38
Hispanic	**Physical health**				**Mental health**	**Poor physical and mental health**
Partnership status	Perfect	Good	Fair	Poor	Depression	
Single	0.80	0.79	0.72	0.62	0.70	0.50
Partner not working	0.85	0.84	0.79	0.71	0.78	0.59
Partner working	0.73	0.71	0.63	0.53	0.61	0.42
Partner not working and poor health	0.73	0.71	0.63	0.53	0.61	0.41
White	**Physical health**				**Mental health**	**Poor physical and mental health**
Partnership status	Perfect	Good	Fair	Poor	Depression	
Single	0.78	0.76	0.69	0.59	0.67	0.47
Partner not working	0.84	0.83	0.77	0.68	0.75	0.56
Partner working	0.70	0.68	0.59	0.49	0.58	0.39
Partner not working and poor health	0.69	0.67	0.59	0.49	0.57	0.39

*education is evaluated its sample mean and occupation is fixed to "manual occupation"

Table 4: Average Structural Function for Selected Health States and Demographic Characteristics at Age 63*

Black	**Physical health**				**Mental health**	**Poor physical and mental health**
Partnership status	Perfect	Good	Fair	Poor	Depression	
Single	0.58	0.56	0.48	0.39	0.46	0.32
Partner not working	0.67	0.65	0.57	0.47	0.55	0.37
Partner working	0.49	0.47	0.40	0.34	0.39	0.28
Partner not working and poor health	0.49	0.46	0.40	0.33	0.38	0.28
Hispanic	**Physical health**				**Mental health**	**Poor physical and mental health**
Partnership status	Perfect	Good	Fair	Poor	Depression	
Single	0.63	0.61	0.52	0.43	0.51	0.34
Partner not working	0.72	0.70	0.62	0.52	0.60	0.41
Partner working	0.53	0.51	0.43	0.36	0.42	0.30
Partner not working and poor health	0.53	0.51	0.43	0.36	0.42	0.30
White	**Physical health**				**Mental health**	**Poor physical and mental health**
Partnership status	Perfect	Good	Fair	Poor	Depression	
Single	0.59	0.57	0.49	0.40	0.47	0.32
Partner not working	0.68	0.66	0.58	0.48	0.56	0.38
Partner working	0.50	0.48	0.41	0.34	0.39	0.28
Partner not working and poor health	0.49	0.47	0.40	0.34	0.39	0.28

*education is evaluated its sample mean and occupation is fixed to "manual occupation"

Table 5: Average Structural Function for Selected Health States and Demographic Characteristics at Age 68*

Black	**Physical health**				**Mental health**	**Poor physical and mental health**
Partnership status	Perfect	Good	Fair	Poor	Depression	
Single	0.46	0.44	0.38	0.32	0.37	0.27
Partner not working	0.56	0.53	0.45	0.37	0.44	0.31
Partner working	0.39	0.37	0.32	0.28	0.32	0.26
Partner not working and poor health	0.38	0.37	0.32	0.28	0.31	0.26
Hispanic	**Physical health**				**Mental health**	**Poor physical and mental health**
Partnership status	Perfect	Good	Fair	Poor	Depression	
Single	0.51	0.49	0.41	0.35	0.40	0.29
Partner not working	0.60	0.58	0.50	0.41	0.48	0.33
Partner working	0.42	0.41	0.35	0.30	0.34	0.26
Partner not working and poor health	0.42	0.40	0.35	0.30	0.34	0.26
White	**Physical health**				**Mental health**	**Poor physical and mental health**
Partnership status	Perfect	Good	Fair	Poor	Depression	
Single	0.47	0.45	0.39	0.33	0.37	0.28
Partner not working	0.57	0.54	0.46	0.38	0.45	0.31
Partner working	0.39	0.38	0.33	0.28	0.32	0.26
Partner not working and poor health	0.39	0.38	0.33	0.28	0.32	0.26

*education is evaluated its sample mean and occupation is fixed to "manual occupation"

Figure 1: Age Profiles for Health and Labor Force Participation, Men, HRS 1992-2002

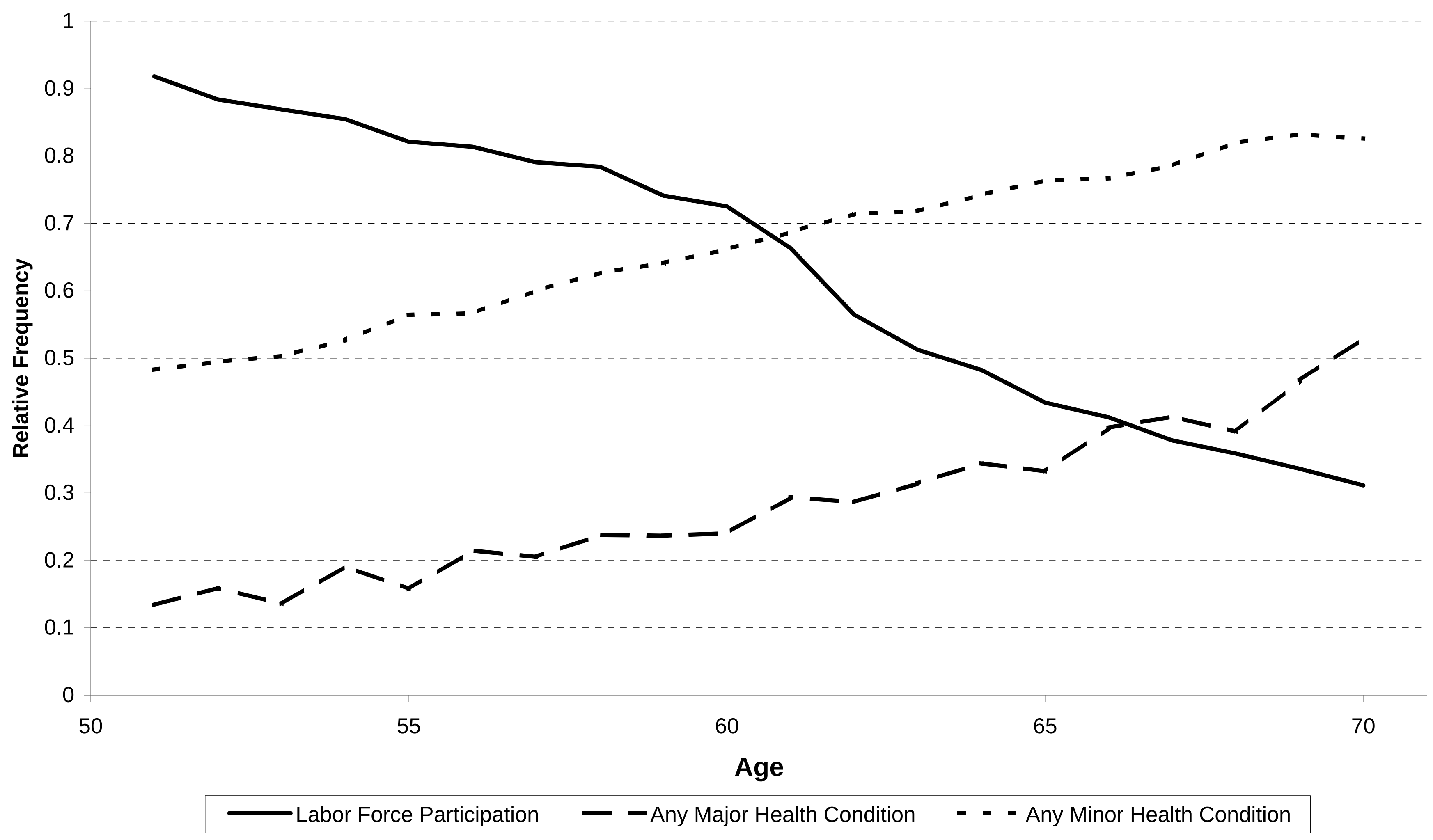
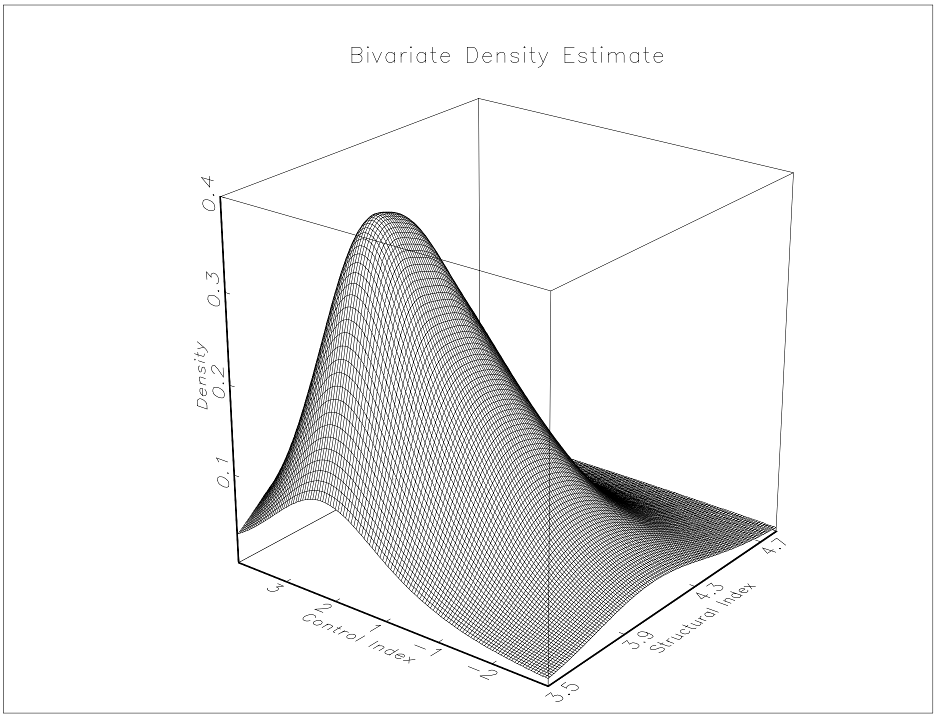


Figure 2: Density Estimates for the Two Indices

A. Surface Plot



B. Contour Plot

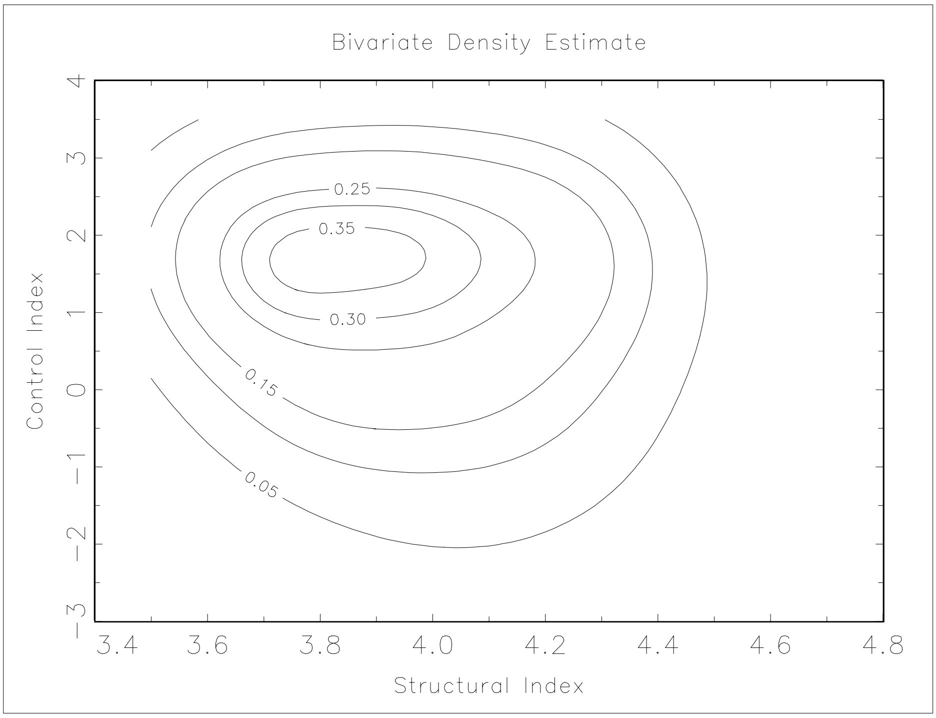
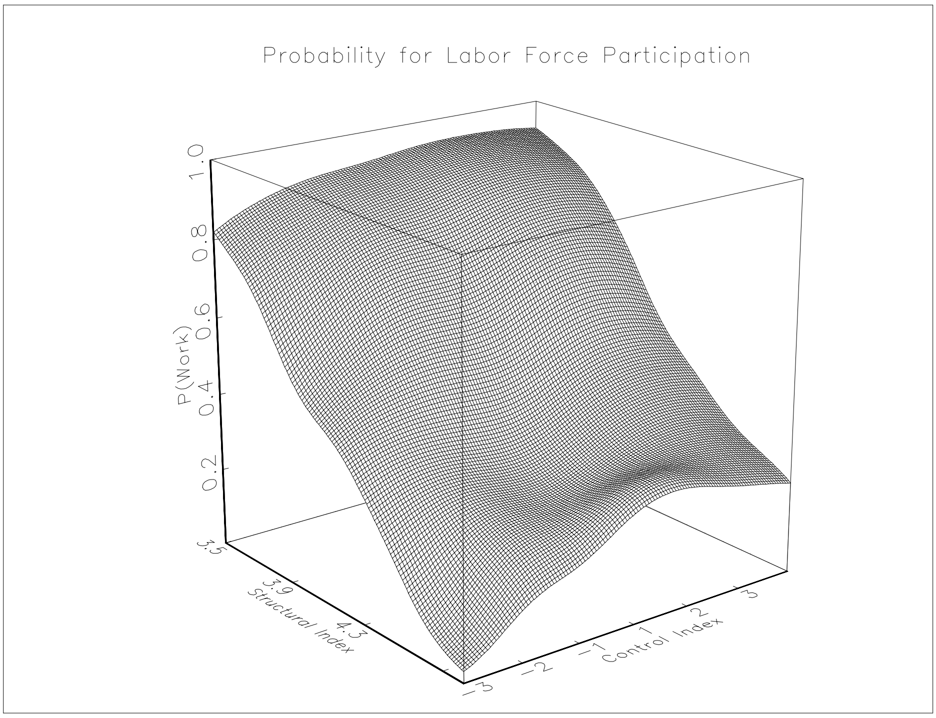


Figure 3: Estimated Labor Force Participation Probabilities

A. Surface Plot



B. Contour Plot

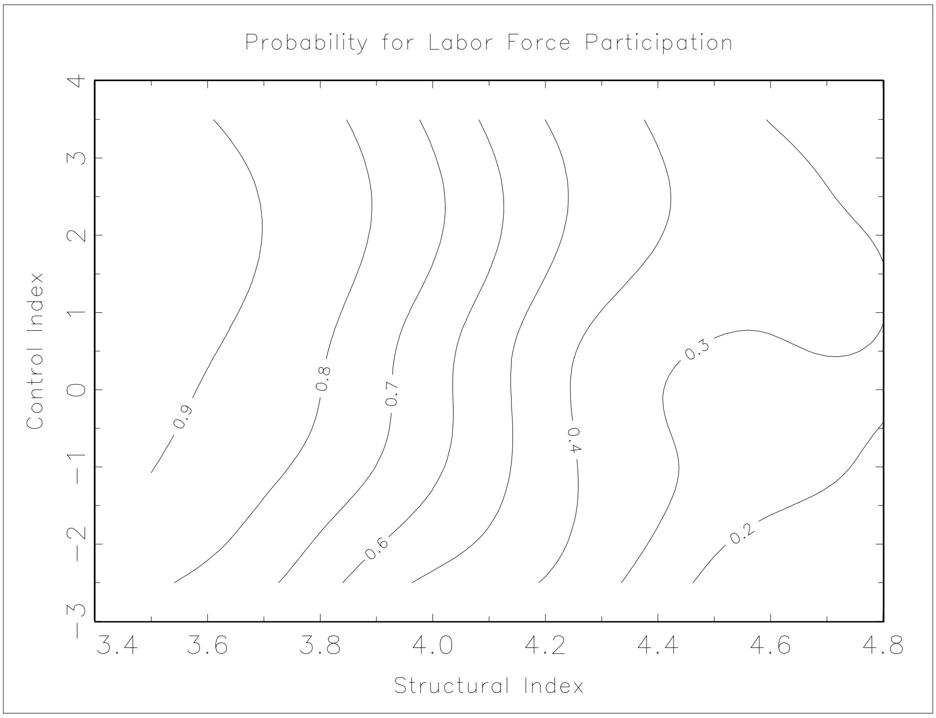
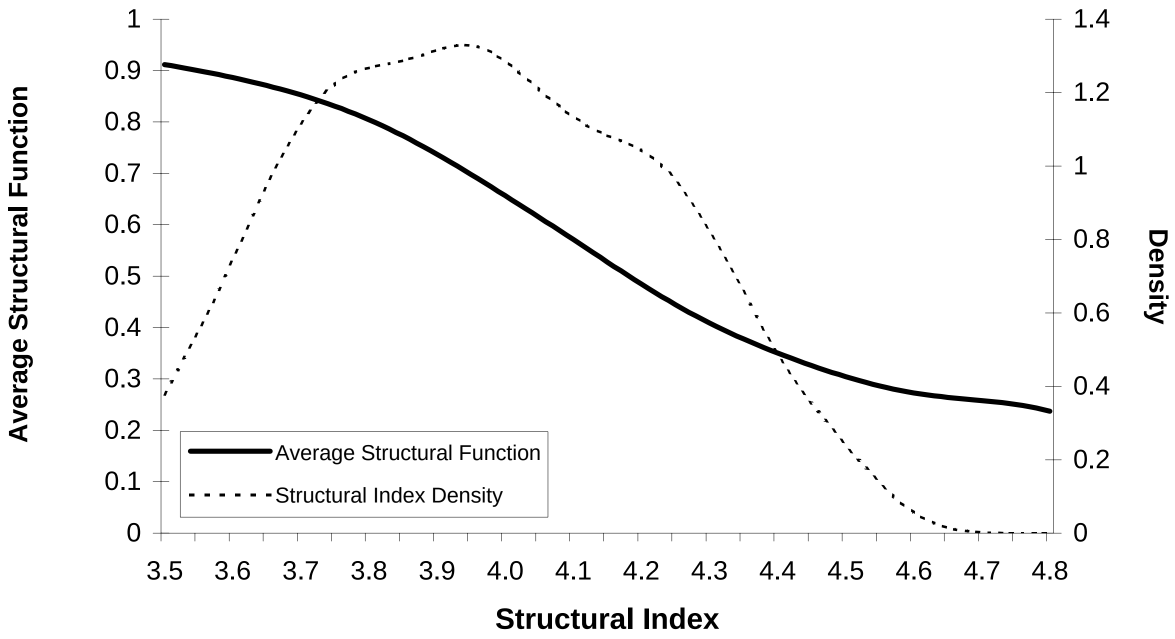


Figure 4: Average Structural Function



Discussion Paper Series

Mannheim Research Institute for the Economics of Aging Universität Mannheim

To order copies, please direct your request to the author of the title in question.

Nr.	Autoren	Titel	Jahr
157-08	Wolfgang Kuhle	Demography and Equity Premium	08
158-08	Axel Börsch-Supan, Tabea Bucher-Koenen, Anette Reil-Held, Christina Wilke	Zum künftigen Stellenwert der ersten Säule im Gesamtsystem der Alterssicherung	08
159-08	Tabea Bucher-Koenen, Christina Benita Wilke	Zur Anhebung der Altersgrenze: Eine Simulation der langfristigen Auswirkungen auf die gesetzliche Rentenversicherung bei unterschiedlichem Renteneintrittsverhalten	08
160-08	Mathias Sommer	Imputation and Harmonisation of Income, Consumption, Savings and Wealth Data from the German Income and Expenditure Survey	08
161-08	Karsten Hank	Generationenbeziehungen im alternden Europa	08
162-08	Axel Börsch-Supan, Karsten Hank, Hendrik Jürges, Mathis Schröder	Longitudinal Data Collection in Continental Europe: Experiences from the Survey of Health, Ageing and Retirement in (SHARE)	08
163-08	Martin Salm	Job loss does not cause ill health	08
164-08	Martin Salm, Daniel Schunk	The role of childhood health for the intergenerational transmission of human capital: Evidence from administrative data	08
165-08	Christina Benita Wilke	On the feasibility of notional defined contribution systems: The German case	08
166-08	Alexander Ludwig Michael Reiter	Sharing Demographic Risk – Who is Afraid of the Baby Bust?	08
167-08	Jürgen Maurer André Meier	Smooth it Like the “Joneses?” Estimating Peer-Group Effects in Intertemporal Consumption Choice	08
168-08	Melanie Lührmann Jürgen Maurer	Who wears the trousers? A semiparametric analysis of decision power in couples	08
169-08	Jürgen Maurer, Roger Klein, Francis Vella	Subjective Health Assessments and Active Labor Market Participation of Older Men: Evidence from a Semiparametric Binary Choice Model with Nonadditive Correlated Individual-specific Effects	08