THE EFFECT OF DISABILITY ON EMPLOYMENT ALLOWING FOR WORK INCAPACITY

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Abstract

Previous modelling of the impact of disability on employment has failed to allow for a direct effect rendering some individuals incapable of work. A model in which both a capacity and a desire for work are necessary conditions for employment is estimated from a sample of British disabled men. Recognition that individuals may be incapable of work helps identify work capacity and leads to a test for errors in reported capacity data. The capacity for work condition is found to be relevant and failure to allow for it results in overestimation of the wage elasticity of employment. The accuracy of self-reported capacity information is rejected.

JEL Classification: I12, J22

Keywords: Disability, Work Capacity, Employment, Labour Supply, Partial Observability, Reporting Errors

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I. INTRODUCTION

The simultaneous decline in male labour force participation and increased enrolment in disability insurance (DI) programmes have been a common experience of many countries in recent decades. These trends have provoked a substantial literature on the relationships between disability, disability insurance and labour supply (*c.f.* Parsons, 1980, 1982; Haveman and Wolfe, 1984; Leonard, 1986; Bound, 1989; Disney and Webb, 1991; Aarts and De Jong, 1992). The models used in this literature have been based on the assumption that employment status is chosen – it is the outcome of a utility comparison between states. Employment is associated with a positive sign on a value of work index, specified to include some measure of work capacity and monetary incentives among its arguments. Within this formulation, disability (or work capacity[1]) can affect employment through monetary incentives, simultaneously reducing earnings potential and raising non-work income through DI entitlement, and by shifting consumption-leisure preferences. Work capacity is expected to take a negative sign in the value of work index, implying the hypothesis that reduced capacity for work shifts preferences away from consumption toward leisure. Most studies have found a large negative impact of disability on labour supply (Diamond and Hausman, 1984; Sickles and Taubman, 1986).

A major limitation of this modelling approach is that it does not explicitly allow for the possibility that disability prevents work. Despite the use of the term ‘work capacity’, there is no explicit recognition that some individuals may be truly incapable of work. Work capacity is assumed to affect employment indirectly, through preferences and financial incentives, and not directly, by constraining employment status. This seems restrictive, particularly given incapacity

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[1] The distinction between disability and work capacity is often obscured. A clear distinction will be made between the concepts later in the paper.

for work is the contingency which DI is intended to cover. If incapacity for work is prevalent, then a participation model which ignores this is misspecified; the stated probability of observing a worker is incorrect. Parameter estimates will consequently be inconsistent.

In this paper, such misspecification is avoided by developing a model of employment which explicitly allows for the possibility that disability leaves some individuals incapable of work. The model is estimated using data from the 1985 British Office of Population Censuses and Surveys (OPCS) survey of disabled adults in private households (Martin *et al*, 1988). In this survey of individuals with some disability, 46% of non-working adults below retirement age reported that their disability made it impossible for them to do any paid work (Martin *et al*, 1989). While care must be taken in the interpretation of such declarations (see below), they suggest support for the hypothesis that the employment status of many disabled individuals is not the outcome of a utility comparison between states; only one state is possible. Further support for the contention is provided by the independent panels who rated 55% of U.S. DI applicants as not fit for any kind of work (Nagi, 1969). In addition, from the fact that less than 50% of *rejected* male U.S. DI applicants were working, Bound (1989) concluded that many DI recipients are truly disabled and would not be working in the absence of the programme[2]. Bound *et al* (1995) recognised the failure of the literature to deal appropriately with complete work incapacity. They point out that many researchers have failed to exploit the distinction between 'some limitation' and 'unable to work' in the responses to a popular self-reported work limitation question (*c.f.* Stern, 1989; Bound, 1991) and argue that ignoring this distinction is to ignore an important dimension of disability.

Explicit recognition of incapacity for work involves specifying a model such that observation of employment requires the satisfaction of two conditions - a capacity for work and a desire for work. This is related to models of labour supply which allow for involuntary

[2] To be fair, this conclusion is somewhat weakened in Bound and Waidmann (1992).

unemployment (*c.f.* Ham, 1982; Blundell *et al*, 1987; Eggink *et al*, 1994). Consistent with Bound *et al* (1995), it is argued that incapacity for work is the result not only of functional limitations (i.e. disability) but also the nature of the labour market. A capacity for work index is specified to be a function of demographics, disability and labour market indicators. A value of work index is specified as a function of (different) demographics, disability, the wage rate and unearned income. A wage equation completes the model. Estimation is by maximum likelihood (ML) using data on working aged males.

The measurement of work capacity has been an important concern in the literature (Anderson and Burkhauser, 1984). Bound (1991) and Bound *et al* (1995) demonstrate the problems with alternative approaches. Using self-reported work limitation introduces the risk of endogeneity bias. In order to relieve the stigma of non-participation and to qualify for DI, non-workers have incentives to exaggerate limitations in work capacity. As a result, the impact of work capacity on participation will be overestimated and that of other determinants, including monetary incentives, underestimated. However, such measures will also suffer from errors-in-variables bias which will work in the opposite direction, leaving the direction of the overall bias ambiguous. In order to avoid endogenous reporting errors, more objective indicators, such as subsequent mortality or specific health conditions, have been used as proxies for work capacity (Parsons, 1980; Chirikos and Nestel, 1981). But such measures do not escape errors-in-variables bias and will tend to lead to underestimation of the work capacity effect and overestimation of the financial effect (Bound, 1991). Stern (1989) proposed using objective indicators to instrument self-reported work capacity. Bound (1991) demonstrates that this allows consistent estimation of the capacity effect but leaves the impact on participation of any factor which also affects reporting behaviour unidentified. Consequently, the impact of financial incentives on participation will be underestimated if they also affect reporting of capacity but no allowance is made for the latter[3]. Bound (1991) concludes that, without outside information on the reliability of the indicators, the impact of true capacity on employment is not identified. Kreider (1996) proposes a solution which makes use of outside information. He argues that, on average, work capacity is reported without error by workers but is unobservable for non-workers. Using the reports of workers, with a correction for selection, a capacity index is estimated as a function of health conditions and socio-economic factors. This index can then be included as an argument of a participation function.

The problems encountered in identifying the work capacity effect in the above models arise because true work capacity is treated as wholly unobservable. In the model proposed here, there is some information from the sample on work capacity, even without recourse to self-reported indicators. This helps to solve the identification problem. Once it is recognised that individuals can be completely incapable of work, it follows, by definition, that those who are working are not incapable. Although the work capacity of non-workers remains unobservable, the split in the sample between workers and non-workers provides some information which can allow identification of a capacity for work index. Of course, the split between workers and non-workers is determined by work preferences, in addition to work capacity, and so, without using additional information, a partial observability model must be estimated (Poirier, 1980). Self-reported information on incapacity provides the opportunity of distinguishing between non-workers who do not want to work and those who are not able to work. If accurate, use of this sample separation information will yield more efficient estimates than the partial observability model, but the risk is that reporting errors will introduce inconsistency. Using the Hausman (1978) framework, estimates obtained with and without use of the self-reported capacity data

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[3] Kerkhofs and Lindeboom (1995) argue that, conditional on labour force status, there is little reason to believe reporting of capacity is influenced by financial variables. They provide a method for purging reported capacity data of state dependent reporting errors. Unfortunately, this procedure cannot be used when simultaneously estimating labour force status due to a problem of logical inconsistency.

from non-workers can be compared to test for errors in these data.

The procedure here has a number of advantages over the existing literature. First, it avoids the potential misspecification arising from failure to allow for part of the sample being truly incapable of work. Second, in Kreider (1996) the capacity index is identified only from information on workers. Since work limitations will be most severe amongst non-workers, the estimates obtained by Kreider will lack efficiency. Here, it is the split between workers and non-workers which identifies the capacity index. Third, no use need be made of self-reported information and so there is no need to assume the absence of reporting errors, even among workers. Finally, the procedure provides a method of formally testing for reporting errors in work capacity data.

The data are described in the next section of the paper. In section III the model is presented. This includes a definition of work capacity and derivation of the likelihood functions. The results are presented in the fourth section. There are three main results. First, a model which does not incorporate a capacity for work condition is rejected in favour of the more general model. Second, ignoring the capacity condition leads to overestimation of the wage elasticity. Third, the accuracy of the self-reported incapacity information is rejected. The final section provides a summary of the paper and acknowledges some limitations.

II. DATA

The 1985 OPCS survey of disabled adults in private households is the most comprehensive data set on disability which exists in Britain (Martin *et al*, 1988). It is used to estimate the prevalence of disability and has been an important reference in the design of reforms to disability policy in recent years. As well as providing detailed information on disability, the survey contains good data on incomes and employment, making it ideally suited to the present purpose. The sample was identified by screening a stratified random sample of the population to identify individuals with some form of disability. The latter is defined as inability to perform certain functions as a result of impairment. Identification of disabilities was achieved by asking individuals whether they experienced specific functional limitations. As an example, someone confirming an inability to walk for a quarter mile without stopping, and without severe discomfort, would qualify as disabled in the dimension of 'locomotion'. Using the criteria of the survey, 11.5% of the British adult population qualify as disabled (Martin *et al*, 1988). The total sample size was 11,158. The present analysis restricts attention to adult males of working age (N=2320)[4].

Consistent with the definition used by OPCS (Martin *et al*, 1989), 'employment' is defined as full/part time work, temporary sickness, or an employment based government training scheme. According to this definition, 818 (35.3%) individuals in the sample are working and 1502 are not working. The low employment rate reflects the nature of the sample – all individuals have some disability. In addition to employment status, information on work capacity is available from a question which asks non-workers the reason they are not working. Available responses are:

- health problem/disability makes it impossible (for you) to do any kind of paid work;
- have not found suitable paid job;
- do not want or need a paid job; or
- other.

Under the null hypothesis of no reporting errors, individuals giving the first of these responses

[4] After selecting on gender and age (16-64 years old), the sample size was 2745. Individuals in employment but not reporting earnings and/or hours data were excluded (N=143), with an appropriate number of non-workers being excluded to preserve population proportions (N=254). Since self-employment was found to be a significant determinant of missing wage data, self-employment status was used in selecting the non-workers to exclude, otherwise this selection was random. Individuals in full time education were excluded (N=20). Finally, individuals who were waiting to take a job they had already obtained, for whom employment related data were missing, were also excluded (N=8).

correspond to those who are ‘incapable of work’. Interpretation of the second reason is difficult. Individuals who believe they could do work but who have failed to obtain a job offer may give this response. According to the discussion to follow in section III, such individuals have no employment opportunities and should be included among those ‘incapable of work’. However, the response may also be given by individuals with employment opportunities but with a preference for not working. In order to limit the potential for endogenous reporting errors, individuals giving the second reason, like those giving the third and fourth reasons, are assumed to be capable and therefore not wanting to work. Early retirees (N=124) are not asked the reason for non-work question and are defined as incapable if they reported leaving their last job because of their disability. Of the 1502 non-workers in the sample, 1088 gave responses which led them to be classified as incapable of work, leaving 414 not working but with a capacity for work.

[TABLES 1 & 2 HERE]

Data are available on the type, cause and severity of disability. Frequencies of the disability types by employment and reported capacity status are given in Table 1. Each individual may experience more than one type of disability. In general, as might be expected, the prevalence of the disabilities is lowest among workers and highest among non-workers reporting incapacity. There are, however, exceptions. For example, the pattern is reversed for hearing disabilities. In the majority of cases, the prevalence of disability among non-workers reporting a capacity for work is closer to that of workers than it is to non-workers reporting incapacity. The latter appear to be a distinct group in terms of functional limitations. This supports the claim that reported capacity is informative of actual capacity. For each disability recorded, respondents were asked what caused it. Answers were classified into the sixteen broad International Classification of Disease (ICD) groups. Frequencies are provided in Table 2. The patterns of prevalence in relation to employment and reported capacity are similar to those for the types of disability. A measure of the severity of disability was constructed by OPCS by asking a sample of disabled individuals, health care professionals and informal carers to rate, along an interval scale, the relative severity of particular functional limitations. A statistical model was developed to explain these assessments and this was used to generate a severity score for the particular combination of functional limitations experienced by each member of the disability survey (Martin *et al*, 1988). Descriptive statistics for this variable and the others used in the analysis are presented in Table 3 (see Appendix 1 for definitions). Non-workers reporting incapacity emerge as a distinct group in relation to all of the disability variables (i.e. agestart, severity and transport).

[TABLE 3 HERE]

III. MODEL SPECIFICATION

A. Capacity for Work

An individual may be described as incapable of work in two senses. First, mental and physical faculties may be inconsistent with those necessary to **do** any available job. Second, even if an individual could do a job, at some productivity level, they may not be able to find an employer willing to offer work. The latter reason for incapacity, effectively being constrained by a lack of job offers, implies labour market disequilibrium. While disability may be expected to reduce productivity (either real or that perceived by employers), equal pay legislation, collective bargaining and/or social pressure may prevent employers from paying lower wages accordingly. In these circumstances, disabled individuals with a desire for work at observed market wages find themselves involuntarily unemployed. Eggink *et al* (1994) estimated a labour supply model which allows for unemployment arising from wage rigidity (see also Ham, 1982; Blundell *et al*, 1987; van Soest *et al*, 1996). Associating work incapacity with a marginal product (real or perceived) below market wages implies that no one would be incapable, providing wages were sufficiently flexible. But this ignores the possibility that some disabled individuals simply cannot

do any available jobs. The idea of individuals finding it impossible to do work does not fit easily with the standard neoclassical description of the labour market. Hartog's (1978) job assignment model provides a useful alternative framework of thought. Jobs are viewed as a bundle of tasks, performance of which demand capabilities, such as intelligence, physical strength, and dexterity. An individual's endowment of such capabilities determines the employment opportunities available to them. In the extreme, an individual's capability endowment may be inconsistent with the range of tasks associated with any job, in which case they can be defined as incapable of doing work. Disability may lead to difficulties in performing tasks which must be undertaken whilst on the job, e.g. operating machinery, concentrating for fixed periods, communicating with customers. Additionally, tasks which are necessary to be ready to do a job, e.g. travelling to and entering the workplace, may be difficult for some disabled individuals to accomplish.

Given likely identification problems, no attempt is made in the model to distinguish between the two types of work incapacity – incapacity to do work and inability to obtain employment. Instead, a single latent index of capacity (C_i^*), specified to be a linear function of observable exogenous variables (X_{1i}), is defined to take a positive value if individual *i* has an employment opportunity (they can do work and, potentially, have a job offer), and is non-positive otherwise:

$$C_i^* = X_{1i}\beta_1 + e_{1i}, \qquad e_{1i} \sim N(0, \sigma_1^2). \tag{1}$$

The arguments of X_{1i} include individual characteristics which affect ability to undertake job related tasks and market productivity. In addition to age and education, the analysis focuses on mental and physical functioning, as reflected through the indicators of the type, cause and severity of disability. In the presence of labour market segmentation, indicators of an individual's market sector - occupation, industry and region - should also be included to allow for variation in work related tasks, productivity and wage flexibility across sectors.

B. Desire for Work

Individuals are assumed to be certain of their employment opportunities. That is, each individual has perfect knowledge of whether they could do, and would be offered, each market job. This is obviously unrealistic, but it avoids the need to consider search behaviour and so simplifies modelling of the participation decision. Given the certainty assumption, the participation decision involves an individual comparing the market wage with their reservation wage. This comparison is represented by a latent index I_i^*, which is positive if work is preferred to non-work and is non-positive otherwise:

$$I_i^* = \alpha \log W_i + \gamma V_i + X_{2i}\beta_2 + e_{2i}, \qquad e_{2i} \sim N(0,\sigma_2^2), \tag{2}$$

where W is the gross wage rate, V is exogenous unearned income and X_2 includes determinants of consumption-leisure preferences.

No attempt is made to directly estimate the impact of social security benefits, such as DI, on the participation decision, since the effect is unlikely to be identified from the data available. In a single cross-section, there is relatively little variation in benefit levels and that which exists is largely explained by demographics, disability and labour market experience, characteristics which also determine wage rates and work-leisure preferences (Bound and Waidmann, 1992; van Soest *et al*, 1996).

C. Sample Separation Information versus Partial Observability

Employment requires both a capacity and a desire for work. Consequently, the probability of observing an individual in work is[5]:

$$\Pr(i \text{ works}) = \Pr(C_i^* > 0,\ I_i^* > 0). \tag{3}$$

[5] Even if decision making is sequential, such that the participation decision is confronted only once capacity is established, individuals who are incapable may still hold preferences over work status and these may be correlated with determinants of capacity. Independence between

Using employment status alone to make inferences about capacity and desire for work, equation (3) and its complement for non-workers provide the sample contributions to a likelihood function. The resulting model is a partial observability bivariate probit (Poirier, 1980)[6]. Such a model yields consistent but inefficient estimates relative to a model which exploits information allowing the sample to be split by capacity status as well as employment status (Poirier, 1980)[7]. If one is prepared to interpret the incapacity reported by non-workers as corresponding to actual incapacity, then observations can be categorised as follows;

$$\begin{aligned} &E_i = 1 && \text{iff} \quad C_i^* > 0 \quad \text{and} \quad I_i^* > 0, \\ &E_i = 0,\ C_i = 1 && \text{iff} \quad C_i^* > 0 \quad \text{and} \quad I_i^* \leq 0, \\ &E_i = 0,\ C_i = 0 && \text{iff} \quad C_i^* \leq 0, \end{aligned} \tag{4}$$

where $E_i = 1$ (0) if i works (does not work) and $C_i = 1$ (0) if i reports that they are capable (incapable) of work. Forming a likelihood on the basis of equation (4) leads to the bivariate probit with sample selection model (van de Ven and van Praag, 1981).

As discussed above and elsewhere in the literature, the problem with using self-declared capacity is that there may be reporting errors which are endogenous to desired participation, potentially jeopardising the consistency of the estimates (Stern, 1989; Bound, 1991; Aarts and De Jong, 1992; Kerkhofs and Lindeboom, 1995; Kreider, 1996). For example, reporting incapacity may relieve stigma associated with voluntary inactivity. Further, incapacity must be reported to the Department of Social Security (DSS), although not to the survey interviewer, in order to be eligible for DI. More directly, the lower an individual's preferences for work, the

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the two conditions for employment is not therefore imposed (Maddala, 1986, pp. 279-81).

[6] This description is not quite accurate since the wage function is to be estimated simultaneously with the index functions.

[7] As noted by Poirier (1980), the identification of partial observability models is a tricky issue. Exclusion restrictions are not necessary for identification but in their absence there is a labelling problem. Neither are exclusion restrictions sufficient for identification, the independent variables must also display sufficient variation. Provided the independent variable can take a continuum of values and there are exclusion restrictions, identification will be achieved.

more easily they are likely to concede incapacity, for a given level of disability.

Given the potential for reporting errors, they are tested for using the Hausman framework by comparing the estimates from the sample separation and partial observability models (Hausman, 1978; Hajivassiliou, 1986). Under the null hypothesis of no reporting errors, both estimators are consistent, while only that which exploits the sample separation information is efficient. Under the alternative hypothesis, the sample separation estimator is rendered inconsistent, while the partial observability estimator maintains consistency since it does not utilise the inaccurate information.

D. Sample Likelihood Functions

Given the wage is observed only for workers, a wage function must be introduced to complete the model:

$$\log W_i = X_{3i}\beta_3 + e_{3i}\,, \qquad e_{3i} \sim N(0,\sigma_3^2). \tag{5}$$

Exploiting the sample separation information on work capacity, the full model consists of the capacity index (1), the desire for work index (2), the wage function (5) and the observation rule (4). The sample likelihood for this model is:

$$L_1 = \prod_{E_i=1} f(\log W_i)\Pr\left(C_i^* > 0, I_i^* > 0 | \log W_i\right) \prod_{\substack{E_i=0,\\ C_i=1}} \Pr\left(C_i^* > 0,\ I_i^* \le 0\right) \prod_{\substack{E_i=0,\\ C_i=0}} \Pr\left(C_i^* \le 0\right), \tag{6}$$

where *f* is a density function.

Let the disturbances of the reduced form of (2) be ε_{2i}. Trivariate normality of the joint distribution of (e_{1i}, ε_{2i}, e_{3i}) is assumed. With variances of the latent index errors standardised to unity, the covariance matrix is,

$$\Sigma = \begin{pmatrix} 1 & \rho_{12} & \rho_{13}\sigma_3 \\ & 1 & \rho_{23}\sigma_3 \\ & & \sigma_3^2 \end{pmatrix}$$

where ρ_{12} is the correlation between e_{1i} and ε_{2i} etc.

The likelihood can be written explicitly as,

$$L_1 = \prod_{E_i=1} \frac{1}{\sigma_3} \phi\left(\frac{e_{3i}}{\sigma_3}\right) \Phi_2 \left[\left(\frac{\Omega_i + \rho_{13} \dfrac{e_{3i}}{\sigma_3}}{(1-\rho_{13}^2)^{1/2}} \right), \left(\frac{\Delta_i + \rho_{23} \dfrac{e_{3i}}{\sigma_3}}{(1-\rho_{23}^2)^{1/2}} \right), \rho_{12.3} \right] \times \prod_{\substack{E_i=0,\\ C_i=1}} \Phi_2\left[\Omega_i, -\Delta_i, -\rho_{12}\right] \prod_{\substack{E_i=0,\\ C_i=0}} \Phi_1\left[-\Omega_i\right] \tag{7}$$

where ϕ is the standard normal p.d.f., Φ_1 and Φ_2 are the univariate and bivariate normal c.d.f.'s respectively, $\Omega_i = X_{1i}\beta_1 / \sigma_1$, $\Delta_i = [\alpha(X_{3i}\beta_3) + \gamma V_i + X_{2i}\beta_2] / \sigma_{\varepsilon_2}$ and,

$$\rho_{12.3} = \frac{\rho_{12} - \rho_{13}\rho_{23}}{\left((1-\rho_{13}^2)(1-\rho_{23}^2)\right)^{1/2}}. \tag{8}$$

Expression (8) gives the correlation coefficient between the index function disturbances $(e_{1i}, \varepsilon_{2i})$ conditional on the wage function disturbances (Johnson and Kotz, 1972, pp.86-87).

The likelihood for the partial observability model is,

$$L_2 = \prod_{E_i=1} \frac{1}{\sigma_3} \phi\left(\frac{e_{3i}}{\sigma_3}\right) \Phi_2 \left[\left(\frac{\Omega_i + \rho_{13} \dfrac{e_{3i}}{\sigma_3}}{(1-\rho_{13}^2)^{1/2}} \right), \left(\frac{\Delta_i + \rho_{23} \dfrac{e_{3i}}{\sigma_3}}{(1-\rho_{23}^2)^{1/2}} \right), \rho_{12.3} \right] \prod_{E_i=0} 1 - \Phi_2\left[\Omega_i, \Delta_i, \rho_{12}\right] \tag{9}$$

Maximisation of the likelihoods (7) and (9) was undertaken using consistent starting values generated by 'two-stage' methods[8].

[8] The reduced forms of the index functions were estimated by bivariate probit with sample selection (van de Ven and van Praag, 1981) and partial observability (Poirier, 1980) for the models with and without the use of sample separation information respectively. The wage function was then estimated, in each case, by OLS with the appropriate correction for selection on workers. The estimated coefficients from the wage function were used to generate fitted values which were substituted for the actual wage before estimating the structural functions by bivariate probit with sample selection or partial observability as appropriate. These two-stage estimates were generated using Limdep v.7.0. ML computation was done in Gauss 3.0, using the BFGS and Newton algorithms and supplying analytical gradients.

Under the restriction that all individuals are capable of work, equation (3) simplifies to $\Pr(i \text{ works}) = \Pr(I_i^* > 0)$. The likelihood for this restricted model is:

$$L_3 = \prod_{E_i=1} \frac{1}{\sigma_3} \phi\left(\frac{e_{3i}}{\sigma_3}\right) \Phi_1 \left[\frac{\Delta_i + \rho_{23} \frac{e_{3i}}{\sigma_3}}{(1-\rho_{23}^2)^{1/2}} \right] \prod_{E_i=0} 1 - \Phi_1[\Delta_i] \tag{10}$$

The relevance of the capacity condition can be tested by a likelihood ratio (LR) test from the maximised values of L_2 and L_3.

IV. RESULTS

ML estimates from both the partial observability and sample separation models are presented in Tables 4-6. The empirical specification presented was arrived at by following a general to specific approach. Identification of the wage effect in the desire for work index is achieved through the exclusion of proxies for the demand side of the labour market in which the individual operates i.e. occupation, industry and region dummies. Testing found that education variables could also be excluded from this index. Financial variables, and some demographics, are excluded from the capacity index. Experimentation found the general results reported to be robust to alternative empirical specifications.

The wage function coefficients presented in Table 4 are generally significant and take the expected signs. There is quite a high degree of consistency between the estimates from the partial observability and sample separation models. These ML estimates are also close to the respective two-stage estimates (not reported). The correlation coefficients suggest unobservable determinants of the wage are negatively correlated with desire for work disturbances and, in the case of the partial observability model, are positively correlated with capacity for work disturbances. The latter result is more intuitively appealing than the former. The diagnostic tests show decisive rejection of normality and homoskedasticity in the marginal distribution of the wage function disturbances[9]. In response to the latter, the heteroskedastic consistent covariance matrix has been used in the calculation of the t-ratios.

The disability variables have been excluded from the wage function since this restriction could not be rejected[10]. There is some inconsistency in the literature with respect to whether disability has a significant impact on wages (as opposed to earnings or income). Lee (1982) found a positive impact of health on wages but Stern (1996) found no significant effect after correcting for selection. The lack of effect in the present application might, in part, be attributable to the fact that all individuals in the sample have some disability and so the impact of the presence of disability on market wages is not identified. The fact that wages do not appear to adjust to variations in disability suggests disequilibrium in the labour market - some individuals will be incapable of obtaining employment because their productivity level is below the established market wage.

[TABLE 4 HERE]

An advantage of the approach employed is that it yields estimates of a capacity for work index (Table 5). This helps to improve understanding of the impact of disability on labour market opportunities and is potentially useful in the design of policy. For example, knowledge of the types of disability which interfere most with work capacity is necessary in order to design an effective test for entitlement to DI[11]. Estimates of the capacity index from both models are again quite close to the respective two-stage estimates (not reported). However, consistency between the estimates from the partial observability and sample separation models is less than was the

[9] Rejection of normality of any of the marginal distributions is sufficient to reject the joint normality assumed in writing the likelihoods. The full implications of joint normality have not been tested. The test statistics, which are χ^2 distributed, are generated following the general procedure of Gourieroux *et al* (1987). See Appendix 2.

[10] No disability variable was individually significant in the two-stage estimates of the wage function and an F-test could not reject their joint insignificance.

[11] The test for entitlement to the main DI transfer in the UK, Incapacity Benefit (IB), is based on the OPCS disability survey questions. Consequently, the degree of consistency between the disabilities given greatest weight in the IB entitlement test and those found here to

case for the wage function. For example, the direction of the age effect differs. The sample separation model offers the more intuitively appealing estimate – a negative effect of age on capacity for work. Both sets of estimates indicate that an individual is less likely to be capable of work, the older they are at the onset of disability (agestart). This suggests that, given time, individuals can adapt to a given disability in order to minimise the impact on their employment prospects. Those who are disabled early in life acquire skills which compensate for their disability and choose to specialise in a labour market in which their particular disability is least constraining. On the other hand, the older person who becomes disabled faces a mismatch between the capabilities required for the job in which they have specialised and their post-disablement capacity. As anticipated, the OPCS measure of severity of disability is negatively correlated with work capacity, but it is only significant in the case of the sample separation model. Individuals who experience difficulty in using buses, cars or trains (transport) are significantly less likely to be capable of work.

The greatest constraints on capacity to work are a lack of mobility (indloc and indreach) and, in the case of the partial observability model, suffering from fits (indfits)[12]. According to the estimates from the sample separation model, individuals in the sample with a limitation in hearing and/or communication (hear) have a greater capacity for work. In interpreting this effect, it needs to be kept in mind that all individuals in the sample have some disability. Consequently, the result suggests a hearing problem impedes work capacity less than other types of disability. This result is consistent with Kreider (1996), who found hearing problems had no significant impact on work capacity. Disabilities caused by mental illness (menill) have the greatest negative effect on work capacity, followed by diseases of the circulatory (sample separation only) and

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interfere most with work capacity can be examined.

[12] Testing indicated that the disabilities indhear and indcomm could be replaced by ‘hear’, which indicates the presence of either or both disabilities. Similarly, indbeh and indint could be combined to form ‘mental’. Two of the ICD groups (7-eye and 8-ear) were omitted due to extremely high correlation with the disability types indsee and indhear. ICD groups 1-4, 12-

respiratory systems. The strong negative impact of mental illness is not consistent with Kreider (1996). The explanation may lie in the difference in samples and the fact that in Kreider the capacity index is identified from limitations experienced by workers only and may not therefore reflect the incapacitating effect of more severe mental illness[13].

[TABLE 5 HERE]

In the partial observability model, education has no significant effect on work capacity. This is consistent with Kreider (1996). However, the estimates from the sample separation model suggest individuals who attended a special school are significantly less likely to be capable of work and those with a degree have a greater capacity for work. The impact of occupation is consistent with intuition and previous results (Bound *et al*, 1995; Kreider, 1996). For a given disability, an individual is less likely to be capable of work if they are unskilled and a manual worker[14]. The region variables reveal a clear role for demand side factors in determining capacity for work. For a given disability, individuals living in regions where the labour market is less buoyant have a lower capacity to work. This is consistent with the interpretation of work incapacity as reflecting labour market disequilibrium.

The ML estimates of the desire for work index (Table 6) are not as close to the respective two-stage estimates (not reported) as was the case with the other functions. In particular, the ML estimates of the wage coefficients are roughly double the respective two-stage estimates. Such changes might be expected given the difference between ML and the two-stage estimators is simultaneous estimation of the wage function parameters with those of the two index functions.

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13 and 15-16 have been excluded given their very low significance and prevalence.

[13] Kreider (1996) uses data from the U.S. Health and Retirement Survey which is a sample of the general population aged 50-62. The estimation procedure used by Kreider does allow for the censoring of the capacity information.

[14] Occupation and industry of non-workers are coded according to their last job. Those who have never worked are included in the omitted category. Given concerns for their potential endogeneity, I experimented with the exclusion of the occupation and industry variables from the capacity function. The exclusion was rejected and resulted in little change in the parameter estimates.

As with the capacity function, there are some discrepancies between the partial observability and sample separation model estimates. Most noticeably, the wage coefficients both take the expected positive sign but differ greatly in magnitude and significance[15]. The income effect is negative, as anticipated, but fails to reach conventional levels of significance. Desire for work appears to decline with age and is greater for individuals with a spouse. The disability variables are included in the desire for work index in order to allow for the possibility that disability affects the probability of employment through preferences, even after allowing for an effect through work capacity. Most of the disability variables lack individual significance but their joint insignificance can be rejected (at least for the partial observability model). The negative sign (not significant at 5%) on the correlation between the disturbances of the capacity and desire for work indices is inconsistent with some previous results (Stern, 1989; Kreider, 1996)[16] and might be considered surprising. Unobservables which raise capacity for work might be expected to also raise the enjoyment of work. But this is not sufficient to give a positive sign on the correlation coefficient since unobservable factors which raise capacity to do work might also raise capacity to perform non-work activities and shift preferences toward leisure.

[TABLE 6 HERE]

Given the discrepancies noted between the estimates from the partial observability and sample separation model, it is not surprising that the Hausman test decisively rejects the null hypothesis of no reporting errors in the work capacity data. With respect to consistency, the estimates from the partial observability model are preferred[17].

Estimates of the index function from a more conventional participation model, without the capacity for work condition, are also presented in Table 6. The LR test rejects this restricted

[15] Using the non-heteroskedasticity corrected covariance matrix, the partial observability model estimate of the wage coefficient is significantly different from zero at the 5% level.
[16] The sign of one of the two correlation coefficients estimated by Stern (1989) is consistent with the present estimates.
[17] This conclusion must be tempered somewhat given the diagnostics indicate rejection of the

model. The wage coefficient in the misspecified restricted model is substantially greater than those estimated for the more general models. The sensitivity of the estimated wage effect to model specification can be observed more directly in Table 7, which gives the elasticity of the employment probability with respect to the wage at various sample points[18]. These elasticities are substantially greater than those which appear in the literature for UK men (c.f. Pencavel, 1986)[19]. However, previous estimates are of the elasticity of work hours, conditional on employment; here we have the elasticity of employment. In general, the labour supply literature has found the latter elasticity to be substantially greater than the former (Heckman, 1993). The estimates from the models which allow for incapacity lie within the range of wage elasticity estimates for UK female participation (0.40-1.41) (Zabalza, 1983; Arrufat and Zabalza, 1986; Duncan and Weeks, 1997). Given the employment rate in this sample is closer to that of females than it is to able-bodied males, estimates from samples of females may actually provide more appropriate comparisons. The nature of the sample might also be expected to lead to large elasticity estimates given previous findings that participation elasticities are positively related to disability (Haveman and Wolfe, 1984; Fenn and Vlachonikolis, 1986).

The large difference in the wage coefficients estimated from the partial observability and sample separation models does not translate into such a large difference in the respective elasticities. However, at all sample points, the wage elasticity from the restricted model, which does not allow for incapacity, is at least two and a half times larger than the elasticities calculated from the more general models. This remains true even when the restricted model is generalised to include all of the arguments of the capacity function, except the region dummies, in the index

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distributional assumptions, on which consistency of all the estimators depend.

[18] Given the insignificance of the income coefficients, income elasticities are not presented. The range of estimates of the mean income elasticity is –0.005 to –0.015.

[19] The average of the uncompensated wage elasticities quoted in Pencavel (1986) is –0.16. These elasticities refer to hours of work, conditional on employment.

function (i.e. specification 2)[20]. When estimating the employment responsiveness of individuals with a disability to financial incentives, it appears important to allow for the possibility that some of these individuals are incapable of work and therefore cannot respond to such incentives. When there is no allowance for the possibility that some non-workers simply cannot work, non-work is over-attributed to the low wages these individuals are assumed to command. This finding is consistent with the evidence on the sensitivity of estimates of overall labour supply elasticities to allowance for constraints on employment and hours (Imakunnas and Pudney, 1990; Euwals and van Soest, 1996)[21].

V. CONCLUSIONS

This paper has extended the literature on the employment consequences of disability by estimating a model which explicitly recognises the contingency against which disability insurance is intended to provide cover - incapacity for work. Ignoring this contingency, and formulating a model on the basis of a single (utility) condition for employment, runs the risk of misspecification. In the presence of sample members who are incapable of doing or getting work, there are two distinct processes determining employment. Failure to recognise this will result in incorrect expressions for the probability of observing a worker and inconsistent parameter estimates. Recognition of the fact that some individuals may be incapable of work provides a solution to the problem of how to identify the impact of work capacity on employment. Observation of employment status provides (partial) information on work capacity, which can be used to estimate a capacity index without recourse to self-reported capacity data. Further, the accuracy of reported information on capacity can be tested.

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[20] The region dummies are excluded for the purpose of identification. The restricted model is rejected relative to the more general single condition model.

[21] Overall labour supply covers employment and hours. Wage elasticities for hours, conditional on employment, do not appear to be very sensitive to allowing for constraints (Ham, 1982; Blundell *et al*, 1987).

The results suggest that, for the sample considered, a specification which incorporates a capacity for work condition is appropriate and ignoring this condition biases the estimated impact of the wage on the employment probability upwards. This bias remains even after making extensive control for disability and demand side factors in the employment index of a single condition model. The accuracy of the self-reported information on work capacity was rejected. Utilisation of such information also raised the estimated wage elasticities but the effect was not as large as that resulting from the failure to allow for incapacity. The estimates of the capacity index are useful in revealing the types of disability which interfere most with employment opportunities. They also confirm that work capacity is not only a function of disability but varies with the skills of the individual and the labour market within which they operate. The latter suggests important interactions between labour demand and claims for disability insurance.

Some qualification of the results is required. The relevance of the capacity condition and the sensitivity of the estimates to this, at least in part, must reflect the nature of the sample employed. A capacity for work condition would be expected to be of particular relevance in modelling the employment status of individuals with some disability. Whether the condition remains relevant when modelling the impact of disability on employment for a sample of the general population is an interesting question for future research.

The diagnostic tests consistently rejected the maintained hypothesis of normality. There is some evidence that these tests tend to over-reject the null (Orme, 1990). Even so, one must be cautious given consistency of the estimators employed is dependent on normality. Examination of the residuals revealed the problem was, in part, caused by outliers on the wage variable. Exclusion of these outliers led to some improvement in the diagnostics. It is reassuring that the main results were robust to these exclusions – the null of accurate self-reports of incapacity was still rejected and the restricted model continued to be rejected, and to produce large wage elasticities, relative to the specification which allows for work incapacity. The two-stage estimates, which should be less sensitive to the distributional assumptions, were also broadly consistent with those from ML, with the exception of the smaller (for all models) wage effects. Nonetheless, adoption of a non- (or semi-) parametric estimation method would be a more appropriate response and this represents another area in which the research could be extended.

The specification adopted for the financial effects – gross wage and exogenous unearned income – is conventional in much of the labour supply literature. It avoids the issue of whether a transfer income, or replacement ratio, effect can be distinguished from a wage effect in a single cross-section (Bound and Waidmann, 1992) and allows attention to be focussed on the introduction of a capacity for work condition. However, this specification is not ideally suited to addressing one of the most important concerns of disability policy – the incentive effects of disability insurance. Development of a model which would be more suited to simulation of reforms to DI, whilst recognising work incapacity, is another important item for the research agenda. Further, the method proposed here to test for reporting errors in capacity data could be used to test for type I and II errors in the DI awards.

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Appendix 1 – Variable Definitions

Financial	
log(wage)	Logarithm of gross wage per hour in £ and pence.
Unearned income	Total unearned income of respondent and spouse exogenous to labour supply (£ and pence divided by 100).
Demographics	
Age	Age of respondent at time of interview divided by 10.
Age^2	Age of respondent squared divided by 1000.
Spouse	1 if respondent is married or cohabiting.
Anykids	1 if is dependent child in household.
Numkids	Number of dependent children in household.
Disability	
Agestart	Age of respondent at onset of disability divided by 10.
Severity	OPCS measure of severity of disability divided by 10.
Transport	1 if disability makes it difficult to travel by bus, car or train.
Education	
Educ1	1 if attended special school and have no qualifications.
Educ2	1 if highest qualification is cse, O-level, ONC or clerical.
Educ3	1 if highest qualification is A-level, teaching, nursing, City & Guilds, HNC or other above A-level.
Educ4	1 if highest qualification is degree level.
Omitted category	No qualification or apprenticeship only and not attended special school.
Occupation	
Prof	1 if occupation classified as professional or intermediate.
Nonman	1 if occupation classified as skilled non-manual.
Skill	1 if occupation classified as skilled manual.
Semiskil	1 if occupation classified as semi-skilled manual.
Omitted category	Unskilled manual.
Industry	
Primary	1 if single digit standard industrial classification of job is 0,1 or 2.
Manuf	1 if single digit SIC of job is 3 or 4.
Build	1 if single digit SIC of job is 5.
Omitted category	single digit SIC of job 6-9 – distribution or services.
Region	
Neast	1 if respondent lives in North East region.
Nwest	1 if respondent lives in North West region.
Yorks	1 if respondent lives in Yorkshire and Humberside region.
Emid	1 if respondent lives in East Midlands region.
Wmid	1 if respondent lives in West Midlands region.
Wales	1 if respondent lives in Wales.
Scot	1 if respondent lives in Scotland.
Omitted category	London, South East, South West and East Anglia.

Note: Occupation and industry of non-workers classified according to last job. Those who have never worked are included in the omitted category.

Appendix 2 – Diagnostic Tests

Tests of normality and homoskedasticity of the marginal distributions are undertaken following the general procedure of Gourieroux *et al* (1987). This involves utilising generalised residuals to implement the score test principle. With binary or censored dependent variables, residuals are not simply the difference between the dependent variable and its estimate. Generalised errors are defined as the expectation of (powers of) a disturbance, given the null and the data. For example, the generalised errors of the capacity index amongst workers are;

$$E\left(e_{1i}^{j} \,\middle|\, e_{1i} > -\Omega_i, \varepsilon_{2i} > -\Delta_i, e_{3i}\,; \quad (e_{1i}, \varepsilon_{2i}, e_{3i}) \sim TVN(0, \Sigma)\right), \qquad j = 1, 2, 3, 4.$$

Generalised residuals are the generalised errors evaluated at the ML parameter estimates. If the null is correct then, across the sample, the difference between a generalised residual and the appropriate error moment, hypothesised under the null, will be zero. Augmenting the score matrix with such differences for the third and fourth error moments and constructing the Outer Product Gradient (OPG) version of the Lagrange Multiplier (LM) test statistic provides tests for skewness and kurtosis respectively. The test statistics are asymptotically χ^2 distributed with degrees of freedom given by the number of restrictions. Similarly, homoskedasticity can be tested by augmenting the score matrix with the product of a (sub-) vector of regressors and the difference between the appropriate generalised residual and the hypothesised constant variance of the disturbance. Again the OPG version of the LM test statistic has a χ^2 distribution with degrees of freedom given by the number of regressors hypothesised to enter the variance function.

The generalised errors required for the present application are available from the author.

Table 1: Percentage with each Disability by Employment and Reported Capacity Status

Type of Disability	Definition	Workers	Non-Workers		All
			Capable	Incapable	
Indloc	1 if limited in locomotion	36.1	40.3	75.2	55.2
Indreach	1 if limited in reaching and stretching	5.3	4.8	18.7	11.5
Indhold	1 if limited in dexterity	8.9	8.9	24.3	16.1
Indsee	1 if limited in seeing	8.6	12.8	14.3	12.0
Indhear	1 if limited in hearing	43.5	38.2	28.0	35.3
Indcont	1 if limited in continence	8.7	6.8	13.6	10.6
Indcomm	1 if limited in communication	19.2	18.4	19.9	19.4
Indint	1 if limited in intellectual functioning	16.9	23.2	30.9	24.6
Indbeh	1 if limited in behavioural functioning	18.1	27.8	33.4	27.0
Indfits	1 if limited in consciousness	5.3	8.7	6.3	6.4
Indadl	1 if limited in personal care	17.6	15.7	3.3	29.3

Note: Individuals can report more than one type of disability.

Table 2: Percentage in each ICD Group by Employment and Reported Capacity Status

Cause of Disability	Definition	Workers	Non-Workers		All
			Capable	Incapable	
Infections	1 if ICD Group 1 – Infections & parasitic	1.0	1.2	1.0	1.0
Neoplasms	1 if ICD Group 2 – Neoplasms	0.5	0.0	1.3	0.8
Endocrine	1 if ICD Group 3 – Endocrine and metabolic	1.0	1.7	2.7	1.9
Blood	1 if ICD Group 4 – Blood & blood forming organs	0.4	0.5	0.6	0.5
Menill	1 if ICD Group 5 – Mental	13.7	22.5	22.1	19.2
Nervous	1 if ICD Group 6 – Nervous system	11.6	13.0	19.9	15.7
Eye	1 if ICD Group 7 – Eye	8.2	12.3	12.7	11.0
Ear	1 if ICD Group 8 – Ear	41.4	36.2	24.9	32.8
Circulatory	1 if ICD Group 9 – Circulatory system	7.0	8.9	25.5	16.0
Respiratory	1 if ICD Group 10 – Respiratory system	7.2	8.2	16.0	11.5
Digestive	1 if ICD Group 11 – Digestive system	5.1	4.6	6.9	5.9
Genourin	1 if ICD Group 12 – Genito-urinary system	1.2	1.7	2.0	1.7
Skin	1 if ICD Group 13 – Skin diseases & disorders	1.3	1.4	1.4	1.4
Musculo	1 if ICD Group 14 – Musculo-skeletal system	29.2	31.6	40.3	34.9
Congenital	1 if ICD Group 15 – Congenital	1.1	1.2	0.6	0.9
Vague	1 if ICD Group 16 – Other and Vague	2.0	1.9	2.8	2.3

Note: Individual coded 1 for group if they report this cause for any of the disabilities they report. Individual may therefore report more than one cause.

Table 3: Descriptive Statistics by Employment and Reported Capacity

	Workers		Non-Workers				All	
			Capable		Incapable			
	(N=818)		(N=414)		(N=1088)		(N=2320)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Financial								
Log (wage)	1.1472	0.4921	-	-	-	-	-	-
Unearned income	0.1057	0.2111	0.1551	1.2911	0.1007	0.3308	0.1122	0.6035
Demographics								
Age	4.4780	1.2428	4.4928	1.4595	5.0504	1.1689	4.7491	1.2823
Age^2	2.1595	1.0496	2.2310	1.2385	2.6871	1.0540	2.4197	1.1162
Spouse	0.7604	0.4271	0.5749	0.4950	0.6930	0.4615	0.6957	0.4602
Anykids	0.3252	0.4687	0.2488	0.4328	0.2040	0.4032	0.2547	0.4358
Numkids	0.5844	0.9862	0.5242	1.0659	0.3879	0.9261	0.4815	0.9774
Disability								
Agestart	2.8075	1.7766	2.8350	1.8423	3.6071	1.8002	3.1874	1.8415
Severity	0.5132	0.4217	0.5792	0.4371	0.8676	0.5163	0.6912	0.4996
Transport	0.2213	0.4154	0.2464	0.4314	0.5083	0.5002	0.3603	0.4802
Education								
Educ1	0.0623	0.2419	0.0870	0.2821	0.0873	0.2824	0.0784	0.2689
Educ2	0.0905	0.2870	0.0580	0.2340	0.0386	0.1927	0.0603	0.2382
Educ3	0.1406	0.3478	0.0652	0.2472	0.0579	0.2337	0.0884	0.2839
Educ4	0.0623	0.2419	0.0507	0.2197	0.0211	0.1439	0.0409	0.1982
Occupation								
Prof	0.2103	0.4077	0.1256	0.3318	0.1213	0.3267	0.1534	0.3605
Nonman	0.1504	0.3576	0.0942	0.2925	0.0653	0.2471	0.1004	0.3006
Skill	0.3631	0.4812	0.3961	0.4897	0.4375	0.4963	0.4039	0.4908
Semiskill	0.2029	0.4024	0.2198	0.4146	0.2077	0.4059	0.2082	0.4061
Industry								
Primary	0.1247	0.3306	0.1111	0.3146	0.1765	0.3814	0.1466	0.3537
Manuf	0.3007	0.4589	0.3309	0.4711	0.2849	0.4516	0.2987	0.4578
Build	0.0990	0.2989	0.1377	0.3450	0.1085	0.3111	0.1103	0.3134
Region								
Neast	0.0562	0.2305	0.1232	0.3291	0.0983	0.2979	0.0879	0.2833
Nwest	0.0831	0.2762	0.1111	0.3146	0.1204	0.3256	0.1056	0.3074
Yorks	0.0966	0.2956	0.1039	0.3055	0.1140	0.3179	0.1060	0.3079
Emid	0.0831	0.2762	0.0580	0.2340	0.0469	0.2115	0.0616	0.2405
Wmid	0.0819	0.2744	0.0894	0.2856	0.1140	0.3179	0.0983	0.2978
Swest	0.0990	0.2989	0.0725	0.2596	0.0699	0.2550	0.0806	0.2723
Wales	0.0477	0.2132	0.0749	0.2635	0.0744	0.2626	0.0651	0.2467
Scot	0.0941	0.2922	0.1232	0.3291	0.1498	0.3571	0.1254	0.3313

Table 4: Maximum Likelihood Estimates of Wage Function

	Partial Observability		Sample Separation	
	Estimates	t-ratio	Estimates	t-ratio
Age	0.6552	7.590	0.5565	6.380
Age^2	-0.5992	-5.242	-0.5700	-5.604
Education				
Educ1	-0.0663	-1.086	-0.0461	-1.233
Educ2	0.1462	2.757	0.0987	2.395
Educ3	0.1521	3.299	0.1196	3.454
Educ4	0.4702	4.246	0.3672	3.706
Occupation				
Prof	0.2499	3.064	0.2435	4.792
Nonman	0.1788	2.519	0.1564	3.504
Skill	0.1239	2.438	0.1169	3.060
Semiskill	0.0347	0.549	0.0516	1.234
Industry				
Primary	0.1088	1.815	0.1126	2.836
Manuf	0.1206	2.141	0.0707	2.280
Build	0.1118	1.979	0.0803	1.823
Region				
Neast	-0.0948	-1.280	-0.1262	-2.362
Nwest	-0.1943	-3.555	-0.1727	-4.496
Yorks	-0.1739	-3.460	-0.1445	-3.902
Emid	-0.1642	-3.328	-0.1567	-4.026
Wmid	-0.1778	-3.287	-0.1557	-3.975
Swest	-0.1484	-2.627	-0.1234	-2.958
Wales	-0.1722	-2.796	-0.1642	-4.081
Scot	-0.2126	-4.078	-0.1664	-3.946
Constant	-0.4972	-2.096	-0.0602	-0.310
ρ_{23}	-0.6997	-3.142	-0.7806	-10.072
ρ_{13}	0.4346	2.065	0.0669	0.747
σ_3	0.4771	6.634	0.4884	14.487
Diagnostics				
Skewness	27.42	(0.0000)	21.20	(0.0000)
Kurtosis	38.95	(0.0000)	25.62	(0.0000)
Normality	38.95	(0.0000)	25.64	(0.0000)
Homosked.	122.42	(0.0000)	115.43	(0.0000)

Notes:
1. t-ratios calculated using heteroskedasticity consistent covariance matrix.
2. All diagnostic test statistics are chi-square distributed under null. Probability values in parenthesis.

Table 5: Maximum Likelihood Estimates of Capacity for Work Index

	Partial Observability		Sample Separation	
	Estimates	t-ratio	Estimates	t-ratio
Age	0.3848	2.438	-0.1886	-5.321
Disability				
Agestart	-0.1172	-2.441	-0.1065	-4.489
Severity	-0.2355	-0.811	-0.4313	-4.472
Transport	-0.4464	-2.931	-0.3966	-5.828
Type of Disability				
Indloc	-0.5271	-2.504	-0.5852	-6.935
Indreach	-0.5929	-1.744	-0.3291	-2.726
Indhold	0.3819	0.901	-0.0882	-0.866
Indsee	-0.2992	-1.227	-0.1368	-1.430
Hear	-0.0385	-0.194	0.2244	3.400
Indcont	0.2045	0.611	0.0800	0.734
Mental	0.0767	0.183	-0.2246	-2.211
Indfits	-1.2372	-2.396	0.0433	0.290
Indadl	-0.2290	-0.829	-0.2482	-3.027
ICD Group				
Menill	-0.6415	-1.769	-0.5245	-4.395
Nervous	0.5422	1.159	-0.2002	-1.809
Circulatory	0.2529	0.395	-0.5063	-5.197
Respiratory	-0.4355	-1.727	-0.2755	-2.773
Digestive	-0.1985	-0.463	-0.1918	-1.347
Musculo	-0.2581	-1.146	0.0968	1.195
Education				
Educ1	0.0024	0.011	-0.4159	-3.061
Educ2	-0.1248	-0.383	0.0565	0.403
Educ3	0.4679	1.504	0.1371	1.131
Educ4	-0.1137	-0.152	0.4033	2.251
Occupation				
Prof	1.2476	2.501	0.5422	3.979
Nonman	1.3266	4.554	0.8768	6.108
Skill	0.4277	2.582	0.3204	2.993
Semiskill	0.8327	3.391	0.4541	3.880
Industry				
Primary	-0.3223	-1.299	-0.2142	-2.280
Manuf	-0.2646	-1.191	0.0329	0.406
Build	-0.3422	-1.171	-0.0031	-0.029
Region				
Neast	-1.1539	-4.526	-0.4391	-3.429
Nwest	-0.7405	-2.986	-0.3807	-3.401
Yorks	-0.4879	-2.222	-0.2759	-2.607
Emid	-0.0397	-0.090	0.0900	0.669
Wmid	-0.4492	-1.724	-0.2603	-2.234
Swest	-0.0272	-0.081	-0.0493	-0.404
Wales	-0.7257	-3.238	-0.3345	-2.603
Scot	-0.6625	-3.079	-0.3868	-3.679
Constant	0.2420	0.247	2.2692	11.554
Diagnostics				
Skewness	1.44	(0.2305)	3.42	(0.0643)
Kurtosis	6.71	(0.0096)	14.33	(0.0002)
Normality	7.04	(0.0296)	16.04	(0.0003)
Homosked.	101.11	(0.0000)	85.78	(0.0000)

1. t-ratios calculated using heteroskedasticity consistent covariance matrix.
2. All diagnostic test statistics are chi-square distributed under null. Probability values in parenthesis.

Table 6: Maximum Likelihood Estimates of Desire for Work Index

	Partial Observability		Sample Separation		Without Capacity Condition	
	Estimates	t-ratio	Estimates	t-ratio	Estimates	t-ratio
Financial						
Wage	0.7926	1.085	1.4506	2.920	2.1856	3.767
Unearned Income	-0.0839	-1.233	-0.0631	-1.415	-0.1004	-1.206
Demographics						
Age	-0.5437	-5.071	-0.1838	-2.338	-0.4364	-5.194
Spouse	0.4884	4.187	0.4753	4.822	0.4079	4.815
Anykids	0.2843	1.412	0.1551	0.967	0.0853	0.642
Numkids	-0.1207	-1.282	-0.1220	-1.731	-0.1091	-1.827
Type of Disability						
Indloc	-0.1754	-1.071	-0.0520	-0.444	-0.4484	-5.186
Indreach	0.0561	0.226	0.0706	0.416	-0.2004	-1.717
Indhold	-0.2704	-1.153	-0.0497	-0.380	-0.1008	-0.988
Indsee	-0.1059	-0.685	-0.2270	-2.040	-0.2914	-3.032
Hear	0.2449	2.065	0.0998	1.337	0.1893	3.052
Indcont	0.1668	0.867	0.2117	1.662	0.1817	1.721
Mental	-0.2668	-0.935	0.0071	0.057	-0.2000	-2.037
Indfits	0.7244	1.588	-0.0769	-0.431	-0.0645	-0.431
Indadl	0.0324	0.216	0.1756	1.646	-0.1463	-1.785
ICD Group						
Menill	-0.1412	-0.588	-0.2419	-1.646	-0.4758	-3.738
Nervous	-0.4420	-1.491	-0.0217	-0.158	-0.1758	-1.564
Circulatory	-0.5811	-1.877	-0.0560	-0.406	-0.4825	-4.462
Respiratory	-0.0215	-0.121	0.0201	0.158	-0.2088	-2.084
Digestive	-0.0278	-0.120	0.0899	0.585	-0.1406	-0.975
Musculo	0.1097	0.834	-0.0990	-1.022	-0.0451	-0.558
Disability						
Severity	-0.2833	-1.522	-0.0419	-0.359	-0.3087	-3.303
Constant	1.7617	1.191	-0.7233	-0.519	-0.7347	-1.053
ρ_{12}	-0.5453	-1.907	-0.2556	-1.305		
Diagnostics						
Skewness	41.30	(0.0000)	30.43	(0.0000)	6.20	(0.0128)
Kurtosis	39.99	(0.0000)	22.96	(0.0000)	12.07	(0.0005)
Normality	44.41	(0.0000)	31.65	(0.0000)	12.10	(0.0024)
Homoskedasticity	47.21	(0.0009)	86.70	(0.0000)	36.72	(0.0181)
Hausman test of no reporting errors		534.36	(0.0000)			
LR test of no capacity condition					157.25	(0.0000)

Notes:
1. t-ratios calculated using heteroskedasticity consistent covariance matrix.
2. All diagnostic test statistics are chi-square distributed under null. Probability values in parentheses.

Table 7: Wage Elasticity of Employment Probability

	With Capacity Condition		Without Capacity Condition	
	Partial Observability	Sample Separation	Specification 1	Specification 2
Mean	0.835	0.960	2.577	3.242
M_{25}	0.442	0.663	1.656	1.975
M_{50}	0.762	0.920	2.462	3.091
M_{75}	1.125	1.212	3.382	4.342

Notes:

1. M_i is the ith percentile.
2. Specification 1 – arguments of index function same as desire for work index in more general models.

   Specification 2 – index function also includes all arguments of capacity index (excluding region).