Calculating compensation for loss of future earnings: Estimating and using work life expectancy*

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November 12, 2007

Abstract

Where personal injury results in displacement and/or continuing disability (or death), damages include an element of compensation for loss of future earnings. This is calculated with reference to the loss of future expected time in gainful employment. We estimate employment risks in the form of reductions to work life expectancies for the UK work force using data from the Labour Force Survey with the purpose of improving the accuracy of the calculation of future life-time earnings. Work-life expectancies and reduction factors are modelled within the framework of a multiple-state Markov process, conditional upon age, sex, starting employment state, educational attainment and disability.

Keywords:

disability-adjusted multipliers, dynamic multiple-state Markov model, Ogden Tables, personal injury compensation, work life expectancy (reduction factor)

1 Introduction

In the English law of tort, any person injured through the fault of another can claim monetary compensation for the impact of injuries sustained. The main impacts of injury in relation to loss of earnings are displacement from employment and continuing disablement. The purpose and measure of compensation is to provide financial restoration to the pre-injury position. Compensation for a future stream of losses is awarded as a lump sum capitalized to the date of settlement. The calculation of the lump sum is based upon assumptions about life expectancy (future care expenses) and work life expectancy (loss of future earnings). In this paper we present an inter-disciplinary approach, using methods from Actuarial Science and Economics,

*Principal financial support from the Economic & Social Research Council Grant RES-000-22-0883 and a further contribution by the Institute and Faculty of Actuaries Research Grant for this research study are gratefully acknowledged.

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for the estimation of the work life expectancy (WLE). Actuarial Science has been concerned with life-time risks (but not particularly in relation to labour market behaviour) and Labour Economics has been concerned with labour market outcomes (but rarely over individual life-times). Our primary interest is in the practical application of the WLE in the calculation of loss of future earnings.

In the opening part of this paper (section 2) we give a short overview of the current UK tort system of valuing compensation for loss of future earnings. For reasons of practical application within the existing law on damages, we are constrained to work within the multiplier–multiplicand method of calculation. We describe this calculation in the context of the courts' valuation of damages for loss of future earnings. Loss of earnings is measured over a future working life-time. We review a number of US studies that seek to model employment outcomes over individual life-times, including applications to future loss of earnings found in the US forensic economics literature. Research on employment in the UK is used to inform our estimation of WLEs using labour market data for the UK. The statistical concept of the WLE is central to the calculation of loss of future earnings and we introduce the statistical theory which underpins our estimates of WLEs and their associated employment-risks reduction factors (RFs).

Section 3 includes a description of the labour market data that we use and our approach to the estimation of WLEs. Mindful of the need to strike a balance between the competing objectives of rigor and accessibility, we develop two models. The first is a simple empirical model based upon observed transition probabilities in a two-state model (employed and non-employed) which is disaggregated by disability status. In this model, the WLE is calculated as a function of age, sex and disability using a spreadsheet in a way which is meaningful to lawyers. The second is a more complex empirical model based upon hazard rates (or transition intensities) estimated from labour force movements, again in a two state setting. Base line transition rates are estimated as a function of age and sex and the analysis is extended to allow for stratification on a number of additional variables, including industry, region, level of educational achievement and disability (unless otherwise stated, disability refers to that which results from the injury for which compensation is being determined). We find that, in the context of the impact of injury, education and disability are the best determinants of the WLE and we conclude our analysis by estimating their joint effects. In section 4, we present our results in the form of a set of age-specific WLEs and RFs disaggregated by sex, initial employment status, disability and level of education.

In the belief that the general principle, in terms of both methodology and consequences, can be usefully illustrated with reference to a specific example, in section 2.2 we provide an example of the existing approach to the calculation of loss of future earnings. Later in section 4.1 this example is reworked using the alternative method developed in this paper. We note that the Labour Force Survey (LFS) is not designed with the intention of estimating WLEs (or the impact of disability or educational achievement on WLEs). Hence, in section 5 we discuss a number of the potential sources of bias which might arise from the use of these data in the particular context of education- and disability-adjusted WLEs. Having made some suggestions for further research concerning the estimation of compensation for loss of earnings in section 5, we present our conclusions in section 6.

2 The multiplier–multiplicand valuation of a future loss

2.1 Background

Historically, the English Legal system has adopted a "broad brush" approach to the calculation of individual future losses with the objective of providing simplicity, certainty and consistency across cases. The intention is that lawyers should be able to undertake the calculation themselves without recourse to expert advice in each case. To this end, the application of science was often rejected in favour of judicial intuition and the precedent of decisions in past cases. The judiciary has justified this position on the basis that, "the exercise upon which the court has to embark is one which is inherently unscientific ... average life expectancy can be actuarially ascertained but to assess the probability of future political, economic and fiscal policies requires not the services of an actuary or an accountant but those of a prophet" (Lord Oliver, 1989 in Hodgeson v. Trapp [1989] 1 A.C. 833). However, the rejection of actuarial and statistical evidence as a means of guidance increases the potential for both inaccuracy and inconsistency and the courts' decisions were regularly criticized on precisely these grounds (Kemp 1997, 1999). When compared with actuarial calculations, the judiciary was found to be overly prudent in terms of applying reductions for mortality and employment risks (Haberman 1996, Luckett and Craner 1994).

Judicial discretion over compensation for future losses was curtailed in a House of Lords' decision in 1999 (Wells v. Wells [1999] 1 A.C. 345). This specified a particular formula for the calculation of all future losses and endorsed actuarial estimates concerning life expectancy and employment risks for inclusion in this formula. The formula is known as the multiplier–multiplicand calculation and it is the foundation of the calculation of loss of future earnings. As a method for calculating future loss, it remains broad brush in character and it continues to be amenable to application by lawyers.

The formula comprises the product of the multiplicand, an annual loss (annual care cost or annual lost earnings), and the multiplier, the discounted number of years over which the annual loss is payable (life expectancy or work life expectancy). The multipliers are prepared by the Government Actuary's Department in consultation with a multi-disciplinary (actuaries, accountants, lawyers) working party and are published every two years together with explanatory notes. The base-line loss of earnings multipliers represent the discounted life expectancy until final separation from the labour market (due to retirement at the statutory age or death). They are published in a set of tables disaggregated by age, sex, discount rate and year of retirement. These multipliers are referred to as Ogden Multipliers and the tables as the Ogden Tables (after the chair of the original working party Sir Michael Ogden QC). The Ogden Tables were in the Fifth Edition at the time of this study. The base-line multipliers are adjusted downwards to take account of non-mortality risks using a set of broadly defined discounted employment risks, expressed as reduction factors (RFs). The RF is simply the WLE expressed as a proportion of the remaining years until retirement (see section 2.5). The reduction factors are reported in the Supplementary Tables A, B and C of the Ogden Tables (Fifth Edition) and are based on Haberman and Bloomfield (1990). They range from 0.98 at age 20 to 0.90 at age 60, calculated at a 2.5 % discount rate, for a man retiring at age 65. It is worth noting that the RF falls as the WLE falls (ceteris paribus), and hence a high RF corresponds to a low employment risk. Employment risks are differentiated according to age group, occupational group, geographical location and level of economic activity. They are not distinguished on the basis of disability, nor are they distinguished on the basis of current employment status.

2.2 Illustration of the multiplier–multiplicand method on a case example

In the following example, we illustrate the valuation of the loss of future earnings following personal injury which makes use of the traditional multiplier–multiplicand calculation method and the risks for contingencies other than mortality contained within the Ogden Tables (Fifth edition). Later on, we return to this case example to compare this award with that calculated on the basis of a new approach proposed in this study.

Case Example

The claimant is female and aged 35 at the date of the trial. She has three *A* levels, but not a degree, and was employed as a PA in a private sector company at the date of injury at a salary of £25,000 net of tax. She had no pre-injury disability. As a result of her injuries, she now has a continuing disability and is employed at the time of the trial as a secretary in local government at an annual salary of £17,000 net of tax.

Valuation based upon the Fifth Edition Ogden Tables recommendations:

The base-line multiplier from the Fifth Edition Ogden Tables (Table 8) is 18.39 on the basis of a $2^1/_2$% discount rate. The reduction for employment risks is 0.97 (Ogden Tables: Table C).

The pre-injury expected future earnings is .... $£\,25{,}000 \times 18.39 \times 0.97 = £\,445{,}958$.

The post-injury expected future earnings is .... $£\,17{,}000 \times 18.39 \times 0.97 = £\,303{,}251$.

A typical Smith v. Manchester Corporation lump sum award
is set to 12 months post-injury earnings (see section 2.3 below) .... $= £\,17{,}000$.

The award for loss of future earnings is $(£\,445{,}958 - £\,303{,}251) + £\,17{,}000 = £\,159{,}707$.

2.3 Shortcomings of the current approach

While the use of the multiplier–multiplicand formula, and the use of the Ogden Tables, undoubtedly provides greater transparency and objectivity in comparison to legal practice before Wells v. Wells (see Judicial Studies Board 2004), a number of shortcomings remain in the method of calculation. This paper addresses those that relate to the calculation of RFs for employment risks, both before and after injury. A lack of precision in individual cases is the unavoidable cost of a "broad brush" approach. However, finding the appropriate compromise between accuracy and simplicity requires some thought about the level of error in individual cases and bias across cases. When Lewis et al. (2003) used a US-style method to re-calculate loss of future earnings damages awarded in 100 personal injury trials in the UK between 1990 and 1999, they found a wide error distribution, generalized under-compensation of claimants and particular under-compensation of certain groups of claimants; for example, young men with post-injury earning capacity. The authors also found that almost a quarter of the cases could be over-compensated when applying these adjustments to some groups of claimants. This is attributed to the RFs used in the Ogden Tables being generally too high and particularly so for women (see section 3 and Figure 2).

The majority of claimants are employed and without a disability at the time of injury and the consequences of ignoring these conditions is likely to be an overstatement of the employment risks (i.e. RFs will be too low) in the pre-injury component of the loss of earnings calculation. Conversely, since any claim for loss of future earnings has as its foundation a long-lasting work-affecting disability, employment risks which account for neither disability nor displacement from employment will tend to be too low (i.e. the RFs will be too high). This additional employment risk is recognized by the courts and an attempt is made to compensate for the resulting loss through an additional lump sum payment. This lump sum is assessed separately from the multiplier–multiplicand calculation and has come to be called a Smith v. Manchester Corporation lump sum. The award is named after the case in which the principle for such an award was established (by Lord Scarman in Smith v. Manchester Corporation [1974] K.I.R. 1). The extensive use of Smith v. Manchester Corporation lump sum awards is discussed in Randolf (2005). The determination of the value of this lump sum is particularly arbitrary. When applied to a claimant who is employed at the time of trial, it is usually in the range of 6 to 24 months of post-injury earnings (Ritchie 1994).

While the tables for the base-line multipliers are updated every two years as life expectancy and interest rates change, the RFs have remained unchanged since their original publication in 1994. These RFs are "unconditional" employment risks and they ignore the importance of past employment status as a determinant of current employment status. It is now possible, and indeed is common practice, to incorporate the transitions between different employment states which characterize the typical employment history, into the estimation of the WLE. Using information on individual transitions between employment states, we use a Markov chain model to "condition" future employment patterns on current employment states. This is particularly relevant to the present context because most claimants are in employment at the time of injury and suffer employment interruptions as a result of injury. This is clearly illustrated in the Lewis et al. (2003) study where, out of 100 claimants, 96 were over the school leaving age and were employed at the time of injury, 63 of these were judged to have post-injury earning capacity but only 28 were in employment after their injury.

Currently, the Ogden Tables contain some recommendations (based on the estimates reported in the Haberman and Bloomfield 1990 study) which attempt to account for the potential impact of occupational group, regional location and level of economic activity on employment risks. We re-examine the influence of each of these, and also the impact of educational attainment, and review the benefits of making adjustments for each. Some recent US studies indicate that following the onset of disability immediate losses are greater and longer-term recovery is lower, in terms of both income and employment, for those with low levels of education (see for example Charles 2003). Disability and displacement will also impact negatively on earnings (see Gregory and Jukes 1997 for UK and Kuhn 2002 for US). This latter impact is accounted for in the reduced post-injury multiplicand which the court determines on the basis of evidence from employment consultants (see Martin 1999 for forensic economic approaches to the estimation of post-injury base-line earnings).

Importantly, the Ogden Tables offer no recommendations on how to account for the impact of disability on employment risks and we have seen that the courts deal with the issue in a peculiarly imprecise and *ad hoc* manner, which has neither empirical nor theoretical foundation. From 1998, there is sufficient information available in LFS data to calculate WLEs and RFs according to disability status and thus to incorporate the employment effects of disability within the multiplier–multiplicand calculation. We propose that employment-risks RFs be calculated separately for individuals who are disabled and that these be applied to the base-line multiplier to produce a *"disability-adjusted multiplier"* in the calculation of post-injury future earnings. We apply this method of calculation for the worked example in 2.2 again in section 4.1 and we suggest that this alternative method of calculation should replace the Smith v. Manchester Corporation approach in the majority of cases.

2.4 Estimating working life-times

While there has been intense socio-economic research conducted into the causes and effects of unemployment and non-participation in the UK (see Verrall et al. 2005), there has been very little interest in estimating labour market risks for the purposes of legal compensation. Although most of the applied modelling approaches are relevant in their own right, and indeed some could be extended to the problem of estimating employment risks over individual life-times, such work has yet to be completed in the UK. The dynamic modeling of employment decisions developed in the USA from the early 1980s (see for example MaCurdy 1981, 1983 and Smith 1983). These "life-cycle" models of labour supply sought to provide a theoretical context to explain the consistent inverted 'u'-shaped participation and hours profiles with respect to age found in empirical studies. The focus at both the theoretical and empirical levels has been the behaviour of hours of work, although the Work Life Tables of Smith (1982) for the US Bureau of Labour Statistics (BLS) provide age-related estimates of life time employment.

The first attempt to estimate life-time employment risks for the UK was undertaken by the actuarial profession in the context of the valuation of loss of earnings in England and Wales (see section 2.1). The study was undertaken by Haberman and Bloomfield (1990) and their results were presented as a set of actuarial RFs which capture the effect of contingencies other than mortality on the discounted number of years to retirement or death. At the time of this study, the modelling of employment outcomes in the UK was limited to static approaches which were based on age-specific prevalence rates. The authors made use of a traditional actuarial tool to construct a working life table based on adjusted labour force participation rates from the 1970s and 1980s, allowing for sickness and unemployment. The authors were well aware of the limitations of the data and the static methodology that was used. They considered that, compared to the multiple state approach advocated by Hoem (1977), their employment risks were understated by as much as 8 %. To date, no other estimates of life-time employment risks have been produced in the UK to replace these early recommendations.

Since the Haberman and Bloomfield (1990) study, there have been some significant advances in the quality of the labour market data in the UK which allow for the dynamic modelling of labour force movements between economic states. Longitudinal labour market surveys for the UK have been available from the early 1990s in the form of the British Household Panel Survey (BHPS), which was started during 1991, and the first LFS matched panel data, which was available from the beginning of 1992. There have been a few short-lived cohort-based studies available before the 1990s (for example the DHSS unemployment registry of men followed up from 1978 to 1980), but these targeted specific segments of the population and were insufficient for broader applications. Longitudinal data, combined with a Markov-type increment-decrement model, allow for the conditioning of future employment risks both on age and on starting economic state.

In contrast with the UK, the study of dynamic statistical modelling towards the measurement of WLEs for the purposes of valuing damages is well established in the North American (US and Canadian) forensic economics literature. The BLS has published work life tables of the US population since the 1950s and regularly publishes reviews of the methodologies and results. These tables generate a large amount of socio-economic research, including research on applied methodology. The first set of work life tables published by the BLS, which used a Markov-chain increment-decrement model, was based on the research of Smith (1982). This early methodology has been revisited in Alter and Becker (1985) who develop a clear mathematical framework for the estimation of WLEs. Further work undertaken by Smith (1986) extends this later model to allow for the impact of some individual characteristics, including race and education. Additional aspects of the multiple-state Markov chain estimation have been explored, for example, in Ciecka et al. (1995, 1997, 2000). Richards (2000) provides an alternative view and points out empirical inconsistencies in comparison to the "conventional" approach of WLE estimates. Krueger (2004) presents a detailed description of the modelling structure and estimation of the multiple-state Markov model from US data and reports on particular issues related to the application of WLE in the area of compensation for loss of earnings. More recently, the logit (and probit) parametric formulation of the odds ratios of the decrements has been the most commonly used approach for modelling the transition probabilities (see Millimet et al. 2003).

The multiplier–multiplicand method of calculation used in the UK is crude by comparison with a US-style approach. Its weaknesses as a method for the valuation of damages are addressed by Lewis et al. (2003), who estimate life-time employment probabilities, and subsequently the actuarial value of a stream of future earnings, from a 3-state Markov model (employed-unemployed-inactive) using 1997 LFS data. The comparison of a 100 adjudicated awards with those calculated using this alternative approach makes a compelling case for the use of dynamic methods in valuing labour market risks in the UK tort system. The value of re-estimated awards were on average 21 per cent higher than the awards actually made by the courts. For those claimants who were considered to have future employment prospects, the difference was 37 per cent. The primary purpose of the Lewis et al. (2003) study was to propose a new methodology for the estimation of work life earnings rather than to document WLEs. The new methodology was proposed as an alternative to, and a replacement for, the multiplier–multiplicand method of calculation. In this study, we take the multiplier–multiplicand method of calculation as the given framework and seek to provide lawyers with an adaptation to this, their chosen method. This adaptation is based on an improved estimation of disaggregated RFs for the UK.

2.5 Work-life expectancy and employment-risks reduction factor

The statistical concept of WLE is central to the calculation of future loss of earnings in both the UK and the USA. The WLE represents the number of years a person of age x is likely to spend working (and earning) until his/her final separation from the labour market, through either death or retirement. This can be formulated mathematically in the framework of a two state Markov model, where the states at age x are denoted by $S_x = \{1, 2\}$, representing the state of being employed and non-employed, respectively. Then, the WLE is calculated as the integral of the expected proportion of people who in t years time will be alive and in the employed state, conditional on being alive at the age x and in a given starting state $S_x = i$. Thus, in a multi state model, the WLE is expressed as the integral of the product between the transition probabilities from state i to j, $p_x^{ij}(t)$, and the corresponding survival probabilities, $p_x(t)$, in t years from age x:

$$w^{ij}_{x:\overline{t_p-x}|} = \int_0^{t_p-x} p_x^{ij}(t)\, p_x(t)\, \mathrm{d}t\,, \qquad \text{for} \quad i = 1 \text{ or } 2 \quad \text{and} \quad j = 1 \text{ or } 2\,, \tag{1}$$

where we make use of the actuarial notation $w^{ij}_{x:\overline{t_p-x}|}$ to represent the total expected time spent in state j from age x over the remaining active time up to retirement age $(t_p - x)$, when starting in state i. From the point of view of compensation for loss of earnings, only the future expected time in the employed state (i.e. $j = 1$) is relevant and we can drop the j notation in the above expression. Further, since we consider only discrete future times ($t \geq 0$), the equation in (1) can be approximated making use of the trapezium rule, leading to the summation:

$$w^{i}_{x:\overline{t_p-x}|} = \sum_{t=1}^{t_p-x-1} p_x^{i1}(t)\, p_x(t) + \frac{p_x^{i1}(0)\, p_x(0) + p_x^{i1}(t_p-x)\, p_x(t_p-x)}{2}\,, \tag{2}$$

where the boundary conditions are given by $p_x^{11}(0) = 1$, $p_x^{21}(0) = 0$ and $p_x(0) = 1$. The way in which the age-specific transition probabilities, $p_x^{i1}(t)$, are estimated depends on the type of data and on the complexity of the modelling method (see section 3). In addition, in this study, we assume that the survival rates, $p_x(t)$, are the same for both economic states, and depend only on age. This simplification is prompted by the shortcomings of the LFS with respect to the individual mortality experience of the participants. While other longitudinal studies record the mortality of the participants together with socio-economic variables (most notably the BHPS), it can be problematic to match these mortality rates against the economic states and covariates used in our study. Thus, we make use of the age-specific survival probabilities reported/contained in the UK Interim Life Table for 1999 – 2001. While we acknowledge that employment status affects mortality (along with educational attainment and disability status), we do not expect that the impact of these simplifications on the RFs to be significant given that the mortality rates over the working age range are relatively small. In addition, we note that it would be open to the court to select a case-specific life expectancy (term certain) based upon medical evidence.

In the legal context, the WLE is the statistical estimate of the future number of years over which the annual loss of earnings occurs. This estimate needs to be discounted to account for early receipt of payments. The resulting measure is better-known in the UK as the *loss of earnings multiplier*, which is computed by adjusting (2) by a real rate of interest r:

$$w^{i}_{x:\overline{t_p-x}|}(\nu) = \sum_{t=1}^{t_p-x-1} p_x^{i1}(t)\, p_x(t)\, \nu^t + \frac{p_x^{i1}(0) + p_x^{i1}(t_p-x)\, p_x(t_p-x)\, \nu^{t_p-x}}{2}\,, \tag{3}$$

where $\nu = \frac{1}{1+r}$. In the computations, we have made use of $r = 2.5\,\%$ (i.e. 0.025) in accordance with the latest recommendations of the Lord Chancellor set in June 2001.

In the USA, population WLE tables are published at the Federal level by the BLS and the courts make extensive use of these and other sources of labour market data which are presented and interpreted in expert evidence from forensic economists. There is no "official" equivalent of the WLE for the UK and there is a long-standing reluctance on the part of the courts to hear evidence from experts in any discipline which might contribute to the assessment of future losses.

The empirical work that we present here is based upon estimating age-specific WLEs for the UK. However, since we are working within the constraints of the multiplier–multiplicand formula (see section 2.1), we convert these into an employment-risks RF, which represents the ratio of the work life expectancy to the expected number of years remaining alive up to pension age. In order to be consistent with the treatment of the WLE measure, we also need to express this as conditional on the starting state $S_x = i$ at age x and to allow for survival and discounting:

$$k_x^i(\nu) \;=\; \frac{w^i_{x:\overline{t_p-x}|}(\nu)}{\ddot{a}_{x:\overline{t_p-x}|}} \;=\; \frac{w^{i1}_{x:\overline{t_p-x}|}(\nu)}{w^{i1}_{x:\overline{t_p-x}|}(\nu) \;+\; w^{i2}_{x:\overline{t_p-x}|}(\nu)}\,, \tag{4}$$

where $\ddot{a}_{x:\overline{t_p-x}|}$ is the discounted value of an annuity of £1 per annum paid up to retirement age t_p. This is equivalent to the total of the discounted expected times in the two (alive) economic states.

The use of RFs has some clear practical advantages to the courts. First, the RF is a standardized measure that provides a simple, intuitive and self-explanatory index for users which can be readily applied to the base-line multipliers (discounted life expectancies) with which the courts are already familiar. Secondly, accounting separately for the effects of various factors (such as employment status, disability and education) in the form of adjusted RFs (see section 3) aids transparency. The RFs are used by the courts as guidelines from which to depart depending upon the individual circumstances of the case. Once the total discount for future employment risks is disaggregated into its component parts, the courts would be able to make any discretionary adjustments.

3 Data and Methodology

Our empirical analyses are based upon recent LFS data. The LFS continuously collects information on an extensive set of socio-economic and labour force characteristics from a rotating sample of around 60,000 households. The survey was originally designed to provide periodic cross-sections of the working population and has been collected on a regular quarterly basis since 1992/93. Each household is interviewed in five waves over a one year observation period. Consequently, each quarterly cross-sectional sample is formed by five separate waves (cohorts) of approximately equal number of respondents. Making use of a matched-files approach, this survey design allows the LFS to re-construct the panel (cohort) segments from the corresponding fractions of the consecutive cross-sectional data sets.

We make use of two multiple-state models to estimate the WLE, w_x^i, utilizing equation (2), and we compare the results of each in terms of the corresponding RF, k_x^i, as given in equation (4). The models differ in terms of the underlying data and the complexity of the method used to estimate age-specific transition probabilities, p_x^{ij}. However, each is based upon the basic increment-decrement model of labour force movements, as depicted in Figure 1, and leads ultimately to the empirical estimation of age-specific transition probabilities of individuals between different economic states, conditional upon surviving to a given age and on the previous economic state.

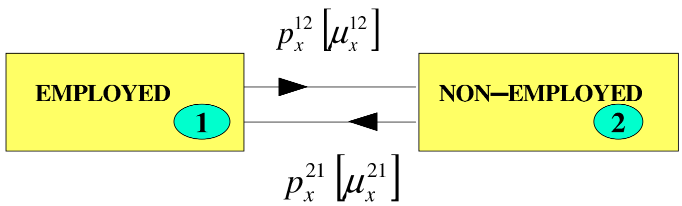


Figure 1: Two state Markov model of labour force transitions.
The Non-employed state includes those who are unemployed and those who are inactive.
a) *Methodology 1*: based on estimates of transition probabilities, p_x^{ij} , disaggregated by disability.
b) *Methodology 2*: based on estimates of hazard rates, μ_x^{ij} , disaggregated by disability and education.

Both models recognize the dynamic nature of the labour market and explicitly model multiple entries into, and exits from, employment as opposed to relying upon a static distribution of the labour force across different economic states. Observations on the timing and the number (or intensity) of the transitions from one state to another make it possible to estimate the likelihood of the time spent in a particular state, conditional on age and on the starting economic state. The theoretical aspects of the application of multiple-state Markov chain models to econometric problems are well developed in the literature and the general consensus is that they provide a technically superior mathematical framework for the analysis of labour market behaviour, albeit with more demanding data requirements.

3.1 Methodology 1

The first approach applies a simple empirical methodology to three spring quarters of the LFS cross section data (2002 – 2004). The purpose is to offer a transparent and accessible (at least intuitively) approach for users without specialist statistical training, particularly the legal profession. The method follows Alter and Becker (1985) and estimates age-specific employment probabilities based upon year-by-year observed transitions between two labour market states, employment and non-employment:

$$p_{x-1}^{ij}(t=1) \;=\; \frac{n_{x-1}^{ij}}{n_{x-1}^{i}}\,, \qquad \text{for} \quad i=1 \text{ or } 2 \quad \text{and} \quad j=1 \text{ or } 2\,, \tag{5}$$

where n_{x-1}^{i} are the total number of participants of age x who one year earlier were in economic state i and n_{x-1}^{ij} are those moving from i to j over the age year $(x-1,\, x)$. Thus, these rates are based on the observations of current employment status at age x and employment status 12 months ago. The economic states in Figure 1(a) are further disaggregated by disability. Finally, the age-specific transition probabilities over any number of years, t, are estimated as a function of the yearly transition probabilities from (5) making use of a recursive formula. (This is equivalent to the matrix approach given by equation (8) and applied in the second methodology, as described in section 3.2.)

Current employment status in the LFS is based on International Labour Office (ILO) definitions of employment and different types of non-employment. The variable which measures employment status 12 months ago is recalled by respondents (i.e. retrospective in nature) and, in its aggregated form, can be mapped onto the aggregated form of current employment status. Both employment status variables include multiple categories of employment and non-employment. Due to small sample sizes, when disaggregated by age, sex, disability and employment status 12 months ago, these multiple category variables indicating various alternative forms of economic activity (i.e. cat. $1-5$) and inactivity (i.e. cat. $6-29$) are aggregated into two main transient states "employed" (cat. $1-3$ and cat. 1 and 3) and "non-employed" (cat. $4-29$ and cat. $2, 4-10$). Table 1.D, in Appendix D, reports the full distribution of the

LFS variable (INECACA), upon which our classification of current employment status is based, and which contain 4 categories of employment. We are interested only in employment which attracts earnings, and hence our definition of employment excludes unpaid work (i.e. cat. 4). Non-employment includes unemployment and the many different forms of inactivity. Aggregation across the multiple categories of non-employment is required due to small sub-sample sizes when disaggregated by sex, age, disability and labour market status. The unemployed account for around 4 % (males) and 3 % (females) of the working population which is insufficient to allow for separate categorization.

There is an inevitable loss of precision. The different sub-categories within the non-employed category will have different levels of attachment to the labour market (see for example Jones and Riddell 1999) and therefore also different WLEs. In particular, those whose status is "unemployed" rather than "inactive" are likely to be characterized by greater labour market attachment, greater WLEs and greater RFs (see again Jones and Riddell 1999). The decision to include the unemployed with the inactive, as opposed to the employed, is justified with reference to their predicted life time employment outcomes. When disaggregated by disability, the employment outcomes of the unemployed are closer to those of the inactive than of the employed (see Butt et al. 2006). Kreider (1999) groups the unemployed with the employed but notes that this has "virtually no effect on the results of the analysis" (see Kreider footnote 16). The potential for bias which results from our classification is considered to be small and is discussed in section 5.

The LFS has collected full information on health indicators from 1998 and provides two compound measures of disability. The first refers to the adverse impact of impairment on either the amount or the type of work that the respondent can undertake. The second is defined in terms of the Disability Discrimination Act 1995 (DDA) as "having a substantial adverse effect on a respondent's ability to carry out day-to-day activities" (in Appendix C we present the LFS classification methodology of this disability variable). Disability is defined here as meeting three criteria: (i) having lasted for over one year, (ii) meeting the DDA condition and (iii) limiting the *amount* or the *type* of work that the respondent can undertake. In the context of the current investigation, disability refers to the disablement that results from the injury which is the subject of the claim for compensation. We make use of this measure of disability to capture the impact of injury on the claimant's future employment prospects. Respondents who fall outside this definition of disability are not necessarily *healthy*. The non-disabled category includes individuals who may have some impairment which either does not meet the DDA criteria or which does not affect their work.

TABLE 1
Population prevalence rates by sex, disability and employment status

Men				Women			
50 % (49.8 %)				50 % (50.2 %)			
Non–Disabled 87.6 % (87.1 %)		**Disabled** 12.4 % (12.9 %)		**Non–Disabled** 88.0 % (87.8 %)		**Disabled** 12.0 % (12.2 %)	
E	**NE**	**E**	**NE**	**E**	**NE**	**E**	**NE**
85.1 % (86.8 %)	14.9 % (13.2 %)	32.5 % (32.0 %)	67.5 % (68.0 %)	74.6 % (76.0 %)	25.4 % (24.0 %)	30.4 % (30.6 %)	69.6 % (69.4 %)

Source: cross-sectional LFS 2002 – 2004 (panel LFS 1998 – 2003 in parentheses).
Notes: E = Employed; NE = Non-employed.

The pooled LFS cross-section sample (2002 – 2004) comprises 191,508 individuals of working age (16–65 years for men and 16–60 years for women). Table 1 summarizes the data in terms of unconditional aggregate employment rates observed in the cross-sectional (and panel, see section 3.2) data sets. We note that each sex is equally represented in the LFS samples, and that both contain a similar proportion of disabled, of about 12 %. It is interesting to note that the employment rates among the disabled are roughly equal for men and women (around 30 %), while there are significant differences among the non-disabled (about 10 % higher for men than for women). The sharp reduction in employment rates for those who are disabled is a first indication as to the inadequacy of the Smith v. Manchester Corporation lump sum.

There is a considerable literature on the measurement error associated with self-reported disability (see Kreider 1999) and the various attempts to estimate the resulting bias in relation to employment outcomes (see Kreider and Pepper 2007). The financial and social incentives for non-workers to over-report disability mean that self-reported disability is not exogenous in the context of labour market outcomes. Berthoud (2006) discusses these deficiencies in relation to the LFS measure of disability. These deficiencies include the subjectivity inherent in self-reported disability, particularly when disability is reported alongside the collection of information on employment (see also Bound 1991). In addition, the LFS definition of disability imposes a binary classification upon a heterogeneous set of conditions and impairments at different levels of severity. These deficiencies are not new to this survey, or to this study (see Burchardt 2000), and the consequences in terms of potential for bias in our estimated RFs are discussed in section 5.

Table 2
Disability prevalence rates and employment rates.

Study	Disability Prevalence %	Employment rate among disabled %	Employment rate among non-disabled %	Employment rate in population %
LFS cross section 2002 – 2004				
DDA and Work-affecting	12.2	31.5	79.8	74.0
Work-affecting	15.6	39.2	80.4	74.0
All disabled	19.8	47.9	80.4	74.0
LFS longitudinal 1998 – 2003				
DDA and Work-affecting	12.6	31.3	81.4	75.1
Work-affecting	16.2	39.4	82.0	75.1
All disabled	20.3	47.8	82.0	75.1
HDS 1996 – 1997	12.6	30.0	76.0	71.0
OPCS Disability Survey 1985	7.8	31.0		

Source: cross-sectional LFS 2002 – 2004, panel LFS 1998 – 2003, Berthoud (2006).

The definition of disability is important in the context of measuring its impact on employment, as employment rates decrease according to the strictness of the definition (see Kruse and Schur 2002 for the US and Berthoud 2006 for the UK). This is illustrated in Table 2 where employment rates increase as the prevalence of disability increases. This study defines disability as strictly as is possible within the confines of the data in order to reflect the type of impairments in which claims are made for loss of future earnings. On this "strict" definition of disability, the percentage of the labour force classified as disabled is consistent with that reported by the Berthoud (2006) study using the Health and Disability Survey (HDS) in 1996/97. Following the methodology developed by the Office for Population Censuses and Surveys (OPCS) in their Disability Survey in 1985–88, respondents do not classify themselves in terms of disability. Rather, respondents report conditions and impairments and are classified, on the basis of these data, by the research team. According to Kreider (1999), "questions about specific conditions are often considered more concrete and less subjective than questions about work capacity". Consistency in disability prevalence rates between our study and Berthoud (2006) provides some level of confirmation that the strict version of the LFS disability variable does not exaggerate the population prevalence of disability nor the impact of disability on employment. The reported incidence of work-related illness also correlates well with the OPCS Disability Survey 1985–88 and the incidence of illness reported in visits by the adult population to G.P. physicians (see Hodgeson et al. 1993).

In this simple methodology, we estimate RFs conditional on sex, age, starting employment status and disability status on a case-by-case basis using cross-section data. The calculation is undertaken using a spreadsheet for each sex, age and disability status. While this methodology meets the objective of simplicity and transparency, and indeed has proved invaluable in enabling specialist injury lawyers to follow and to understand the calculation at each stage, it suffers from three obvious deficiencies:

(i) Information on employment status 12 months ago is collected retrospectively and is therefore subject to a potential for recall and/or misclassification error;

(ii) Interim transitions during the 12 month period are ignored;

(iii) The small sample size when disaggregated by sex, age, disability status and employment status precludes further analysis of any occupational, regional or educational effects.

These deficiencies provide the motivation for the more sophisticated approach that is described next.

3.2 Methodology 2

In our second approach, we make use of a total of 20 longitudinal five-quarter LFS data sets (i.e. cohorts of respondents) covering the period of Spring 1998 – Winter 2003. There are a total of 203,966 working age respondents in the pooled sample, made up by approximately 11,000 participants per data set (Table 1 presents the aggregate employment rates by sex and disability).

This methodology is based upon the empirical estimation of age-specific transition intensities between economic states i and j (see Figure 1(b)), given by the following ratio:

$$\mu_x^{ij} = \frac{n_x^{ij}}{E_x^i}\,, \qquad \text{for} \quad \forall\, i \neq j\,, \tag{6}$$

where E_x^i represents the expected total time (or exposure to risk) spent in the initial state i across all individuals of age x. The E_x^i are estimated from the observed quarterly flow of the labour force between the two economic states over individual ages. As in the first approach, it is possible to calculate the transition rates conditionally on additional factors (other than age), by disaggregating the original two state model by additional variables. However, the estimation procedure is improved because the transitions between the layers of the additional covariate (e.g. shifts in the type of disability occurring in a year) contribute to the estimate of the total exposure to risk and hence no information is lost. Nevertheless it is a constraint of both approaches that the initial conditions at age x, as defined by the additional factors (e.g. disability, education, etc.), are fixed over the individual's life-time. For a detailed description of the methodology applied, the reader is referred to Butt et al. (2006). It should be noted that there are potential deficiencies in the data, due to factors such as attrition of the sample, non-response among panel members and the presence of third party proxy responses. The effect of sample attrition has been investigated but was found to have no significant effect on the results.

We form a transition intensity matrix

$$\boldsymbol{M}_x = \begin{bmatrix} -\mu_x^{12} & \mu_x^{12} \\ \mu_x^{21} & -\mu_x^{21} \end{bmatrix},$$

that facilitates mathematical tractability and also simplifies the calculations, given that all the remaining computations are implemented by means of matrix operations that can be readily extended to any number of states. The crude estimates of transition intensities have been further smoothed using cubic splines (see Appendix A). While smoothing is appropriate for ameliorating the effect of either zero or undetermined transition intensities (i.e. either $n_x^{ij} = 0$ or $E_x^i = 0$), resulting from extensive subgrouping of the original data set, we note that our analysis shows that it does not strongly influence the WLE estimates.

The transition probabilities, conditional on starting economic state and age, are derived from the empirical estimates of the transition intensities using a matrix approach. The one year transition probability matrix is calculated from the age-specific transition intensity matrix, as follows:

$$\boldsymbol{P}_x(t=1) = \boldsymbol{P}_x = \exp(\boldsymbol{M}_x) = \boldsymbol{A}_{\boldsymbol{x}} \exp[\,\mathrm{diag}(\boldsymbol{d}_x)\,]\, \boldsymbol{A}_x^{-1}\,, \tag{7}$$

where $\mathrm{diag}(\boldsymbol{d}_x)$ is a diagonal matrix with entries formed by the eigenvalues of $\boldsymbol{M}_x$ ($\boldsymbol{d}_x = \{d_1, d_2\}_x$) and $\boldsymbol{A}_x$ is a matrix made up by the corresponding eigenvectors.

Then the transition matrix over any number of years, t, conditional on being alive at age x, is given by the product of yearly transition matrices for each consecutive age-year up to age $x+t$:

$$\boldsymbol{P}_x(t) = \boldsymbol{P}_x \times \boldsymbol{P}_{x+1} \times \boldsymbol{P}_{x+2} \times \cdots \times \boldsymbol{P}_{x+t-1} = \prod_{k=0}^{t-1} \boldsymbol{P}_{x+k}\,. \tag{8}$$

Making use of the first column entries of the transition matrix in (8), one can proceed to estimate the discounted age-specific WLEs and the corresponding RFs based on equations (3) and (4), as described in section 2.5. Alternatively, we provide matrix versions of the above expressions, which yield the age-specific WLEs (RFs) for all of $w^{ij}_{x:\overline{t_p-x}|}$ $\left(k^{ij}_{x:\overline{t_p-x}|}\right)$ for any possible combinations of i and j economic states (for full details see Butt et al. 2006).

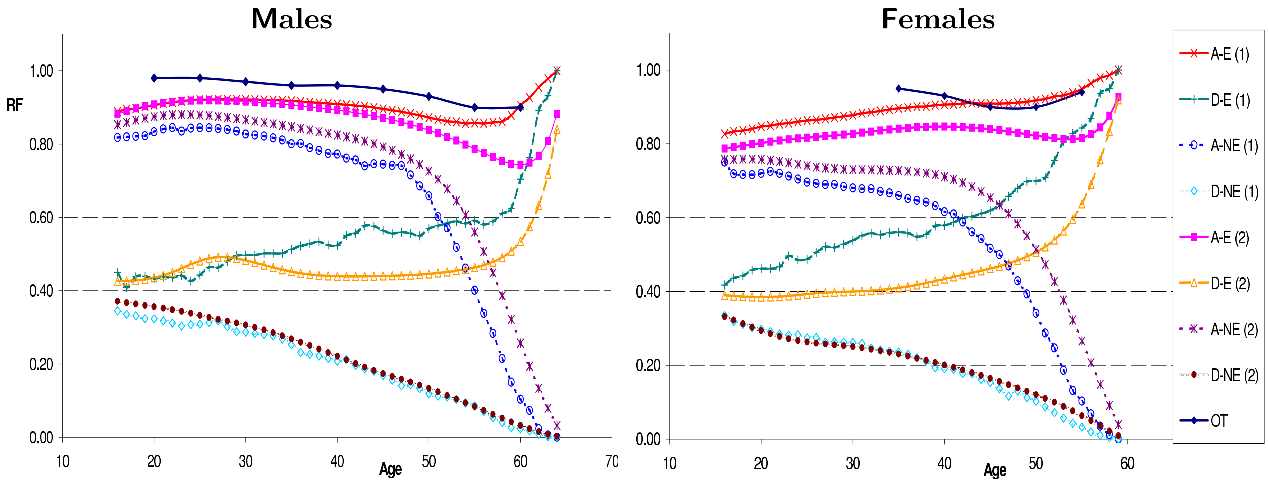
As a means of estimating standard errors on the RFs we make use of the variance of the smoothing regression, as in equations (10) and (11) in Appendix A, to simulate random samples of ($n = 1{,}000$) independent age-specific transition intensities that are applied, in turn, to obtain samples of age-specific RFs. These random samples are used to estimate the standard errors (SE) of the reported RF figures.

4 Results

In this section, we present the age-specific RFs (and their corresponding WLEs) for the UK, conditional on sex, initial employment status, educational attainment and disability status. The advantage of reporting the RFs over the WLEs is that they provide a scaled measure for the life-time employment risks, allowing a systematic and efficient comparison of the results. Figure 2 illustrates the age-specific RFs resulting from methods 1 and 2 for males and females, conditional on disability and starting economic states. The RFs are compared to the current recommendations in the Ogden Tables (using the average economic conditions scenario and ignoring the effects of industry and region). These results demonstrate clearly that the current Ogden Tables recommendations are:

1. over-optimistic in terms of the RFs corresponding to the pre-injury conditions of those claimants who are employed at the time of the injury;
2. not suited for those who are non-employed at the time of the injury;
3. inadequate to assess the employment risks faced by an injured claimant with post-injury earning potential because they do not account for the negative impact of disability on future employment prospects, irrespective of the employment state of the claimant at the time of the trial.

It can be observed in Figure 2 that the results are broadly similar using each model, although neither the levels nor the profiles are identical. This may seem unsurprising given that the data cover different time periods and different methods were used for estimating age-specific transition probabilities. Upon further investigation, we find the source of the difference to



A-E = Non-Disabled and Employed; *A-NE* = Non-Disabled and Non-employed;
D-E = Disabled and Employed; *D-NE* = Disabled and Non-employed;

Figure 2: Age-specific RFs by sex, starting economic state and disability based on models (1) and (2), in comparison to the Ogden Tables (OT) reduction factor.
All RFs are discounted at 2.5 %.

be the frequency of observations on transitions between employment states. The effect of the frequency of observation depends on the starting economic state and on the disability status. Thus, for the employed starting state, the quarterly data yield systematically less time in employment than annual data, over a working life-time, most especially for those who are disabled (see curves *D-E (1)* and *D-E (2)*). The lower employment risks (i.e. higher RFs) for those in employment, when measured annually, suggest that short spells of non-employment exceed short spells of employment and particularly so for those who are disabled. Alternatively, for the non-disabled population when initially in non-employment, the quarterly data lead to systematically more time in employment than the annual data (see curves *A-NE (1)* and *A-NE (2)*). The difference is negligible for the disabled whose employment prospects are poor (when already in non-employment) and who are unlikely to experience short term employment spells. The differences are slightly greater for females, suggesting that women experience more frequent short term transitions between the employed and non-employed economic states over a working life-time.

As the frequency of measurement of labour force activity yields systematic differences in transition probabilities over a working life-time so, in turn, the differences in transition probabilities generate differences in RFs. Short spells in employment or non-employment which are not captured in the annual data are sufficiently important to affect the total time spent in employment over a working life-time. Since substantial bias due to attrition seems unlikely, we conclude that transition probabilities based upon quarterly observations are the more accurate guide to life-time employment prospects and we use the results of model 2. The numerical outcomes for the employment-risks RFs and WLEs, corresponding to model 2, are reported in detail (together with their simulated standard errors) in Tables 1.B and 2.B, respectively (see Appendix B).

Focusing on model 2, Figure 2 (and Table 1.B) shows that for men between the ages of 20 and 40 who are not disabled, and whose starting state is employed, the percentage of their remaining working life that they can expect to be in employment is around 90 per cent. The risk of non-employment increases steadily between the ages of 40 (0.11) and 60 (0.26). The shallow dip, at around 55 years, may reflect the difficulties faced by job seekers in middle age and the effect of early retirement (which is stronger for men). The percentage of their remaining working life that non-disabled men can expect to spend in employment increases from the age of 60. This is not unexpected and it is most likely a product of selection effects in the labour market. The individuals who remain in employment until their 60s are likely to be those who are more motivated towards employment and/or who have achieved a good match in terms of skills and job requirements compared to those who have already left the labour market. The lower RFs for non-disabled women reflect the impact of child care. In contrast to men, the RFs for women increase with age so that the gap between male and female RFs narrows and achieves parity at the age of 52.

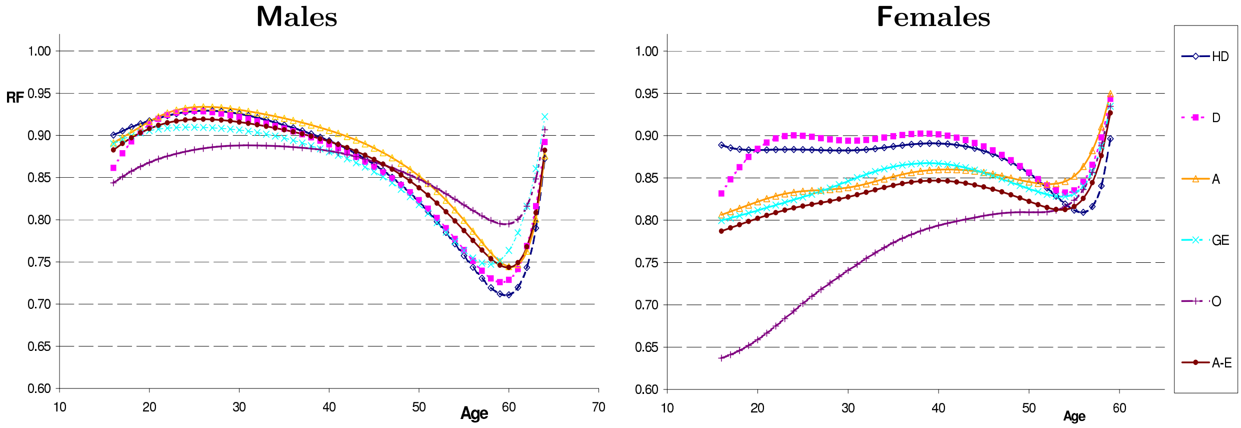
The most striking feature of Figure 2 (and Table 1.B) is the negative impact of disability on life-time employment prospects, even for those whose starting state is employed. There is an average difference in the RFs between a disabled and a non-disabled man (whose starting state is employed) of about 40 percentage points until the age of 55, after which the differences begin to diminish. Disability appears to become less of a disadvantage in the labour market with increasing age for those starting in employment. The pattern is much the same for disabled women whose starting economic state is employed, although the difference between male and female RFs is lower than for the non-disabled at all ages and the parity year is earlier at 41 years. We note that a similar effect can be observed in Table 1, which shows an approximate 10 % difference between the overall rate of employment of non-disabled men and women which reduces to only about 1 % for those who are disabled.

Figure 2 (and Table 1.B) also indicate that a starting state of non-employed is not a major disadvantage to the young who are not disabled. This is partly because, at this age, the non-employed include many whose inactivity is purposeful (for example higher education) and also because unemployment is less “scarring” for the young in terms of future unemployment (see Mroz and Savage 2006 for the US and Burgess et al. 2003 for the UK). However, a starting employment state of non-employed for the non-disabled has a progressively increasing impact on future employment risks with age. Based on model 2, the increase in the employment risks for males from starting as non-employed (as opposed to employed) is around 7 percentage points at the age of 40 after which it increases rapidly to 23 per cent at age 55. Employment risks for women whose starting economic state is non-employed are around 10 to 15 percentage points greater than for equivalent men until the age of 45, again reflecting women’s greater role in child care. After the age of 45, this gap increases steadily until retirement age, reflecting the diminishing employment prospects of unemployed women after their childbearing age.

In addition to the impact of disability on employment risks, we also consider the level of economic activity and the effects of region, type of industry and educational attainment. While we find some evidence for an industry and region effect (for further details see Butt et al. 2006), it seems that once the level of education and disability are taken into account, these effects become largely insignificant. Educational attainment captures a great deal of the variability of the future working experience and has a strong impact on life-time employment risks, both when estimated individually and when estimated jointly with disability. Tables 2.D and 3.D, in Appendix D, show the categories of the LFS variable HIQUAL (highest qualification) and the observed prevalence rates by education, sex, disability and employment status.

Figures 3–5 illustrate the joint impact of education and disability on the RFs, conditional on age, sex and starting economic state. In Appendix B, Table 3.B reports the average differences in the disability-adjusted RFs for broad age ranges. Educational attainment has the least impact on the employment risks for able bodied employed men (see Figure 3). The difference between the RFs of those with the highest and with the lowest qualifications is less than 5 percentage points over the first half of the working age range (see Table 3.B). This initial difference gradually reduces over the years and eventually the RF profiles cross over at the age of 45. Thereafter, those with the lowest level of qualifications spend more time in employment until retirement than those with any other level of qualifications.

Educational achievement has a much greater influence on the life-time employment prospects of non-disabled employed women than men (see Figure 3), so that a 20 year old woman with a



HD = Degree or higher; *D* = Higher Education (below degree); *A* = A level or equivalent; *GE* = GCSE A-C or equivalent; *O* = Other or no qualifications; *A-E* = Overall Non-Disabled;

Figure 3: Age-specific employment-risks reduction factor (2.5 %) of non-disabled population by sex and educational attainment when initially employed (LFS 1998 – 2003).

higher education qualification or above (D or HD) can expect to spend 22 % more time in employment until retirement than an unqualified woman. The difference between highly qualified and unqualified non-disabled women gradually reduces with age and achieves parity at the age of 54. It is worth noting that the results suggest that young women with higher degrees can expect to spend just as much time in future employment as their male counterparts (nearly 90 %) and, that after the age of 40, they are likely to experience more time in employment than males.

However, it is amongst the disabled that educational achievement has the strongest impact on employment risks. The average difference between the RFs of disabled workers with high and low education levels, who are already in employment (Figure 4), and below the age of 30, is 23 and 43 percentage points for males and females, respectively (see Table 3.B). This difference between the employment risks profiles at the two ends of the education spectrum stays relatively constant until the age of 50, estimated at 20 and 30 percentage points on average for males and females, respectively. Thereafter, the difference gradually reduces up to retirement age.

A particularly striking feature that can be observed in Table 3.B (and Figures 4 and 5) is the positive impact of a degree on the employment prospects of the disabled. Thus, a highly educated disabled woman under the age of 30 can expect to spend as much as 29 %

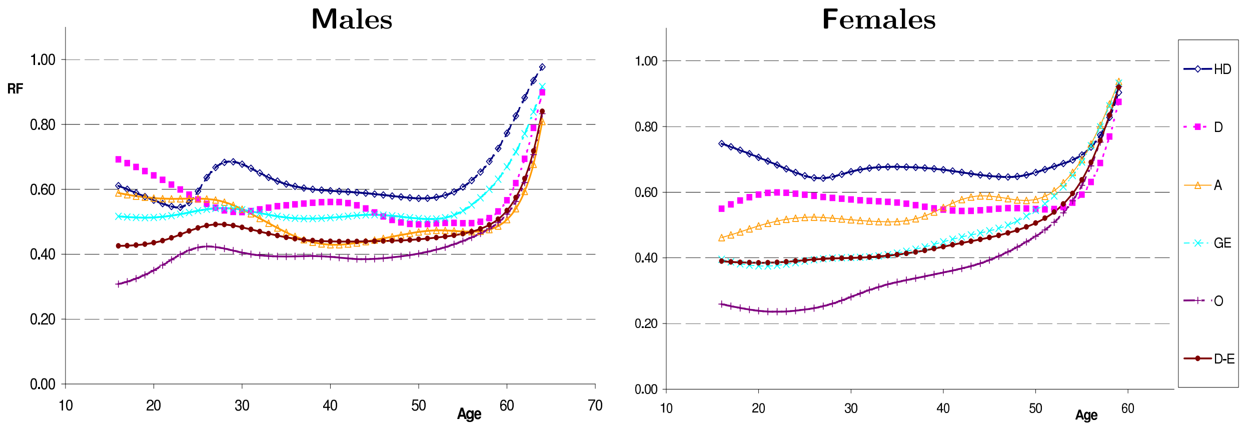


Figure 4: Age-specific employment-risks reduction factor (2.5 %) of disabled population by sex and educational attainment when initially employed (LFS 1998 – 2003).

HD = Degree or higher; *D* = Higher Education (below degree); *A* = A level or equivalent; *GE* = GCSE A-C or equivalent; *O* = Other or no qualifications;
D-E = Overall of Disabled and Employed; *D-NE* = Overall of Disabled and Non-Employed;

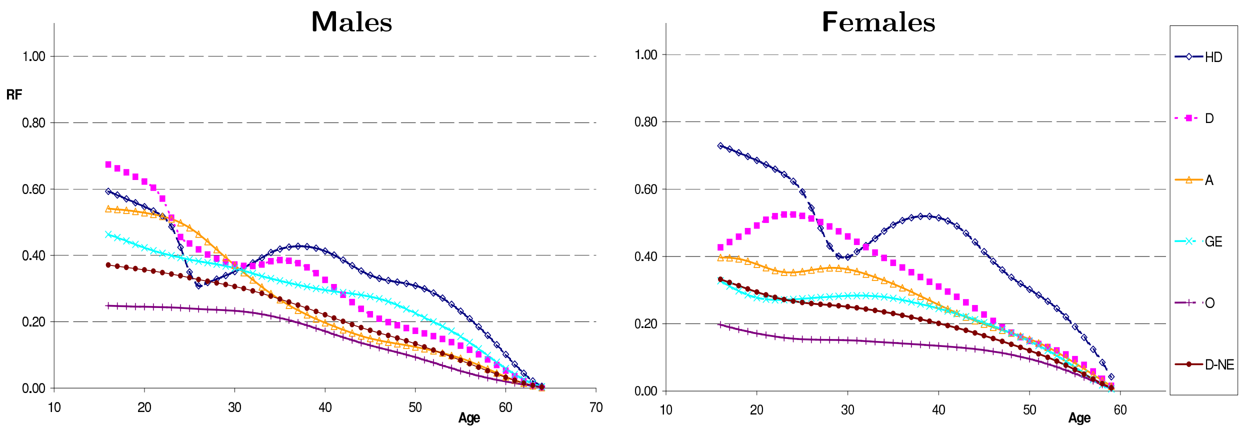


Figure 5: Age-specific employment-risks reduction factor (2.5 %) of disabled population by sex and educational attainment when initially non-employed (LFS 1998 – 2003).

(when employed) and 32 % (when non-employed) more time in future employment than the average disabled woman. Higher education appears to compensate for many of the employment disadvantages brought about by disability.

However, the disabled are less likely to be more highly qualified than the non-disabled and particularly so if they are not in employment (see Table 3.D). For the non-employed and disabled participants in the survey 56 % and 63 % for males and females, have only low level of qualifications. This compares to about 23 % and 26 % for males and females, who are employed and not-disabled. Low prevalence rates for those with higher education qualifications (around 8 %) explains the more randomly progressing RF profiles observed in Figure 5. Clearly, both educational achievement and disability have major impacts on individual life-time employment prospects and it is therefore important to account for both in valuing damages following personal injury. There are also important wider policy implications here in favour of increasing participation in higher education for those who are disabled.

Previous recommendations in the Ogden Tables included adjustments to RFs to reflect the impact of economic climate (high, medium and low). In practice the middle range figures are almost always used. When we examine the impact of level of economic activity on RFs by comparing aggregate RFs for the periods 1993 – 1997 and 1998 – 2003 we find no significant differences (see Butt et al. 2006). Although average employment rates are lower in the first period than in the second, both periods are ones of economic growth. A less propitious economic climate would potentially result in lower RFs, but it is beyond the scope of the LFS data to explore such effects. Moreover, it is not possible to predict economic conditions over the period for which any award of compensation is designed to cover.

4.1 Application to case example

Valuation based upon the education- and disability-adjusted multipliers:

We revisit the worked example at 2.2 above and apply the revised RFs to the pre- and post-injury earnings calculations.

The base-line multiplier discounted at a rate of $2\frac{1}{2}$ % remains the same as above (18.39). The discounted reduction for employment risks for a non-disabled women employed at the age of 35 is 0.84 (Table 1.B). This RF is adjusted upwards on account of the claimant's educational achievement by 0.01 (Table 3.B).

The disability-adjusted reduction for employment risks for this woman, on the basis that she is employed at the age of 35, is 0.41 (Table 1.B). This reduction factor is adjusted upwards on account of the claimant's educational achievement by 0.11 (Table 3.B).

The pre-injury loss of future earnings is . . . $£\,25{,}000 \times 18.39 \times (0.84 + 0.01) = £\,390{,}788$.

The post-injury earnings are . . . . $£\,17{,}000 \times 18.39 \times (0.41 + 0.11) = £\,162{,}568$.

The award for loss of future earnings is . . . . $£\,390{,}788 - £\,162{,}568 = £\,228{,}220$.

The damages award for loss of future earnings would be almost 43 % higher (£ 68,513) using the education- and disability-adjusted multipliers method of calculation. This is consistent with the findings of Lewis et al. (2003) who report that their method of calculation produces an average uplift of 38 % on loss of future earnings for women who have post-injury earning capacity.

Alternatively, if the claimant had not been employed at the time of trial (or settlement) but earnings in part time employment at £ 17,000 pa were anticipated then the post-injury calculation would be as follows: $£\,17{,}000 \times 18.39 \times (0.23 + 0.06) = £\,90{,}663$. Hence, post-injury employment risks are higher and RFs are lower for the non-employed. Compensation is then higher (£ 300,125) to reflect the higher expected loss.

5 Discussion

While the approach to the compensation for loss of future earnings which is based on these revised employment-risks RFs, and which uses education- and disability-adjusted multipliers to calculate post-injury earnings, represents a major improvement, there still remains the potential for bias. We discuss some of the main sources of bias in this section.

Disability and education level are assumed to remain unchanged from the date of measurement. This ignores the possibilities that a non-disabled or an unqualified individual will become disabled or gain some qualifications during the course of their working life-time. While it is fairly straightforward using the panel data to extend the multiple-state model to allow for changes in the levels of disability or education, further disaggregation to this level (e.g. age-specific changes of health, educational level, etc.) would produce statistically unreliable sub-samples. However, further disaggregation could be accommodated by using age ranges (e.g. over five year age intervals) instead of individual ages.

Disability is self-classified and there can be a tendency for people to exaggerate the limitations of their disability. This is particularly true when disability information is collected in the context of employment outcomes since there is less of a stigma attached to non-employment where the cause is ill health or disability. This over-reporting of health problems generates downward bias in the estimation of the post-injury employment risks. The simultaneous determination of employment status and disability generates upward bias (see Charles 2003 and Hotchkiss 2006). There is also a financial incentive to non-employment by reason of disability (in the UK) in the form of payment of Incapacity Benefit.

The definition of disability is a broad one and does not distinguish different levels of severity. Disability is a heterogeneous variable and severity has an important impact on employment (see Charles 2003 and Berthoud 2006). Similarly, we cannot distinguish in the LFS data between individuals who are disabled from their early years and those who become disabled after completing their education. The timing of disablement is likely to influence an individual's future employment prospects (see Charles 2003) and create a selection effect over time. Those who are disabled from birth, but whose disability does not preclude them from future employment, may be better able to adapt their education and training to suit the restrictions that disability places upon their employment and thus to minimize the impact of disability on their employment prospects. For the older injured claimant, the potential mismatch between the capabilities required for the pre-injury job and the post-disablement capacity for employment may be greater. For example, the skills and capabilities of a middle-aged man who was employed in manual work prior to injury will be ill-suited to the clerical work for which he is physically restricted to following injury (see Charles 2003 for explanation). For a given level of severity of disability, employment prospects diminish with age and with the mismatch between pre- and post-injury skill requirements. Since most personal injury claims involve injury or disease following the completion of education and training, LFS-based employment estimates will tend to understate the impact of disability on future employment.

Currently, the health variable in the LFS distinguishes different disability conditions but does not distinguish by impairment or by severity (see Appendix C). Without information on the nature of the condition which is the cause of disability, the effects of impairment and severity, which may differ in important ways, are conflated. Nevertheless, additional information in relation to disability, number of years since onset and cause of disability, were collected in the LFS Spring quarter of 2002. These provide scope to control for two aspects of heterogeneity on labour market outcomes, that of cause and timing of disability.

The use of a two-state (employed, non-employed) model in which the non-employed category includes the inactive and the unemployed is likely to bias the RFs in an upward direction for the inactive non-employed and in a downward direction for the active non-employed. Given the low incidence of unemployment within non-employment, the magnitude of any upward bias is likely to be very small. The incidence of unemployment among claimants is likely to be less than for the population generally, both pre-injury (most common form of tortious injury occurs at work) and post-injury (the basis for any claim for loss of earnings is a significant and long lasting disability which suggests non-employment due to inactivity), so the downward bias will impact on very few cases. Again, the only way to accommodate a three employment state model is to combine different ages.

6 Conclusions

This paper uses dynamic labour market modelling to predict future expected time in employment for the purpose of valuing future earnings. The purpose is to provide greater accuracy in fulfilling the objective of the damages' principle, that is, financial restoration for the claimant. The results of this study have been substantiated by two different methodologies applied to different types of labour market data. We use the results to propose improvements to the multiplier–multiplicand method of calculation of loss of future earnings.

Through the use of a multiple-state Markov chain for the modelling of life-time employment patterns, we estimate RFs which are conditioned upon starting employment status (employed or not employed). The model allows for disaggregation by disability and thus for the separate calculation of post-injury future earnings. This provides a more accurate and reliable measure than does the Smith v. Manchester Corporation lump sum. Disaggregating by educational attainment accounts for the impact on employment of different levels of educational qualification. The results indicate that RFs vary substantially according to starting economic state, disability status and level of educational attainment.

We demonstrate, in an example, the application of both the traditional and adapted methods of calculation and the consequences for the claimant in terms of level of compensation. We recognize that the long-term future employment risks of a heterogeneous work force cannot be fully described by the means of a few variables (i.e. age, sex, starting economic state, education and disability) measured at a single point in time. In this regard, we have some sympathy for Lord Oliver's view (see section 2.1). Our purpose, however, is to provide a more accurate starting point within the established broad brush framework used by the courts. The intention is that the courts may deviate from this starting point subject to the particular characteristics and circumstances of individual cases.

Appendix

A Cubic B smoothing spline regression

Lets consider n distinct realizations of a response variable $\boldsymbol{y} = (y_1,\, y_2,\, \ldots\, ,\, y_n)^{\mathrm{t}}$, corresponding to a given predictor $\boldsymbol{x} = (x_1,\, x_2,\, \ldots\, ,\, x_n)^{\mathrm{t}}$. Then a cubic B smoothing splines regression model of $\boldsymbol{y}$ is defined as follows:

$$\boldsymbol{y}(x) \;=\; \hat{\boldsymbol{y}}(x) + \boldsymbol{\varepsilon}_x \;=\; \hat{\boldsymbol{\theta}}^{\mathrm{t}}\boldsymbol{f}(x) + \boldsymbol{\varepsilon}_x\,. \tag{9}$$

where $\boldsymbol{\theta} = (\theta_1,\, \theta_2,\, \ldots\, ,\, \theta_p)^{\mathrm{t}}$ is an underlying p parameter vector of the model and $\boldsymbol{f}(x) = (f_1(x),\, f_2(x),\, \ldots,\, f_p(x))^{\mathrm{t}}$ is a vector of cubic B splines of the same length.

It is possible to show that the maximum likelihood estimate of $\boldsymbol{\theta}$ is given by the following matrix product:

$$\hat{\boldsymbol{\theta}} \;=\; \left(\boldsymbol{F}^{\mathrm{t}}\,\boldsymbol{F}\right)^{-1}\boldsymbol{F}^{\mathrm{t}}\,\boldsymbol{y}\,,$$

where $\boldsymbol{F}$ is often referred to as the *smoother matrix*, which is formed by the vector $\boldsymbol{f}(x)$ at the observation points $\boldsymbol{x}$, that is:

$$\boldsymbol{F} \;=\; (\boldsymbol{f}(x_1),\, \boldsymbol{f}(x_2),\, \ldots\, ,\, \boldsymbol{f}(x_n))^{\mathrm{t}}\;.$$

It can be shown that the estimator of the cubic B splines model (9) is asymptotically normally distributed with a variance given by the equation:

$$\mathrm{Var}\,[\hat{y}(x)] \;=\; \hat{\sigma}^2_{\varepsilon}\,\boldsymbol{f}(x)^{\mathrm{t}}\left(\boldsymbol{F}^{\mathrm{t}}\,\boldsymbol{F}\right)^{-1}\boldsymbol{f}(x) \;=\; \hat{\sigma}^2_{\varepsilon}\,\mathrm{lev}_x \tag{10}$$

where $\hat{\sigma}^2_{\varepsilon}$ is the overall variance of the error term and $\left[\boldsymbol{f}(x)^{\mathrm{t}}\left(\boldsymbol{F}^{\mathrm{t}}\,\boldsymbol{F}\right)^{-1}\boldsymbol{f}(x)\right]$ is a quadratic form representing the leverage (lev_x) of the response variable at point x.

In the current paper we have applied the findings of Rice (1984), which show that the overall variance, under the normal distribution assumption, can be estimated based on the following sum of squares:

$$\hat{\sigma}^2_{\varepsilon} \;=\; \frac{1}{n-2}\sum_{i=1}^{n-2}\left(0.809\,y_i - 0.5\,y_{i+1} - 0.309\,y_{i+2}\right)^2\;. \tag{11}$$

B Reduction Factors and Work-life Expectancies

TABLE 1.B

EMPLOYMENT RISKS REDUCTION FACTOR (STANDARD ERRORS) BY SEX, AGE, INITIAL EMPLOYMENT STATUS AND DISABILITY 1998 – 2003 (2.5 %).

	MALES				**FEMALES**			
	Employed		**Non-Employed**		**Employed**		**Non-Employed**	
Age	A–E	D–E	A–NE	D–NE	A–E	D–E	A–NE	D–NE
16	0.883	0.426	0.853	0.371	0.787	0.390	0.757	0.332
	(0.0027)	(0.0076)	(0.0028)	(0.0075)	(0.0031)	(0.0060)	(0.0031)	(0.0056)
17	0.890	0.426	0.859	0.367	0.791	0.388	0.758	0.323
	(0.0027)	(0.0076)	(0.0027)	(0.0076)	(0.0031)	(0.0061)	(0.0032)	(0.0057)
18	0.897	0.428	0.865	0.364	0.795	0.386	0.759	0.313
	(0.0027)	(0.0079)	(0.0027)	(0.0079)	(0.0032)	(0.0063)	(0.0032)	(0.0059)
19	0.903	0.431	0.870	0.360	0.799	0.385	0.759	0.303
	(0.0028)	(0.0081)	(0.0028)	(0.0081)	(0.0033)	(0.0064)	(0.0033)	(0.0060)
20	0.908	0.435	0.875	0.356	0.802	0.385	0.758	0.294
	(0.0029)	(0.0084)	(0.0029)	(0.0084)	(0.0035)	(0.0066)	(0.0035)	(0.0062)
21	0.912	0.442	0.878	0.352	0.806	0.385	0.756	0.286
	(0.0030)	(0.0087)	(0.0030)	(0.0087)	(0.0036)	(0.0067)	(0.0036)	(0.0064)
22	0.915	0.450	0.880	0.348	0.809	0.386	0.753	0.278
	(0.0031)	(0.0090)	(0.0031)	(0.0089)	(0.0037)	(0.0070)	(0.0037)	(0.0066)
23	0.917	0.461	0.881	0.344	0.812	0.388	0.749	0.272
	(0.0032)	(0.0094)	(0.0032)	(0.0091)	(0.0038)	(0.0073)	(0.0039)	(0.0067)
24	0.918	0.471	0.880	0.338	0.815	0.390	0.745	0.267
	(0.0032)	(0.0097)	(0.0032)	(0.0093)	(0.0039)	(0.0073)	(0.0040)	(0.0069)
25	0.919	0.481	0.879	0.333	0.817	0.393	0.741	0.263
	(0.0033)	(0.0102)	(0.0033)	(0.0092)	(0.0040)	(0.0076)	(0.0041)	(0.0071)
26	0.919	0.488	0.878	0.327	0.819	0.395	0.737	0.260
	(0.0034)	(0.0104)	(0.0034)	(0.0093)	(0.0041)	(0.0078)	(0.0042)	(0.0072)
27	0.919	0.492	0.875	0.322	0.821	0.397	0.734	0.258
	(0.0035)	(0.0105)	(0.0035)	(0.0096)	(0.0042)	(0.0080)	(0.0043)	(0.0074)
28	0.918	0.491	0.872	0.317	0.823	0.398	0.732	0.256
	(0.0036)	(0.0106)	(0.0035)	(0.0094)	(0.0043)	(0.0080)	(0.0043)	(0.0074)
29	0.917	0.488	0.869	0.312	0.825	0.399	0.731	0.253
	(0.0036)	(0.0109)	(0.0036)	(0.0096)	(0.0044)	(0.0082)	(0.0044)	(0.0077)
30	0.916	0.483	0.866	0.306	0.827	0.400	0.730	0.251
	(0.0037)	(0.0109)	(0.0036)	(0.0095)	(0.0045)	(0.0083)	(0.0045)	(0.0078)

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Table 1.B: RF (SE) by sex, initial economic state and disability (continued)

	MALES				FEMALES			
	Employed		Non-Employed		Employed		Non-Employed	
Age	A–E	D–E	A–NE	D–NE	A–E	D–E	A–NE	D–NE
31	0.914	0.476	0.863	0.300	0.830	0.401	0.730	0.247
	(0.0038)	(0.0109)	(0.0038)	(0.0096)	(0.0045)	(0.0085)	(0.0047)	(0.0078)
32	0.913	0.470	0.859	0.293	0.833	0.402	0.729	0.244
	(0.0038)	(0.0109)	(0.0038)	(0.0097)	(0.0046)	(0.0086)	(0.0047)	(0.0079)
33	0.911	0.463	0.855	0.285	0.836	0.404	0.729	0.240
	(0.0039)	(0.0112)	(0.0040)	(0.0098)	(0.0047)	(0.0088)	(0.0049)	(0.0080)
34	0.909	0.457	0.851	0.277	0.839	0.407	0.728	0.235
	(0.0040)	(0.0112)	(0.0041)	(0.0098)	(0.0048)	(0.0092)	(0.0050)	(0.0081)
35	0.907	0.452	0.847	0.268	0.841	0.410	0.727	0.230
	(0.0041)	(0.0111)	(0.0042)	(0.0099)	(0.0050)	(0.0095)	(0.0051)	(0.0084)
36	0.904	0.448	0.843	0.259	0.843	0.414	0.726	0.225
	(0.0043)	(0.0111)	(0.0043)	(0.0099)	(0.0051)	(0.0098)	(0.0052)	(0.0085)
37	0.902	0.444	0.838	0.250	0.845	0.418	0.724	0.219
	(0.0044)	(0.0114)	(0.0045)	(0.0102)	(0.0052)	(0.0103)	(0.0054)	(0.0087)
38	0.899	0.442	0.834	0.241	0.846	0.423	0.721	0.213
	(0.0044)	(0.0116)	(0.0044)	(0.0105)	(0.0054)	(0.0106)	(0.0055)	(0.0089)
39	0.896	0.440	0.829	0.231	0.847	0.428	0.717	0.207
	(0.0045)	(0.0118)	(0.0045)	(0.0106)	(0.0056)	(0.0108)	(0.0056)	(0.0091)
40	0.893	0.440	0.825	0.221	0.847	0.434	0.711	0.201
	(0.0047)	(0.0119)	(0.0047)	(0.0108)	(0.0058)	(0.0111)	(0.0058)	(0.0092)
41	0.889	0.439	0.820	0.211	0.846	0.440	0.704	0.194
	(0.0048)	(0.0119)	(0.0048)	(0.0110)	(0.0060)	(0.0117)	(0.0059)	(0.0095)
42	0.885	0.439	0.814	0.201	0.845	0.445	0.695	0.188
	(0.0049)	(0.0120)	(0.0048)	(0.0113)	(0.0063)	(0.0117)	(0.0061)	(0.0096)
43	0.881	0.439	0.808	0.191	0.844	0.451	0.684	0.180
	(0.0051)	(0.0123)	(0.0051)	(0.0115)	(0.0065)	(0.0122)	(0.0064)	(0.0098)
44	0.877	0.440	0.801	0.182	0.842	0.456	0.670	0.173
	(0.0053)	(0.0125)	(0.0053)	(0.0115)	(0.0067)	(0.0126)	(0.0066)	(0.0099)
45	0.871	0.440	0.792	0.174	0.839	0.462	0.654	0.165
	(0.0056)	(0.0129)	(0.0056)	(0.0116)	(0.0070)	(0.0127)	(0.0069)	(0.0101)
46	0.866	0.441	0.783	0.166	0.837	0.468	0.634	0.156
	(0.0059)	(0.0129)	(0.0059)	(0.0116)	(0.0071)	(0.0130)	(0.0073)	(0.0106)
47	0.860	0.442	0.772	0.159	0.834	0.476	0.611	0.148
	(0.0062)	(0.0128)	(0.0063)	(0.0118)	(0.0073)	(0.0130)	(0.0075)	(0.0110)
48	0.853	0.443	0.759	0.151	0.830	0.484	0.583	0.139
	(0.0066)	(0.0130)	(0.0066)	(0.0117)	(0.0077)	(0.0130)	(0.0078)	(0.0111)

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Table 1.B: RF (SE) by sex, initial economic state and disability (continued)

	MALES				FEMALES			
	Employed		Non-Employed		Employed		Non-Employed	
Age	A–E	D–E	A–NE	D–NE	A–E	D–E	A–NE	D–NE
49	0.846	0.444	0.744	0.142	0.826	0.494	0.551	0.130
	(0.0069)	(0.0128)	(0.0069)	(0.0118)	(0.0081)	(0.0129)	(0.0082)	(0.0110)
50	0.838	0.446	0.726	0.134	0.822	0.506	0.514	0.120
	(0.0073)	(0.0130)	(0.0073)	(0.0120)	(0.0085)	(0.0132)	(0.0088)	(0.0113)
51	0.829	0.448	0.704	0.124	0.818	0.521	0.473	0.111
	(0.0077)	(0.0132)	(0.0075)	(0.0120)	(0.0088)	(0.0134)	(0.0095)	(0.0114)
52	0.820	0.451	0.678	0.114	0.815	0.540	0.427	0.100
	(0.0082)	(0.0137)	(0.0082)	(0.0124)	(0.0089)	(0.0140)	(0.0105)	(0.0114)
53	0.809	0.455	0.645	0.104	0.813	0.564	0.377	0.089
	(0.0087)	(0.0137)	(0.0089)	(0.0125)	(0.0093)	(0.0146)	(0.0113)	(0.0116)
54	0.799	0.458	0.606	0.094	0.813	0.596	0.323	0.077
	(0.0092)	(0.0135)	(0.0095)	(0.0128)	(0.0097)	(0.0150)	(0.0121)	(0.0120)
55	0.787	0.463	0.560	0.084	0.816	0.638	0.266	0.064
	(0.0098)	(0.0132)	(0.0106)	(0.0130)	(0.0094)	(0.0149)	(0.0129)	(0.0117)
56	0.775	0.470	0.507	0.073	0.826	0.691	0.207	0.050
	(0.0103)	(0.0133)	(0.0116)	(0.0128)	(0.0093)	(0.0158)	(0.0134)	(0.0114)
57	0.764	0.478	0.449	0.063	0.844	0.757	0.148	0.036
	(0.0109)	(0.0133)	(0.0132)	(0.0123)	(0.0089)	(0.0161)	(0.0131)	(0.0113)
58	0.754	0.490	0.386	0.052	0.876	0.835	0.091	0.022
	(0.0114)	(0.0126)	(0.0154)	(0.0124)	(0.0083)	(0.0153)	(0.0129)	(0.0106)
59	0.746	0.508	0.322	0.042	0.927	0.920	0.039	0.009
	(0.0117)	(0.0133)	(0.0174)	(0.0124)	(0.0068)	(0.0125)	(0.0102)	(0.0076)
60	0.743	0.535	0.257	0.032				
	(0.0118)	(0.0132)	(0.0184)	(0.0118)				
61	0.749	0.574	0.194	0.023				
	(0.0115)	(0.0133)	(0.0196)	(0.0109)				
62	0.768	0.633	0.134	0.015				
	(0.0112)	(0.0135)	(0.0199)	(0.0104)				
63	0.808	0.718	0.079	0.008				
	(0.0107)	(0.0127)	(0.0201)	(0.0089)				
64	0.882	0.840	0.032	0.003				
	(0.0082)	(0.0103)	(0.0154)	(0.0063)				

$A\text{–}E$ = Non-Disabled and Employed; $A\text{–}NE$ = Non-Disabled and Non-employed;
$D\text{–}E$ = Disabled and Employed; $D\text{–}NE$ = Disabled and Non-employed;

TABLE 2.B

WORK-LIFE EXPECTANCY (STANDARD ERRORS) BY
SEX, AGE, INITIAL EMPLOYMENT STATUS AND DISABILITY 1998 – 2003 (2.5 %).

	MALES				**FEMALES**			
	Employed		**Non-Employed**		**Employed**		**Non-Employed**	
Age	A–E	D–E	A–NE	D–NE	A–E	D–E	A–NE	D–NE
16	24.36	11.75	23.53	10.24	20.87	10.34	20.06	8.81
	(0.0749)	(0.2089)	(0.0765)	(0.2080)	(0.0812)	(0.1604)	(0.0817)	(0.1491)
17	24.30	11.64	23.45	10.02	20.70	10.15	19.84	8.45
	(0.0733)	(0.2072)	(0.0747)	(0.2082)	(0.0820)	(0.1600)	(0.0825)	(0.1501)
18	24.20	11.55	23.34	9.81	20.52	9.98	19.59	8.08
	(0.0738)	(0.2127)	(0.0740)	(0.2120)	(0.0833)	(0.1619)	(0.0830)	(0.1514)
19	24.07	11.49	23.20	9.60	20.33	9.81	19.32	7.72
	(0.0747)	(0.2166)	(0.0745)	(0.2165)	(0.0849)	(0.1640)	(0.0850)	(0.1538)
20	23.91	11.46	23.03	9.38	20.13	9.66	19.01	7.38
	(0.0761)	(0.2217)	(0.0766)	(0.2219)	(0.0872)	(0.1649)	(0.0873)	(0.1546)
21	23.71	11.49	22.82	9.16	19.92	9.52	18.68	7.06
	(0.0779)	(0.2256)	(0.0778)	(0.2254)	(0.0879)	(0.1664)	(0.0885)	(0.1580)
22	23.48	11.56	22.57	8.93	19.68	9.40	18.31	6.77
	(0.0792)	(0.2301)	(0.0793)	(0.2276)	(0.0895)	(0.1700)	(0.0910)	(0.1602)
23	23.21	11.66	22.29	8.70	19.43	9.28	17.92	6.51
	(0.0799)	(0.2390)	(0.0801)	(0.2291)	(0.0904)	(0.1740)	(0.0924)	(0.1614)
24	22.92	11.76	21.97	8.44	19.16	9.18	17.52	6.28
	(0.0804)	(0.2421)	(0.0810)	(0.2315)	(0.0913)	(0.1727)	(0.0938)	(0.1623)
25	22.60	11.83	21.62	8.18	18.88	9.08	17.12	6.08
	(0.0811)	(0.2496)	(0.0808)	(0.2259)	(0.0929)	(0.1748)	(0.0938)	(0.1638)
26	22.25	11.82	21.25	7.92	18.57	8.96	16.72	5.90
	(0.0819)	(0.2523)	(0.0824)	(0.2258)	(0.0929)	(0.1769)	(0.0942)	(0.1641)
27	21.89	11.72	20.85	7.67	18.26	8.83	16.34	5.73
	(0.0830)	(0.2506)	(0.0824)	(0.2277)	(0.0927)	(0.1778)	(0.0946)	(0.1635)
28	21.51	11.52	20.44	7.43	17.93	8.68	15.96	5.57
	(0.0833)	(0.2480)	(0.0816)	(0.2212)	(0.0928)	(0.1742)	(0.0947)	(0.1621)
29	21.12	11.24	20.02	7.18	17.60	8.52	15.60	5.40
	(0.0830)	(0.2503)	(0.0834)	(0.2201)	(0.0938)	(0.1749)	(0.0942)	(0.1633)
30	20.71	10.92	19.58	6.93	17.27	8.35	15.24	5.23
	(0.0833)	(0.2466)	(0.0825)	(0.2137)	(0.0932)	(0.1741)	(0.0947)	(0.1619)

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Table 2.B: WLE (SE) by sex, initial economic state and disability (continued)

	MALES				FEMALES			
	Employed		Non-Employed		Employed		Non-Employed	
Age	A–E	D–E	A–NE	D–NE	A–E	D–E	A–NE	D–NE
31	20.29	10.57	19.14	6.66	16.92	8.17	14.87	5.04
	(0.0835)	(0.2429)	(0.0840)	(0.2134)	(0.0922)	(0.1729)	(0.0959)	(0.1581)
32	19.85	10.22	18.69	6.37	16.57	8.00	14.51	4.85
	(0.0837)	(0.2370)	(0.0834)	(0.2111)	(0.0919)	(0.1714)	(0.0941)	(0.1572)
33	19.41	9.88	18.22	6.08	16.21	7.83	14.13	4.64
	(0.0837)	(0.2381)	(0.0853)	(0.2098)	(0.0912)	(0.1715)	(0.0943)	(0.1548)
34	18.95	9.54	17.75	5.78	15.83	7.67	13.74	4.44
	(0.0844)	(0.2329)	(0.0854)	(0.2041)	(0.0911)	(0.1736)	(0.0945)	(0.1538)
35	18.48	9.22	17.27	5.47	15.43	7.52	13.34	4.22
	(0.0844)	(0.2259)	(0.0853)	(0.2009)	(0.0910)	(0.1740)	(0.0938)	(0.1546)
36	18.00	8.91	16.78	5.17	15.01	7.36	12.92	4.00
	(0.0848)	(0.2208)	(0.0858)	(0.1975)	(0.0915)	(0.1753)	(0.0934)	(0.1518)
37	17.51	8.63	16.28	4.86	14.57	7.20	12.48	3.78
	(0.0845)	(0.2207)	(0.0867)	(0.1986)	(0.0899)	(0.1772)	(0.0925)	(0.1505)
38	17.01	8.36	15.78	4.55	14.11	7.05	12.02	3.56
	(0.0840)	(0.2201)	(0.0838)	(0.1987)	(0.0906)	(0.1763)	(0.0910)	(0.1479)
39	16.50	8.11	15.27	4.25	13.63	6.89	11.53	3.34
	(0.0836)	(0.2167)	(0.0837)	(0.1943)	(0.0903)	(0.1746)	(0.0898)	(0.1457)
40	15.97	7.86	14.75	3.95	13.12	6.73	11.02	3.11
	(0.0839)	(0.2129)	(0.0849)	(0.1925)	(0.0894)	(0.1713)	(0.0898)	(0.1424)
41	15.43	7.62	14.22	3.66	12.60	6.55	10.48	2.89
	(0.0835)	(0.2070)	(0.0830)	(0.1905)	(0.0894)	(0.1747)	(0.0882)	(0.1410)
42	14.88	7.38	13.68	3.38	12.06	6.35	9.91	2.68
	(0.0826)	(0.2023)	(0.0814)	(0.1891)	(0.0893)	(0.1671)	(0.0875)	(0.1373)
43	14.31	7.13	13.13	3.11	11.50	6.14	9.32	2.46
	(0.0833)	(0.2006)	(0.0829)	(0.1870)	(0.0884)	(0.1667)	(0.0872)	(0.1332)
44	13.74	6.89	12.55	2.86	10.92	5.92	8.70	2.24
	(0.0831)	(0.1961)	(0.0832)	(0.1802)	(0.0872)	(0.1632)	(0.0851)	(0.1288)
45	13.15	6.64	11.95	2.62	10.33	5.68	8.05	2.03
	(0.0841)	(0.1953)	(0.0845)	(0.1757)	(0.0860)	(0.1567)	(0.0843)	(0.1248)
46	12.54	6.39	11.34	2.41	9.72	5.44	7.37	1.81
	(0.0854)	(0.1869)	(0.0853)	(0.1686)	(0.0828)	(0.1509)	(0.0846)	(0.1230)
47	11.93	6.13	10.71	2.20	9.10	5.20	6.67	1.61
	(0.0864)	(0.1773)	(0.0869)	(0.1636)	(0.0799)	(0.1417)	(0.0817)	(0.1203)
48	11.31	5.87	10.06	2.00	8.47	4.94	5.95	1.42
	(0.0873)	(0.1729)	(0.0876)	(0.1555)	(0.0786)	(0.1323)	(0.0800)	(0.1129)

Continued on next page

Table 2.B: WLE (SE) by sex, initial economic state and disability (continued)

	MALES				FEMALES			
	Employed		Non-Employed		Employed		Non-Employed	
Age	A–E	D–E	A–NE	D–NE	A–E	D–E	A–NE	D–NE
49	10.67	5.60	9.39	1.80	7.82	4.68	5.22	1.23
	(0.0875)	(0.1617)	(0.0873)	(0.1486)	(0.0763)	(0.1221)	(0.0778)	(0.1037)
50	10.03	5.34	8.69	1.60	7.16	4.41	4.48	1.05
	(0.0877)	(0.1557)	(0.0870)	(0.1433)	(0.0744)	(0.1153)	(0.0764)	(0.0987)
51	9.37	5.07	7.96	1.40	6.50	4.14	3.76	0.88
	(0.0871)	(0.1489)	(0.0853)	(0.1356)	(0.0702)	(0.1066)	(0.0752)	(0.0906)
52	8.71	4.79	7.20	1.21	5.83	3.86	3.05	0.72
	(0.0872)	(0.1453)	(0.0875)	(0.1319)	(0.0639)	(0.1001)	(0.0749)	(0.0818)
53	8.03	4.51	6.40	1.04	5.15	3.58	2.39	0.56
	(0.0868)	(0.1364)	(0.0884)	(0.1238)	(0.0591)	(0.0924)	(0.0717)	(0.0737)
54	7.36	4.22	5.58	0.87	4.47	3.28	1.78	0.42
	(0.0847)	(0.1241)	(0.0879)	(0.1175)	(0.0534)	(0.0824)	(0.0663)	(0.0659)
55	6.68	3.93	4.75	0.71	3.80	2.96	1.24	0.30
	(0.0830)	(0.1121)	(0.0897)	(0.1104)	(0.0435)	(0.0693)	(0.0598)	(0.0543)
56	6.00	3.63	3.92	0.57	3.11	2.61	0.78	0.19
	(0.0800)	(0.1032)	(0.0901)	(0.0990)	(0.0349)	(0.0597)	(0.0507)	(0.0431)
57	5.33	3.34	3.13	0.44	2.42	2.17	0.43	0.10
	(0.0764)	(0.0931)	(0.0919)	(0.0860)	(0.0255)	(0.0461)	(0.0375)	(0.0323)
58	4.67	3.04	2.39	0.32	1.70	1.62	0.18	0.04
	(0.0706)	(0.0781)	(0.0951)	(0.0767)	(0.0162)	(0.0297)	(0.0251)	(0.0205)
59	4.02	2.74	1.73	0.23	0.91	0.91	0.04	0.01
	(0.0632)	(0.0714)	(0.0937)	(0.0668)	(0.0067)	(0.0123)	(0.0101)	(0.0074)
60	3.39	2.44	1.17	0.15				
	(0.0536)	(0.0601)	(0.0841)	(0.0538)				
61	2.78	2.13	0.72	0.09				
	(0.0425)	(0.0493)	(0.0728)	(0.0404)				
62	2.17	1.79	0.38	0.04				
	(0.0316)	(0.0382)	(0.0564)	(0.0294)				
63	1.55	1.38	0.15	0.02				
	(0.0206)	(0.0244)	(0.0386)	(0.0171)				
64	0.86	0.82	0.03	0.00				
	(0.0080)	(0.0101)	(0.0151)	(0.0061)				

A–E = Non-Disabled and Employed; *A–NE* = Non-Disabled and Non-employed;
D–E = Disabled and Employed; *D–NE* = Disabled and Non-employed;

TABLE 3.B

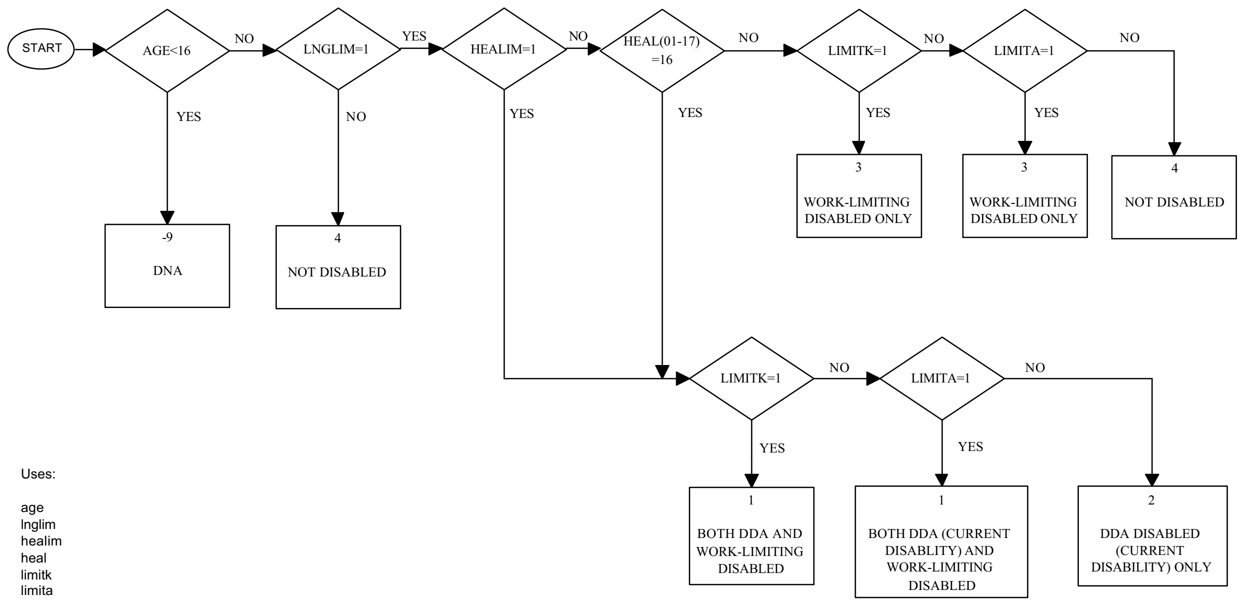
Average differences in employment-risks reduction factor (2.5 %) based on model 2 classified by sex, age, initial employment status, disability and education level.

D	HQ	Employed < 30	Employed 30 – 50	Employed > 50	Non-Employed < 30	Non-Employed 30 – 50	Non-Employed > 50
Males							
Non-Disabled	**HD**	0.011	−0.001	−0.026	0.008	0.017	0.009
	D	0.004	−0.004	−0.014	0.003	0.000	0.001
	A	0.012	0.014	0.006	0.011	0.022	0.007
	GE	−0.005	−0.013	0.003	−0.008	−0.017	−0.029
	O	−0.036	−0.010	0.035	−0.049	−0.036	−0.014
Disabled	**HD**	0.147	0.155	0.178	0.113	0.159	0.103
	D	0.142	0.090	0.040	0.178	0.080	0.028
	A	0.110	0.010	−0.009	0.145	−0.010	0.002
	GE	0.066	0.070	0.095	0.064	0.077	0.048
	O	−0.080	−0.055	−0.019	−0.100	−0.051	−0.021
Females							
Non-Disabled	**HD**	0.074	0.044	−0.004	0.089	0.086	0.107
	D	0.075	0.052	0.022	0.087	0.092	0.072
	A	0.017	0.014	0.032	0.023	0.027	0.045
	GE	0.012	0.019	0.014	0.003	0.024	−0.001
	O	−0.124	−0.049	0.004	−0.146	−0.093	−0.038
Disabled	**HD**	0.292	0.223	0.070	0.319	0.251	0.118
	D	0.193	0.114	−0.032	0.208	0.105	0.025
	A	0.114	0.109	0.053	0.090	0.060	0.020
	GE	−0.003	0.015	0.043	0.004	0.040	0.008
	O	−0.142	−0.075	−0.016	−0.116	−0.063	−0.011

Source: Model 2 (Quarterly Longitudinal LFS 1998 – 2003)

C Disability Algorithm (DISCURR)

Figure 1.C: illustrates the LFS algorithm used to derive a 4 category health variable, representing a long lasting disability status of the participants (DDA and work-limiting, DDA only, work-limiting only or not disabled). The applied classification algorithm is based on a series of questions related to health status and work-limiting conditions. Thus, only those participants are classified as disabled who experience health problems for more than a year (LNGLIM). However, those who report a long lasting disability, but this does not limit their day to day activity (HEALIM), and it is not a progressive illness (HEAL=16), and also does not have any work-limiting effects, e.g. limits neither the type nor the amount of paid works (LIMITK, LIMITA), are also classified as non-disabled. In any other cases, the participants will be classified as disabled at one of the 3 predefined levels. In the current investigation, we have considered as *severely* disabled only those participants who have been known to suffer both by DDA and by work-limiting conditions. This level of disability corresponds to persons with conditions that either limit their day to day activities or it is a progressive illness, and in addition is also perceived by the participants as disadvantaging them in the labour market both in terms of type of work and amount of earnings.



Source: Labour Force Survey User Guide (Volume 4): LFS Standard Derived Variables

Figure 1.C: LFS classification algorithm to determine the current disability status of the participants (DISCURR).

D Summary of LFS Variables

Table 1.D
Employment categories (INECACA/R) by sex and
disability based on LFS longitudinal data over the period of 1998 – 2003

No	INECACA/R CATEGORIES	MEN All %	MEN D %	MEN ND %	WOMEN All %	WOMEN D %	WOMEN ND %
1	Employee	66.48	25.23	72.81	65.28	27.68	70.68
2	Self-employed	12.59	6.46	13.52	4.78	2.75	5.07
3	Government employment and training programmes	0.43	0.32	0.45	0.27	0.20	0.28
4	Unpaid family worker	0.12	0.14	0.12	0.34	0.42	0.32
5	ILO unemployed	3.98	4.03	3.98	2.84	2.78	2.86
6	Inactive – seeking, unavailable, student	0.20	0.05	0.22	0.17	0.05	0.19
7	Inactive – seeking, unavailable, looking after family, home	0.02	0.03	0.02	0.19	0.16	0.20
8	Inactive – seeking, unavailable, temporarily sick or injured	0.03	0.09	0.02	0.02	0.08	0.01
9	Inactive – seeking, unavailable, long-term sick or disabled	0.02	0.16	0.00	0.01	0.08	0.00
10	Inactive – seeking, unavailable, other reason	0.08	0.07	0.08	0.09	0.06	0.09
11	Inactive – seeking, unavailable, no reason given	0.02	0.04	0.02	0.02	0.04	0.02
12	Inactive – not seeking, would like work, waiting results of job application	0.01	0.02	0.01	0.01	0.02	0.01
13	Inactive – not seeking, would like work, student	0.56	0.27	0.61	0.58	0.30	0.62
14	Inactive – not seeking, would like work, looking after family, home	0.37	0.60	0.34	3.04	3.11	3.04
15	Inactive – not seeking, would like work, temporarily sick or injured	0.23	0.89	0.14	0.25	0.97	0.15
16	Inactive – not seeking, would like work, long-term sick or disabled	2.68	19.51	0.18	1.79	13.85	0.11
17	Inactive – not seeking, would like work, believes no job available	0.18	0.32	0.16	0.12	0.18	0.11
18	Inactive – not seeking, would like work, not started looking	0.19	0.17	0.19	0.29	0.26	0.30
19	Inactive – not seeking, would like work, not looked	0.36	0.46	0.34	0.47	0.52	0.47
20	Inactive – not seeking, would like work, no reason	0.00	0.01	0.00	0.00	0.00	0.00
21	Inactive – not seeking, not like work, waiting results of job application	0.01	0.01	0.01	0.00	0.00	0.00
22	Inactive – not seeking, not like work, student	2.14	0.91	2.33	2.39	0.96	2.60
23	Inactive – not seeking, not like work, looking after family, home	0.58	1.00	0.51	9.21	9.00	9.24
24	Inactive – not seeking, not like work, temporarily sick or injured	0.12	0.53	0.05	0.24	1.07	0.13
25	Inactive – not seeking, not like work, long-term sick or disabled	4.63	33.48	0.33	4.19	31.73	0.32
26	Inactive – not seeking, not like work, not need or want job	0.35	0.33	0.35	0.95	0.79	0.96
27	Inactive – not seeking, not like work, retired	3.23	4.39	2.83	1.69	2.00	1.49
28	Inactive – not seeking, not like work, other reason	0.27	0.29	0.27	0.61	0.76	0.59
29	Inactive – not seeking, not like work, no reason given	0.11	0.17	0.10	0.14	0.18	0.13

TABLE 2.D
Groupings of the highest educational attainment categories.

HQ	HIQUAL Categories
HD	**Higher degree** **NVQ level 5** **First degree** **Other degree**
D	**NVQ level 4** **Diploma in higher education** **HNC/HND, BTEC higher etc** **Teaching – further education** **Teaching – secondary** **Teaching – primary** **Teaching level not stated** **Nursing etc** **RSA higher diploma** **Other higher education below degree level**
A	**NVQ level 3** **GNVQ advanced** **A level or equivalent** **RSA advanced diploma or certificate** **OND/ONC, BTEC/SCOTVEC national** **City and Guilds advanced craft** **Scottish 6th year certificate (CSYS)**
A	**SCE higher or equivalent** **AS level or equivalent** **Trade apprenticeship**
GE	**NVQ level 2 or equivalent** **GNVQ intermediate** **RSA diploma** **City and Guilds craft** **BTEC/SCOTVEC first or general diploma** **O level, GCSE grade A-C or equivalent**
O	**NVQ level 1 or equivalent** **GNVQ/GSVQ foundation level** **CSE below grade 1, GCSE below grade C** **BTEC first or general certificate** **SCOTVEC modules or equivalent** **RSA other** **City and Guilds other** **YT/YTP certificate** **Other qualification** **No qualifications** **Don't know**

TABLE 3.D
Prevalence rates by education (grouped highest qualifications),
sex, employment status and disability over the period of 1998 – 2003.

HQ	Males						Females					
	Employed (79.5 %)			Non-Employed (20.5 %)			Employed (70.3 %)			Non-Employed (29.7 %)		
	All %	D %	ND %	All %	D %	ND %	All %	D %	ND %	All %	D %	ND %
HD	17.84	10.64	18.23	8.18	4.40	11.09	15.14	11.43	15.34	6.24	3.18	7.48
D	8.82	6.92	8.92	5.18	3.85	6.19	12.11	12.28	12.10	5.73	5.81	5.70
A	32.59	33.53	32.54	25.69	26.11	25.37	17.29	15.88	17.37	13.61	9.50	15.28
GE	17.36	15.49	17.46	17.08	9.36	23.03	29.10	25.44	29.31	25.73	18.22	28.77
O	23.39	33.42	22.84	43.88	56.28	34.33	26.36	34.98	25.87	48.69	63.29	42.78

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