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Participation in disability benefit programmes.

A partial identification analysis of the British Attendance Allowance system

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Non-technical summary

In the UK, state support for older people with disabilities comes in two forms: means-tested help with the costs of specific care services arranged by local authorities; and non-means-tested cash benefits, which include the system of *Attendance Allowance* (AA). The recent Wanless inquiry into this system proposed some re-direction of resources from cash benefits into care services. That proposal raises the question of how effective are cash benefits as a form of disability support for the pensioner population.

This study examines the working of the AA system, with the aim of understanding better the problems of targeting raised by the failure of some disabled pensioners to bring forward potentially successful AA claims, because of the 'hassle' or 'stigma' of benefit claims, or because disability itself reduces individuals' capacity to derive benefit from additional cash income. The paper shows theoretically that barriers of this kind may counteract the tendency for increasing disability to raise the probability that the individual will choose to make a claim for AA.

The empirical analysis combines household-level survey data on family circumstances, disability and receipt of AA with aggregate administrative data on the average success rate for AA claims, to analyse the factors influencing individuals' probabilities of claiming and their chances of success. The paper also gives estimates of the range of possible values for the proportion of over-65s who have an unpursued, but potentially successful, claim for AA.

There are two main findings. First, the probability of an individual pensioner making a claim for AA appears to rise strongly with his or her degree of disability, irrespective of personal and household circumstances. This suggests that claim costs do not rise with disability (at least not sufficiently to negate the value of the benefit) and that disability does not seriously impair the capacity to benefit from additional cash income. Therefore, cash benefits appear to make an effective contribution to the system of support for disabled older people. Second, there is evidence of a substantial volume (possibly 30% or more of the over-65 household population) of unpursued but potentially successful AA claims. This estimate suggests that the reluctance of older people to claim disability benefit plays at least as large a part in restraining public expenditure on disability benefits as does the claim adjudication system.

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Abstract

We investigate the processes underlying payment of Attendance Allowance (AA) in the older UK population, using a partial identification approach. Receipt of AA requires that (i) a claim is made and (ii) programme administrators assess the claim as warranting an award. These processes cannot be analysed directly because we observe neither potentially successful unpursued claims, nor rejected claims. Combining survey data with weak prior restrictions and aggregate information on claim success rates, we are able to distinguish clearly the behaviour of potential claimants and assessors. Results suggest that there are many potentially successful AA claims which are not pursued.

Keywords: Family Resources Survey; disability; partial identification; welfare participation

JEL codes: C14, I18, I38

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1 Introduction

In many OECD countries, population ageing has been accompanied by a rapid rise in the cost of support for older people, in the form of disability-related welfare payments and direct provision of care. The difficulty of maintaining this part of the welfare system in the face of growing future demands is a major concern (Halpern and Hausman 1986, Bound and Burkhauser 1999, Wanless 2006). In this area of policy, there is a continuing debate about the role of disability-related cash benefits as an element of the public programme of care for people with physical or mental impairments that lead to disability. Some (for example, the UK King's Fund review of social care, Wanless 2006) have argued that the payment of disability-related universal benefits is an inefficient form of support that is increasingly difficult to justify as the size of the older, disabled population expands. A particularly contentious issue is the control of a benefit system in which eligibility is adjudged by medical or quasi-medical assessors, who are called upon to exercise subjective judgement in a way that the administrators of other cash benefit programmes are not (Daly and Noble 1996, Hirst 1997, Kreider and Riphahn 2000, Banks and Lawrence, 2005, McVicar 2008).

One of the difficulties faced by researchers analysing individual-level survey data is that it is usually only possible to observe the outcomes of successful applications for disability benefit, so that the eligibility assessment is confounded with the individual's decision to make an application. Conversely, any attempt to understand claiming behaviour is complicated by the difficulty of predicting who would be judged eligible by programme administrators, making it difficult to identify entitled non-claimants. The object of this paper is to develop and apply a method of identifying the process of eligibility assessment in the presence of this confounding.

A major difficulty here arises largely from the unavoidable lack of verifiable eligibility criteria expressed in exact, quantitative form, like the income / asset tests used to establish eligibility for means-tested welfare benefit systems. Without a clear judgement-free definition of eligibility, the concept of 'take-up' of benefit entitlements is not particularly helpful in the context of disability benefits, although Kasparova et al 2007 have discussed the prospects for measurement of a take-up rate in this context. Two different programme administrators, processing the same application in the same circumstances, may often – quite reasonably – reach different conclusions. Uncertainty is an inherent part of the programme design.

A simple choice model of claim behaviour can give clear qualitative predictions. Suppose that a potential claimant has utility function $U(Y, D)$ in the absence of disability benefit, where Y is income and D is the severity of disability. There are then three possibilities, yielding the following utility outcomes:

$$\begin{array}{ll} \text{No claim:} & U(Y, D) \\ \text{Unsuccessful claim:} & U(Y, D) - C(D) \\ \text{Successful claim:} & U(Y + A, D) - C(D) - \gamma \end{array} \tag{1}$$

where A is the (fixed) cash amount of the disability benefit and $C(D)$ is an individual-specific subjective claim cost, arising from the 'hassle' of making and maintaining a claim. Disability may make the claim process more difficult to negotiate, so that the claim cost is a function of D. We also allow the possibility that claim costs depend on the outcome of the claim. Success generates a recurrent benefit amount A, entailing a persistent relationship with the benefit system. This welfare dependency may bring social stigma or impaired self-esteem. The distinction between the one-time 'hassle' cost of making an application and the continuing stigma of dependency may be anticipated at the time of the claim decision and the quantity γ is included as the anticipated present value of the subjective dependency costs of a successful claim. For simplicity, we assume that γ is constant, but this is not essential.

For any potential claimant, there is a perceived probability of success $P_e^*(D)$.[1] An

[1] If the individual has no awareness of the disability benefit system, then we have the trivial case $P_e^*(D) = 0$ and $Pr(\text{claim}|Y, D, A) = 0$.

individual who maximises expected utility will make a claim if expected claim costs are less than the expected gain:

$$C(D) + P_e^*(D)\gamma < P_e^*(D)\left[U(Y + A, D) - U(Y, D)\right] \tag{2}$$

Claim costs appear random to the outside observer and, to reflect this, write $C(D) = C_0(D) + \varepsilon$ where ε is the apparently random component of $C(D)$. The probability of a claim is:

$$Pr(\text{claim}|Y, D, A) = F\left(\, P_e^*(D)\left[U(Y + A, D) - U(Y, D)\right] - C_0(D) - P_e^*(D)\gamma\,\right) \tag{3}$$

where $F(.)$ is the distribution function of ε. Assuming increasing, concave utility, this probability is decreasing in income Y and increasing in the benefit amount A. It is also increasing in disability D if:

$$P_e^{*\prime}(D)\left[U(Y + A, D) - U(Y, D) - \gamma\right] \; - C_0{}'(D) \; + \; P_e^*(D)\left[U_d(Y + A, D) - U_d(Y, D)\right] > 0 \tag{4}$$

where $U_d(y, d) = \partial U(y, d)/\partial d$ is the marginal (dis)utility of disability. The first term in (4) is the expected marginal benefit arising from the increased chance of being judged eligible for AA as disability increases, which is positive if the perceived stigma of dependency is not large enough to outweigh the utility gain of the additional benefit income.[2] The second term in (4) is the marginal increase in claim costs induced by increasing disability, which is positive if disability tends to impair the individual's capacity to cope with the application process. This might seem reasonable, but it is not inevitable since there are advisory and support mechanisms which tend to come into play with deteriorating health. The third term in (4) is the expected marginal effect of disability on the individual's capacity to benefit from an additional amount A of income, which may be positive or negative. If positive, it implies that disability brings an increased need for income; if negative, it implies that disability reduces the capacity to benefit from the additional income A.

[2] In that case, the probability of a claim would be zero.

We would expect the claim probability to increase with disability unless disability substantially increases claim costs or reduces the capacity to benefit from income. The latter possibility is important because it is central to the debate on cash benefits versus direct care provision as the preferred instrument of disability policy. A locally 'perverse' negative gradient for the claim probability is not completely implausible, in view of (4), so we do not impose monotonicity of claims behaviour *a priori*.

The probability of receiving the benefit is the joint probability of making a claim and that claim being successful. In this simple model:

$$Pr(\text{benefit receipt}|Y, D, A) = F\left(P_e^*(D)\left[U(Y + A, D) - U(Y, D)\right] - C_0(D) - P_e^*(D)\gamma\right) \times P_e(D) \tag{5}$$

where $P_e(D)$ is the true (rather than perceived) probability of success. The additional term $P_e(D)$ in (5) is increasing in D, so the disability gradient of the probability of benefit receipt always exceeds the gradient of the underlying claim probability.

2 The UK Attendance Allowance programme

Attendance Allowance (AA) is a programme of tax-free financial support for people resident in Great Britain and aged 65 or over, "with an illness or disability who need help with personal care". There is no income- or asset-related eligibility condition and such information is not requested during the application process (a summary of the application form is given in Appendix 1). Entitlement to AA is, in principle, judged purely on grounds of need arising from physical or mental impairment so, except for the minimum age restriction, entitlement should be independent of age and all other personal characteristics except disability-related need. In section 7.1 below, we consider the possibility that a relevant component of disability is not captured by the survey measure D. Other than this, our analysis maintains the assumption that the probability of being judged eligible is independent of age and other personal attributes, as the programme rules assert it to be.

There exists another disability benefit programme relevant to older people. Disability Living Allowance (DLA) can be claimed initially only by people under the age of 65, but receipt of DLA can then be continued past age 65 and there is no automatic transfer of DLA claimants onto AA at age 65. A claim for DLA cannot be initiated after the age of 65. Moreover, there is nothing to be gained by switching from DLA to AA, since DLA benefit rates are either identical to, or greater than, AA rates. To avoid complications associated with the long duration of many episodes of DLA receipt, we exclude from our analysis all individuals who receive DLA rather than AA.

Income from the AA programme is ignored when assessing the individual's eligibility for other means-tested benefits (such as Pension Credit, Housing Benefit and Council Tax Benefit), but receipt of AA can trigger higher needs assessments for other benefits and also entitlement to an additional Carer's Allowance if there is a person providing full-time informal care. We do not model this indirect benefit entitlement directly, but instead use original income (income from pensions, savings and other sources, excluding disability and means-tested benefits) as our measure of household resources.

3 Data

3.1 Micro data

Our individual-level data come from the UK Family Resources Survey (FRS) for the three fiscal years, 2002/3 to 2004/5. The FRS is a large household survey with full coverage of incomes and assets and questions covering a range of disabilities. Our disability indicator is based on impairments identified in answers to a question listing eight specific categories of difficulty with "activities of daily living" (ADLs). These questions are detailed in the appendix, where Table A1 shows the sample proportion and the rate of AA receipt of people reporting each of the eight types of disability. The construction of a single composite disability indicator is explained in section 5 below.

3.2 Aggregate claims data

We do not observe claims for disability benefit at the individual level but the Department for Work and Pensions (DWP) publishes aggregate figures on the caseload of the benefit system (DWP, 2008). These figures allows us to construct a crude estimate of the average success rate for claims by expressing the number of successful new claims as a proportion of the total. This is only an approximation to the relevant success rate, since the stock of people currently in receipt of disability benefit is the result of a set of successful applications that were made at some time in the past. We deal with this possible mismatch by using the minimum and maximum success rates over the past five years as the basis for a lower and upper bound on the relevant average success rate. The published figures are summarised in Table 1.

Table 1 Attendance Allowance caseload and success rates

Year	No. new claims	No. rejections	Success rate
1998-99	396.8	104.3	73.7
1999-00	378.3	96.8	74.4
2000-01	419.8	103.1	75.4
2001-02	381.3	89.1	76.6
2002-03	400.0	87.9	78.0
2003-04	420.0	90.9	78.3
2004-05	392.6	82.4	79.0

Source: DWP (2008 Table 1.2). Numbers of claims and rejections in thousands

Success rates show a monotonically rising trend, ranging from just under 74% in 1998/9 to 79% in 2004/5. However, there are some difficulties in comparing these aggregate figures with FRS survey data, since the latter relate to members of the household population, whilst a substantial (but unknown) proportion of the AA caseload are in institutional care. One would expect people in long-term care to have more severe disability on average and consequently a higher success rate. If this is so, success rates relevant to the FRS target population will be somewhat lower than in the aggregate. A reasonable assumption is that the relevant success rate for people observed in the 2003/4 FRS lies somewhere in the interval 60-80%.

4 The identification problem

Define the following notation. Disability status is measured in survey data by an ordinal variable $D \in \mathbb{D} = 0 \ldots n_d$, where $D = 0$ indicates absence of impairment. Disability may in principle be multi-dimensional with D a vector of ordinal variables but, for simplicity, we work with a composite scalar measure in this study. Here, D is assumed to be observed accurately; the measurement error case is considered in section 5 below. The receipt of disability benefit is recorded by a binary variable $R = 1$ for receipt and $R = 0$ for non-receipt. We do not observe any unsuccessful claims. Other variables relevant to the assessment of entitlement or to claims behaviour are in three groups. Personal and household circumstances which influence the propensity to make a claim but are not relevant to entitlement appear in a vector X. The support set of X is $\mathbb{X}$, which is assumed to contain a finite number of points n_x.

The eligibility probability, $P_e(d)$, is the probability that, if a claim were made, it would prove successful, conditional on disability level $D = d$. The disability indicator D may be scalar or vector-valued. It must either be a complete description of the information relevant to the eligibility decision or it must satisfy the condition $\delta \perp\!\!\!\perp X|D$, where δ is the complete set of relevant disability information. The probability of a claim being made is written

$P_c(d,x)$. We can estimate neither $P_e(d)$ nor $P_c(d,x)$ directly from the FRS survey data, since unclaimed entitlements and unsuccessful claims are not observed. Instead, we can estimate a joint probability $\pi(R|d,x)$ which is related to P_e and P_c in the following way:

$$\pi(R=1|d,x) = P_e(d)P_c(d,x) \tag{6}$$

Although P_e and P_c cannot be fully identified from data on R, D and X, some features of P_c can be identified through the exclusion restrictions on P_e. In particular, the marginal effect $\partial ln P_c(d,x)/\partial x$ is identifiable (as $\partial ln\pi(R=1d,x)/\partial x$) from an econometric analysis of AA receipt conditional on D and X. However, our focus here is on the disability gradients of P_e and P_c and the volume and nature of unpursued potential AA claims, none of which is revealed by an analysis of AA receipt alone.

One objective is to estimate some functional of the eligibility probability, which we take to be linear:

$$\psi(P_e) = \theta_0 + \sum_{d\in\mathbb{D}} \theta_d P_e(d) \tag{7}$$

where θ_d is the weight assigned to the point $D=d$. The linearity assumption can be relaxed, but it covers most important practical examples. One such is $\theta_0 = 0$ and $\theta_d = \mathbb{1}(d=d^*)$, which gives the value of the entitlement probability at a specific point d^*. Another case of interest is the proportion of the population with an unclaimed potential entitlement, given by:

$$\sum_{d\in\mathbb{D}} P_e(d)f(d) - \pi(R=1) \tag{8}$$

where $f(.)$ is generic notation for the marginal distribution of any subset of variables D, X and $\pi(R=1)$ is the population proportion in receipt of benefit.

Without further restrictions, the eligibility and claim probabilities are not identified. If $P_e^0(d)$ and $P_c^0(d,x)$ are their true values, any pair of functions $P_e^*(d) = \lambda(d)P_e^0(d)$ and $P_c^*(d,x) = P_c^0(d,x)/\lambda(d)$ will produce the same value for $\pi(R=1|d,x)$ in (6), for any positive function $\lambda(d)$ satisfying $1/P_e^0(d) \geq \lambda(d) \geq P_c^0(d,x)$ for all $x \in \mathbb{X}$. Consequently, $\{P_e^0,\ P_c^0\}$ and $\{P_e^*,\ P_c^*\}$ are observationally equivalent.

Assume that $P_c(d,x)$ and $P_e(d)$ both lie in the open interval $(0,1)$ for all $D \in \mathbb{D}$ and $X \in \mathbb{X}$. Then the probabilities $P_c(d,x)$ can be eliminated from the identification problem by expressing them as:

$$P_c(d,x) = \frac{\pi(R=1|d,x)}{P_e(d)} \tag{9}$$

Any identification point or interval for $P_e(d)$ can immediately be translated into an identification region for $P_c(d,x)$ using (9).

As in the missing data cases considered by Horowitz and Manski (2006), this identification problem takes the form of a mathematical programming problem. Although generally nonlinear, it becomes a linear programme in the absence of aggregation restrictions. If we minimise or maximise the objective function with respect to the (n_d+1) unknown probabilities $P_e(d)$ subject to the constraints set out above, the results give sharp upper and lower bounds on the eligibility probabilities. Let $\mathbb{F}(\mathcal{P})$ be the feasible set defined by a set of *a priori* constraints, where $\mathcal{P}$ is the set of observable probabilities $\pi(R=1|d,x)$. Then the tightest possible bounds on the functional ψ are given by the solutions to the following programming problem:

$$\operatorname*{opt}_{P_e \in \mathbb{F}(\mathcal{P})} \psi(P_e) \tag{10}$$

where 'opt' denotes the minimisation and maximisation operations.

We estimate the bounds by substituting sample estimates for the population probabilities $\pi(R=1|d,x)$ in the programme (10). This requires a sufficiently coarse classification in the definition of D, X to give adequate sample numbers in the cells defined by $D \times X$.[3]

[3] Too fine a classification can lead to small cell sample sizes and erratic results. Sampling error may cause the estimated feasible set $\mathbb{F}(\hat{\mathcal{P}})$ to be empty. This would occur, for instance, if we impose monotonicity on P_e and P_c, but there is non-monotonicity in $\hat{\pi}(R=1|d,x)$.

4.1 Exclusion constraints

The eligibility and claim probabilities are subject to elementary range constraints:

$$0 < P_e(d) \leq 1 \qquad \text{for } d \in \mathbb{D} \tag{11}$$

This implies nonnegativity for P_c. Together with the exclusion of X from P_e, the constraint $P_c(d,x) \leq 1$ is equivalent to:

$$P_e(d) \geq \max_{x \in \mathbb{X}} \pi(R = 1|d,x) \ , \qquad \text{for } d \in \mathbb{D} \tag{12}$$

4.2 Monotonicity restrictions

For simplicity, assume that disability D is scalar but note that the analysis can be extended to the multi-dimensional case without difficulty. It is reasonable to assume that assessed eligibility is non-decreasing in the degree of disability, giving the following set of n_d constraints:

$$P_e(d+1) \geq P_e(d) \ , \quad \text{for } \ d = 0 \ldots n_d - 1 \tag{13}$$

If the indicator D is J-dimensional, we have J sets of restrictions like (13), giving a total of $\sum_{j=1}^{J} n_d^j \left(\prod_{k \neq j}(n_d^k + 1)\right)$ constraints, where n_d^j is the number of scale points for the j-th dimension of disability.

It is less natural to assume that the claim probability is monotonic in D, since theory suggests that the claim probability may be non-increasing in D if disability tends to impair the individual's capacity to derive benefit from the additional income or increase the 'hassle' costs of making a claim. Consequently, no monotonicity constraint is imposed on $P_c(d,x)$.

4.3 Smoothness restrictions

It is reasonable to rule out the possibility of large changes in outcomes for small changes in circumstances. The assumption that the eligibility probability is smooth in D in this sense implies the following constraints:

$$|P_e(d+1) - P_e(d)| \le \Delta_e(d) \qquad \text{for } \; d = 0 \ldots n_d - 1 \tag{14}$$

A comparable smoothness constraint on P_c takes the form:

$$\left| \frac{\pi(R=1|d+1,x)}{P_e(d+1)} - \frac{\pi(R=1|d,x)}{P_e(d)} \right| \le \Delta_c(d) \qquad \text{for } \; x \in \mathbb{X}\,; \; d = 0 \ldots n_d - 1 \tag{15}$$

The smoothness thresholds Δ_e and Δ_c are dependent on d to allow for the possibility that we might want to use a weaker smoothness requirement at some points (for example, between $D = 0$ and $D = 1$) than at others.

4.4 Boundary restrictions

Exclusion and monotonicity restrictions on the eligibility and claim probabilities are not sufficient to solve the identification problem, since the trivial extreme choice $P_e(d) = 1$ and $P_c(d,x) = \pi(R = 1|d,x)$ remains a feasible solution. One way of excluding this kind of solution is to impose boundary conditions requiring that the probability of eligibility is low for non-disabled people (small D) and high for severely disabled people (large D). These constraints take the form:

$$P_e(d) \le L \qquad \text{for } d \le D^* \tag{16}$$

$$P_e(d) \ge U \qquad \text{for } d \ge D^{**} \tag{17}$$

where L and U are the *a priori* bounds and D^* and D^{**} are the cutoff points used to define low and severe disability.

4.5 Aggregation restrictions

Assume we have external information on the average success rates of AA claims. In practice, such information is unlikely to be exact, so we assume it consists of a known interval containing the aggregate proportion of claimants who are successful:

$$A_1 \le \frac{\pi(R=1)}{\sum_{d\in\mathbb{D}}\sum_{x\in\mathbb{X}} P_c(d,x)f(d,x)} \le A_2 \tag{18}$$

where $f(d,x)$ is the (known) population distribution of D, X. Using (9):

$$\frac{\pi(R=1)}{A_2} \le \sum_{d\in\mathbb{D}} \frac{\pi(R=1|d)f(d)}{P_e(d)} \le \frac{\pi(R=1)}{A_1} \tag{19}$$

where $\pi(R=1)$ and $\pi(R=1|d)$ are the unconditional and disability-conditional empirical rates of AA-receipt.

This constraint introduces nonlinearity into an otherwise linear programming problem. The optimisation problem (10) can be simplified to a linear programme if the aggregation constraint (18) is not used, or if the objective function is specified as the probability $P_e(D)$ evaluated at a single point d. In the latter case, the optimisation can be recast as a programming problem linear in the variables $1/P_e(d)$.

5 Construction of the disability indicator and population clusters

Define a vector H containing the eight FRS disability indicators and an additional dummy variable identifying people with no recorded disability. The first step in the analysis is to estimate empirically the relationship between the probability of AA receipt and these disability variables H and personal characteristics X. We do this using a generalisation of the ordered probit model which replaces the conventional normality assumption by the semi-nonparametric (SNP) distributional specification of Gallant and Nychka (1987).[4] We find that the AA receipt probability is separable in H and X, so that $\pi(R=1|H,X)$ can be written $\pi(R=1|\delta,X)$, where $\delta=\varphi(H)$ is the scalar disability index that emerges from the empirical analysis. It is straightforward to show that the conditional probability of

[4] See Stewart 2004 for details of the implementation.

AA receipt has the separable form $\pi(R = 1|\varphi(H), X)$ if either $P_e(H) = P_e(\varphi(H))$ and $P_c(H, X) = P_c(\varphi(H), X)$ or if P_c is multiplicatively separable so that $P_c = a(H)b(X)$, which implies $\varphi(H) = P_e(H)a(H)$. The latter case is highly restrictive and we suggest that it is much more plausible to assert that claimants and benefit assessors share the same view of what constitutes disability, implying that P_e and P_c are functions of the same index $\varphi(H)$. This assumption, at least in approximate form, underlies our analysis.

A process of testing simplifying restrictions on an initial detailed model was used to develop the parsimonious generalised ordered probit model presented in Appendix Table A2. The structure of the coefficients H in the SNP model implies that the index $\varphi(H)$ is approximately proportional to the following simple form:

$$\delta = \mathbb{1}\left(\sum_{j=1}^{8} \xi^j > 0\right) + \xi^m + 1.5 \sum_{j=1}^{8} \xi^j \tag{20}$$

where $\mathbb{1}(.)$ is the indicator function, ξ^j is a binary variable indicating the presence of the jth type of disability listed in the FRS questionnaire and ξ^m is the mobility indicator. Thus our disability index has three additive components: a 1-unit fixed value for the existence of any disability, a further unit for the existence of a mobility problem and 1.5 times the total number of reported disabilities. Note that our aim here is different from that underlying some other disability indices, such as the index constructed for the OPCS surveys of disabilities (Martin et al. 1988), which sought to achieve consensus among experts on the contribution of severity of disability in different domains to overall disability. Our aim instead is the more modest one of identifying the combinations of impairments and contexts which are predictive of applications for, and award of, disability benefit.

To keep the number of cells in the $X \times D$ distribution to a manageable number, we consolidate some points to give a 6-point disability scale (by combining the points 3.5 and 4; 5 and 5.5; 6.5 and 7; and 8 and above). The resulting simplified index is labeled $D = 0...5$

and the smoothness and monotonicity constraints are imposed directly on this consecutively-labeled scale. The relatively large difference between the $D = 0$ and $D = 1$ points in terms of their impact on AA receipt and in terms of their sample proportions suggests that we should consider a weaker smoothness constraint at $D = 0$ than at other points on the scale.

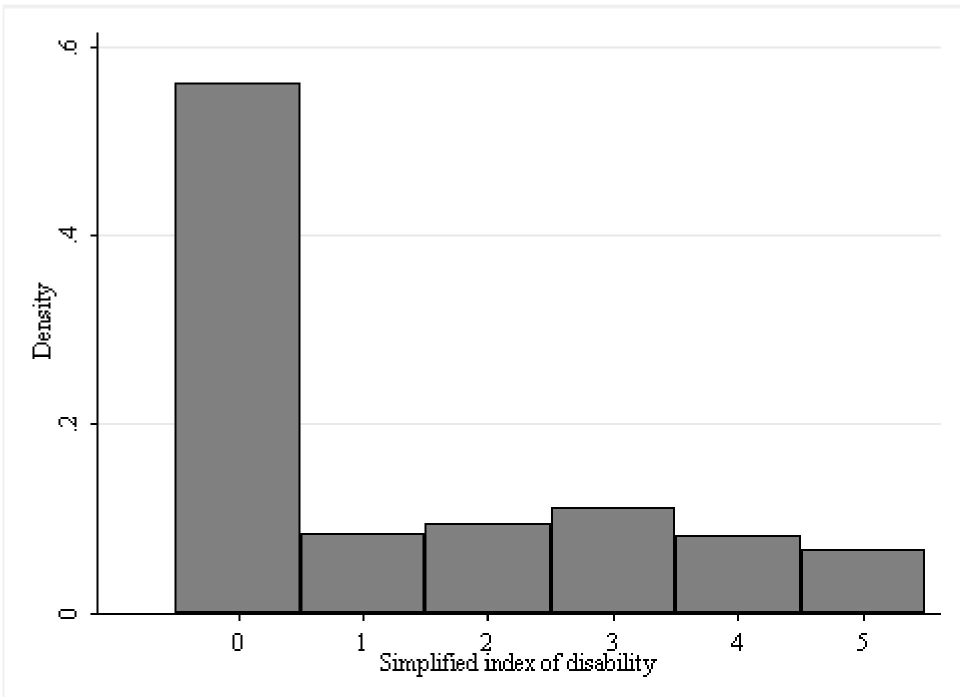

Figure 1: Sample distribution of disability index (FRS2002/3-2004/5)

We also simplify the X-distribution in two ways. First, note that the exclusion constraints make it unnecessary to use all relevant X-variables in the analysis, since $\pi(R = 1|D, X^*) = P_e(D)E[P_c(D,X)|X^*] = P_e(D)P_c(D,X^*)$ for any subset X^* of X. Thus, for example, although the wife's disability status is found empirically to influence the AA-receipt probability of married men, the application procedure does not require information about the spouse's health, so it is safe to assume that P_e is unaffected. Ignoring wives' disability in constructing bounds then leads to some loss of resolution on P_c, but no loss of validity.

A second simplification is the use of clustering methods to define a moderate number of cells in X-space, whilst avoiding an unduly great sacrifice of resolution. We use a k-

means algorithm to produce a classification of nine X-cells, in a two-stage process. First the sample is partitioned into three groups: non-homeowners; single homeowners; and home-owning couples. Within each of these sample groups, clustering is done on two continuous variables: the percentile positions in the distributions of age and equivalised income, using the Euclidean distance similarity measure. We specify three clusters for each subsample, running the clustering algorithm from 250 randomly-selected initial values for the cluster means as a way of overcoming the problem of multiple optima. This procedure has proved far superior in terms of sample discrimination to the usual method of adopting a coarse categorical classification for each $X-$variable. The characteristics of the resulting nine groups are shown in Table 2.

Table 2 Cluster attributes

Cluster	**% of sample**	**Mean age**	**% single**	**% home-owner**	**Mean p.c. original income**	**Mean disability index δ**	**% with any disability**	**% receiving AA**
1	12.1	68.2	0	100	90	1.76	37.1	3.2
2	8.2	68.8	100	100	184	1.34	29.5	2.7
3	8.3	68.8	47.9	0	77	2.46	48.7	6.7
4	8.4	79.9	100	100	205	2.42	46.9	11.3
5	20.9	70.6	0	100	218	1.32	28.7	2.1
6	13.9	78.6	0	100	96	2.61	50.6	13.5
7	7.2	75.7	70.5	0	154	2.57	49.1	14.9
8	9.4	80.1	100	100	79	2.97	52.7	21.9
9	11.6	81.2	66.5	0	75	3.58	63.2	29.9
Total	100	74.4	42.8	72.9	136	2.25	43.8	11.1

Note: FRS 2002/3, 2003/4, 2004/5 respondents aged 65 or over; total sample size = 29,978

The procedure is validated by checking that cluster membership dummies have good predictive power in a probit model of AA receipt conditional on disability × age and cluster membership. A Wald test of the explanatory power of cluster membership is highly significant ($\chi^2(8) = 1010.6$) and the use of nine X-clusters is a good compromise between the competing demands of detail for explanatory power and adequacy of cell sample sizes. As Figure 2 shows, within each of the nine clusters, the sample incidence of AA receipt is monotonically increasing in the disability index (with the exception of cluster $X = 3$ between $D = 1$ and

D = 2) and rather smooth. There is no evidence of a large jump in the AA receipt rate in passing from D = 0 to D = 1 as might be expected: the largest increase (from (0.07 to 0.25) also occurs for cluster 3. Nevertheless, we allow the possibility of such a jump in specifying the smoothness constraints.

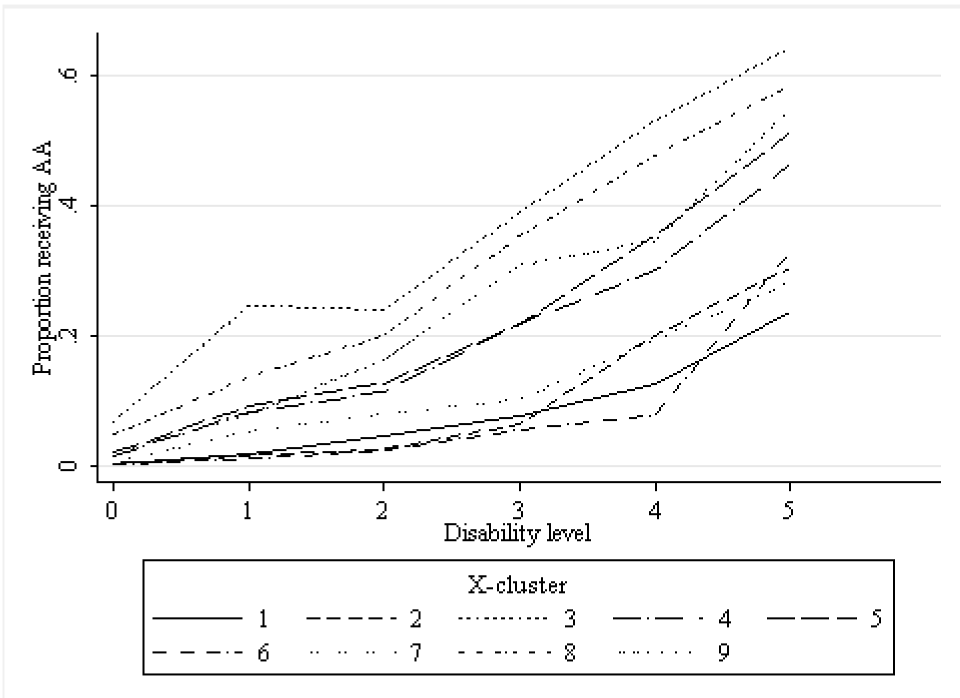

Figure 2: Sample incidence of AA receipt by disability level and X-cluster (FRS2002/3-2004/5)

6 Results

The AA programme is intended to deliver cash benefits to those with significant needs arising from disability, irrespective of other factors such as age, income and household living arrangements. If we assume the system does indeed work in this way, can we then draw useful inferences about the way eligibility is related to observed disability and about claim behaviour? We attempt to answer this question, using an analysis that is entirely non-parametric, apart from the semiparametric methods used initially to construct an empirical index of disability. Three alternative specifications of the identifying constraints are set out in Table 3, in three variants. Variant 1 is the weakest form, with the aggregate success rate assumed to lie in the wide range 60-80% and the boundary and smoothness constraints specified so as to allow an entitlement rate of up to 25% for non-disabled individuals and a rapid initial rise in $P_e(d)$ between the points $D = 0$ and $D = 1$. Variant 2 narrows the range of allowable aggregate success rates to 65-78% and imposes tighter smoothness restrictions and a lower maximum entitlement rate at $D = 0$. Variant 3 then tightens further the aggregation constraint. All of the constraints in Table 3 are mild and plausible.

Table 3 Constraints

	Constraint		Variant 1	Variant 2	Variant 3
E	Exclusion		P_e independent of X		
M	Monotonicity		P_e non-decreasing in D		
A	Aggregate success rate:		60-80%	65-78%	68-78%
B	Boundary:	$P_e(D = 0) \leq$	0.25	0.20	0.20
		$P_e(D = 6) \geq$	0.75	0.75	0.75
S	Smoothness:	$\lvert P_e(1) - P_e(0)\rvert \leq$	0.6	0.5	0.5
	all x:	$\lvert P_c(D = 1\lvert x) - P_c(D = 0\lvert x)\rvert \leq$	0.6	0.5	0.5
	all $d > 0$:	$\lvert P_e(d + 1) - P_e(d)\rvert \leq$	0.3	0.25	0.25
	all $x; d > 0$:	$\lvert P_c(d + 1\lvert x) - P_c(d\lvert x)\rvert \leq$	0.3	0.25	0.25

We estimate bounds on the award and claim probabilities $P_e(.)$ and $P_c(.)$, the proportion of the population with potentially successful unpursued claims (analogous to unclaimed entitlements in a system with objective entitlement rules) $E\ P_e(D) - \pi(R = 1)$, and the composition of this set of unpursued claims in terms of the characteristics X.

6.1 Computation

The generic optimisation problem (10) is difficult. It involves optimisation subject to inequality constraints, some of which are nonlinear. Such problems can have multiple local optima, with problems of numerical overflow in some regions outside the feasible set. We use a composite algorithm, starting with an initial search over a sequential grid of over a million values for $(P_e(0)...P_e(n_d))$ in the region $[\ \max_x \pi(R=1|0,x)) \le P_e(0) \le 1,\ \max\{P_e(0),\ \max_x \pi(R=1|1,x))\} \le P_e(1) \le \min\{1, P_e(0)+\Delta_e(0)\},\ \dots,\ \max\{P_e(n_d-1),\ \max_x \pi(R=1|n_d,x))\} \le P_e(n_d) \le \min\{1, P_e(n_d-1)+\Delta_e(n_d-1)\}]$. The best five feasible points in this grid are used as starting points for a constrained optimisation algorithm.[5] Random perturbations of these five points are then used for 500 further optimisation runs. The best feasible point reached by this process is adopted as the estimate of the bound. Detailed examination of specific cases confirms that this approach works well in locating the global optimum, but it is far from efficient in computer time and alternative algorithms are being investigated.

The construction of standard errors in nonparametric partial identification problems is not straightforward, because of the complex structure of the solution set and the possibility of solutions on the boundary of the parameter space. Resampling methods such as the bootstrap are of doubtful validity. Subsampling methods (Politis et al, 1999) offer a way forward, but the long computing times required to find solutions to (10) are an obstacle. Consequently, we give no confidence intervals for the estimated bounds presented below, but the large sample size used here and preliminary experiments with subsampling suggest that confidence intervals would be very narrow.

6.2 Eligibility probabilities

Pointwise bounds for the function $P_e(D)$ are shown in Figures 3-7. The tightness of the bounds depends on which constraints are imposed and how strongly they are specified. If we impose only exclusion and monotonicity constraints (Figure 3), the result is a low-resolution

[5] We use the Gauss constrained optimisation module, version 2.0

picture of the entitlement probability, with the upper bound at $P_e(D) = 1$ for all D. This tells us little about the nature of the claims assessment process.

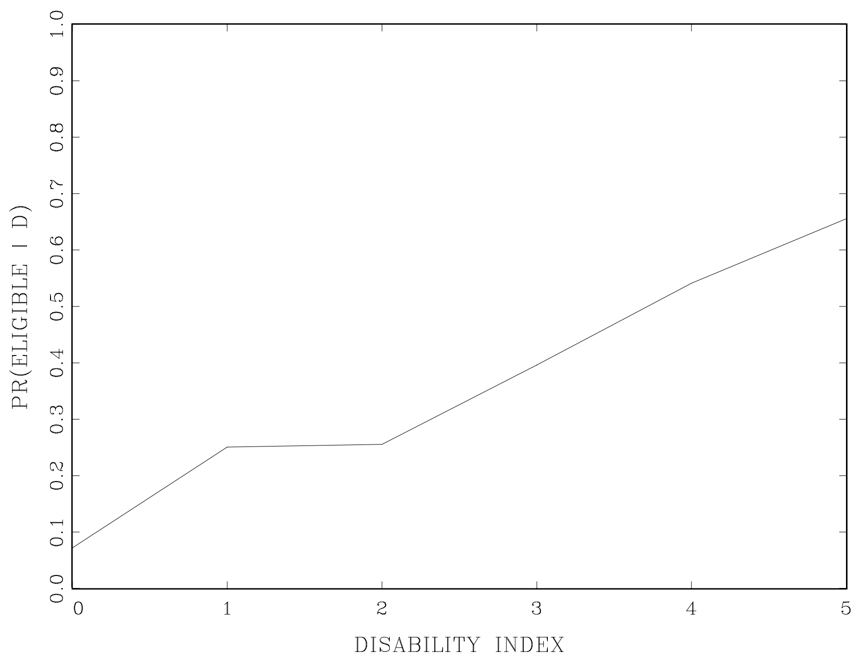

Figure 3: Lower bound on $P_e(d)$: exclusion and monotonicity only

Figure 4 shows that imposition of the aggregation constraint in addition to exclusion and monotonicity gives better resolution but still leaves considerable uncertainty about the shape of P_e.[6] The reason for the width of these bounds is that they have to accommodate functions forms for P_e with large jumps or implausible end points. If we impose mild smoothness and boundary constraints, the bounds become much tighter, as shown in Figures 5-7. Variants 2 and 3, which use greater (but still mild) degrees of smoothing, give very good resolution for the eligibility function.

[6]The bounds for weak and strong variants of the aggregation constraint are very similar and only variant 1 is shown.

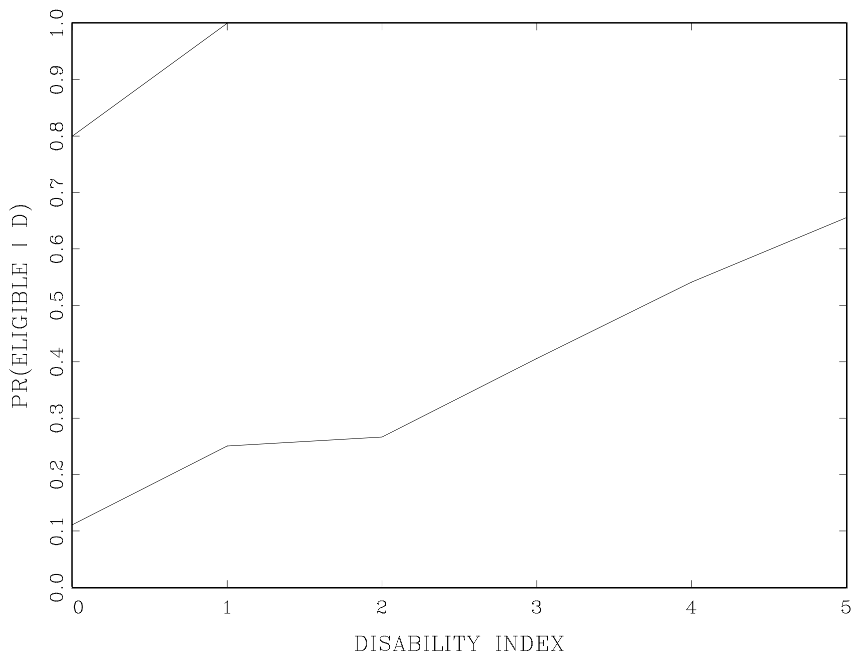

Figure 4: Bounds on $P_e(d)$: exclusion and monotonicity, with weak aggregation constraints (variant 1)

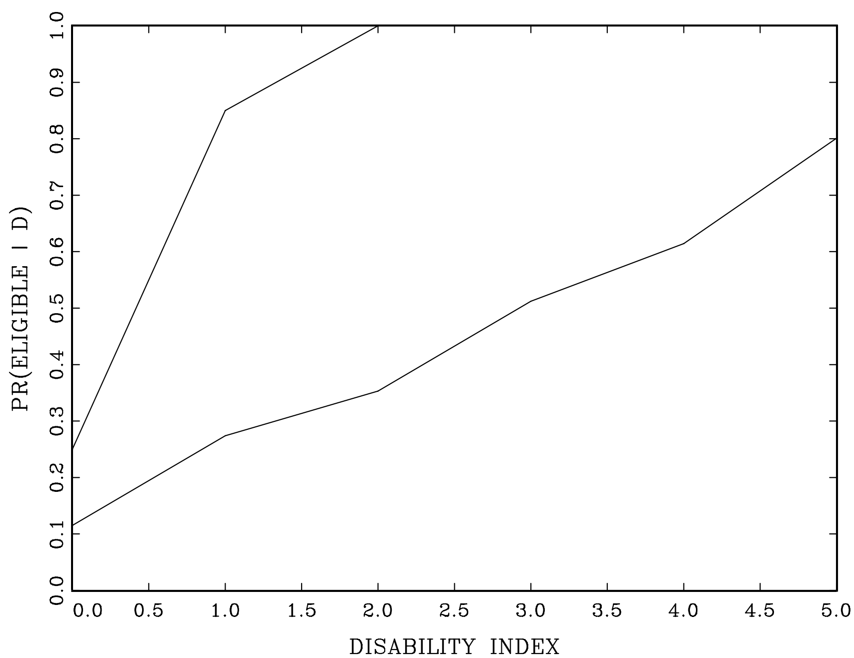

Figure 5: Bounds on $P_e(d)$: exclusion and monotonicity, with weak boundary, smoothness and aggregation constraints (variant 1)

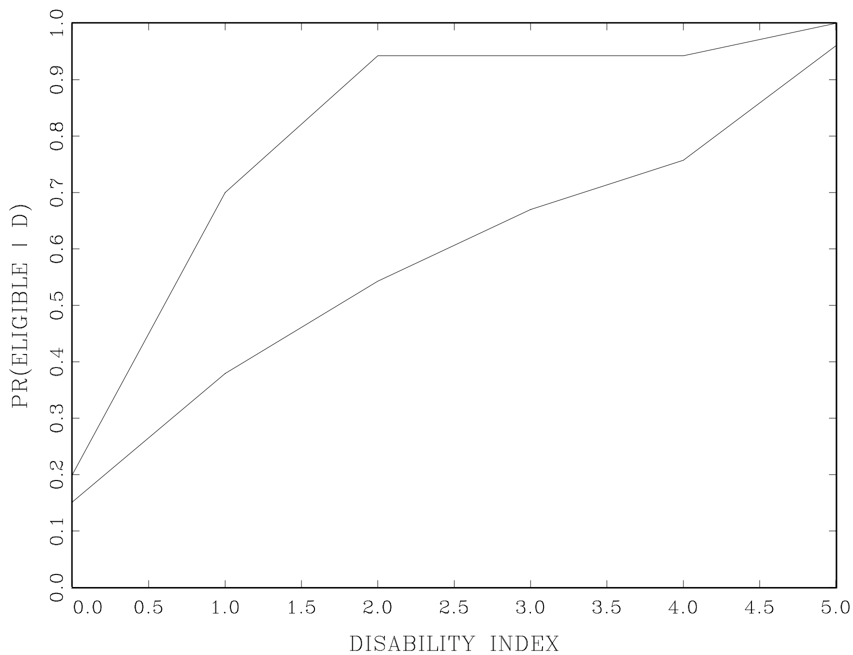

Figure 6: Bounds on $P_e(d)$: exclusion and monotonicity, with intermediate boundary, smoothness and aggregation constraints (variant 2)

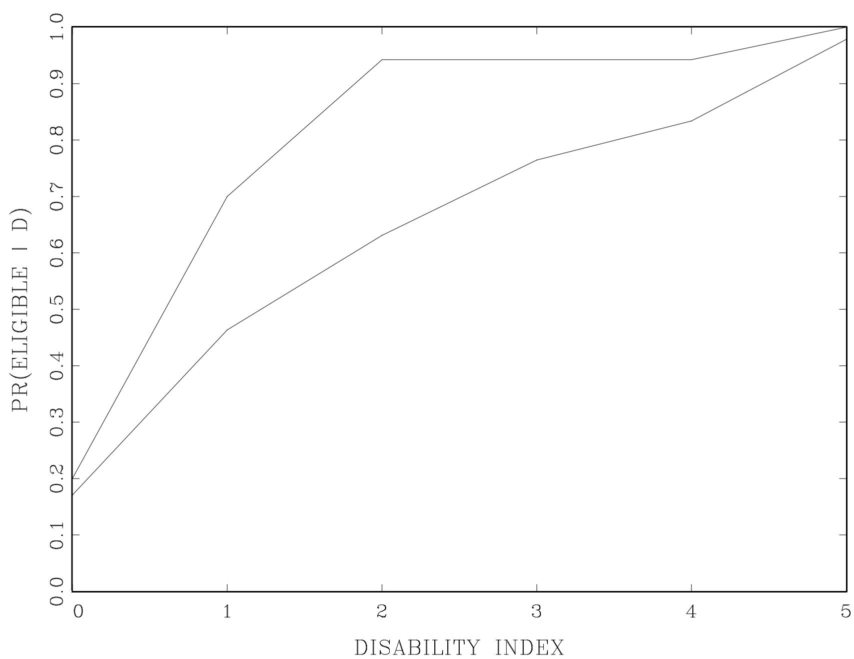

Figure 7: Bounds on $P_e(d)$: exclusion and monotonicity, with stronger boundary, smoothness and aggregation constraints (variant 3)

6.3 Claim probabilities

The relationship between claim probabilities and the covariates X which describe the characteristics and circumstances of potential claimants can be summarised by constructing bounds on the mean claim probability $Pr(\text{claim}|X = x) = \sum_d P_c(d,x)f(d|x)$ for each cluster x. These are presented in Table 4, using the full set of constraints in the two extreme variants. Claim probabilities are highest in clusters 4 and 7, which have above-average age and disability, despite their above-average income. Clusters 5, 6 and 8 have particularly low claim probabilities, for quite different reasons. Members of cluster 5 are relatively young couples with high average incomes and a low rate of disability, while clusters 6 and 8 contain older people with low incomes and high disability. What all three groups have in common is their home ownership status. Clusters 4-8 are also those with the highest rates of AA receipt, empirically.

Table 4 Bounds on cluster-specific means of P_c

	Cluster characteristics					Bounds			
						Variant 1		Variant 3	
Cluster	**Mean age**	**% single**	**% home-owners**	**Mean disability δ**	**Mean p.c. income**	P_c^{min}	P_c^{max}	P_c^{min}	P_c^{max}
1	68.2	0	100	1.76	90	0.165	0.220	0.182	0.193
2	68.8	100	100	1.34	184	0.139	0.190	0.153	0.163
3	68.8	47.9	0	2.46	77	0.088	0.122	0.096	0.103
4	79.9	100	100	2.42	205	0.289	0.400	0.322	0.343
5	70.6	0	100	1.32	218	0.021	0.029	0.023	0.025
6	78.6	0	100	2.61	96	0.054	0.075	0.059	0.063
7	75.7	70.5	0	2.57	154	0.391	0.518	0.432	0.456
8	80.1	100	100	2.97	79	0.035	0.049	0.040	0.042
9	81.2	66.5	0	3.58	75	0.169	0.234	0.186	0.199
Total	74.4	42.8	72.9	2.25	136	0.139	0.184	0.154	0.163

The bounds on claim probabilities $P_c(d,x) = \pi(R = 1|D = d, X = x)/P_e(d)$ have the same proportionate width as the bounds on $P_e(d)$, but their absolute width varies across $X-$clusters, being greatest for clusters with high rates of AA receipt. Figure 8 shows the bounds for the $X = 7$ cluster, where we have imposed only exclusion, monotonicity and the weakest aggregation constraint. The use of slightly stronger constraints narrows these bounds considerably. Figure 9 shows the effect of adding weak boundary and smoothness constraints (variant 1).

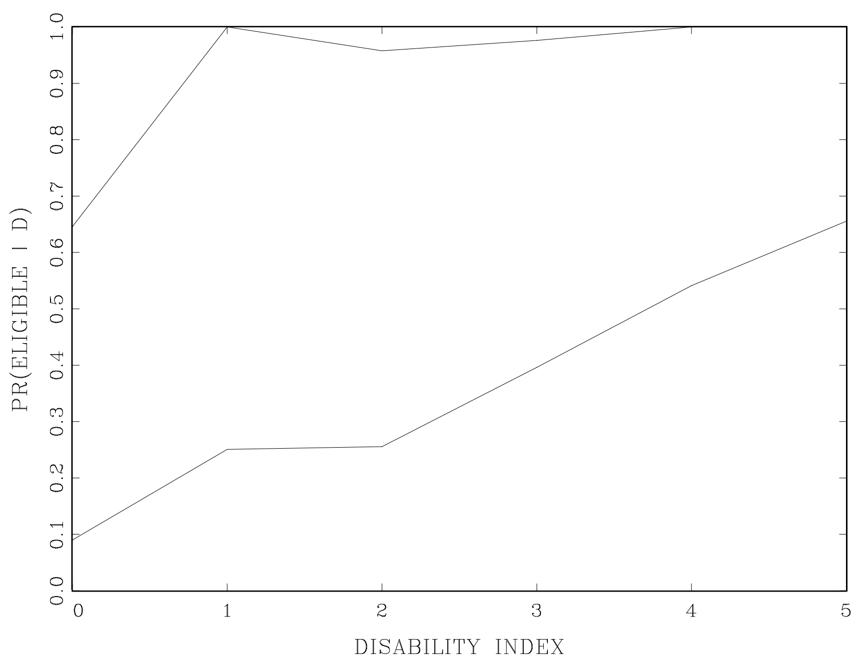

Figure 8: Bounds on $P_c(d, x)$ for high-disability cluster $X = 7$: exclusion, monotonicity and weak aggregation constraints (variant 1)

Imposition of the stronger constraints of variant 3 produces very tight bounds on the claim probability $P_c(D, X)$ for all of the X−clusters, including those with high rates of disability and AA receipt (see Figure 10). With few exceptions, the bounds on $P_c(D, X)$ suggest that claim probabilities are increasing functions of the disability level D. The largest deviation from monotonicity of $P_c(D, X)$ relates to the cluster $X = 7$ under the relatively strong constraints of variant 3 (Figure 10), where there is a possibility of local decrease between $D = 1$ and $D = 2$. However, the general picture is one of claim probabilities that are strongly increasing in the disability level. There is therefore little evidence to support the hypothesis that disability greatly increases claim costs or reduces the capacity to benefit from additional income.

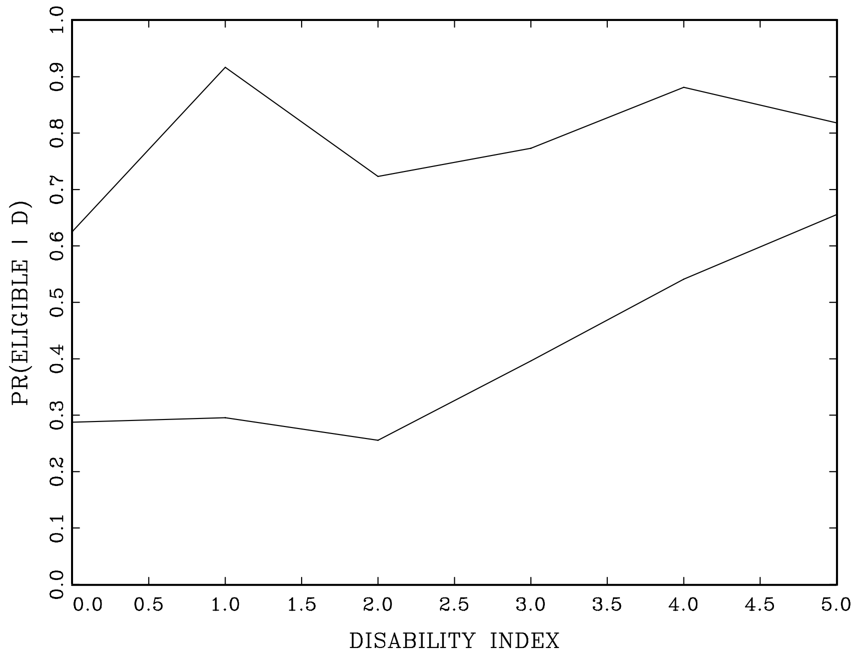

Figure 9: Bounds on $P_c(d,x)$ for high-disability cluster $X = 7$: exclusion, monotonicity and weak boundary, smoothness and aggregation constraints (variant 1)

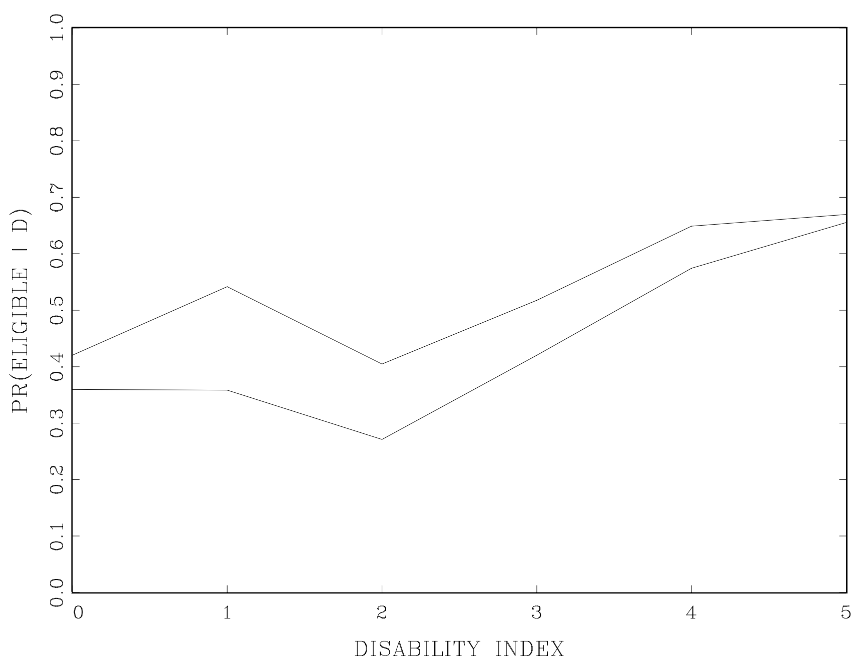

Figure 10: Tighter bounds on $P_c(d,x)$ for high-disability cluster $X = 7$: exclusion, monotonicity, boundary, smoothness and aggregation constraints (variant 3)

6.4 Unpursued potential awards

The proportion of the population who would be able to receive AA if a claim were made is $\sum_d P_e(d) f(d)$. Of these, the group who do not pursue their potentially successful claims form a proportion $\sum_d [P_e(d) - \pi(R = 1|d)] f(d)$ of the population. In the part of the population with characteristics $X = x$ and disability level $D = d$, the proportion of unpursued entitlements is $P_e(d) - \pi(R = 1|d, x)$. These quantities are special cases of the objective functional (7) and bounds can be constructed by optimisation.

Table 5 gives estimates of the bounds on the expected proportion of the over-65 non-claimant population who are not current AA recipients but who would, under present assessment arrangements, be awarded AA. When aggregation constraints are used, the lower bound very clearly suggests a large volume of unclaimed potential entitlements, of at least 29% of the over-65 population. This in turn implies that, among the over-65s who do not receive AA, a third could expect to be successful if they were to make a claim. It must be emphasised that our high figure for the lower bound on the volume of unpursued potential AA awards does not rest on strong assumptions. The weakest exclusion, monotonicity and aggregation constraints are sufficient to generate estimates of at least this magnitude.

Table 5 Bounds on the aggregate proportion of unpursued potential AA awards

Constraints	Variant 1	Variant 2	Variant 3
None	0.000 - 0.890	0.000 - 0.890	0.000 - 0.890
EM	0.107 - 0.889	0.107 - 0.889	0.107 - 0.889
EMA	0.294 - 0.689	0.329 - 0.669	0.350 - 0.670
EMAS	0.294 - 0.683	0.329 - 0.635	0.350 - 0.635
EMABS	0.294 - 0.455	0.329 - 0.410	0.353 - 0.410

Constraints: E = exclusions; M = monotonicity; A = aggregation; B = boundary; S = smoothness

Our conclusions on this are also supported by the raw FRS data: of those not currently receiving AA, over 37% report at least one disability; among that group, the mean number of disabilities reported is 2.03. A further revealing feature of the FRS sample is that, among those who are recorded as being in actual receipt of personal care, only 46% are receiving AA. Among the most severely affected group, who are reported as receiving day and night care, only 57% are recorded by the survey as receiving AA payments. Even allowing for a degree of under-reporting of AA receipt by FRS respondents, these figures suggest that there is a considerable volume of potentially successful AA claims that are currently not being pursued.

This general conclusion is not a special feature of the FRS data alone. Although not directly comparable, the English Longitudinal Survey of Ageing (ELSA) and the British Household Panel Survey (BHPS) also contain information on disability and receipt of AA. In the 2002/3 wave of ELSA, there are 1,476 respondents who are: aged over 65; not in receipt of DLA; and receiving assistance (from any source) with activities which are limited by a health problem. Of these people, only 21.1% were recorded as receiving AA. The BHPS only records care received from household members. In the 2002 wave, there were 98 cases of people over 65 receiving care from another household member and not receiving DLA. Of this group, only 33.7% were in receipt of AA. Together, these AA receipt rates for disabled people in ELSA and BHPS give strong evidence to support our finding of a large number of latent AA claims which have not been brought forward.

It is important to interpret this finding appropriately. It is *not* a prediction of what would happen if claim behaviour were to change, since a very large increase in the volume of applications would undoubtedly bring in its wake a change in the way assessments are made in practice, with or without conscious action on the part of the government. Instead, these estimates should be interpreted as saying that the main factor restraining the growth in AA awards to the older population appears not to be the rigour of assessment procedures, but rather the reluctance of people to pursue any but very strong claims. This is something that should be borne in mind when the argument is made that the disability benefit system encourages a culture of benefit dependency.

In which population groups do we find the unpursued potential awards of AA? We can construct bounds for the probability of an unclaimed potential award for any population cluster x by optimising the following objective:

$$Pr(\text{unpursued award} \mid X = x) = \sum_d [P_e(d) - \pi(R = 1 \mid d, x)] f(d \mid x) , \qquad x = 1...9 \qquad (21)$$

The probability (21) tells us the incidence of unpursued claims in each part of the population. In contrast, the probability that a (randomly-selected) unpursued potential AA award comes from a member of the $X = x$ subpopulation tells us about the X-structure of the subpopulation of non-claimant potential eligibles:

$$Pr(X = x \mid \text{unpursued award}) = \frac{\sum_d [P_e(d) - \pi(R = 1 \mid d, x)] f(d, x)}{\sum_x \sum_d [P_e(d) - \pi(R = 1 \mid d, x)] f(d, x)} , \qquad x = 1...9 \qquad (22)$$

Table 6 gives estimates of the bounds on these two measures, for the three variants, using all available constraints. Cluster 3, which has low average income, age and slightly above-average disability, has the highest incidence of unclaimed potential awards (UPAs) but contributes a modest volume of unpursued claims owing to its relatively small size. Cluster 5, which is on average younger, wealthier and less disabled than the the over-65 population as a whole, has lower than average incidence of UPAs but makes a larger than average contribution to the total.

Table 6 Bounds on the X-distribution of unpursued AA awards

	Variant 1		Variant 2		Variant 3	
x	$Pr(\text{UPA}\|x)$	$Pr(x\|\text{UPA})$	$Pr(\text{UPA}\|x)$	$Pr(x\|\text{UPA})$	$Pr(\text{UPA}\|x)$	$Pr(x\|\text{UPA})$
1	0.303 - 0.480	0.137 - 0.147	0.343 - 0.422	0.141 - 0.145	0.372 - 0.422	0.142 - 0.144
2	0.307 - 0.478	0.083 - 0.087	0.345 - 0.420	0.084 - 0.086	0.372 - 0.420	0.085 - 0.086
3	0.354 - 0.531	0.103 - 0.109	0.395 - 0.472	0.105 - 0.107	0.424 - 0.472	0.105 - 0.106
4	0.245 - 0.415	0.077 - 0.089	0.289 - 0.361	0.083 - 0.087	0.316 - 0.361	0.085 - 0.087
5	0.284 - 0.431	0.176 - 0.217	0.317 - 0.372	0.184 - 0.199	0.338 - 0.373	0.186 - 0.194
6	0.321 - 0.482	0.139 - 0.149	0.356 - 0.424	0.140 - 0.144	0.381 - 0.424	0.140 - 0.142
7	0.207 - 0.407	0.075 - 0.107	0.269 - 0.353	0.090 - 0.102	0.303 - 0.353	0.095 - 0.101
8	0.287 - 0.436	0.075 - 0.089	0.321 - 0.378	0.078 - 0.083	0.342 - 0.378	0.078 - 0.081
9	0.289 - 0.460	0.067 - 0.072	0.329 - 0.402	0.069 - 0.071	0.357 - 0.402	0.070 - 0.071
Total	0.294 - 0.455	-	0.329 - 0.398	-	0.356 - 0.398	-

Notes: UA = unpursued potential AA award; Exclusion, Monotonicity, Aggregation, Boundary & Smoothness constraints imposed

7 Robustness

Surveys have the advantage that they give more complete contextual information than administrative register data. Against this, their (arguably) greater vulnerability to reporting error introduces bias into the analysis. We now investigate the robustness of our finings to two kinds of measurement error: inaccurate self-assessment of the disability level and under-reporting of benefit receipt.

7.1 Measurement error in disability

It has long been acknowledged by health researchers that self-reported disability may be subject to misreporting. The possible incentive to over-report disability is a major concern, but errors in both directions may coexist in the same sample and there is no consensus of opinion in the research literature on the nature and seriousness of the problem (Bound 1991, Kerkhofs and Lindeboom 1995, Dwyer and Mitchell 1999, Baker et al. 2004, Benitez-Silva et al. 2004, Kreider and Pepper 2007)). Behaviour may be complicated: for example, some respondents may overstate their difficulties (relative to a specific 'objective' yardstick) as a conscious or unconscious attempt to gain sympathy, while others may deny the existence of a significant problem to avoid feelings of inadequacy. Some relevant aspects of disability may also be unobservable, in the sense that the FRS questionnaire does not exactly reproduce the set of information requested by programme administrators in the AA application form. The measurement error and partial observation problems are conceptually distinct but closely related in their implications. Consider first the case of reporting error.

We allow for misreporting in a simple way by making two assumptions about the nature of misreporting: first, that self-reporting yields a misclassified response which deviates from the 'true' disability level by at most one category; and, second, that the probabilities of over-reporting (p^+) and under-reporting (p^-) are constant. The distribution of AA receipt conditional on observed (D^*) rather than actual (D) disability is then:

$$\pi(R=1|D^*=0,x) = P_e(0)P_c(0,x)\left[1-p^+\right]+P_e(1)P_c(1,x)p^- \tag{23}$$

$$\pi(R=1|D^*=d,x) = P_e(d)P_c(d,x)\left[1-p^- - p^+\right]+P_e(d+1)P_c(d+1,x)p^- + P_e(d-1)P_c(d-1,x)p^+ \tag{24}$$

$$\pi(R=1|D^*=n_d,x) = P_e(n_d)P_c(n_d,x)\left[1-p^-\right]+P_e(n_d-1)P_c(n_d-1,x)p^+ \tag{25}$$

This system of equations is linear in the claim probabilities $P_c(d,x)$, which can be solved out, leaving a nonlinear programme in the n_d+2 unknowns $P_e(d), r^+, r^-$. Following Horowitz and Manski (1995), *a priori* bounds can be placed on the misclassification probabilities to sharpen identification of P_e.

$$0 \le p^+, p^- \le p^{\max} \tag{26}$$

For identification of the volume of unpursued potential awards, $\sum_d P_e(d)f(d) - \pi(R=1)$, it is important to use a disability distribution $f(d)$ adjusted for classification error, rather than the empirical distribution $f^*(d)$. The two are related by the following equations:

$$f^*(D^* = d) = \begin{cases} f(d)\left[1 - p^+\right] + f(d+1)p^- & \text{if} \quad d = 0 \\ f(d)\left[1 - p^- - p^+\right] + f(d+1)p^- + f(d-1)p^+ & \text{if} \quad 1 \leq d \leq n_d - 1 \\ f(d)\left[1 - p^-\right] + f(d-1)p^+ & \text{if} \quad d = n_d \end{cases} \tag{27}$$

which can be solved to recover the required distribution $f(.)$ from the empirical distribution $f^*(.)$ and any given values for p^+ and p^-. The resulting $f(.)$ automatically sums to unity, but additional non-negativity constraints must now be imposed:

$$f(d) \geq 0 \qquad\qquad d = 0...n_d \tag{28}$$

Unobserved components of disability can be handled in a similar way. Let the unobserved element be U and suppose that entitlement and claim behaviour depend on an additive index, $D + U$. For example, U could be a measure of severity, which is unobserved in the FRS. Assume that the index is constructed in such a way that it takes values on the same grid $\{0...n_d\}$ as the observed indicator D. Then $U|D = d$ can take values in $\{-d...n_d - d\}$ and the observable conditional distribution of benefit receipt is:

$$\pi(R = 1|d, x) = \sum_{u=-d}^{n_d-d} P_e(d+u)P_c(d+u, x)f(u|d) \tag{29}$$

In the special case where $f(u|d) = 0$ for $u < -1, u + d < 0, u > 1$ or $u + d > n_d + 1$ and otherwise $f(U = -1|d) = p^+$ and $f(U = 1|d) = p^-$, the observable distribution (29) is identical to the reporting error case (23)-(25). However, there is an important difference of interpretation: in the measurement error case, we construct bounds on P_e defined as the probability of being judged eligible, conditional on the 'true' disability level D. In the heterogeneity case, our bounds relate to P_e interpreted as the probability of eligibility conditional only on the observable part of true disability. Bearing this interpretational difference in mind, the distribution (23)-(25) provides a good starting point for the investigation of the impact of both reporting error and heterogeneity.

7.2 Under-reporting of benefit receipt

Studies of matched survey and benefit register data from the US (Bollinger and David 1997, 2005) and Europe (Kapteyn and Ypma 2007; Lynn et al 2004) have found various degrees of under-reporting of the receipt of benefit income, which tend to exaggerate the degree of non-take-up apparent in survey data. The work of Lynn et al (2004) for the UK suffers from small sample sizes and consequently generates under-reporting rates covering a wide range from zero for the Basic State Pension to 50% for working-age Incapacity Benefit. However, their work suggests clearly that over-reporting of benefit receipt is negligible in comparison to under-reporting, so we assume a zero probability of over-reporting here. We also assume that under-reporting occurs completely at random among benefit recipients, with constant probability ρ. Then the true conditional benefit receipt rate is $\pi(R = 1|D, X)/(1 - \rho)$ rather than the lower rate $\pi(R = 1|D, X)$ suggested by uncorrected survey data. Since the true receipt probability cannot exceed 1 for any (D, X), this gives bounds on ρ

$$0 \leq \rho \leq 1 - \max_{d,x} \pi(R = 1|D = d, X = x) \tag{30}$$

For our data, the upper bound on the under-reporting probability is estimated as 0.36.

7.3 Results

Figure 11 shows the consequences of making allowance for measurement error in self-assessed disability. The bounds widen only slightly, except for high disability levels of $D = 4$ or above, where the upper bound is now 1. Accepting the possibility of classification error thus admits the possibility of very high potential success rates for AA applications from very severely disabled people. In making these calculations, we imposed an upper bound of 0.3 on p^+ and p^-, which proved to be non-binding in every case. The value of p^- turned out to be 0 for every boundary point, while p^+ was generally positive, but never greater than 0.13. Thus the error-adjusted bounds are consistent with (but do not necessarily imply) a moderate degree of over-reporting of disability.

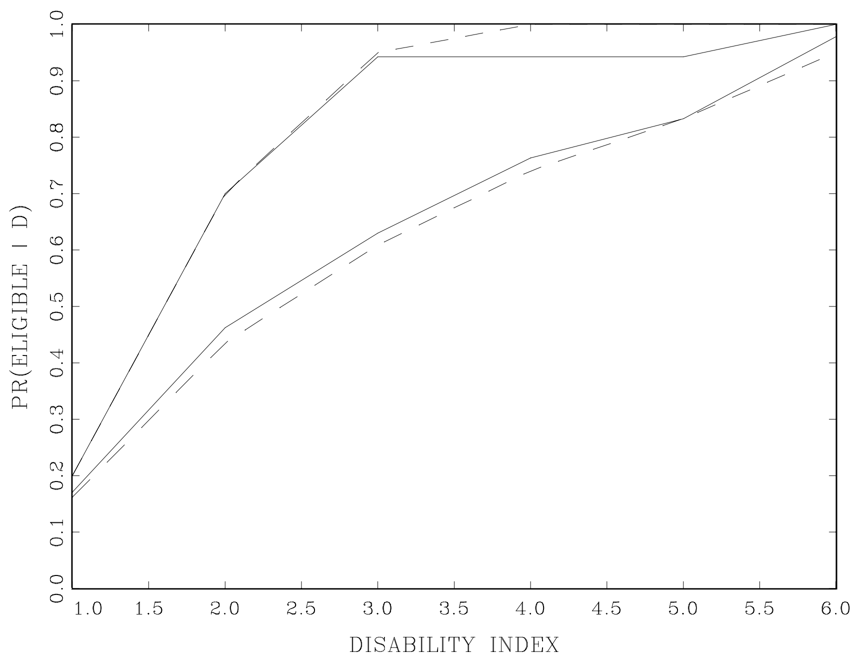

Figure 11: The effect of allowance for disability classification error on bounds for $P_e(d)$: variant 3 (dashed lines with, and solid lines without, measurement error)

Figure 12 shows the impact on the P_e-bounds of allowing instead for under-reporting of benefit receipt. The upper bounds on P_e are unaffected but the lower bound is reduced substantially for intermediate disability levels.

Table 7 shows the joint impact of both types of measurement error on our estimates of the bounds on the volume of unpursued potential AA awards. In the presence of measurement error the strength of the a priori constraints we choose to impose becomes more critical. Using all constraints in weak form (variant 1), the lower bound on the volume of unpursued potential awards falls from 29% to 10%, while the stronger form (variant 3) sees a more modest fall from 35% to 22%.

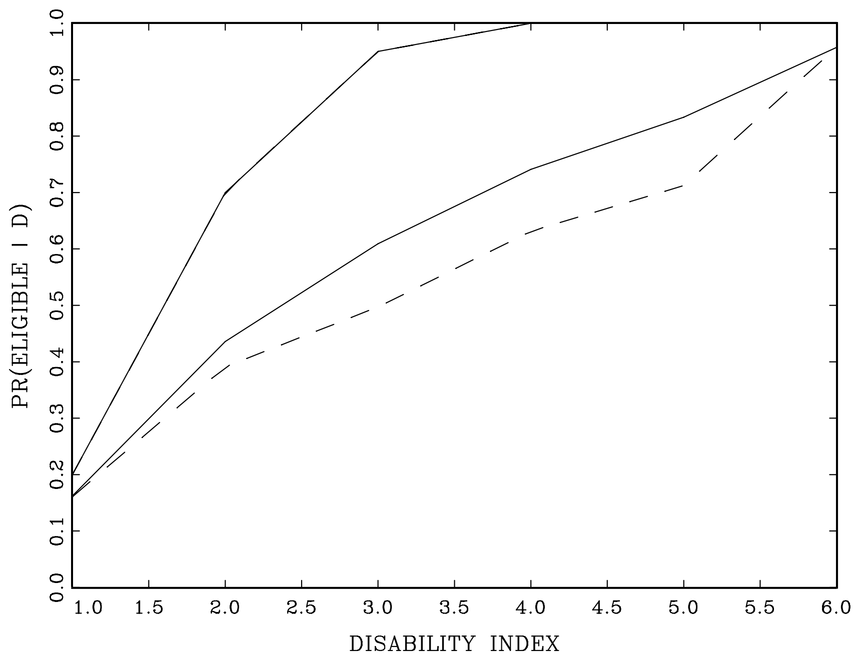

Figure 12: The effect of allowance for under-reporting of benefit receipt on bounds for $P_e(d)$: variant 3 (dashed lines with, and solid lines without, measurement error)

Table 7 Bounds on the aggregate proportion of unpursued potential AA awards. Measurement error in disability and AA receipt (Roman type); no measurement error (Italic type)

Constraints	**Variant 1**	**Variant 2**	**Variant 3**
EMA	0.066 - 0.700	0.086 - 0.681	0.098 - 0.681
	0.294 - 0.689	*0.329 - 0.669*	*0.350 - 0.670*
EMAS	0.098 - 0.690	0.201 - 0.641	0.216 - 0.641
	0.294 - 0.683	*0.329 - 0.635*	*0.350 - 0.635*
EMABS	0.097 - 0.467	0.201 - 0.410	0.216 - 0.410
	0.294 - 0.455	*0.329 - 0.410*	*0.353 - 0.410*

Constraints: E = exclusions; M = monotonicity; A = aggregation; B = boundary; S = smoothness

In every case, the lower bound requires a zero rate of disability under-reporting and high rates of benefit under-reporting and disability over-reporting (for example 17% and 13% respectively for the variant 3 EMABS case). If we restrict the rates of under-reporting of AA receipt and over-reporting of disability to a more modest level of 10%, the lower bound (for the variant 3 EMABS case) rises from 0.216 to 0.265.

8 Conclusions

Survey-based analysis of participation in a disability benefit system faces several obstacles. The concept of eligibility (and consequently of take-up) is ill-defined because the outcome of a claim depends upon the judgement made by a programme administrator, without formulaic criteria of the sort used in means-tested benefit programmes. The concepts of disability and care needs are difficult to measure and surveys like the FRS used in this study tell us only about successful claims, not unsuccessful ones. Analysis based on administrative data sources are limited for some of the same reasons, but also because administrative records omit important contextual information (such as income in our case) and they tell us nothing about potential claims that have not been put forward.

In this study, we have used a survey-based method to analyse the Attendance Allowance (AA) programme. We face a fundamental problem: that the (observable) event of disability benefit receipt is the outcome of two (unobservable) processes: submission of a claim and positive assessment of the claim by programme administrators. We have shown these two processes can be distinguished empirically by combining FRS survey data with rather mild a priori assumptions and external data on the average success rate of claims at the aggregate level. This approach does not give unambiguous identification of eligibility and claim probabilities, but it does have good enough resolution to draw useful conclusions about some important aspects of claimants' and administrators' decision-making behaviour.

We find that the probability of a claim being upheld is a strongly increasing function of the measured extent of the individual's disability, as one would expect, given the aims of the AA programme.

A simple theoretical analysis emphasises the importance of the disability gradient of the conditional probability of making a benefit claim. If this probability rises steeply with increasing disability, then one can argue that AA is an effective form of support for disabled pensioners. If the claim probability is only weakly related to the degree of disability, then it is evidence that the 'hassle' or 'stigma' costs of the AA programme are serious barriers to its effectiveness or, more fundamentally, that disability has a tendency to impair the individual's ability to benefit from support in the form of cash payments rather than provision of services. We find that claim probabilities are clearly increasing in the extent of disability for all types of individual, suggesting that disability-related cash benefits are an effective form of support for disabled pensioners. We also find that the probability of a claim being made varies markedly with the characteristics of the individual: in particular, age, disability and low income are associated with a high claim probability.

We are able to estimate the range of possible values for the proportion of pensioners who have an unpursued but potentially successful AA claim. This proportion is estimated to be 30% or more, implying that, among over-65s who are not currently receiving AA, at least a third could expect to be successful if they were to make a claim. This result is supported by the low rates of AA receipt among people receiving personal care which are observed in a number of surveys.

Finally, we have assessed the robustness of these findings by allowing for survey response error in measured disability and for under-reporting of benefit receipt. The effect of error is to increase the range of uncertainty associated with our findings, but not to alter them fundamentally. To alter the results so that the volume of unpursued potentially successful claims is as low as 22% requires us to accept the existence of a very high degree of survey measurement error: a 13% rate of overstatement of the extent of disability (with no understatement of disability) and a 17% 'false negative' rate for reported AA receipt.

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Appendix 1: Disability questions from the AA application form and the FRS questionnaire

A2 The AA application form

The following is an edited list of the principal questions about "illnesses or disabilities" on the AA application form. The full current form is available at http://www.dwp.gov.uk/advisers/claimforms/aa1a_print.pdf.

- Please tell us about your illnesses or disabilities. By this we mean physical or sensory impairments or mental health problems.
- Please tell us, if you can, how long you have had each of these illnesses or disabilities.
- If you have arthritis or rheumatism or something like this, please tell us which parts of your body are affected.
- Please list any current tablets, medicines or other treatments you have been prescribed for your illness or disability. If you can, tell us which illness or disability they have been prescribed for.
- Please tell us, if you can, the dosage and how often you take each of the tablets, medicines or other treatments you have told us about.
- Please tell us, if you can, how long you have been taking each of the tablets, medicines or other treatments you have told us about.
- Please put a tick against any tablets or medicines that are on repeat prescription.
- If you have seen anyone in connection with your illnesses or disabilities in the past 12 months, please give their details. For example, hospital doctor, specialist nurse, community psychiatric nurse, district nurse, physiotherapist, occupational therapist or social worker.
- Does anyone else help you because of your illnesses or disabilities? This could be someone like a carer or support worker, a friend, neighbour or family member.
- We need to know what help you need and why you need it. Some of the things you need to think about and tell us are:
  - When do you need help (only during the day / only during the night / during the day and night
  - Where do you need help (indoors / outdoors / both indoors and outdoors)
  - What happens or would happen if you do not get the help you need
  - Any tasks that would take you longer than usual because of your illnesses or disabilities

– Any variations in your condition

– Whether or not you use any equipment because of your illnesses or disabilities

A2 FRS questions

- Do you have any long-standing illness, disability or infirmity? By 'long-standing' I mean anything that has troubled you over a period of time or that is likely to affect you over a period of time?
- Does this physical or mental illness or disability (Do any of these physical or mental illnesses or disabilities) limit your activities in any way?
- Does this health problem(s) or disability(ies) mean that you have significant difficulties with any of these areas of your life? Please read out the numbers from the card next to the ones which apply to you.

  SHOW CARD:
  1: Mobility (moving about)
  2: Ability to lift, carry or otherwise move everyday objects
  3: Manual dexterity (using your hands to carry out everyday tasks)
  4: Continence (bladder control)
  5: Communication (through speaking, listening, reading or writing)
  6: Memory or ability to concentrate, learn or understand
  7: Understanding when you are in physical danger
  8: Other area of life
  9: None of these

Free text follow-up to response 8 was coded post hoc, yielding a further category of difficulty: co-ordination / balance problems. Sample proportions and rates of AA receipt for these 8 categories are as follows:

Table A1 Sample proportions and AA rates of disability types

Disability	**Sample %**	**AA receipt (%)**
Mobility	31.5	28.2
Lifting	28.2	28.2
Dexterity	11.6	37.3
Continence	7.0	35.3
Communication	7.0	34.5
Memory	6.8	37.5
Danger	1.4	50.1
Co-ordination	6.3	32.0

Appendix 2: Conditional benefit receipt models for construction of the disability index

Table A2 Semi-nonparametric ordered probit model of AA receipt

Covariate	Coefficient	Std. Err.
Age × Disability index / 100	0.228***	0.031
Age spline 65-67/10	0.924***	0.032
Age spline 67-73/10	0.675***	0.115
Age spline 73-79/10	0.294***	0.066
Age spline 79+/10	0.352***	0.071
Income spline 1	-0.920***	0.226
Income spline 2	-0.455***	0.090
Income spline 3	-0.089***	0.028
Female	0.073***	0.026
Couple	-0.145***	0.030
Homeowner	-0.151***	0.028
No. of wife's disabilities	0.038***	0.014
Shape parameter 1	1.119	1.459
Shape parameter 2	0.414	0.588
Shape parameter 3	-0.274	0.297
LR test of semi-nonparametric model against ordered probit:	$\chi^2(3) = 141.17$***	

* $P < .1$, ** $P < .05$, *** $P < .01$