Disability and Labour Force Participation in Ireland 1995-2000

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Summary

This paper aims to analyse the effect of disability on participation in the labour force, using the Irish component of the European Community Household Panel Survey 1995-2000. A range of panel models are considered, but to allow for any unobserved influences or state dependence in labour force participation, our preferred model is a dynamic panel model. We show how the estimates of current disability are changed once we control for the effect of past disability and previous participation. We compare base estimates of disability with those controlling for unobserved heterogeneity and past participation. The results suggest that the base effect of disability is overestimated by between 40-60 per cent for men and by 5-10 per cent for women.

Keywords Disability; labour force participation; static and dynamic panel models

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I. Introduction

People with disabilities face many barriers to full participation in society, not least in the labour market, and the extent and nature of participation in the labour market has a multitude of direct and indirect effects on their living standards and quality of life. In studying the effect of disability on labour force participation, we are faced with a variety of analytical challenges, such as the effect of unobserved characteristics of disabled individuals and the effect of their past participation in the labour market. This paper uses panel data methods to control for these factors and we estimate the impact of disability on participation, controlling for unobserved heterogeneity and past participation.

Internationally, the first generation of econometric studies on the effect of disability on labour force participation emerged around the late 1970's. Bartel and Taubmann [1] estimate an OLS model of weekly hours worked to analyse the effect of health on earnings and labour supply, whereas Chirokos and Nestel [2], estimate a Tobit model relating annual hours worked to health history by looking at the degree of poor, good, improved or deteriorating health over the previous ten years. More recent research emphasises the importance of the way health and limitations are captured, with the type of health status variable used leading to different patterns in terms of labour force participation. Wolfe and Hill [3], for example, measure health status using an index of limitation in daily activities, Madden and Walker [4] measure health in terms of those who report a longstanding illness or disability, while Mete and Schultz [5] also measure health status using a health index. Using Labour Force Survey data, Kidd, Sloane and Ferko [6] analyse the effect of health limitations on the kind of paid work possible in the UK. They confirm the presence of substantial wage and participation rate differences between disabled and non-disabled individuals.

The focus of previous policy for disabled people has been on the provision of services, whereas more recently, there is a campaign for civil rights and the provision of legislation for equality and full participation. Employers and policy makers are therefore interested in whether or not disability has an effect on participation. In this paper, we aim to determine whether it is disability that determines the participation decision, or if there may be some other unobservable characteristics involved that distort the disability effects.

Previous studies analysing unobserved individual effects in this context emerged in the mid-eighties. Sickles and Taubman [7] were one of the first to use longitudinal data in estimating retirement decisions, and allow for unobserved heterogeneity in the retirement function. Estimating a binary random effects probit model, they allow for unobserved affects by simultaneously estimating the health and retirement equation, allowing the errors to be correlated. They allow for correlation of the unobserved effect with the disability variable, but they do not include the effect of labour market history. Their findings show that moving from poor health to good health decreases the probability of retirement, but they do not show how the health effect changes as a result of allowing for unobserved effects.

Bound [8] looks at a retirement equation in the cross sectional context, and shows that if the errors in the health and retirement equation are correlated, then there is an upward bias in the effect of health. He aims to identify the effects of financial incentives on reporting behaviour and retirement decisions, and investigates if objective measures may be used as a proxy for subjective measures of health. The author concludes that the self-reported measure is not reliable in estimating the effect of health on retirement. Kreider [9] also analyses work participation with cross section methodology and arrives at the same conclusion. He finds that when the true measure of disability is used, the effect on participation is lower, by 17.2% for men and 24.9% for women. Both Bound [8] and Kreider [9] use cross section data to estimate the effect of the true effect of disability on participation, but identification of their models requires a variable, that affects health but that is not correlated with participation. Kidd, Sloane and Ferko [6] apply a decomposition approach to cross section data and find that approximately 50 per cent of the difference in participation rates is due to unexplained effects.

Our data offer the possibility of analysing the relationship between disability and labour force participation over a significant period rather than just at a point in time, and allow us to use panel data techniques in our estimation. Using panel data, we capture the effects of variables that are particular to an individual and are constant over time. We can control for these unobservables by using a panel model and we therefore do not need to include an identifying variable. Labour force participation may also be influenced by past participation**,** where non-participants in the previous year may be less likely to participate in the current year. Although this may be true for all individuals, it may also be a specific characteristic of disabled people and lead to an incorrect interpretation of the disability effect. It may be that disability reduces the probability of previous participation, and therefore indirectly influences current participation. Using panel data, we can incorporate this state dependence effect and re-estimate the effect of disability on participation. It may also be that individuals report a disability as an ex-post justification for not being in work in the previous year. Again, we would expect the effect of disability to be misinterpreted, and can use the results of the dynamic model to disentangle the unobserved heterogeneity and past participation effects.

More recently, Lindeboom and Kerkhofs [10] also include the effect of past labour market outcomes on current health in their retirement model. They find that for elderly people, working in the previous period only slightly decreases the value of health. They estimate a multinomial logit model, to facilitate the three different labour market states compared to working, available to individuals nearing retirement age in the Netherlands. Although they only have two waves of panel data, by using information on previous labour market history, they specify an equation for initial participation and estimate the probability of working initially. This is included into the overall likelihood function from which unobserved effects are integrated out. They find that the effects of health are exaggerated for elderly people in a simple multinomial model, compared to their preferred model.

In this paper, we follow a different approach to Lindeboom and Kerkhofs [10] mainly because we use six waves of panel data and can therefore identify the effect of past participation within a less complicated model. The main focus in this paper is to model two labour market outcomes – participation and non-participation – and hence we concentrate on a binary response variable. In contrast to Lindeboom and Kerkhofs [10], we follow an approach by Wooldridge [11] that allows us to avoid specifying a distribution for the initial participation. The likelihood function from our approach is easier to estimate and serves the same purpose in terms of looking at the effect of unobserved heterogeneity. Our findings using Irish data are similar to those of Lindeboom and Kerkhofs [10] among others, in that their reported disability variable over estimates the impact of disability on participation in the Netherlands. In addition, we show exactly how much unobserved heterogeneity contributes to variation in participation and how this changes the effect of disability. Finally, we show the effect of past disability (via it's effect on previous participation), on current labour force participation.

II. Theoretical Framework

We model participation firstly as a static process with current participation, and secondly as a dynamic process. In our dynamic model, we account for the fact that the choice between consumption and leisure is considered as a lifetime decision, so we assume that individuals maximise their expected utility over their lifetime. Following Bound et al [12], in general, the participation equation is based on the assumption that individuals maximise a utility function given by:

$$\max E_t \sum_{j=t}^{T} \beta^{j-t} U(C_j, L_j, Z_j) \qquad [1]$$

where C_j and L_j are consumption and leisure in period j respectively. Z_j is a vector of taste shifters and includes disability. The utility function is maximised subject to an intertemporal budget constraint:

$$A_{j+1} = (W_j H_j - C_j) + (1 + r_{j+1}) A_j \qquad [2]$$

where W_j is the wage, H_j is hours of work, A_j represents assets, and r_j is the rate of interest.

In this paper, our empirical model shows how individuals compare the utility between two states – participation and non-participation. Solving this model provides an expression for optimal leisure as a function of *W*, *H*, A_j and Z_j. Much of the literature on the effect of health on labour force behaviour has treated health as an exogenous taste shifter. We take this approach, and hence do not specify a health production function. In this context, we obtain estimates from a reduced form model[a] and concentrate on how the disability effect changes once we allow for unobserved individual effects and state dependence in labour force participation.

III. Data

The data on disability and labour force participation in Ireland are from the Living in Ireland Survey 1995-2000.[b] The Living in Ireland Survey is the Irish component of the European Community Household Panel, conducted by the ESRI for Eurostat. We wish to focus on individuals of working age, hence we exclude those aged 65 and over.

In the Living in Ireland Survey, detailed information on current labour force status was obtained. For current purposes this allows us to distinguish between those who were at work, or unemployed but seeking work – who we will count as active in the labour force – and all others, whom we will count as inactive. The percentage of those unemployed but seeking work is quite low ranging from 7.5% in 1995 to 2.8% in 2000, giving a panel average of 5.1%. For this reason, we do not include them as a separate category in our dependent variable. A measure of disability can also be constructed from the Living in Ireland survey on the basis of individual responses to the following question:

"Do you have any chronic, physical or mental health problem, illness or disability?"

It may well be, that not only the presence of such an illness or disability but also the extent to which it limits or restricts a person, is important. To capture this, we use responses to a follow-up question concerning the impact of the disability to distinguish

a) those reporting a chronic illness or disability and saying that it limits them severely in their daily activities
b) those who report a chronic illness or disability and saying it limits them to some extent, and
c) those who report such a condition but say it does not limit them at all in their daily activities.

The extent to which respondents say they are limited relates to their daily activities rather than work, but similar measures have been shown to have significant discriminatory power in terms of labour force participation in research elsewhere (e.g. Malo [13]). Furthermore, as Table 1 shows there are different rates of participation for each sub-group, so it is important that we distinguish between the different levels of disability, in our analysis of labour force participation.

The effects of disability on labour force participation may differ among individuals, depending on other characteristics, for example age or education. Since disability may be correlated with other variables, we include measures of age, education, region, unearned income, age of youngest child and marital status. These variables are defined in detail in Table 2 and summary statistics are provided in Table 3. The youngest individuals in this sample are aged 16 and the number of observations of males and females are 7,188 and 7,670 respectively.

IV. Panel models and Results

Static Pooled Probit Model:

Using the Living in Ireland Survey 1995-2000, we estimate a range of panel models to capture the effect of disability on participation. We exclude 1994 because the questions regarding health problems and limitations differed from 1995 and subsequent years. Firstly, we estimate a static pooled model, assuming that the errors are independent over time and uncorrelated with the explanatory variables. This model provides us with base estimates, with which we can compare results from models that incorporate unobserved heterogeneity and state dependence.

The log likelihood function for the pooled panel data is similar to that of the cross sectional probit:

$$\log L(\beta) = \sum_{i=1}^{N} \sum_{t=1}^{T} y_{it} \log F(x_{it}^{'}\beta) + \sum_{i=1}^{N} \sum_{t=1}^{T} (1 - y_{it}) \log(1 - F(x_{it}^{'}\beta)) \qquad [3]$$

and maximising this across all *i* with respect to β, we obtain the pooled probit estimator. The standard errors are adjusted to account for serial correlation in the errors at the individual level. The main variables of interest are, disability and the associated limitations in daily activities, but we also control for other factors that may be correlated with disability, as mentioned earlier. In addition, it is likely that past disability has a direct effect on current participation, so we include lagged variables for the three types of disability. Pooling all available data for the years 1995 to 2000, and estimating a standard probit model, we obtain estimates from the pooled balanced sample.[c] We present results from this pooled static model in Table 4, Columns 1 and 4, for men and women respectively. These results are presented as parameter co-efficients, but we will later discuss some of the main results in terms of percentage effects.

The effects of current disability are quite high for both men and women, reducing the probability of current labour force participation significantly. At a first glance, disability has a greater negative effect on the labour force participation probability of men, compared to women. Although the effect of a severely limiting disability is less for women than men, it is still substantial. In the case of men, even those with no limitations have a slight reduction in the probability of participation. For women, we see that the probability of participation for those with no limitations, is not significantly different from women with no disability. The gap between the effects of severe and some limitations is quite large for men and even more pronounced for women, suggesting that severe disability has a more negative effect on women's participation. Past disability, in the previous year, also has a substantial effect on current participation, and is not much lower than the effect of current disability. This applies in the case of severe and some limitations, for both men and women. Similar to current disability and severe limitations, we see that individuals who previously had a severely limiting disability have a much lower probability of current participation, compared to those with no previous disability.

In terms of the other explanatory variables (see Table A1), we see that labour force participation increases with age up to 34 (compared to those aged 55-64), but the effect falls slightly after the age of 44. Those with secondary or third level education have a greater probability of participating in the labour market. As expected, we see that women with children are less likely to participate, and this effect gets smaller as the youngest child is older. The opposite effect is found for men, where children increase the probability of participation, in particular when the youngest child is either aged less than 4, or in the older age group of 12-18.

The results from the static pooled model raise two important questions. The first interesting question is whether or not past disability affects current participation directly, or does it work through a separate channel by negatively affecting past participation? If so, we would expect to see that past participation influences current participation, and the effect of past disability should disappear. This would suggest that past disability still does have an effect on current participation, but does so by a) directly influencing past participation and therefore, b) indirectly affecting current participation. The second question arising from these results is whether or not the control variables appropriately account for any unobserved characteristics of disabled people that also influence their labour force participation decision? Again, if this were not true, we would expect that the actual effect of current disability should be lower. We now explore a dynamic model of participation that incorporates both past participation and unobserved effects.

State Dependence and Unobserved Heterogeneity:

In order to distinguish between the two effects – unobserved individual effects and past participation - we now include a lagged dependent variable into the model.[d] In general terms the following likelihood is derived and maximised;

$$f(y_{i0},...,y_{iT} \mid x_{i0},...,x_{iT},\beta) = \int_{-\infty}^{\infty} f(y_{i0},...,y_{iT} \mid x_{i1},...x_{iT},\alpha_i,\beta) f(\alpha_i \mid x_i) d\alpha_i$$

$$= \int_{-\infty}^{\infty} [\prod_{t=1}^{T} f(y_{it} \mid y_{i,t-1}, x_{it}, \alpha_i, \beta)] f(y_{i0} \mid x_{i0}, \alpha_i, \beta) f(\alpha_i \mid x_i) d\alpha_i \qquad [4]$$

We must specify $f(y_{i0} \mid x_i, \alpha_i)$ - known as the initial conditions problem. Heckman [14] suggests approximating $f(y_{i0} \mid x_i, \alpha_i)$ and then specifying $f(\alpha_i \mid x_i)$. Then $f(y_{i0},...,y_{iT} \mid x_i)$ is obtained by integrating out the unobserved effect. The main difficulty in this approach is in specifying the distribution of initial participation. We therefore follow an alternative approach suggested by Wooldridge [11] where we consider:

$$f(y_{i1},...,y_{iT} \mid y_{i0}, x_i) = \int_{-\infty}^{\infty} f(y_{i1},...,y_{iT} \mid y_{i0}, x_i, \alpha_i) f(\alpha_i \mid y_{i0}, x_i) d\alpha_i \qquad [5]$$

and specify the distribution of the unobserved effect conditional on the initial value y_{i0} and any exogenous variables:

$$\alpha_i = \alpha_0 + \alpha_1^{'} y_{i0} + \alpha_2^{'} \overline{x}_i + a_i \,. \qquad [6]$$

The estimate of α_1 is of interest as it shows the direction of the relationship between the unobserved effect and the initial value of labour force participation**.** The relative importance of the unobserved effect in the error variance of the labour force participation equation is measured as $\rho = \sigma_a^2 / (1 + \sigma_a^2)$. This is also the correlation between the composite latent error ($\alpha_i + \varepsilon_{it}$) across any two time periods.

The likelihood function is now:

$$\int_{-\infty}^{\infty} [\prod_{t=1}^{5} f(y_{it} \mid y_{i,t-1,} x_{it}, \alpha_i, \beta)] f(\alpha_i \mid y_{i0}, x_{it}, \beta) d\alpha_i \qquad [7]$$

where $f(\alpha \mid y_{i0}, x_{it}, \beta) = \Phi(\alpha_1 y_{i0} + \alpha_2 \overline{x}_i, \sigma_a^2)$ if y_{it}=1.

In this model of labour force participation, the data is a random sample from a larger population so we assume the unobserved individual effects are random but correlated with the explanatory variables. We estimate a dynamic random effects probit model and maximise this likelihood function with respect to β and σ_α^2. This model assumes that the errors can now be correlated over time through the unobserved effect. The explanatory variables are assumed to be strictly exogenous, and are uncorrelated with the error term, ε_{it}, for each individual. The advantage of using this model over the pooled model is that we can now estimate parameters with greater efficiency. While the pooled model would allow us to obtain consistent estimates of these parameters, it is inefficient relative to our full conditional maximum likelihood model. Furthermore, the pooled model does not allow for correlation between the unobserved effect and explanatory variables.

The means of variables are added as a set of controls for unobserved heterogeneity and we are now estimating the effects of changing explanatory variables but holding the average fixed. However, we should note that in this model, it is only possible to identify the effect of time-constant explanatory variables if we assume that the unobserved effect is partially uncorrelated with the time constant variable, where the coefficient for the correlated random effect part of that variable is zero.

In the pooled probit model we obtained estimates of β / σ_u and because the total error variance was normalised to 1, the estimated βs were population-averaged parameters by default. However, the random effects model parameter estimates will only be the same as those from the pooled model when $\sigma_\alpha^2 = 0$. Therefore we need to rescale the βs that are estimated from the model. This is achieved by dividing the parameter estimates from the random effects model by $\sqrt{(1+\sigma_a^2)}$.

The results from the dynamic random effects probit model with correlated heterogeneity are presented in Table 4, columns 2 and 5 for men and women respectively. We discuss these results in three steps, (1) state dependence, (2) the effect of current and lagged disability and (3) unobserved heterogeneity.

The co-efficient on lagged participation is viewed as an indicator of state dependence, and suggests that previous participation has a significant positive effect on current participation, for both men and women. This suggests, that even after controlling for observed and unobserved differences among individuals, participation in the previous year is associated with a higher probability of participation in the current year. This effect is similar for men and women.

Current disability with severe and some limitations now has a lower effect on current participation, and this difference is more pronounced for men. Previous disability is now insignificant for men and women. By including past participation into the model, the effect of previous disability appears to have no effect on current participation. This suggests that previous disability may have influenced previous participation, and now influences current participation via the channel of past participation. This does not imply, that past disability has no effect on current participation - it simply suggests that its effect is now operating through the channel of past participation.

The results from this dynamic model, suggest that unobserved characteristics may have been part of the effect of current disability in the pooled model for men. Indeed, if we look at the correlated part of the random effect (time averages), this would suggest that having severe or some limitations is associated with unobserved characteristics that reduce the probability of participation for men, i.e. part of the original current disability effect is due to unobserved characteristics. For women, the disability results of the random effects model are generally the same as in the static pooled model. The extent of unobserved effects is higher in the model for men, with 47 per cent of the total variance due to unobserved heterogeneity. The corresponding result for women is 40 per cent.

The dynamic random effects model assumes that there may be no feedback from labour force participation to disability. This assumption may be unrealistic, so we now explore this aspect of the model in more detail.

Strict Exogeneity of Regressors:

The dynamic random effects probit model relies on the assumption of strict exogeneity of the explanatory variables (x_i) conditional on α_i:

$$P(y_{it} = 1 | x_i, y_{it-1}, ..., y_{i0}, \alpha_i) = P(y_{it} = 1 | x_{it}, y_{it-1}, \alpha_i) \quad . \qquad [8]$$

This means, that conditional on participation in the previous year and conditional on the unobserved individual effect, participation in the current year should not be related to any explanatory variable in past or future years. However, in our dynamic model, misspecification may arise from feedback effects from current labour force participation to future disability. We tested for exogeneity of the three limitation variables, by including future values of disability into the pooled probit model, (following Wooldridge [11]). If the current disability variables are strictly exogenous, we should find the future values to be insignificant. We found that severe and some limitations are significant, meaning that these two variables are subject to feedback effects in the model for men. In that case, we should not rely on the results of the dynamic random effects model, as the assumption of strict exogeneity has been violated. However, the pooled probit model provides consistent (yet inefficient) estimates and in that sense is more reliable than the random effects model. The pooled probit model only requires contemporaneous exogeneity, i.e. it only restricts the relationship between the disturbance and explanatory variables in the same time period. The pooled probit model does not rely on the strict exogeneity assumption, and so allows us to estimate a dynamic model of participation, providing consistent but inefficient estimates. It does not however, inform us of the existence, or direction of feedback effects, but this is our preferred model for men, as disability may be subject to feedback effects from labour force participation. The strict exogeneity assumption was only violated in the model for men, but for comparison purposes we continue to estimate the models for both men and women. Although this simple model cannot estimate the direction or magnitude of feedback effects, it still provides us with a more refined estimate of disability once we have controlled for past disability and participation.

Two different patterns emerge for men and women when we use the pooled estimator of the dynamic model. The results of the dynamic pooled probit model are presented in columns 3 and 6 of Table 4. Firstly, for men the effects of all variables are generally the same, compared to the random effects model, with the exception of lagged and initial participation. Previous participation has a higher effect, and initial participation has a lower effect. This could indicate that the random effects estimate of state dependence, may be biased due to a violation of the no-feedback assumption. For women, the effects of current disability are now higher compared to those in the random effects model. The effect of young children has increased slightly. The estimate on lagged disability has increased, and the effect of initial participation is now lower.

We note that although the random effects model for women may be preferable, we would still expect reasonably similar results from the pooled dynamic model. This is not the case, as the pooled model provides more negative estimates of disability. To explore this further, we again followed Wooldridge [11] and tested for the exogeneity exogeneity of two variables – age of youngest child and education. Third level education failed the strict exogeneity test, and it is possible that there is some interaction between disability and education for women. This will be explored in future work.

Average partial effects:

So far, we have presented the results as parameter estimates, but it is also interesting to present some of the results as percentage effects. So we now estimate some average partial effects, using the population-averaged parameters $\beta_a = \hat{\beta} / \sqrt{(1+\sigma_a^2)}$. This allows us to get partial effects, that are averaged over the population distribution of the unobserved effect and we can then compare these to the partial effects of the pooled model. The probability of participation is $N^{-1}\sum_{i=1}^{N} \Phi(\hat{\psi}_a + x_{it}\hat{\beta}_a + \bar{x}_i\hat{\xi}_a) = N^{-1}\sum_{i=1}^{N} \Phi[(\psi + x_{it}\beta + \bar{x}_i\xi).(1+\sigma_a^2)^{-1/2}]$ and for a discrete variable we evaluate this expression at different values for x_{it}, i.e. 0 and 1, and form the difference to obtain the average partial effect. The average partial effect for a continuous variable x_j is obtained by using the average across i of $\hat{\beta}_{aj}\phi(\hat{\psi}_a + x^0\hat{\beta}_a + \bar{x}_i\hat{\xi}_a)$.

Our main variables of interest are current and lagged disability, but the parameter estimates for lagged disability in the dynamic models are insignificant. For this reason, we only discuss the average partial effects calculated for current disability and lagged participation. In Table 5, columns 1 and 4, we see that the average partial effect of current disability is similar for men and women in the pooled static model. Once we introduce unobserved heterogeneity and state dependence into the model, this effect is much lower for men. In the pooled dynamic model, disabled men who are severely limited in daily activities are approximately 8 percentage points less likely to participate compared to those with no disability. Although this effect is quite small, we also see that men who did not participate in the previous year have a lower probability of current participation by 40 percentage points. The parameter estimates of lagged disability were insignificant in this model, suggesting that part of the non-participation in the previous period is due to the effect of previous disability.

The results for women are quite different, in that when we control for unobserved heterogeneity and state dependence, the effect of current disability is now slightly higher in the pooled dynamic model, compared to the pooled static model. However, the preferred dynamic model for women may be the random effects model, given that we did not reject strict exogeneity of the disability variables. Therefore, the results suggest that women who are currently severely limited have a lower probability of current participation by 25 percentage points. The effects of some and no limitations are much lower. Similar to the case of men, when we compared the static and dynamic models, we saw earlier that the effect of lagged disability is no longer significant. In Table 5, we show that the average partial effect of lagged participation is 13 percentage points - this is the magnitude of state dependence.

Within the context of similar research using data from other countries, the contribution of unobserved effects to the base disability effect is quite similar in this paper. Using data for the UK, Kidd, Sloane and Ferko [6] show that 50 per cent of the difference in participation rates between disabled and non-disabled men is due to unexplained effects. Likewise, Kreider [9] uses US data and finds that the estimate of disability for men is overestimated by 17.2%. Lindeboom and Kerkofs [10] use data from the Netherlands and show that the effect of bad health on the probability of receiving disability benefit is overestimated, but the effect on the probability of receiving unemployment benefit is underestimated. The co-efficients for the base models are –4.179 and -0.826, and for the corrected models are –2.261 and –2.131 respectively. Compared to all of these findings, our parameter estimates for currently disabled men with severe or some limitations, suggest that approximately 40-50% of the base effect is due to unobserved individual effects/state dependence. For women, we find that the original estimates of severe and some limitations are overestimated by about 5-10%.

In terms of policy, the results from this paper show that unobserved effects are an important factor in the participation decision for disabled people. In this paper, we cannot determine the nature of these unobserved characteristics, but further knowledge on these effects are necessary for integration of disabled people into the labour force. We find that past participation is also an important factor in the participation decision for disabled people, and the effect of past disability on past participation is relevant in this context. Therefore, the focus of disability policy should be on identifying these unobserved individual effects, in addition to early targeting of disabled individuals into employment. Additional information on how participation affects future disability will also prove useful, in that we may be able to establish how past occupational injuries from past participation affect current disability and participation, and people with these disabilities may re-join the labour force. The incentive effects of disability benefits may also play a role here and these factors will be investigated in future research.

V. Conclusions

People with disabilities face many barriers to full participation in the labour market, with serious implications for living standards and quality of life. This paper has analysed the factors associated with participation or non-participation in the labour market, using data on people reporting chronic illness or disability in a large-scale Irish representative survey. The results of the panel analysis presented in this paper, bring out the scale of the impact on labour force participation, of having an illness or disability that limits the individual severely in their daily life.

We controlled for state dependence and unobserved heterogeneity by estimating a dynamic model with correlated random effects. The results show that unobserved heterogeneity contributes substantially to the base effect of disability for men, and to some extent for women. In our preferred model, (pooled dynamic) disabled men with a current severe limitation are now only 9 percentage points less likely to participate compared to non-disabled men. However, the effect of past participation is quite high, at 40 percentage points. For women, our preferred model is the dynamic model with correlated random effects. Those with a severely limiting disability have a lower probability of participation by 26 percentage points, compared to women with no disability. The effects of some and no limitations are less substantial. The effect of past participation is lower in the model for women, reducing current participation by 13 percentage points. The interaction of disability, education and participation of women, should be explored further.

In this paper, we aimed to provide more accurate estimates of the effect of disability on participation. However, we acknowledge some limitations. In particular, if the reporting of disability in the survey is prone to measurement error, we cannot estimate the true effect of disability on participation. This may help to explain the substantial contribution of unobserved individual effects, but without extending the model to allow for measurement error in reporting behaviour, our results on the effect of disability on participation are not conclusive. Again, this will form part of future research where we will model labour force participation and disability, while controlling for reporting behaviour.

Footnotes:

a. Our specification includes a measure of unearned income but does not include a control for wages. Correctly accounting for the relationship between disability and wages is a topic for future research.

b. Another data source is a special module on disability included with the Quarterly National Household Survey (QNHS) in the second quarter of 2002, which focused on the extent and nature of restriction of activities for people with disabilities and their labour force status. Similar analyses of disability labour force participation in a cross sectional context, were carried out using QNHS data and we arrive at similar conclusions obtained from the Living in Ireland 2000 data.

c. In this paper, we are assuming that although there is attrition in the sample between 1995 and 2000, it does not bias the results of the effect of disability on participation. This is especially evident in the pooled model, where we follow Wooldridge [11] and test for the effect of attrition using inverse probability weights on the pooled model for the unbalanced sample. The probability of being in each wave is not influenced by disability, for both men and women. In the participation model for men there was no change in the overall co-efficients. For women, we find that there is a slight overestimation of the effect of severe disability, changing the co-efficient in the unbalanced sample from –0.3678 in the original pooled model to –0.4203 in the weighted pooled model. However, in this paper we assume overall that attrition is not a problem in biasing estimates of disability, and focus on the balanced sample throughout.

d. We could introduce a lag of two years for participation, and then include initial participation and previous participation as the two initial values. However, this increases data requirements and without a larger T, we cannot afford to be so flexible in the dynamics of the model. Furthermore, the transition matrix probabilities of participation in each year show that the rate of change from participation to non-participation or vice versa is the same for each pair of years. The correlation between participation and previous participation is 0.79, likewise the correlation between previous participation and lagged previous participation is 0.79.

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Table 1 Labour Force Status by level of restriction for those with Chronic Illness or Disability, age 15-64, Living in Ireland Survey 1995-2000

	Severe limitation	*Some limitation*	*No limitation*	*No chronic illness or disability*
Men				
Participation	34.92	58.02	81.45	91.59
Non-participation	65.08	41.98	18.55	8.41
N	189	655	318	6026
Women				
Participation	13.82	31.82	44.65	55.15
Non-participation	86.18	68.18	55.35	44.85
N	123	707	318	6522

Table 2 Variable definitions for Dependent and Independent Variables

Variable	Definition
LFP	=1 if participating in the labour market, =0 otherwise
Disabled with severe limitation	=1 if disabled and severely limited in daily activities, =0 otherwise
Disabled with some limitation	=1 if disabled and limited to some extent in daily activities, =0 otherwise
Disabled with no limitation	=1 if disabled and not limited in daily activities, =0 otherwise
	(Base category=No disability)
Age 15-24	=1 if aged 15-24 years, =0 otherwise
Age 25-34	=1 if aged 25-34 years, =0 otherwise
Age 35-44	=1 if aged 35-44 years, =0 otherwise
Age 45-54	=1 if aged 45-54 years, =0 otherwise
	(Base category=aged 55-64 years)
BMW	=1 if living in Border, Midlands, West region, =0 otherwise
	(Base category=Rest of Country)
Secondary Education	=1 if highest level of education completed is secondary, =0 otherwise
Third Level Education	=1 if highest level of education completed is third level, =0 otherwise
	(Base category=No qualifications or highest level of education completed is primary)
Married	=1 if married or living with a partner, =0 otherwise
Age Youngest Child<4	=1 if age of youngest child is less than 4, =0 otherwise
Age Youngest Child>=4 and <12	=1 if age of youngest child is greater than or equal to 4 and less than 12, =0 otherwise
Age Youngest Child>=12and <18	=1 if age of youngest child is greater than or equal to 12 and less than 18, =0 otherwise
	(Base category=No children)
Unearned Income	=Net Household Income – Net Individual Disposable Income
	(Net Individual Disposable Income includes net incomes from work, social welfare payments and child benefit. Net Household Income aggregates individual data to household level)

Note: The regional classifications are based on the NUTS (Nomenclature of Territorial Units) classification used by Eurostat.

Table 3 Summary Statistics for all Variables

Variable	Percentage of Sample in each Category	
	Men	*Women*
LFP	86.6	51.9
Disabled with severe limitation	2.6	1.6
Disabled with some limitation	9.1	9.2
Disabled with no limitation	4.4	4.1
No Disability	83.8	85.0
Age 15-24	12.3	10.1
Age 25-34	16.4	17.2
Age 35-44	26.2	27.1
Age 45-54	24.4	25.6
Age 55-64	20.7	20.0
BMW	24.7	21.9
Secondary Education	51.8	59.0
Third Level Education	16.7	13.3
No education or primary only	31.4	27.6
Married	68.7	73.3
Age Youngest Child<4	12.5	13.3
Age Youngest Child>=4 and <12	21.3	24.5
Age Youngest Child>=12and <18	15.2	17.7
Unearned Income	228.64	389.5
	(240.13)	(307.7)
N	7188	7670

Note: For unearned income we present the mean and standard deviation (in parentheses)

Table 4 Panel Model Results

	Men (co-efficients)			Women (co-efficients)		
	Pooled Static	Random effects dynamic (re-scaled)	Pooled Dynamic	Pooled	Random effects dynamic (re-scaled)	Pooled Dynamic
Lag LFP		0.7511**	1.687**		0.7494**	1.7974**
		(0.1194)	(0.0918)		(0.0835)	(0.0623)
Disabled with severe limitation	-1.2368**	-0.6639**	-0.5653**	-0.9173**	-0.8256**	-1.1359**
	(0.1314)	(0.2653)	(0.2218)	(0.1736)	(0.2827)	(0.2393)
Disabled with some limitation	-0.7886**	-0.5159**	-0.4757**	-0.3296**	-0.3137**	-0.4210**
	(0.0814)	(0.1594)	(0.1285)	(0.0755)	(0.1283)	(0.1106)
Disabled with no limitation	-0.2066**	-0.3464**	-0.3397**	-0.0175	-0.1811**	-0.2732**
	(0.1042)	(0.2161)	(0.1380)	(0.0928)	(0.1497)	(0.1326)
Lagged Disability						
Disabled with severe limitation	-1.0555**	-0.2534	-0.0765	-0.6203**	-0.1470	0.0102
	(0.1275)	(0.2593)	(0.2465)	(0.1626)	(0.2863)	(0.2643)
Disabled with some limitation	-0.5802**	0.0259	0.1796	-0.2742**	-0.0056	0.0514
	(0.0783)	(0.1592)	(0.1302)	(0.0714)	(0.1303)	(0.1177)
Disabled with no limitation	-0.0925	0.0887	0.1298	-0.0290	-0.0495	-0.0464
	(0.1175)	(0.2254)	(0.1461)	(0.0962)	(0.1566)	(0.1363)
Initial condition						
LFP in 1995		1.2059**	0.6399**		0.8984**	0.6315**
		(0.2096)	(0.0944)		(0.1353)	(0.0626)
Random effect (time averages)						
Disabled with severe limitation		-0.8815**	-0.9013**		-0.3077	-0.2653
		(0.5948)	(0.4588)		(0.7211)	(0.5607)
Disabled with some limitation		-0.7265**	-0.7146**		-0.1387	-0.1209
		(0.3237)	(0.2371)		(0.2744)	(0.2041)
Disabled with no limitation		0.3616	0.2146		0.4464*	0.5171*
		(0.5068)	(0.3297)		(0.3844)	(0.3087)
Constant	0.4642**	-0.8210**	-1.0449**	-0.5446**	-0.1118**	-1.5214**
	(0.1332)	(0.2167)	(0.1332)	(0.1074)	(0.1595)	(0.0945)
N	5930	5930	5930	6330	6330	6330
Pseudo R^2	0.2772		0.5371	0.1700		0.5303
Rho		0.4684**			0.3984**	

Note: $**p \leq 0.05, *p \leq 0.10$. *Note:* $**p \leq 0.05, *p \leq 0.10$ *(Significance in random effects models are based on t-stats on base co-efficients).*

Table 5 **Average Partial Effects**

	Pooled Static	Random effects dynamic (re-scaled)	Pooled Dynamic	Pooled	Random effects dynamic (re-scaled)	Pooled Dynamic
	Men			Women		
Disabled with severe limitation	-0.3346** (0.0504)	-0.1111**	-0.0865** (0.0471)	-0.3377** (0.0502)	-0.2557**	-0.3979** (0.0598)
Disabled with some limitation	-0.1680** (0.0238)	-0.0746**	-0.0654** (0.0230)	-0.1308** (0.0295)	-0.0787**	-0.1666** (0.0428)
Disabled with no limitation	-0.0330** (0.0187)	-0.0461**	-0.0438** (0.0221)	-0.0069 (0.0369)	-0.0435**	-0.1086** (0.0524)
Lag LFP		0.1292**	0.3927**		0.1296**	0.6286**

Note: $**p \leq 0.05, *p \leq 0.10$ *(Significance in random effects models are based on t-stats on base co-efficients).*

Appendix

Table A1: Panel model results - other explanatory variables

	Men (co-efficients)			Women (co-efficients)		
	Pooled Static	Random effects dynamic (re-scaled)	Pooled Dynamic	Pooled	Random effects dynamic (re-scaled)	Pooled Dynamic
Age 15-24	0.0881**	-0.8044*	-0.5994	0.9325**	-0.1242	0.0592
	(0.1631)	(0.6526)	(0.4252)	(0.1408)	(0.3934)	(0.3009)
25-34	0.9489**	-0.2594	-0.2330	1.2672**	-0.0685	-0.0317
	(0.1594)	(0.5269)	(0.3671)	(0.1118)	(0.3048)	(0.2232)
35-44	0.9263**	-0.2174	-0.2452	1.2020**	-0.0020	0.0226
	(0.1431)	(0.3834)	(0.2523)	(0.1078)	(0.2496)	(0.1789)
45-54	0.5843**	0.0922	0.0223	0.7312**	0.0905	0.0609
	(0.1066)	(0.2447)	(0.1685)	(0.0935)	(0.1784)	(0.1269)
Secondary	0.3396**	-0.0350	-0.0513	0.4454**	-0.0354	-0.0590
Education	(0.0941)	(0.1923)	(0.1365)	(0.0687)	(0.1422)	(0.0902)
Third level	0.4645**	0.6479**	0.5838**	1.2310**	0.2164*	0.2114
Education	(0.1275)	(0.2693)	(0.2174)	(0.1041)	(0.2059)	(0.1574)
Married	0.2918**	0.6706	0.5780	-0.3147**	-0.3427**	-0.3765**
	(0.1309)	(0.6458)	(0.4449)	(0.0894)	(0.2915)	(0.1842)
Age youngest	0.3949**	0.2806	0.2240	-0.6454**	-0.6096**	-0.7032**
child <4	(0.1913)	(0.4664)	(0.2715)	(0.1051)	(0.2177)	(0.1754)
>=4 and <12	0.1202	0.2101	0.0871	-0.3852**	-0.3356**	-0.3934**
	(0.1435)	(0.3776)	(0.2241)	(0.0917)	(0.1987)	(0.1563)
>=12 and <18	0.3626**	0.2887	0.1881	-0.1006	-0.2261**	-0.2767**
	(0.1177)	(0.2512)	(0.1491)	(0.0885)	(0.1566)	(0.1227)
Unearned	-0.0021	0.0077	-0.0043	-0.0228**	0.0026	-0.0031
Income/100	(0.0142)	(0.0274)	(0.0244)	(0.0092)	(0.0145)	(0.0106)
BMW	0.1935**	0.1534	0.1836*	-0.0942	-0.0253	-0.0200
	(0.0846)	(0.1787)	(0.1026)	(0.0664)	(0.1222)	(0.1067)
Random effect (time averages)						
Age 15-24		1.1475**	0.8998*		0.9388**	0.8116**
		(0.7107)	(0.4639)		(0.4491)	(0.3238)
25-34		0.8831**	0.8192**		0.7351**	0.7433**
		(0.5869)	(0.4005)		(0.3594)	(0.2513)
35-44		0.9544**	0.9506**		0.8458**	0.8774**
		(0.4605)	(0.2951)		(0.3078)	(0.2084)
45-54		0.3444	0.3871*		0.4373**	0.5064**
		(0.3034)	(0.2013)		(0.2386)	(0.1579)
Married		-0.6698	-0.5980		0.1869	0.1999
		(0.6708)	(0.4587)		(0.3168)	(0.2058)
Secondary		0.4802**	0.4405**		0.2498**	0.2794**
Education		(0.2467)	(0.1637)		(0.1731)	(0.1113)
Third level		-0.3652	-0.3497		0.3795**	0.4228**
Education		(0.3198)	(0.2347)		(0.2567)	(0.1877)
Age youngest		0.2600	0.2245		0.1913	0.2489
child <4		(0.5784)	(0.3555)		(0.2803)	(0.2116)
>=4 and		-0.1027	-0.0108		0.2234	0.2855
<12		(0.4472)	(0.2590)		(0.2405)	(0.1802)
>=12 and		0.1202	0.1151		0.2012	0.2574*
<18		(0.3339)	(0.2052)		(0.2158)	(0.1555)
Unearned		-0.0137	-0.0018		-0.0310**	-0.0248*
Income/100		(0.0393)	(0.0311)		(0.0225)	(0.0146)
BMW		0.1183	0.0743		-0.0233	-0.0291
		(0.2250)	(0.1343)		(0.1552)	(0.1166)

Note: $^{**}p \leq 0.05, ^{*}p \leq 0.10$ *(Significance in random effects models are based on t-stats on base co-efficients).*