Netspar Network for Studies on Pensions, Aging and Retirement

Maarten Lindeboom

A. Llena Nozal

Bas van der Klaauw

Health Shocks, Disability and Work

Discussion Paper 2007 - 026

November, 2007

Health Shocks, Disability and Work

Maarten Lindeboom[a]

Ana Llena-Nozal[b]

Bas van der Klaauw[c]

November 2007

Abstract: This paper focuses on the relation between the onset of a disability and employment outcomes. We develop an event-history model that includes accidents as a measure for health shocks and we estimate the model using data from the British National Child Development Study (NCDS). We show that experiencing such a health shock increases the likelihood of an onset of a disability by around 172%. However, accidents are relatively rare events and therefore the larger part of observed disability rates result from gradual deteriorations in health. The absence of a direct effect of accidents on employment outcomes, allows instrumenting the onset of disabilities by the occurrences of accidents. We find that onset of a disability at age 25 causally reduces the employment rate at age 40 with around 14 percentage points. The effect is stronger for males and for low educated workers. Our results indicate that about two-third of the association between disability and employment can be explained by the causal effect of the onset of a disability on employment. This fraction is higher for men and for lower educated workers.

---

[a] Free University Amsterdam, Tinbergen Institute, HEB, IZA & Netspar.
[b] OECD
[c] Free University Amsterdam, Tinbergen Institute & CEPR.

Address: Department of Economics, Free University Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, the Netherlands. Email: mlindeboom@econ.vu.nl, ana.llena-nozal@oecd.org, bklaauw@econ.vu.nl.

We would like to thank Ana Rute Cardoso, Regina Riphahn, Owen O'Donell and participants of the IZA workshop "The Older Worker", Lisbon, 2005, the iHEA world conference, Kopenhagen 2007, the European Association for Labour Economists and seminar participants at Antwerp University and the Paris School of Economics for useful comments.

1. Introduction

A substantial share of the working age population in the industrialized world suffers from a long standing illness or disability that restricts in daily activities and/or work (Dupre and Karjalainen, 2002). Disability prevalence rates are already high at relatively young ages. For instance, in the UK around 5% of the 20-24 year old have a long standing disability and this number increases to around 13% for the 40-44 year old and 28% for those aged 55-59 (Berthould, 2006). Similar disability rates are found for the US (Kapteyn et al., 2006). Disability is associated with, higher benefit take up, poverty and lower employment rates.

This paper focuses on the causal effect of the onset of a long standing illness or disability on employment. This issue is of direct importance for policies that intend to prevent the onset of disabilities and to increase the labor market prospects of people with disabilities, such as the UK's Disability Discrimination Act (DDA) or the Americans with Disability Act (ADA). Deleire (2000), Acemoglu and Angrist (2001) and Hotchkiss (2005) study the employment effects of the ADA and Bell and Heitmuller (2005) the employment effects of DDA. The size of the causal effect indicates the potential effects of such programs. Besides the disability, an individual's employment status also strongly depends on other demographic and socioeconomic factors. Therefore, for policy purposes it is important to know how much of the difference in employment rates of disabled and non-disabled workers can be ascribed to background characteristics and how much to the direct causal effect of disabilities.

The issue is also of interest for the large literature on the association between socioeconomic status (SES) and health (see e.g. Smith, 1999, for a survey). Even though many economic and epidemiological studies have established a strong positive association ('gradient') between health and SES, little is known about causal mechanisms. Assessing causal relations with observational data is non-trivial. Not only may there be direct effects of health (disability) on SES and the other way around, but also unobserved individual specific effects can relate to both health and work. Therefore, independent variation in health is required to assess its causal effect on work.

We use accidents that have caused a visit to a hospital, an outpatient facility or a casualty department as a measure for unanticipated health shocks. These accidents include for example traffic accidents, work place accidents, heart attacks and sport injuries. Such health shocks contain new information to the individual and thereby provide some unanticipated variation. We use this information to first assess the causal effect of an accident on the disability status and next use this as an instrument to assess the causal effects of a disability on employment outcomes. In our context no anticipation means that the exact timing of the accident is not known in advance. This does not rule out that individuals may be aware that at some moments the risk of experiencing an accident may be higher than in other periods, for instance because this risk depends on current employment status. Also we do not require accidents to be exogenous, conditional on observable characteristics. To be a bit more specific about the model, we construct a discrete-time discrete-choice model for accidents, disability and work. The transition rates between disability and work states can be affected by accidents and accidents can in turn be influenced by the individual's employment and disability status. The three endogenous variables of the model are related via unobserved components that remain fixed across time. Identification of this kind of models have been discussed extensively by Abbring and Van den Berg (2003) and Heckman and Navarro (2007).

Our approach relates to a growing literature that uses (natural) experiments to identify causal relations between socioeconomic status and health. For instance, Lindahl (2005) used lottery prize winners and Snyder and Evans (2002) used changes in the social security law to assess the causal effect of income on health. They find small effects of income on health. This is in agreement with Case and Deaton (2005) and Smith (2007), who conclude that the larger part of the association between health and SES at middle and older ages is driven by an effect of health on SES, rather than the other way around. Møller-Danø (2004) uses a propensity score and a difference-in-difference matching method to estimate the causal effect of road injuries on income and employment. She finds short and long-run effects of road accidents on employment status for men, but not for women. Lechner and Vasquez-Alvarez (2006) and García Gómez and López Nicolás (2006) use matching methods to identify the effects of work limitations on employment and income. Both papers find significant nagtive effects of health on employment and income. There are some studies in the development literature that use social experiments to assess the effect of health on socioeconomic outcomes. For instance, Miguel and Kremer (2004) used a randomized experiment to evaluate a program of a school-based treatment with a deworming drug in Kenya.

We estimate our model using data from the British National Child Development Study (NCDS). The NCDS is a longitudinal study of around 17,000 individuals born in Great Britain in the week of 3-9 March 1958. These individuals are followed from birth up to the year 2000, when they were 42 years old. At age 40 already about 12% of the respondents face a permanent disability and about 29% of these disabled are out of work. The results show that accidents causally increase the probability of the onset of a disability with 172%. However, because accidents are rare events, the larger part of the onset of disabilities come from a gradual deterioration in health. We find that accidents affect an individual's labor market status only indirectly through the onset of a disability. Therefore, accidents act as instrumental variables for the onset of a disability. Calculations with the model show that the causal effect of the onset of a disability at age 25 on the employment rate at age 40 is -0.144. We furthermore estimate the model for different subgroups and find large differences between males and females and high and low educated workers. Male employment rates at age 40 are about 23 percentage points reduced due to a disability, for females this is 12 percentage points. Employment rates at age 40 of low educated workers (O-level or below) are reduced with 21 percentage points, for high educated workers this is only 9 percentage points. We show that in the complete sample about two-third of the association between disability and employment can be explained by the causal effect of the onset of a disability on employment. The remaining one-third is heterogeneity. It should however be noted that for women heterogeneity is more important in explaining the association, while for men and lower educated workers the association is mainly explained by the causal effect from disability to work. This may imply that policies that aim directly at the employment effects of the disability can be effective in increasing employment rates for these groups.

The structure of the paper is as follows. Section 2 discusses the theoretical background and the empirical model. Section 3 introduces the NCDS data and reports on the variables used in the empirical part. Empirical results are discussed in Section 4. Section 5 concludes.

2. Theoretical background and the empirical model

Health production models (Grossman, 1972) or related models (e.g. Cropper, 1978, Ehrlich and Chuma, 1990, Sickles and Yazbeck, 1998 and Case and Deaton, 2003) assume that individuals inherit an initial stock of health, which depreciates with age and increases with health investments. Individuals are rational agents who include expectations about their health when making health investments (such as health care consumption and work). If health trajectories are predictable, individuals anticipate to that and change their behavior accordingly. So an observed change in labor market status that precedes a health transition can be the result of anticipated behavior rather than labor market status causally affecting health. An unforeseen shock contains new information to the individual and thereby provides some unanticipated variation in health that is unrelated to work status.

Accidents should be considered as unanticipated health shocks, which provide new information to the individual. We will be more specific about the definition of accidents in the next section when we discuss the data. An accident may cause the onset of a permanent disability of chronical condition. Here our approach differs from for example Smith (2003) and Adams et al. (2003) who use the onset of a chronic condition as a measure for health shocks. Accidents occur at different moments in life and therefore our model should be dynamic. A dynamic model also has the advantage that we can substantially relax the requirements for accidents to be valid health shocks. Within our dynamic model we do not restrict accidents to be exogenous. Instead we explicitly model the occurrence of an accident and allow unobservables to affect jointly the probability of experiencing an accident, the onset of disabilities and labor market outcomes. Unanticipation of accidents means that people cannot fully predict the exact *timing* of the occurrence of an accident. This allows identifying the causal effects of accidents on the disability and employment status without exclusion restrictions or strong functional form restrictions. Abbring and Van den Berg (2003) and Heckman and Navarro (2007) provide extensive discussions on the identification of causal effects in event-history models and discrete-time discrete-choice models, respectively. We return to identification issues after we have discussed our empirical model.

Empirical specification

The data contain individuals who were all born in the week of 3-9 March 1958. These individuals are followed from birth up to age 42. We have constructed individual labor market histories from the moment the individual leaves full-time education up to the end of the observation period. The labor market histories contain yearly information on employment status and health status. Let $S_l(t)$ denote the individual's labor market status on his/her t^{th} birthday, which can either be working (1) or non-working (0). Since we only start following individuals after leaving full-time education, non-working does not include full-time education. The variable $S_h(t)$ denotes the health status on the individual's t^{th} birthday, which can either be disabled (1) or non-disabled (0). Because we only focus on permanent disabilities (and thus ignore short-term limitations), being disabled is an absorbing state. This implies that $S_h(t+k)=1$ if $S_h(t)=1$ (for all $k=1,2,\ldots$). For each year we observe whether an individual experienced an accident, the variable $A(t)$ equals 1 if an individual experienced an accident at age t and 0 otherwise.

We observe the sequence $(S_l(T_0+1),S_h(T_0+1),A(T_0+1)),\ldots,(S_l(T_1),S_h(T_1),A(T_1))$ for an individual who leaves full-time education at age T_0 and remains participating in the surveys until age T_1. Each year the individual can move between four different states, (1) employed/non-disabled, (2) non-employed/non-disabled, (3) employed/disabled and (4) non-employed/disabled. To analyze the transitions between these states we use a discrete-time discrete-choice model, where transition probabilities depend on current and past accidents.

Accidents do not occur exogenously, for example those at work may be exposed to adverse working conditions which may increase the risk of having an accident. We allow the probability of the occurrence of an accident in time interval <t, t+1] to depend on the individual's labor market and disability status at time t, and also on observed

characteristics at time t ($x(t)$) and a time-invariant unobserved component v_a. We use a logit specification to model the probability of an accident at age t:

$$q(s_l(t), s_h(t), x(t), v_a) = \Pr(A(t)=1 \mid S_l(t)=s_l(t), S_h(t)=s_h(t), x(t), v_a) \\ = \frac{\exp(x(t)\gamma + \delta_l s_l(t) + \delta_h s_h(t) + v_a)}{1+\exp(x(t)\gamma + \delta_l s_l(t) + \delta_h s_h(t) + v_a)} \qquad (1)$$

The parameters δ_l and δ_h describe the effects of being employed and being disabled on the incidence rate of accidents, respectively. The vector of observed individual characteristics $x(t)$ includes an intercept, a set of socioeconomics characteristics and a fourth order polynomial in age. Recall that because all individuals in the data are born in the same week, the polynomial in age also includes calendar time effects such as business cycle fluctuations.

Accidents can affect the probability that individuals move between different disability and employment states in two ways. First, there is an instantaneous, effect, which we allow for by including the indicator function $A(t)$ as one of the regressors in the transition model. Second, we allow accidents to have a permanent, long-run effect. Once an individual has had an accident, this might affect his/her transition probabilities in all following years. Therefore, we define the indicator function $\bar{A}(t)$, which takes on the value 1 if the individual experienced an accident prior to age t and zero otherwise.[1] The transition probabilities between the different disability and work states are given by:

$$p_{(i,j),(k,m)}(a(t), \bar{a}(t), x(t), v_{(i,j),(k,m)}) = \Pr(S_l(t+1)=i, S_h(t+1)=j \mid \\ S_l(t)=k, S_h(t)=m, A(t)=a(t), \bar{A}(t)=\bar{a}(t), x(t), v_{(i,j),(k,m)})$$

which we parameterize again as a logit function

$$p_{(i,j),(k,m)}(a(t),\bar{a}(t),x(t),v_{(i,j),(k,m)}) =$$

$$\frac{\exp(x_t\beta_{(i,j),(k,m)}+\eta_{(i,j),(k,m)}a(t)+\mu_{(i,j),(k,m)}\bar{a}(t)+v_{(i,j),(k,m)})}{1+\sum_{(i',j')\neq(k,m)}\exp(x_t\beta_{(i',j'),(k,m)}+\eta_{(i',j'),(k,m)}a(t)++\mu_{(i,j),(k,m)}\bar{a}(t)+v_{(i',j'),(k,m)})} \quad (2a)$$

if $(i,j)\neq(k,m)$ and

$$p_{(k,m),(k,m)}(a(t),\bar{a}(t),x(t),v_{(k,m),(k,m)}) = \frac{1}{1+\sum_{(i',j')\neq(k,m)}\exp(x_t\beta_{(i',j'),(k,m)}+\eta_{(i',j'),(k,m)}a(t)+\mu_{(i',j'),(k,m)}\bar{a}(t)+v_{(i',j'),(k,m)})} \quad (2b)$$

Since disability is an absorbing state this transition probability equals 0 if *m* is disabled and *j* is non-disabled.

The parameters $\eta_{(i,j),(k,m)}$ describe the instantaneous effects of an accident on the different transition probabilities, while the parameters $\mu_{(i,j),(k,m)}$ describe the permanent effects of ever having experienced an accident. The impact of an accident can thus be different for individuals in different employment and disability states. Accidents are not only related to the transition probabilities through these effects, but we also allow for interdependence through the time-invariant unobserved heterogeneity components. The unobserved component in the accident probability v_a may be related to the unobserved components in the transitions probabilities $v_{(i,j)(k,m)}$, $\forall$ *i,j,k,m*. We use a random effects specification for the unobserved heterogeneity, and in particular a so-called factor-loading specification to allow for correlations between the different unobserved

[1] In our model this indicator remains 1 if the individual gets additional accidents.

heterogeneity terms. When estimating the model we take two random factors (w_1,w_2), which both have two discrete mass points at 0 and 1. The parameters θ_1 and θ_2 denote the probability that the variables w_1 and w_2 take the value 1, respectively. The unobserved heterogeneity terms follow

$$v_a = \alpha_{a,1} w_1 + \alpha_{a,2} w_2 \tag{3a}$$

and

$$v_{(i,j),(k,m)} = \alpha_{(i,j),(k,m),1} w_1 + \alpha_{(i,j),(k,m),2} w_2 \tag{3b}$$

The factor-loading specification implies that the term v_a equals 0 with probability $(1-\theta_1)(1-\theta_2)$, $v_a=\alpha_{a1}$ with probability $\theta_1(1-\theta_2)$, $v_a=\alpha_{a2}$ with probability $(1-\theta_1)\theta_2$ and $v_a=\alpha_{a1}+\alpha_{a2}$ with probability $\theta_1\theta_2$. The terms $v_{(i,j),(k,m)}$ are defined in a similar way. The unobserved heterogeneity could, for example, pick up the difference between white and blue-collar workers, where the blue-collar workers might have higher probabilities of being disabled and non-employed and a higher incidence rate of health shocks. The parameters α_a and $\alpha_{(i,j)(k,m)}$ determine the sign and the magnitude of the correlation between the accident rate and the transition probabilities. These parameters are estimated along with the other model parameters (as well as the parameters θ_1 and θ_2).

Identification of the model

The main parameters of interest are η and μ, describing the instantaneous and permanent effects of an accident on disability and work outcomes. Abbring and Van den Berg (2003) discuss the identification of such parameters in event-history models. Identification hinges on the assumption that individuals do not anticipate the exact moment of arrival of the accident. No anticipation in our context means that transition probabilities prior to the occurrence of an accident are not affected by the future accident and also not by the moment at which this accident will occur. For example, conditional on the observables and unobservables the transition probabilities at age 25 are the same if this individual is hit by an accident at age 26 or at age 40. The accident does not have any impact on transition probabilities prior to the moment at which the individual is actually hit by the accident. This does not imply that accidents are exogenous or that each individual has in each time period the same probability of experiencing an accident. It rather implies that individuals cannot foresee the exact moment at which an accident occurs to them. So individuals might know that in particular periods the probability of getting an accident is high, for example when they are employed or as they get older. Furthermore, the probability that an accident occurs can differ between individuals, based on both observed and unobserved characteristics.

The intuition behind the identification comes from splitting the data in two parts, (*i*) transition before individuals are hit by an accident and (*ii*) transitions after individuals have been hit by an accident. The assumption of no anticipation implies that we can identify all model parameters except η and μ from data until the moment individuals are hit by the accident, so part (*i*) of the data. Part (*ii*) of the data should thus be used to identify the parameters η and μ. Indeed identification of η and μ comes from comparing transition probabilities before and after the occurrence of the accident conditional on observables and unobservables, which have been identified by part (*i*) of the data. Whereas Abbring and Van den Berg (2003) have a continuous-time framework, Heckman and Navarro (2006) discuss a discrete-time analogue such as our model. They achieve semi-parametric identification for dynamic discrete-choice models under less strong assumptions than Abbring and Van den Berg (2003).

An accident is defined in our data by a question whether an individual had "been admitted to a hospital or attended a hospital outpatient or casualty department as a result of any kind of accident". It is clear that this measure satisfies the condition that the event can not be anticipated. It is important to note here that the UK has a National Health Care system and that in principle health care is accessible for all.[2] Of course, it remains an

[2] It is possible to buy supplemental private health insurance. This private insurance allows individuals to have more freedom in the choice of provider, to have a private room, when hospitalized and to have shorter waiting times for specialized care. Only about 15% of the individuals have private insurance.

individual decision whether or not to go to hospital after an accident. For example, an individual's socioeconomic status may affect the probability that the individual visits the hospital after having experienced an accident. Such differences are controlled for by the observed characteristics x and unobserved characteristics v_a in the model for accidents (see equation (1)).

Models equivalent to our model have been used to estimate the causal effect of active labor market policies on the reemployment of unemployed workers. Bonnal et al. (1997) estimate the causal effect of training programs for unemployed workers and Van den Berg et al. (2004) evaluate imposing punitive temporary benefits reductions on welfare recipients.

The identification results apply in our model to the effects of accidents on the disability and employment status. Our ultimate interest is in the causal effect of the onset of a disability on employment. Our empirical results presented later show that accidents do not have a direct effect on employment if the individual's health status remains unchanged. The accident thus causes some variation in the disability status, which in turn could be used to identify the causal effect of the onset of a disability on employment status. This is similar to an instrumental variable setting. We exploit this finding in our model simulations to estimate the causal effect of the onset of a disability on later employment outcomes.

Estimation

Since the model is fully parameterized, we can use maximum likelihood to estimate the parameters. For each individual, we observe the sequence of realizations ($s_l(T_0+1)$, $s_h(T_0+1)$, $a(T_0+1)$), …, ($s_l(T_1)$, $s_h(T_1)$, $a(T_1)$)). In the estimation we condition on the initial labor market status $s_l(T_0+1)$ and health status $s_h(T_0+1)$ of the individual (i.e. the moment the individual leaves full-time education). The contribution to the likelihood function of for this individual is given by:

$$\ell = \sum_{w_1, w_2 = 0}^{1} \theta_1^{\,w_1} (1-\theta_1)^{1-w_1} \theta_2^{\,w_2} (1-\theta_2)^{1-w_2} \prod_{t=T_0+1}^{T_1-1} q(s_l(t), s_h(t), x(t), \alpha_{a,1} w_1 + \alpha_{a,2} w_2)^{a(t)}$$
$$(1 - q(s_l(t), s_h(t), x(t), \alpha_{a,1} w_1 + \alpha_{a,2} w_2))^{1-a(t)}$$
$$p_{(s_l(t), s_h(t)),(s_l(t+1), s_h(t+1))}(a(t), \bar{a}(t), x(t), \alpha_{(s_l(t), s_h(t)),(s_l(t+1), s_h(t+1)),1} w_1 + \alpha_{(s_l(t), s_h(t)),(s_l(t+1), s_h(t+1)),2} w_2)$$

The total likelihood function is the sum of the logarithm of these individual likelihood contributions.

3. Data

Sample

We use the National Child Development Study (NCDS), a longitudinal study that follows about 17,000 individuals born in Great Britain in the week of 3-9 March 1958. The study started as the “Perinatal Mortality Survey” and surveyed the economic and obstetric factors associated with stillbirth and infant mortality. Since the first survey in 1958, cohort members have been traced on six other occasions to monitor their physical, educational and social circumstances. The waves were carried out in 1965 (age 7), 1969 (age 11), 1974 (age 16), 1981 (age 23), 1991 (age 33) and 1999/2000 (age 42). In addition to the main surveys, information about the public examinations was obtained from the schools in 1978. For the birth survey, information was gathered from the mother and the medical records. The interviews for wave 1 to 3 (covering age 7, 11 and 16) were carried out with parents, teachers, and the school health service; while ability tests were administered to the cohort members. The subsequent surveys included information on employment and income, health and health behavior, citizenship and values, relationships, parenting and housing, education and training of the respondents. In waves 4, 5 and 6, individuals were asked to retrospectively give information on their employment, unemployment, out-of-the-labor-force and education/training periods, recording their starting and ending dates. The NCDS is therefore highly appropriate to look at life histories.

Our model describes transitions between disability and labor market states from the moment that individuals leave full-time education. We therefore use a sample of 12,375 individuals who participated in the 1981-survey at age 23 and for who we can construct labor market, health and accident histories.[3] Case et al. (2005) investigated attrition from the survey by comparing low birth weight and father's occupation across different NCDS waves. They did not find any evidence for non-random attrition with respect to these variables. Furthermore, advisory and user support groups of the NCDS compared respondents and non-respondents in the later surveys in terms of social and economic status, education, health, housing and demographics. It was found that the distribution of these variables among the sample survivors did not differ from the original sample to any great extent (NCDS User Support, 1991). In addition, the 1981 sample was compared to the UK 1981 Population Censuses in terms of the distributions of key variables such as marital status, gender, economic activity, gross weekly pay, tenure and ethnicity (Ades, 1983). The overall conclusion was that the sample appears to be representative with respect to these variables.

Dependent variables: labor market status, disability status and accidents

<u>The labor market status</u> is measured each year in March, around the time of the birthday of the individuals. We distinguish two labor market outcomes, employed and non-employed. An individual is considered to be employed if either the individual has a full-time or part-time job, is self-employed or on maternity leave. Also an apprenticeship scheme which is part of a job is considered as employment. Currie and Hyson (1999), who use the same data to examine the long-run effect of low birth weight on educational attainment and labor market outcomes, find that their empirical results are not sensitive to the exact definition of employment. In Figures 1 and 2, we show for males and females at different ages the employment rate, the unemployment rate and the fraction of individuals out of the labor force and in full-time education. The figures show that employment rates are higher for males, that a substantial share of the females is out of the labor force and

[3] 60% of the individuals in our sample are present in wave 4 (age 23), 5 (age 33) and 6 (age 42), 28% only in wave 4 and 12% in waves 4 and 5.

that this fraction declines with age. For males the fraction of workers out of the labor force increases gradually with age. The unemployment rates are higher between the ages of 22-25, these ages coincide with a period when the UK experienced a severe recession.

We define a <u>disability/ longstanding illness</u> from the response to the following question:

Do you have any longstanding illness, disability or infirmity of any kind?

The respondents are asked to report whether they had longstanding illnesses, disabilities and infirmities for every year at around the time of their birthday. And if so, from which conditions the respondent suffered. We only consider conditions that are included in the International Classification of Diseases (ICD-9) produced by the World Health Organization (1977). The ICD-9 is extensively used in epidemiological and health management studies to classify diseases and health problems (World Health Organization, 2004). These include, for instance, serious disabilities that limit work/daily activities such as epilepsy, blindness, deafness, multiple sclerosis, mental retardation, a congenital condition, or a traumatic amputation or internal injury (see the Appendix for the complete list). We only consider an individual as disabled if the individual reports having the same longstanding illness, disability or infirmity for at least three consecutive years.[4] [5] Case et al. (2005), use responses to the question "How good is your health" and find that these self reports are strongly correlated to the question on the prevalence of long standing illnesses, disabilities and infirmities. Bajekal et al. (2004) show in a report commissioned by the UK Department for Work and Pensions that age-specific disability

[4] We added this condition to be sure that we have long lasting impairments. For instance, if an individual reports to have complications of pregnancy (code 11 in the ICD-9 classification) during one year, then the individual is not counted as permanently disabled. Disabilities listed in the ICD-9 code lasting more than 3 years are considered to be permanent. The data confirm that recovery rates after 3 years are very low.

[5] We follow our respondents up to age 42. The extra condition that the impairment should last at least three years implies therefore that in the estimation of the model we only use the disability and work history information up to the age of 40.

rates for employed workers do not vary much across surveys using different definitions for disabilities.

Figure 3 shows the fraction of individuals with a disability after age 16. Disability rates are very similar for men and women. At age 20 over 4% of the individuals in the sample has some disability. This increases up to about 12% at age 40. Some people already have long standing disabilities that started during childhood, but the majority of the disabilities started during working ages. In fact, the slope becomes somewhat steeper at older ages, which means that the hazard of the onset of a disability becomes larger as people get older.

We derive our measure for an <u>accident</u> from the following question:

> *Have you been admitted to hospital or attended a hospital outpatient or casualty department as a result of any kind of accident?*

We observe both the date of the accident and the cause.[6] Men are much more likely to experience an accident than women. In our sample, around 77% of the men had at least one accident during the observation period, while this was only about 42% for women. We follow individuals for more than two decades and therefore quite a few respondents have experienced more than one accident during this period. Not only the incidence of accidents differs between men and women, but also the cause differs. Table 1 lists accidents by cause and gender. For each cause men are much more likely to experience an accident than women. The most substantial difference in incidence rates occurs for work and sports-related accidents. Because of this large share of work-related accidents, it is particularly important in our empirical analyses to allow the accident probability to depend on labor market status. Figure 4 plots annual incidence rates by age and shows

[6] The questionnaire restricts the number of accidents that can be reported to 8 in the 1981-wave and 6 in the 1991 and 1999/2000-wave. In each wave only between 1 and 2 percent of the individuals actually reports this maximum.

that for both men and women the probability of getting an accident is relatively high until the mid-twenties and drops substantially afterwards.

We use the annual labor market status and disability status to classify each individual in each year in one of four states: (1) work and disabled, (2) non-work and disabled, (3) work and non-disabled and (4) non-work and non-disabled. In Figure 5 we show for different ages the fraction of individuals in each state. At all ages most individuals are employed and non-disabled. At later ages the fraction of individuals in the non-work non-disabled state decreases while the fractions of individuals increase in both disabled states (either with or without work). The figure shows a fall in employment rate at ages 22-25, this is in line with the observed patterns in Figure 1 and 2. Our empirical model is specified in terms of yearly transition probabilities between the four states. Table 2 provides for both men and women a summary of the yearly transitions. The table shows that there is a high degree of state dependence and that individuals are much more likely to change labor market status than disability status. The table also shows that 16.8% of the men with a disability find a job in the subsequent period. This means that there remain employment opportunities for people with a disability. However, note that this number should be contrasted with the 41.9% of non-disabled workers who find a job in the next period. For females the differences between the job-finding rate of disabled and non-disabled workers is much smaller (12.8% versus 19.3%).

Background variables

The NCDS is very rich on individual characteristics. For each individual we observe a range of variables that give information on an individual's initial health, socioeconomic status and cognitive ability during childhood. In constructing the relevant background variables we follow the definitions used by Case et al. (2005) and Currie and Hyson (1999). Table 3 provides sample means on these variables. For many variables there is some item non-response. To avoid losing many observations we follow Case et al. (2005) by constructing dummy variables that indicate if the information on a variable is missing. So if an individual's characteristics are missing, then the variables describing these characteristics take value 0 while the dummy variable indicating that these variables are missing takes value 1.

For each individual we observe the educational attainment. The level of education is derived by compiling an education variable with categories aggregated to national vocational qualification levels. We include the following categories: less than O-level, O-level equivalent, A-level equivalent and degree equivalent.

The family's socioeconomic status is derived from the father's social class at birth. The social class corresponds to a system used by the British Registrar General and consists of: professional, supervisory, skilled non-manual, skilled manual, semi-skilled non-manual, semi-skilled manual, and unskilled. We classify socioeconomic status as high if the father is in a professional, supervisory, skilled non-manual job; medium if the father is in skilled manual, semi-skilled non-manual; and low if the father is in a semi-skilled manual and unskilled job. Following Currie and Thomas (1999), we classify individuals whose father's information is missing by the mother's social class. In case the social classes of both parents are missing, we assign the individual to low socioeconomic status if the mother was single and to missing if both parents were present.

Low birth weight is a dummy variable for infants with a birth weight below 2500 grams. There is evidence from the epidemiological literature that low birth weight is strongly associated with infant and later life mortality (World Health Organization, 2004). Low weight at birth can be the result of either preterm birth (before 37 weeks of gestation) or restricted fetal growth. In the empirical analyses we do not make a distinction between these two categories. We create a dummy variable that indicates if the mother smoked after the fourth month of pregnancy. Smoking during pregnancy has been found to be related with cognitive deficiencies and other health problems in the medical and epidemiological literature (see for instance Blair et al., 1995; Conter et al., 1995; Naeye and Peters, 1984; Williams et al., 1998). Furthermore, we observe the mother's age at birth. Mother's age at the child's birth can influence the child's health through, for instance nutritional deficiencies if the mother is very young, or delivery complications if the mother is older. Therefore, in the empirical analyses we include also the mother's age at birth squared. We use the region at birth to control for geographical differences and/or differences in labor market conditions.

For each individual we observe test scores on math and social adjustment at age 7. The math test is designed for the NCDS and assesses arithmetic ability. The score ranges from 0 to 10. Currie and Thomas (1999) show that test scores at the age of 7 have significant impacts on later education attainments and labor market outcomes. The Bristol Social Adjustment Guide, is designed to assess the child's social behavior in school and at home. The test is completed by the teacher who knows the child best. Higher scores indicate higher maladjustment. The data also include information on the Southgate Reading Test. However, including this test score in our analyses did not improve our empirical results after inclusion of the math score and Bristol Social Adjustment Guide. Therefore, we decided not to use this reading test score in the analyses.

4. Results

Table 4a and 4b show the parameter estimates of our model. In Figure 6 we show some indication for the fit of our model. In this figure we compare the observed data to model predictions.[7] The model predictions manage to pick up the general life cycle trends in employment and disability. Only around age 23/24 the model has difficulties to match the fluctuations in observed employment rates.

We start with a brief discussion of the results for the mixing distribution (unobserved heterogeneity). The parameters of this distribution are reported in the lower panels of Tables 4a and 4b. Almost all parameters of the mixing distribution are highly significant, indicating the importance to allow for a stochastic relationship between disability, work and accidents. Recall from equations (3a) and (3b) that we impose a factor-loading specification with two elements that each can take on two values. For each transition we thus have four mass points. The first mass point is normalized to 0 because each model

[7] Our model describes transitions between health and labor market states after having left full-time education. We have estimated a multinomial logit model for the first state after leaving full-time education.

equation includes an intercept. Most probability mass (about 42%) is located at mass point 2, describing individuals with a low probability of experiencing accidents. Mass point 3 has less probability mass (about 10%) and describes individuals who are most likely to get an accident. It is not straightforward to detect a clear pattern in the effects of the unobservables in the transition probabilities. But compared to mass point 1, all other mass points describe individuals who are less likely to get disabled and who are more likely to stay in employment or move to employment if the health status remains unchanged.

Table 4a shows the parameter estimates from the logit specification for the probability of getting an accident. Employed individuals have about a 41% (=exp(0.342)-1) higher probability of getting an accident. Recall from Table 1 that indeed a substantial share of the accidents is work-related. The accident rate of an individual with a disability is only about 5% higher than the accident rate for a non-disabled person. Males are more than three times more likely to get an accident than females. This is also what we directly observe in the data when comparing males and females (see Table 1). Apparently, differences in background characteristics between males and females can not explain the differences in accidents rates. The age coefficients indicate that the probability of getting an accident decreases up to age 37 and increases afterwards. The socioeconomic characteristics of the parents of the cohort member all have significant impacts on the accident rate. Individuals with medium socioeconomic status and whose mother smoked during pregnancy have higher accident rates. The accident rate also increases with the age of the respondent's mother at birth. Individual characteristics are also important. We find significant effects for birth weight, region and the test scores and education. Most of these effects are in line with a priori expectations. We find a somewhat puzzling effect of the math test score at age 7. Individuals with a higher test score have higher accident rates. It should be noted, that the coefficients purely reflect associations and that one should not connect a strong causal interpretation to these findings.

Table 4b shows the parameter estimates of a multinomial logit model for the transitions between different labor market and disability states. The main parameters of interest are the parameters describing the effects of accidents on transition probabilities.

We allow accidents to have a direct instantaneous effect and a long-run effect. It can be seen from the table that the instantaneous effects are almost always larger than the long-run effect. Furthermore, the instantaneous effects of the accident are largest on the transition rates from the non-disabled states to disabled states. The estimated coefficients for transitions between employment states where the disability status remains the same are much smaller. The long-run effects mainly show that in the long-run accidents not only have an effect on the disability status, but also on the employment status.

Interpreting the coefficients separately is difficult. To illustrate the impact of an accident we therefore consider a representative individual and perform calculations with the estimated model.[8] Suppose this individual did not experience an accident until age 23. The probability that this individual is non-disabled at his/her 24th birthday is 0.933 (with standard error 0.00034 computed using the Delta method). Without experiencing an accident at age 24 the probability of becoming disabled before his/her 25th birthday is 0.0025 (s.e. 0.000062). However, if the individual did experience an accident at age 24, this probability becomes 0.0069 (s.e. 0.00015). So the accident increases the instantaneous onset of a disability with around 172% (s.e. 20%). The t-test for significance of the impact of an accident on the onset of a disability is thus 8.58, which implies that an accident not only has a very substantial effect, but the effect is also strongly significant. Not only has an accident an instantaneous effect on disability rates, but the effect is also long lasting. More specifically, if this individual does not get any other accident, then with an accident at age 24, the disability rate at age 40 is 0.141 (s.e. 0.0022). The disability rate at age 40 equals 0.128 (s.e. 0.0018) if the individual never had an accident. We can conclude from this that accidents are important for the onset of disabilities and that there are both short-run and long-run effects.

The occurrences of accidents are relatively rare events. Until age 40 men experience on average about 2.4 accidents and women only 0.8. Model calculations show that accidents can only account for about 12% of all disabilities at age 40. Hence, the larger part of long standing disabilities arises from a gradual deterioration in health. Although we should be somewhat cautious, our definition of an accident includes that it

[8] In fact, we simulate the model for all individuals and compute averages over all individuals.

should lead to a hospital, outpatient or casualty department visit. Health events that did not directly lead to hospital visits are thus included in the gradual deterioration of health. This also holds for health events that may have caused hospital care in the longer run. The distinction between gradual and sudden changes of health therefore strongly depends on the definition of the health shock variable. Of prime importance for this paper is the causal effect of the onset of a disability on employment and for this we require random variation in the timing of accidents. With this strict definition of an accident we ensure that this condition is satisfied.

The instantaneous effect of an accident on employment rates is negligible. Consider again a non-disabled 24 year old individual. We compare the situation where this individual does not experience an accident with the situation where s/he does experience an accident. To get the instantaneous effect of an accident on employment we assume that the accident does not lead to a disability (i.e. at his/her 25th birthday the individual is still non-disabled). In this case the employment rate at age 25 is 0.805 (s.e 0.0018) with the accident compared to 0.804 (s.e. 0.0018) without an accident. This difference is thus very small and not significant. There are therefore two potential ways in which an accident can affect employment in the long-run. First, the model allows for permanent effects and second the effect can run via the onset of a disability. We find that long-run direct effects of accidents on employment rates are also small. An individual who receives an accident at age 24 and who does not become disabled in later years has only a 1.1 percentage point lower employment rate at age 40 (the employment rates at age 40 falls from 0.890 (s.e 0.0020) to 0.879 (s.e. 0.0024)). Now suppose that this accident actually leads to a disability at age 25, then the employment rate at age 40 is 9 percentage point lower (the employment rate falls from 0.890 (s.e. 0.0020) to 0.799 (s.e. 0.0078)).

So from the above we can conclude that an accident causally affects disability rates both in the short and long-run. Accidents have no instantaneous and small long-run effects on employment if individual remains in good health after accident. We exploit this to estimate the causal effect of the onset of a disability on employment. In particular, we construct a simulation in which the instantaneous effect of an accident acts as instrumental variable for the onset of a disability. This implies that we turn off the permanent effect of accidents, which corresponds for example to the occurrence of a second accident to an individual. Recall that accidents have a substantial effect on the onset of a disbility and that this effect is strongly significant. Again we focus on accidents at age 24. Now with the accident as an instrument we can compute the Wald estimator for the causal effect of the onset of a disability at age 25 on the employment rate at age 40

$$\frac{\Pr(S_1(40)=1\,|\,A(24)=1,\overline{A}(24)=1)-\Pr(S_1(40)=1\,|\,A(24)=0,\overline{A}(24)=1)}{\Pr(S_h(25)=1\,|\,A(24)=1,\overline{A}(24)=1)-\Pr(S_h(25)=1\,|\,A(24)=0,\overline{A}(24)=1)}=-0.144$$

(s.e. 0.048)

The onset of a disability at age 25 causes a significant reduction in the probability of being employed at age 40 by 14.4 percentage points. This estimator exploits the estimated causal effects of the accidents on the different transition probabilities. However, it provides an estimator for individuals at the margin where an accident triggers the onset of a disability. We can compare this estimator to an alternative estimator, which is derived from taking the difference in employment rates between those who become disabled at age 25 and who do not. The reduction in employment rates at age 40 due to the onset of a disability at age 25 is 0.205 (0.00478).[9] This estimator is substantially larger and much more precise than the Wald estimator above.

Recall that the raw data do not show any differences in disability rates between males and females, but males have much higher accident risks. Also the types of accidents differ between males and females. This might also imply that accidents have different effects for males and females. Therefore, we estimate separate models for males and females. We also estimate separate models for high educated (A-level and Degree equivalent) and low educated (O-level and below). High educated and low educated individuals have different types of jobs and may work in different sectors and therefore the causal effects of the onset of a disability on employment may differ. We do not show

[9] So we use $Pr(S_l(40)=1|S_h(25)=1)$-$Pr(S_l(40)=1|S_h(25)=0)$.

the parameter estimates for these models, but only show the results from simulation experiments in Table 5.

From Table 5 we can see that there is no difference in disability rates at age 40 between men and women (column three), but that women have much lower employment rates (column two). Until age 40 men experience on average 3 times as many accidents as women (column four) and for men an accident is more likely to cause a disability (column five). This implies that for men a much larger share of the disabilities is explained by accidents. Low educated individuals have lower employment rates and higher disability rates than high educated individuals. There is no substantial difference in the accident rate of high and low educated workers, but for low educated an accident is more likely to trigger the onset of a disability.

Table 5 also shows that the causal effect of a disability on employment differs with respect to gender and education (column six). The onset of a disability has a large and significant causal effect on employment rates of male and lower educated workers. For females and higher educated workers smaller and insignificant effects are found. The relatively small and insignificant effect for females may be explained from differences in the type of jobs that men and women are holding. In our analyses we do not make a distinction between part-time and full-time work. Females are more often employed in part-time jobs and it may be easier to continue working in these jobs after the onset of a disability. Also, females have lower participation rates and the marginal working female may be different from her male counterpart. The difference between low and high educated individuals may (again) be due to the different type of jobs and characteristics of the working environment. For instance, continuing working with a chronic condition may be easier for a high educated worker in the service sector than a low educated construction worker.

Column seven of Table 5 reports the difference in employment rates between different groups of workers. This difference is derived from a direct comparison of the employment rate between disabled and non-disabled workers and thus consists of a causal impact of the disability and differences in background characteristics.[10] So this is employment gap merely reflects an association between disability and employment outcomes. For the full sample 14.4 percentage points of the 22.9 percentage point difference in employment rates between disabled and non-disabled workers is due to a causal effect. The remainder is due to different observed and unobserved background characteristics of disabled and able bodied workers. For males virtually all of the employment gap between non-disabled and disabled workers can be explained by the causal effect, whereas for females the difference in employment rate is primarily due to differences in background characteristics. This implies that for males policies directly aimed at disabled workers, such as the UK DDA or the US ADA, may be more effective than for females. For females other factors are largely explaining the association and hence policies aimed at disabled workers (like for instance workplace accommodations) may not be effective in increasing employment rates. We find similar results for the different education groups. For lower educated workers, the employment difference between non-disabled and disabled workers is substantial (about 27 percentage points) and the larger part of this employment difference can be explained by the causal effect of disability on work. This finding corresponds to Case and Deaton (2005), who argue that health related absences from work are important for the differences in socioeconomic outcomes (like income and work) and that this effect is stronger for workers in manual occupations. Indeed, we find that for higher educated workers the employment gap is much smaller (only about 11 percentage points). The larger part of this employment gap can be explained by the causal effect, but it has to be noted that the causal effect is not significantly different from zero.

5. Conclusions

In this paper we have focused on the relation between disability and employment outcomes and particularly the causal effect of disability on employment. We have

[10] More precise, we simulate our model for all workers in our sample and we compute the employment gap at age 40. This association is thus the consequence of both the causal effect of a disability and differences in observed and unobserved background characteristics.

developed an event-history model that describes transitions between disability and work states and we allowed the transitions rates to be affected by health shocks. These health shocks are endogenous in the sense that their arrival depends on the same observed and unobserved characteristics that affect the transition rates between health and employment states. As measure of the health shocks we have used accidents that caused admittance to a hospital, hospital outpatient or casualty department. We have exploited the unanticipated nature of these accidents to identify the causal effect of such shocks on the onset of a disability and subsequently the causal effect of the onset of a disability on later employment.

The empirical results show that accidents substantially increase the probability of the onset of a disability, but accidents have no direct effect on employment (if the health status remains unchanged). Even though an accident has a large effect on the onset of a disability, the fact that accidents are rare events causes that only about 12% of all disabilities at age 40 can be explained from the occurrences of accidents. The causal effect of the onset of a disability at age 25 on employment rates at age 40 is in the complete population -0.144. When estimating separate models for men and women and high and low educated individuals, we found that the onset of a disability has a much larger causal impact on the employment rates of men and low educated than their counterparts.

Finally we have compared the causal effect of the onset of a disability on employment to the association between disability and employment. The latter is the gap in employment between non-disabled and disabled workers, which includes not only the causal effect of disability on employment but also differences in observed and unobserved individual characteristics. Our analyses show that within the complete sample about two-third of the association between disabilities and employment can be explained from a causal effect of disability on employment. This percentage is much lower for women implying that for women observed and unobserved heterogeneity is the primary cause for the association between disability and employment. For males and lower educated workers the larger part of the employment gap can be explained by the causal effect of the disability on employment. This may imply that for these groups policies that aim directly at getting disabled workers back to work can be effective.

References

Abbring, J.H. and G.J. van den Berg (2003), The nonparametric identification of treatment effects in duration models. *Econometrica* **71**, 1491-1517.

Acemoglu, D. and J. Angrist (2001), Consequences of employment protection? The case of the Americans with Disabilities Act. *Journal of Political Economy* **109**, 915-957.

Adams, P., M.D. Hurd, D. McFadden, A. Merrill and T. Ribeiro (2003), Healthy, wealthy, and wise? Tests for direct causal paths between health and socioeconomic status. *Journal of Econometrics* **112**, 3-56.

Ades, T. (1983), Comparing NCDS4 to the 1981 UK Census. *National Children's Bureau*, National Child Development Studies Working Paper, Fourth Follow-up: No. 11.

Bajekal M., T. Harries, R. Breman and K. Woodfield (2004), Review of disability estimates and definitions. *Department for Work and Pensions*, IAD Social Research Division, In-house Reports 128.

Bell, D. and A. Heitmuller (2005), The disability discrimination act in the UK: helping or hindering employment amongst the disabled?. IZA working paper 1476.

Berthould, R. (2006), The employment rates of disabled people. Department for Work and Pensions, Research Report No.298.

Blair, P.S., P.J. Fleming, D. Bensley, I. Smith, C. Bacon, E. Taylor, J. Gloding and J. Tripp (1996), Smoking and the sudden infant death syndrome: results from 1993-5 case-control study for confidential inquiry into stillbirths and deaths in infancy. *British Medical Journal* **313**, 195-198.

Bonnal, L., D. Fougère and A. Sérandon (1997), Evaluating the impact of French employment policies on individual labour market histories. *Review of Economic Studies* **64**, 683-713.

Case, A. and A. Deaton (2005), Broken down by work and sex: how our health declines. In D.A. Wise (ed.), *Analyses in the Economics of Aging*, Chicago University Press.

Case, A., A. Fertig and C. Paxson (2005), The lasting impact of childhood health and circumstance. *Journal of Health Economics* **24**, 365-389.

Conter, V., I. Cortinovis, P. Rogari and L. Riva (1995), Weight growth in infants born to mothers who smoked during pregnancy. *British Medical Journal* **310**, 768-771.

Cropper, M.L. (1977), Health, investment in health, and occupational choice. *Journal of Political Economy* **85**, 1273-1294.

Currie, J. and R. Hyson (1999), Is the impact of health shocks cushioned by socioeconomic status? The case of low birth weight. *American Economic Review Papers and Proceedings* **89**, 245-250.

Currie, J. and B.C. Madrian (1999), Health insurance and the labour market. In Ashenfelter O, Card D, (ed.), *Handbook of Labor Economics 3C*. Amsterdam Elsevier North Holland.

Currie, J. and D. Thomas (1999), Early test scores, socioeconomic status and future outcomes, NBER Working Papers 6943.

Deleire, T. (2000), The wage and employment effects of the Americans with Disability Act. *Journal of Human Resources* **35**, 693-715.

Dupre, D. and A. Karjalainen (2002), Employment of disabled people in Europe, Eurostat.

Ehrlich, I and H. Chuma (1990), A model for the demand for longevity and the value of life extension. *Journal of Political Economy* **98**, 761-782.

García Gómez, P. and Á. López Nicolás (2006), Health shocks, employment and income in the Spanish labour market. *Health Economics* **15**, 997-1009.

Grossman, M. (1972), On the concept of health capital and the demand for health. *Journal of Political Economy* **80**, 223-255.

Heckman, J.J. and S. Navarro (2007), Dynamic discrete choice and dynamic treatment effects. *Journal of Econometrics* **136**, 341-396.

Hotchkiss, J. (2003), The labor market experience of workers with disabilities: the ADA and beyond. W.E. Upjohn Institute for Employment Research, Kalamazoo.

Kapteyn, A., J.P. Smith and A. van Soest (2007), Vignettes and self-reports of work disability in the United States and the Netherlands. *American Economic Review* **97**, 461-473.

Lechner, M. and R. Vasquez-Alvarez (2004), The effect of disability on labor market. Outcomes in Germany: Evidence from Matching. CEPR working paper 4223.

Lindahl, M. (2005), Estimating the effect of income on health and mortality using lottery prizes as exogenous source of variation. *Journal of Human Resources* **40**, 144-168.

Miguel E. and M. Kremer (2004), Worms: identifying impacts on education and health in the presence of treatment externalities. *Econometrica* **72**, 159-217.

Møller-Danø, A. (2005), Road injuries and long-run effects on income and employment. *Health Economics* **14,** 955 -970.

Naeye, R.L. and E.C. Peters (1984), Mental development of children whose mothers smoked during pregnancy. *Obstetric Gynecoogy* **64**, 601-607.

NCDS User Support Group (1991), *NCDS5 Report*. City University: London.

Sickles, R. C. and A. Yazbeck (1998), On the demand for leisure and the production of health. *Journal of Business and Economic Statistics* **16**, 187-197.

Smith, J.P. (1998), Socioeconomic status and health. *American Economic Review Papers and Proceedings* **88**, 192-196.

Smith, J.P. (1999), Healthy bodies and thick wallets: the dual relation between health and economic status. *Journal of Economic Perspectives* **13**, 145-166.

Smith, J.P. (2003), Consequences and predictors of new health events. NBER working paper 10063.

Snyder, S.E. and Evans, W. N. (2002), The impact of income on mortality: evidence from the social security notch. NBER working paper 9197.

Van den Berg, G.J., B. van der Klaauw and J.C. van Ours (2004), Punitive sanctions and the transition rate from welfare to work. *Journal of Labor Economics* **22**, 211-241.

Williams, G.M., M. O’Callaghan, J.M.. Najman, W. Bor, M.J. Andersen, D. Richards and U. Chinlyn (1998), Maternal cigarette smoking and child psychiatric morbidity: A longitudinal study. *Pediatrics* **102**, e11.

World Health Organization (1977), *International Classification of Diseases*, Ninth Revision. Geneva: WHO Publications.

World Health Organization (2004), *Low birth weight*. Geneva: WHO Publications.

Table 1: Yearly incidences of different types of accidents

	Male	Female
Overall	0.1199	0.0391
Road (pedestrian)	0.0018	0.0013
Road (driver)	0.0179	0.0080
Workplace	0.0398	0.0072
Home	0.0127	0.0107
Sports	0.0338	0.0047
Other	0.0139	0.0072

Table 2: Transition matrices between work and disability states by gender

	Male			
	state in year t+1			
state in year t	work/ disabled	nonwork/ disabled	work/ nondisabled	nonwork/ Nondisabled
work/disabled	95.3%	4.7%		
nonwork/disabled	16.8%	83.2%		
work/nondisabled	0.3%	0.1%	96.8%	2.8%
nonwork/nondisabled	0.3%	0.7%	41.9%	57.2%

	Female			
	state in year t+1			
state in year t	work/ disabled	nonwork/ disabled	work/ nondisabled	nonwork/ Nondisabled
work/disabled	90.3%	9.7%		
nonwork/disabled	12.8%	87.2%		
work/nondisabled	0.3%	0.0%	91.7%	7.9%
nonwork/nondisabled	0.1%	0.4%	19.3%	80.2%

Table 3: Sample mean of the individual characteristics

	Total	Male	Female
Female	50.2%		
Education (National Vocational Qualification level)			
Below O-level equivalent	26.6%	24.6%	27.7%
O-level equivalent	31.5%	27.9%	35.1%
A-level equivalent	17.1%	20.9%	13.3%
Degree equivalent	25.2%	26.6%	23.8%
Parental information at birth missing	7.3%	7.6%	7.1%
High parental socioeconomic status at birth	25.2%	25.5%	24.9%
Medium parental socioeconomic status at birth	46.7%	46.0%	47.4%
Low parental socioeconomic status at birth	20.8%	20.9%	20.6%
Mother smoked after the fourth month of pregnancy	30.5%	30.0%	31.0%
Mother did not smoke after the fourth month of pregnancy	62.2%	62.4%	61.9%
Birth information missing	5.5%	5.8%	5.3%
Mother's age at birth (in years)	27.6	27.5	27.6
Low birth weigh (less than 2500 grams)	4.8%	4.1%	5.4%
Normal birth weight (more than 2500 grams)	89.7%	90.1%	89.3%
Born in North	27.1%	26.5%	27.7%
Born in Midlands	23.5%	24.3%	22.6%
Born in South & Wales	16.3%	16.1%	16.5%
Born in Scotland	10.4%	10.0%	10.7%
Born in London & South-East	17.3%	17.3%	17.2%
Test scores at age 7 missing	12.0%	12.6%	11.5%
Math	5.2	5.3	5.1
Bristol Social Adjustment Guide	8.4	9.8	7.0
Number of observations	12375		

Table 4a: Parameter estimates of the logit model for accident probabilities

	Parameter estimates
Intercept	0.987 (0.013)
Being employed	0.342 (0.014)
Being disabled	0.048 (0.004)
Female	-1.203 (0.010)
Age (divided by 40)	-2.547 (0.006)
$(Age/40)^2$	-1.190 (0.007)
$(Age/40)^3$	0.094 (0.007)
$(Age/40)^4$	1.493 (0.008)
O-level equivalent education	0.041 (0.009)
A-level equivalent education	0.171 (0.011)
Degree equivalent education	0.041 (0.011)
Childhood background variables	
Low socioeconomic status at birth	-0.035 (0.007)
Mother smoked at pregnancy	0.076 (0.005)
Birth information missing	-0.730 (0.009)
Mother's age at birth (divided by 10)	-0.290 (0.008)
Mother's age at birth squared (divided by 100)	0.423 (0.014)
Low birth weight	-0.016 (0.004)
Born in London or South-East	0.055 (0.005)
Born in Scotland	-0.103 (0.004)
Born in South or Wales	0.007 (0.005)
Born in North	0.043 (0.005)
Born in Midlands	0
Scores at age 7 missing	0.066 (0.008)
Math score (divided by 10)	0.156 (0.008)
Bristol Social Adjustment Guide (divided by 10)	0.051 (0.005)
Parameters of the mixing distribution	
Probability 1: $\theta_1\theta_2$	0.129 (0.002)
Probability 2: $(1-\theta_1)\theta_2$	0.423 (0.005)
Probability 3: $\theta_1(1-\theta_2)$	0.105 (0.001)
Probability 4: $(1-\theta_1)(1-\theta_2)$	0.344 (0.004)
Location mass point 1	0
Location mass point 2	-0.998 (0.010)
Location mass point 3	1.204 (0.013)
Location mass point 4	0.206 (0.019)

Standard errors in parentheses

See Table 4b for the number of observations and the value of the log likelihood function

Table 4b: Multinomial logit with unobserved heterogeneity on transitions between work and disability states

From	Disabled		Nondisabled					
	Work	Nonwork	Work			Nonwork		
To	Disabled		Disabled		Nondisabled	Disabled		Nondisabled
	Nonwork	Work	Work	Nonwork	Nonwork	Work	Nonwork	Work
Intercept	-2.491 (0.010)	-1.213 (0.004)	-6.185 (0.005)	-9.216 (0.021)	-4.166 (0.014)	-3.411 (0.004)	-4.023 (0.006)	2.241 (0.025)
Instantaneous effect accident	-0.074 (0.004)	0.462 (0.003)	0.862 (0.004)	1.658 (0.006)	-0.019 (0.010)	1.021 (0.005)	0.863 (0.004)	0.045 (0.033)
Permanent effect of accident	-0.003 (0.010)	0.474 (0.006)	0.159 (0.004)	0.409 (0.005)	-0.059 (0.007)	-0.322 (0.003)	0.116 (0.005)	-0.172 (0.027)
Gender	0.922 (0.010)	-0.359 (0.010)	0.315 (0.006)	1.164 (0.005)	1.241 (0.008)	-1.450 (0.006)	-0.635 (0.005)	-1.290 (0.008)
Age (divided by 40)	-0.116 (0.004)	0.358 (0.004)	0.245 (0.006)	0.062 (0.003)	3.668 (0.035)	-0.128 (0.005)	-0.212 (0.004)	-2.595 (0.021)
$(Age/40)^2$	-0.533 (0.005)	-0.408 (0.004)	0.588 (0.005)	0.101 (0.004)	0.039 (0.009)	-0.113 (0.004)	0.302 (0.004)	-1.295 (0.006)
$(Age/40)^3$	-0.262 (0.004)	-0.450 (0.004)	0.342 (0.003)	0.381 (0.003)	-1.630 (0.011)	-0.055 (0.004)	0.328 (0.003)	0.507 (0.012)
$(Age/40)^4$	0.017 (0.004)	-0.623 (0.004)	0.219 (0.004)	0.676 (0.006)	-2.429 (0.010)	-0.035 (0.003)	0.543 (0.005)	1.513 (0.009)
O-level equivalent education	-0.265 (0.007)	-0.659 (0.007)	-0.691 (0.004)	0.666 (0.004)	0.683 (0.010)	0.869 (0.007)	-0.216 (0.004)	-0.272 (0.004)
A-level equivalent education	-0.523 (0.005)	-0.468 (0.009)	-1.121 (0.018)	-0.857 (0.016)	-0.521 (0.013)	-0.789 (0.011)	-0.913 (0.014)	0.193 (0.003)
Degree equivalent education	-0.460 (0.010)	-0.009 (0.004)	-0.171 (0.003)	0.090 (0.004)	0.291 (0.004)	0.430 (0.013)	0.524 (0.011)	0.774 (0.012)
Parental socioeconomic status at birth								
Missing	0.450 (0.003)	-0.080 (0.005)	0.448 (0.005)	0.719 (0.011)	0.347 (0.013)	-0.041 (0.003)	-0.850 (0.007)	-0.115 (0.010)
High	-0.099 (0.003)	-0.316 (0.004)	-0.085 (0.004)	-0.299 (0.004)	-0.056 (0.005)	0.314 (0.004)	-0.152 (0.003)	0.037 (0.007)
Low	0.111 (0.005)	-0.028 (0.005)	0.147 (0.003)	0.132 (0.003)	0.183 (0.005)	0.576 (0.003)	-0.235 (0.003)	-0.125 (0.010)
Mother smoking at pregnancy	0.123 (0.003)	0.007 (0.004)	0.159 (0.004)	0.358 (0.003)	0.122 (0.010)	-0.315 (0.003)	0.184 (0.003)	0.006 (0.009)
Birth info missing	0.551 (0.003)	-0.069 (0.003)	-0.514 (0.004)	-0.559 (0.006)	-0.571 (0.016)	-0.081 (0.003)	0.090 (0.007)	0.213 (0.009)
Mother's age at birth (/10)	0.193 (0.009)	0.003 (0.009)	-0.098 (0.008)	0.472 (0.007)	-0.252 (0.004)	-0.004 (0.005)	-0.062 (0.003)	0.007 (0.016)
Mother's age at Age (/10) squared	-0.029 (0.007)	-0.129 (0.009)	0.127 (0.007)	-0.691 (0.015)	0.414 (0.006)	0.048 (0.003)	0.111 (0.004)	0.033 (0.022)
Low birth weight	-0.072 (0.005)	-0.323 (0.004)	0.157 (0.003)	-0.042 (0.004)	-0.081 (0.007)	0.044 (0.003)	-0.522 (0.004)	-0.084 (0.007)
Region of residence at birth								
London	0.054 (0.003)	-0.012 (0.003)	-0.121 (0.003)	-0.336 (0.004)	-0.006 (0.004)	-0.471 (0.004)	0.138 (0.003)	-0.024 (0.004)
Scotland	0.217 (0.003)	-0.005 (0.004)	0.044 (0.003)	-0.275 (0.003)	0.236 (0.007)	0.603 (0.005)	0.167 (0.003)	-0.076 (0.004)
South & Wales	0.165 (0.004)	-0.094 (0.003)	0.179 (0.003)	0.117 (0.003)	0.030 (0.003)	0.364 (0.004)	0.070 (0.003)	-0.030 (0.005)
North	0.374 (0.004)	-0.101 (0.003)	-0.056 (0.003)	0.215 (0.003)	0.211 (0.004)	0.217 (0.004)	0.257 (0.003)	-0.055 (0.004)
Score at age 7 missing	-0.145 (0.003)	-0.441 (0.003)	0.161 (0.003)	-0.516 (0.007)	0.156 (0.004)	-0.351 (0.006)	-0.072 (0.007)	0.009 (0.013)
Math score (/10)	-0.387 (0.007)	0.118 (0.006)	-0.043 (0.004)	-0.709 (0.006)	-0.040 (0.009)	0.209 (0.004)	-0.653 (0.008)	0.088 (0.012)
Bristol social adjustment guide (/10)	0.209 (0.004)	-0.185 (0.004)	0.055 (0.004)	0.180 (0.003)	0.140 (0.013)	-0.329 (0.004)	0.101 (0.003)	-0.088 (0.009)
Parameters of the mixing distribution								
Location mass point 1	0	0	0	0	0	0	0	0
Location mass point 2	-1.518 (0.009)	0.443 (0.020)	-0.691 (0.011)	-1.104 (0.014)	-1.365 (0.014)	-0.533 (0.008)	-0.440 (0.010)	0.209 (0.096)
Location mass point 3	-1.003 (0.006)	-0.073 (0.034)	-0.065 (0.005)	-0.962 (0.009)	-0.785 (0.016)	-1.021 (0.008)	0.007 (0.004)	0.983 (0.033)
Location mass point 4	-2.521 (0.007)	0.370 (0.053)	-0.755 (0.012)	-2.066 (0.022)	-2.150 (0.013)	-1.554 (0.004)	-0.433 (0.013)	1.192 (0.088)
Number of observations	12375							
Value of the -log-likelihood	104848.05							

Table 5: Simulation experiments

	Fraction	Employment rate age 40	Disability rate age 40	Number of accidents	Effect accident on disability	Effect disability on employment	Association disability and employment
Full population	1.00	0.862	0.124	1.58	172%	-0.144 (0.048)	-0.229
Males	0.50	0.932	0.127	2.40	177%	-0.226 (0.041)	-0.234
Females	0.50	0.790	0.125	0.77	157%	-0.116 (0.124)	-0.253
Low educated	0.58	0.827	0.147	1.57	185%	-0.205 (0.045)	-0.272
High educated	0.42	0.916	0.094	1.60	169%	-0.087 (0.078)	-0.108

Note: The employment rate at age 40, the disability rate at age 40 and the number of accidents (until age 40) are based on simulating the model. The effect of an accident on the onset of a disability reflects the effect of an accident at age 24 on the disability rate at the 25th birthday. The effect of a disability on employment is the causal effect of the onset of a disability at age 25 on the employment rate at age 40 computed using the Wald estimator. And the association of disability and employment is based on simulating the model and taking the difference in employment rate at age 40 of those who were and were not disabled at age 25 (this is thus non-causal).

Figure 1: Labor market states of males.

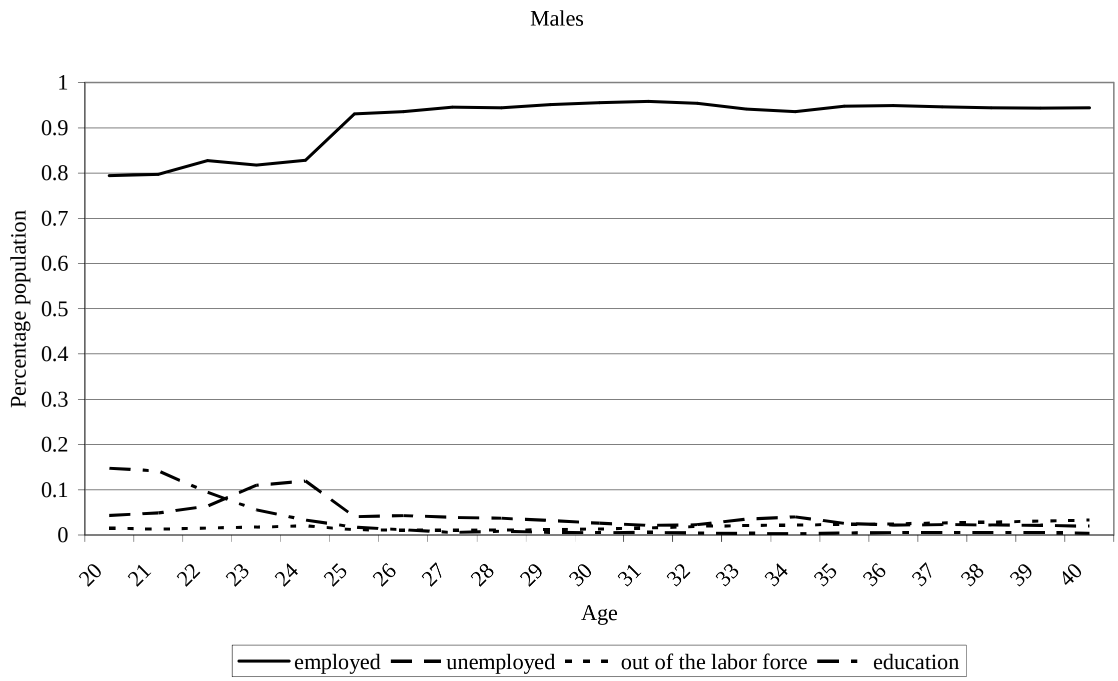


Figure 2: Labor market states of females.

Figure 3: Disability rates of males and females.

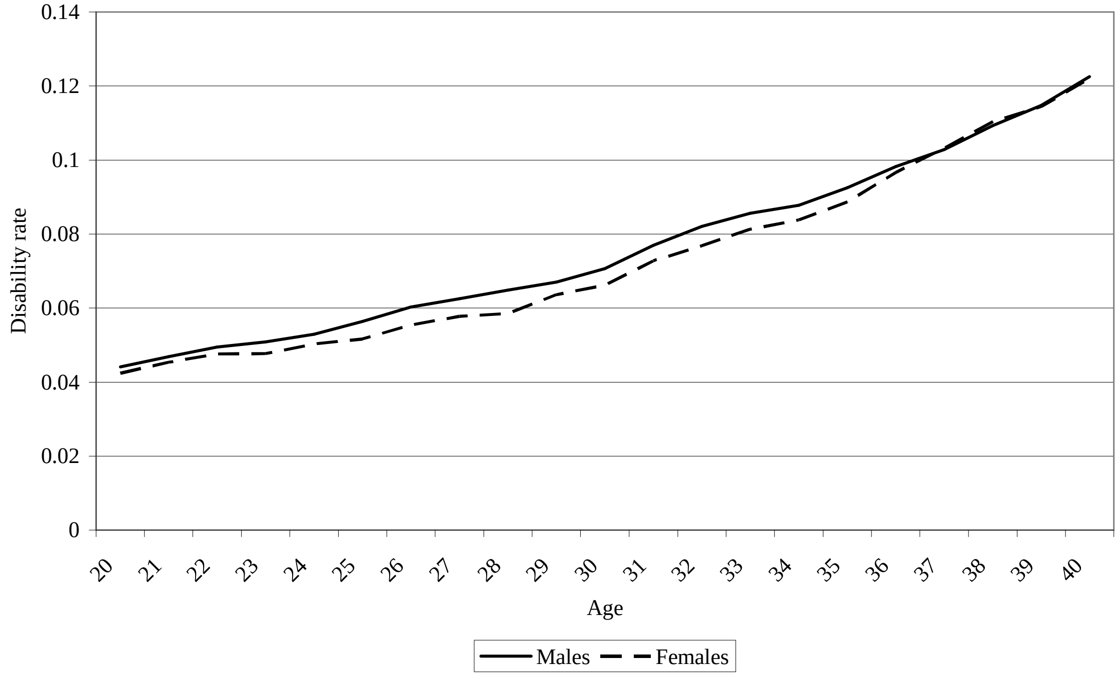


Figure 4: The annual incidence rates of accidents for males and females.

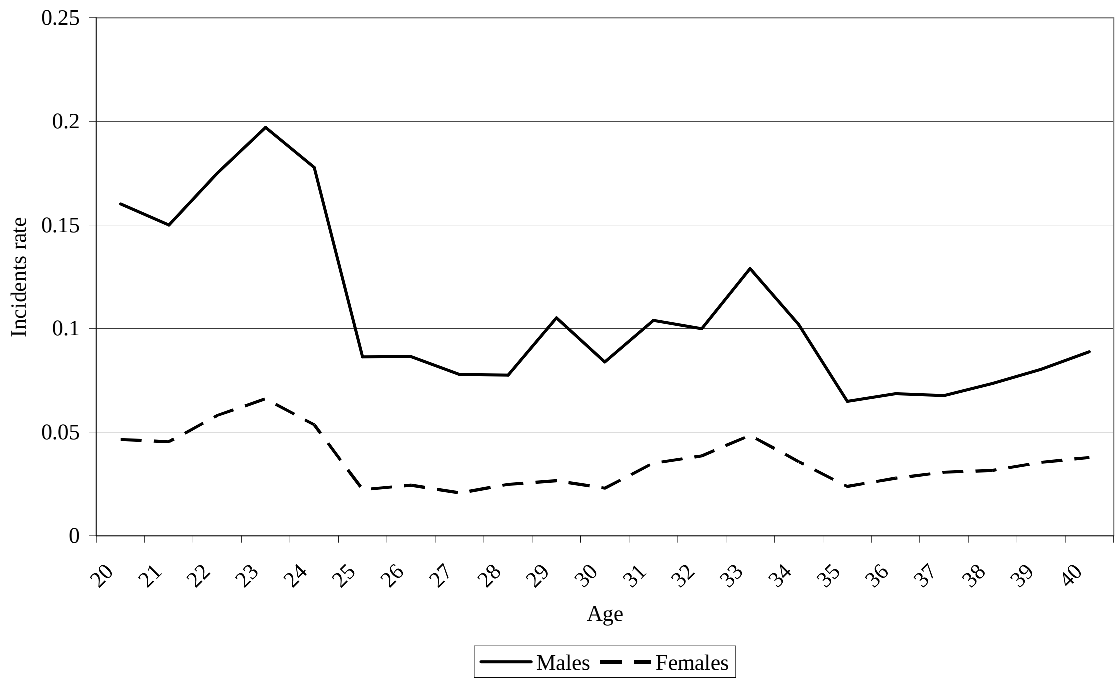


Figure 5: Disability and employment states.

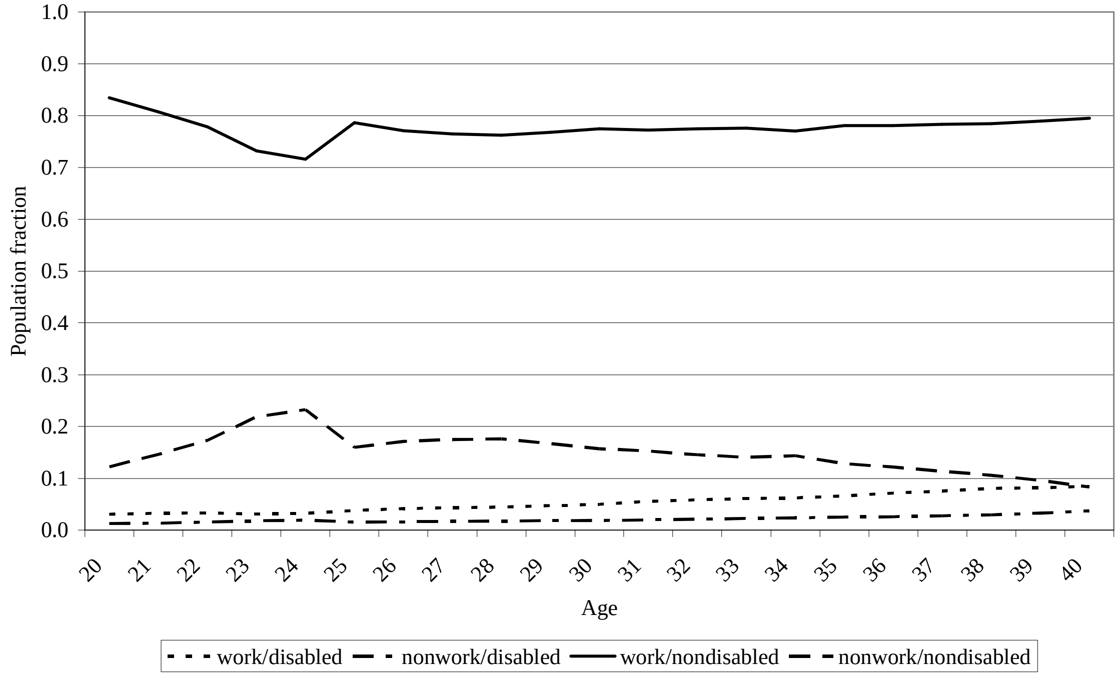
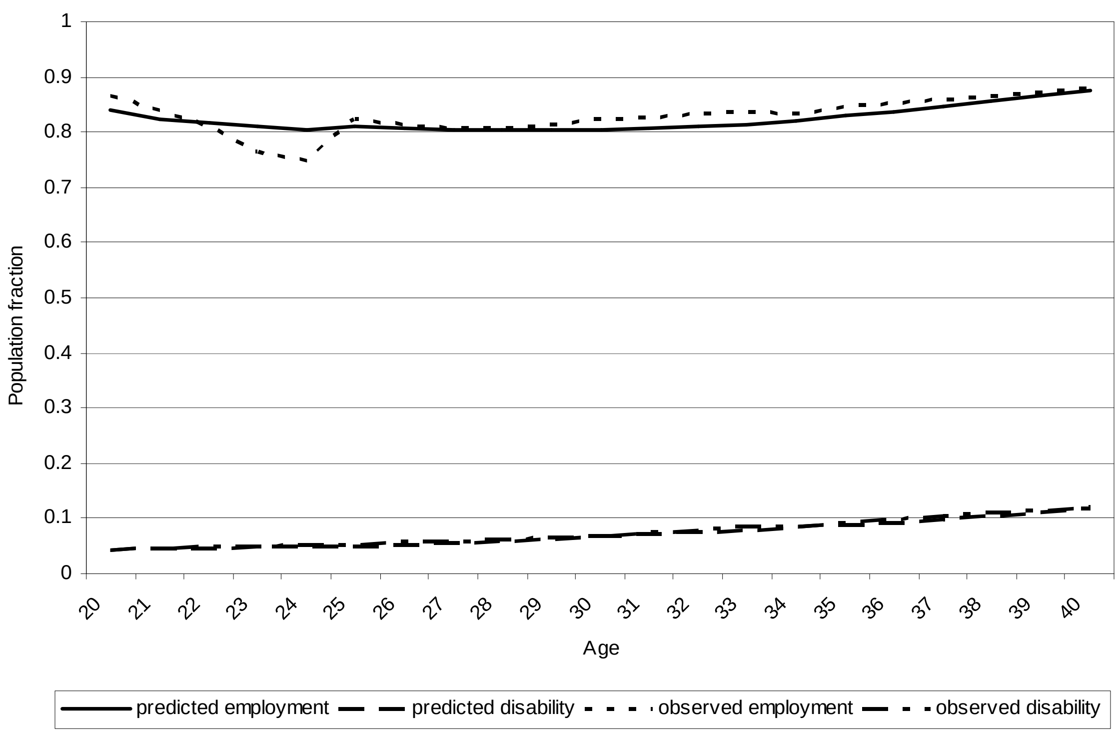


Figure 6: Fit of the model.



Appendix A: Definition of disability

We base our definition of disability on Curie and Madrian (1999) as the mental and physical characteristics that, either constrain normal daily activities, or cause a substantial reduction in productivity on the job. The NCDS data contains a set of question on health status. Individuals are asked at ages 23, 33 and 42 whether they have a longstanding illness, disability or infirmity which limits their activities compared to people their own age. They are subsequently requested to document whether it limits their daily activities or the work they can do, the age of the disability onset and the type of disability. Disability types are coded according to the international classification of disease (ICD-9) produced by the World Health Organization (1977).

The ICD is extensively used in health studies and is grouped into 17 broad categories:

1. Infections and parasitic diseases (e.g. tuberculosis, shingles, herpes simplex, glandular fever),
2. neoplasms (e.g. Hodgkin's disease, leukemia),
3. endocrine, nutritional and metabolic diseases and immunity disorders (e.g. obesity, diabetes),
4. diseases of the blood and blood-forming organs (e.g. anemia, coagulation defects),
5. mental disorders (e.g. depression, neurotic disorders, mental retardation),
6. diseases of the nervous system and sense organs (e.g. epilepsy, migraine, blindness, deafness),
7. diseases of the circulatory system (e.g. hypertension, pericarditis, aortic aneurysm),
8. diseases of the respiratory system (e.g. bronchitis, asthma, pleurisy),
9. diseases of the digestive system (e.g. duodenal ulcer, appendicitis, cirrhosis of the liver),
10. diseases of the genitourinary system (e.g. renal failure, cystitis, infertility),
11. complications of pregnancy, childbirth and the puerperium (e.g. spontaneous abortion, etopic pregnancy),
12. diseases of the skin and subcutaneous tissue (e.g. eczema, psoriasis),
13. diseases of the musculoskeletal system and connective tissue (e.g. rheumatoid arthritis, derangement of joint)
14. congenital anomalies,
15. certain conditions originating in the Perinatal period,
16. symptoms, signs and ill-defined conditions,
17. Injury and poisoning (e.g. fractures, sprains, dislocations, traumatic amputation).