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Dynamics of Work-Limitation and Work in Australia

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Abstract:
This paper examines the impact of self-reported work-limitation on the employment of the Australian working age population. Five consecutive waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey are used to investigate this relationship. A two-equation dynamic panel data model demonstrates that persistence and unobserved heterogeneity play an important role in the work-limitation reporting and its effect on work. Unobserved factors that jointly drive work-limitation and work are also shown to be crucial, especially for women.

Key Words: Work-limitations, dynamic panel probit, Maximum Simulated Likelihood

1. Introduction

This paper investigates the effect of work-limitations on employment in the presence of persistence, unobserved heterogeneity and joint determination of work and work-limitations. I focus on these issues for the Australian working age population using a comprehensive panel data source, the Household, Income and Labour Dynamics in Australia Survey (HILDA). The effect of disability on the probability of work is analysed using a model that allows state dependence and unobserved heterogeneity. To account for irregular patterns of work-limitation, a lag disability variable is included in the model. Finally, to control for the factors that shape unobserved heterogeneity in employment, as well as unobserved heterogeneity in disability reporting, I estimate the disability and employment equations jointly.

Employment restrictions are an important component of the employment decision of people with disabilities. Only 48% of disabled Australians with work-limitations participate in the labour force, compared with 72% of the disabled who do not have a work-limitation (Year Book Australia, 2006). The *ceteris paribus* effect of work-limitation, however, is difficult to measure. First, both employment and work-limitations are moving targets. Determinants of one's capacity to work are often not constant while conditions causing work-limitations also vary across time. Disabling conditions can improve or worsen, completely disappear or new onsets can create new limitations. Second, persistence in employment can mask or overemphasize the real impact of a work-limitation. For example, a disabled person's failure in the search for jobs may be due to previous search failures rather than to the disabling conditions themselves. Like disabilities, out-of-employment spells can erode acquired skills and suspend acquisition of new ones. Even if periods of unemployment do not cause human capital loss, lapses in recent employment history may give a 'bad signal' to employers. As a result, past employment status of a work-limited individual can directly affect her future employment. If this persistence is not controlled for, the impact of the current work-limitation can be exaggerated. Third, some permanent unobservable factors can influence the labour market outcomes and the prevalence of work-disability together. Therefore, the effect of work-disability, even after controlling for observed

characteristics and employment history, can still be different for different people. Finally, the work-limitation data may not be an objective measure of true health; it can be error ridden and endogenous.

Comprehensive panel data sources, which can be used to address above problems, have only recently emerged for Australia. Knight et al (2002) estimate a dynamic panel probit model for labour force participation for a sub-sample of the Australian Longitudinal Survey covering the period from 1985 to1988. In addition, studies using Australian data to explain disability and employment links are scarce. Exceptions are cross-sectional studies, such as Brazenor (2002), Wilkins (2004) and Cai & Kalb (2006) and panel data models as in Cai (2007). Until now, the time variant effect of disability has not been investigated for Australia in a dynamic framework.

This paper is organized as follows: section 2 discusses the work limiting disability measure, section 3 explains the data and reports summary statistics, section 4 introduces the econometric model, section 5 reports the results. Section 6 concludes.

2. Work-limiting disability

Many authors criticise self-assessed work-disability measures for various reasons. First, self-evaluated work-limitation is a subjective measure that may not be comparable across individuals. Kapteyn et al (2006b) use Dutch survey data to track how individuals assess the disability status of artificially created respondents with work related health problems. They show that the social norm towards perception of disability significantly affects the way individuals label themselves as work-disabled. Second, self-reported limitations may be endogenous to the employment status that one wants to analyse. Hence, the impact of disability on employment can be overemphasized. Third, poor health can be used as an excuse to rationalize an early exit from the labour force because of stigma towards unemployment in a society. For example, using estimates from a simultaneous equation model Kreider (1999) suggests that nonworkers substantially overreport limitations. Finally, depending on the purpose of the survey, one can obtain different rates of disability using identical samples. For

example, a work-limitation question in a health survey may produce different answers from a work-limitation question in an employment survey such as HILDA.

However, work-limitation measures have also their supporters. Burkhauser et al (2002) conclude that even though the subjective work-disability in an employment survey can seriously underestimate the exact size of the disabled population in a society, it can be successfully used to analyse the employment outcomes of people with work-limitations. Benitez-Silva et al (2004) compare disability benefit applicants' own reported disability with the Social Security Administration's final assessment. Overall, they conclude that people's own judgement of their disability is not significantly different from the Social Security Administration's evaluation of their disability. There is also a battery of empirical work suggesting that objective measures such as mortality, BMI or detailed health questions generally exhibit high correlation with the self-assessed measures (see Burkhauser et al (2002)). Additionally, studies that use detailed health information to instrument the subjective health variables find that the effect of health on employment is in fact underestimated when only subjective health is used (Bound 1991). Lastly, analysing the endogeneity of self reported disability, Stern (1989) found only weak evidence of endogeneity, moreover, when there is evidence of endogeneity the effect actually worked opposite to what the theoretical literature suggested. Similar results are reported using Australian data by Cai and Kalb (2006) and Cai (2007).

3. Data

The data used for this paper come from the first five waves of the Household, Income and Labour Dynamics in Australia (HILDA) Survey. Details of this survey are documented in Watson and Wooden (2002). In the first wave, 7,683 households representing 66 percent of all in-scope households were interviewed, generating a sample of 15,127 persons who were 15 years old or older and eligible for interviews, of whom 13,969 were successfully interviewed. Subsequent interviews for later waves were conducted one year apart. In addition to the data collected through personal interviews, each person completing a personal interview was also given a self-completion questionnaire to be returned upon completion by mail or handed back to the interviewer at a subsequent visit to the household. The HILDA attrition rates for waves

2, 3 and 4 were 13.2 percent, 9.6 percent and 8.4 percent respectively, which is not much higher than other longitudinal surveys. The proportion of Wave 4 respondents who were successfully interviewed in Wave 5 is 94.4%.

The HILDA survey contains detailed information on each individual's labour market activities and history. Socio-demographic characteristics of the respondents and information indicating health status also recorded. In each wave, respondents are asked the following question to assess if they have a long-term health condition:

"…do you have any long-term health condition, impairment or disability that restricts you in your everyday activities, and has lasted or is likely to last, for 6 months or more?"

While the preceding question is asked, specific examples of the "long-term health conditions" were shown on a card. These include, among many others, limited use of fingers or arms, or problems with eyesight that could not be corrected with glasses or contact lenses. Respondents who indicate that they have a long term condition are further asked if this condition is work limiting. The work-disability variable that is used in this paper is derived from following HILDA question:

"Does your condition limit the type of work or the amount of work you can do?"

This question is asked in each wave. In the self-completed questionnaire, the Short Form 36 health status questions (SF-36) are asked. This detailed information on individuals' general well-being is used to construct eight health indices. For example, Physical Functioning Index summarises respondents' answers to questions on physical limitations, such as walking up the stairs, lifting or carrying groceries. The index value ranges from 0 to 100, with 100 indicating perfect physical condition.[1]

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[1] See Ware et al., (2000) for the construction and interpretation of the index.

3.1 Sample Selection and Summary Statistics

The sample used contains men between 24 and 64 years of age and women between 24 and 60 years of age at the time of the interview. In order to isolate the effect of disability on employment, young people in full time study, older people who are eligible for Old Age Pension (age 65 for men and age 60 for women) and anyone with missing data points are excluded from the analysis. The final sample consists of a balanced sample of 2,200 male and 2,368 female respondents that were observed throughout five waves of HILDA.

Table 1 summarises demographic characteristics of the sample used in this paper. The results are in line with what is observed in different data sets. On average, people with work-limitations tend to be older, less educated and (not surprisingly) in worse physical condition than their counterparts who do not report a work-limitation. They also live outside of major cities more often, and a larger percentage of them are single. We also observe that most of the people with a work-disability have lower employment rates and lower annual (both personal and household) income.

Table 1: Mean of Demographic Characteristics, Disabled vs Non-Disabled

	MEN				WOMEN			
	Work Limited		Not Work Limited		Work Limited		Not Work Limited	
	Mean	S.E.	Mean	S.E.	Mean	S.E.	Mean	S.E.
Age	48.61	0.22	43.53	0.10	45.19	0.20	41.55	0.08
Education*								
B.A or higher	0.13	0.01	0.27	0.00	0.20	0.01	0.28	0.00
Other Post Sec.	0.43	0.01	0.41	0.01	0.26	0.01	0.24	0.00
High School	0.09	0.01	0.10	0.00	0.10	0.01	0.14	0.00
Not finished High School	0.35	0.01	0.22	0.00	0.43	0.01	0.33	0.00
Marital Status & Children*								
Married or De facto	0.70	0.01	0.80	0.00	0.63	0.01	0.78	0.00
Youngest kid 0-4 yrs old	0.11	0.01	0.19	0.00	0.08	0.01	0.21	0.00
Youngest kid 5-15 yrs old	0.21	0.01	0.32	0.00	0.26	0.01	0.42	0.00
Major city*	0.48	0.01	0.63	0.01	0.58	0.01	0.62	0.00
Australian Born*	0.75	0.01	0.77	0.00	0.78	0.01	0.77	0.00
Physical Functioning Index	62.36	0.63	91.67	0.14	62.47	0.59	90.54	0.14
Employed*	0.48	0.01	0.92	0.00	0.45	0.01	0.75	0.00
Household Income	55357	1210	83598	595	57889	1174	81524	589
Personal Income	33155	938	55343	456	23149	558	31027	253
Obs.	1795		9205		1661		10184	

Note: Above estimates are obtained from a pooled sample of 5 waves of HILDA
S.E. columns contain the standard errors of the estimates
Income measures are imputed gross annual income.
* indicates a dummy variable

In order to present the time variant nature of the variable of interest, Table 2 and Table 3 report the breakdown of the sample in terms of the patterns of work-limitations being reported. The first row of Table 2 represents individuals who never reported a work-limitation during the five waves of HILDA and the last row represents respondents who always report a work-limitation. The row labelled as 'Irregular' consists of people who reported no work-limitation after reporting a disability in the previous wave. Respondents who report a work-disability in two or more (but less than five) consecutive waves are labelled as "Consistent New Onset". According to Table 2, 71% of men and 73% of women sample never reports a work-disability whereas about 8% of men and 5.5% of women always do. People who report irregular patterns of work-

limitation is a substantial portion of the sample. About 18% of men and women exhibit an irregular pattern of limitation. Given that a big majority of individuals who ever report a work-disability do so irregularly, it is important to model the year-to-year changes in work-limitation status.

Table 2. Work-Disability Reporting Patterns (%)

Work-limitation Reported During 5 Years	**MEN**	**WOMEN**
Never	71.05	73.7
Consistent New Onset	3.23	2.83
Irregular	18.14	17.94
Always	7.59	5.53

I present a subset of demographic characteristics of these groups in Table 3. Generally there is no significant difference between the "Consistent New Onset" sample and the "Irregular" sample. However, these two groups are substantially dissimilar to respondents who regularly report either a disability or no disability. Their observed characteristics show that people in these groups ("Consistent New Onset" and "Irregular") demonstrate lower employment rates, lower education levels and lower income levels than people who never reported a work-limitation. People who always reported a work-limitation, on the other hand, were less educated, less frequently employed and lower income earners than individuals who belong to Irregular or Consistent New Onset groups.

Table 3. Demographic Characteristics by Work-Disability Reporting Patterns

	MEN							
			Consistent					
	Never		*New Onset*		*Irregular*		*Always*	
	Mean	S.E	Mean	S.E	Mean	S.E.	Mean	S.E
Age	43.15	0.11	46.21	0.54	46.30	0.21	50.28	0.31
B.A or higher*	0.29	0.01	0.17	0.02	0.19	0.01	0.07	0.01
Not Completed High School*	0.20	0.00	0.38	0.03	0.29	0.01	0.40	0.02
Married or De facto*	0.81	0.00	0.74	0.02	0.76	0.01	0.65	0.02
Physical Functioning Index	92.66	0.15	84.45	0.92	80.06	0.45	50.21	0.89
Employed*	0.93	0.00	0.77	0.02	0.77	0.01	0.27	0.02
Household Income	85941	646	68000	3389	68495	1243	42598	1274
Personal Income	57087	494	46511	2954	43909	966	22396	748
	WOMEN							
			Consistent					
	Never		*New Onset*		*Irregular*		*Always*	
	Mean	S.E	Mean	S.E	Mean	S.E.	Mean	S.E.
Age	41.19	0.09	43.09	0.47	44.19	0.18	46.22	0.30
B.A or higher*	0.30	0.00	0.24	0.02	0.21	0.01	0.19	0.02
Not Completed High School*	0.32	0.00	0.33	0.03	0.40	0.01	0.49	0.02
Married or De facto*	0.79	0.00	0.75	0.02	0.70	0.01	0.54	0.02
Physical Functioning Index	91.94	0.14	79.95	0.97	76.33	0.44	52.20	0.98
Employed*	0.77	0.00	0.69	0.03	0.58	0.01	0.32	0.02
Household Income	83199	628	75434	3863	68239	1206	45485	1606
Personal Income	31988	278	27139	1205	24751	502	20583	784

Note: * indicates a dummy variable.

Table 4 illustrates the association between work-limitation and work patterns. The first column of Table 4 consists of individuals who never worked during the period analysed. Respondents who were in and out of employment irregularly are summarized in the second column. Individuals who exited the workforce permanently (at least during the 5 waves of HILDA) are labelled as "Consistent Exit" in the third column. The last column of Table 4 shows individuals who were not employed during the entire sample window.

Table 4.Association between Work-Limitation and Work Patterns (%)

	MEN			
	Work Pattern			
	Never	*Irregular*	*Consistent Exit*	*Always*
Limitation Pattern				
Never	2.5	9.15	3.26	85.09
Irregular	11.75	15.56	6.35	66.35
Consistent, New Onset	10.32	32.26	3.23	54.19
Always	55.09	24.55	7.19	13.17
Total	8.36	12.86	4	74.77
	WOMEN			
	Work Pattern			
	Never	*Irregular*	*Consistent Exit*	*Always*
Limitation Pattern				
Never	10.94	19.53	9.91	59.62
Irregular	24.78	23.58	9.85	41.79
Consistent, New Onset	25.48	28.66	5.73	40.13
Always	48.85	23.66	6.11	21.37
Total	15.96	20.94	9.41	53.69

According to Table 4, 74% of men were employed during all five waves, compared to 53% of women. Women are more likely to exhibit irregular employment patterns than men and more likely to be out of employment during all of five waves. Table 4 emphasizes the dynamic relationship between employment patterns and patterns that work-limitations are reported. Among men who never reported a work-limitation, 85% were always workers. However, only 13% of men that always reported a work-limitation were working during the entire 5 year period. The econometric models of the next sections shall control for this dynamic relationship between work and work-limitations.

4. The Model and the Estimation Strategy

This section presents the econometric model and the estimation methods used in this paper. Section 4.1 introduces a single-equation dynamic model of employment where persistence in the work status and the unobserved heterogeneity are controlled for. The model also addresses the year-to-year changes in work-disability status by adding current and lagged work-disability variables. I present the augmented two-equation model in section 4.2. In this framework, the employment equation is estimated jointly with a model that captures the probability of reporting a work-disability. The model that is utilized here is largely influenced by Kapteyn et. al (2006a), who examine the role of pain and disability in the employment of older people in the US.

4.1. Single-Equation Model:

For an individual *i* at period *t*, the model determining the probability of currently working can be summarised as follows:

$$y_{it} = \gamma y_{i,t-1} + X'_{it}\beta_1 + \delta_1 D_{it} + \delta_2 D_{i,t-1} + \alpha_i + \varepsilon_{it} \qquad (1)$$

Where y_{it} is a dummy variable capturing the employment status, X_{it} is a kx1 vector of individual characteristic and D_{it} is the disability status. Here, I allow a direct effect of past disability status on current employment by adding a lagged disability term (D_{it-1}). In model (1), the unobserved heterogeneity α_i is assumed to be distributed normally with mean zero and variance σ_α^2. The random disturbance term ε_{it} is normally distributed with mean zero and variance σ_ε^2.

In the absence of the lagged dependent variable (y_{it-1}) and conditional on the distributional assumption of α_i, the estimation of the above model is straightforward using quadrature techniques (Butler & Moffit (1982)). However the presence of "state dependence" introduces what is called an initial conditions problem due to our lack of knowledge of the data generating process governing the first observation, y_{i1}. Treating y_{i1} as an exogenous variable is possible; however this requires the assumption that the first labour market choice observed by the researcher is in fact the first observation of the data generating process. This assumption is clearly too restrictive for the data source

at hand. Since we start to observe respondents in HILDA after a considerable amount of employment transitions have already passed (except for very young people), the estimation of the model (1) requires more sophisticated techniques.

In this paper the approach by Heckman (1981) is used to address the initial condition problem. In this approach, the initial conditions are approximated by a linear reduced form equation;

$$y^*_{i1} = x'_{i1}\pi + \theta\alpha_i + \varepsilon_{i1} \tag{2}$$

Where x_{i1} contains information from the first period and ε_{i1} is the standard normally distributed error term. Under the assumption of normality the probability of work in the first wave can be written as

$$\Phi\left[\left(x'_{i1}\pi + \theta\alpha_i\right)\right] \tag{2.1}$$

Where Φ is the normal cumulative density function (CDF). Heckman (1981) suggests that a cross sectional probit model capturing (2.1) and a dynamic equation for periods t>2 can be jointly estimated by Full Information Maximum Likelihood (FIML) to produce consistent estimates. An individual's contribution to the likelihood function can be determined by:

$$\begin{aligned} L_i = \int_{-\infty}^{\infty} & \Phi\left[\left(x'_{i1}\pi + \theta\alpha_i\right)(2y_{i1} - 1)\right] \\ & \times\left\{\prod_{t=2}^{T}\Phi\left[\left(\gamma y_{it-1} + x'_{it}\beta + \delta_1 D_{it} + \delta_2 D_{i,t-1} + \alpha_i\right)(2y_{it} - 1)\right]\right\} dF(\alpha_i) \end{aligned} \tag{3}$$

Where F(.) is the distribution function of α_i. The above model contains only a one-dimensional integral and therefore can be computed using existing quadrature techniques (Butler and Moffitt (1992)) A serially correlated error structure is possible but requires the evaluation of multiple integrals and therefore infeasible to estimate using quadrature methods.

4.2. Two-Equation Model:

The model of the previous section does not take into account unobserved individual characteristics that can simultaneously drive employment and reporting of work-limitations. Unobserved individual characteristics that make an individual more likely to be unemployed may also make them more likely to report a disability. If a significant correlation exists between unobserved components of these two outcomes, the work-limitation in the employment becomes endogenous. Given the concerns about the subjective nature of the work-limitation data, I shall model the endogeneity of work-disability in a two-equation setup. In this alternative model, the work equation in (1) is estimated jointly with the following work-disability reporting equation.

$$D_{it} = \gamma_1 D_{i,t-1} + X'_{it}\beta_2 + \eta_i + \nu_{it} \tag{4}$$

Where D_{it} is the work-limitation status for the individual i at time t. X_{it} are the usual demographic characteristics..

Models (1) and (4) are assumed to be linked through unobserved heterogeneity captured by α_i and η_i. (α_i, η_i) is distributed bivariate normal with means 0 and covariance matrix Σ.

$$\Sigma = \begin{bmatrix} \sigma^2_{\alpha} & \sigma_{\alpha}\sigma_{\eta}\rho \\ \sigma_{\alpha}\sigma_{\eta}\rho & \sigma^2_{\eta} \end{bmatrix} \tag{5}$$

The initial conditions:

For both the employment and work-disability equations, the initial conditions are modelled as in Heckman (1981). Models for the initial level of work and the initial level of disability include the same set of variables as their dynamic counterparts (1) and (4), excluding the lagged variables. The random effects in these equations satisfy the same distributional assumptions as (α_i, η_i). To freely correlate unobserved heterogeneity in the dynamic and initial equations, an arbitrary linear combination of (α_i, η_i) is included in the equations for wave 1. The initial work equation can be written as follows:

$$y_{i1} = +X'_{i1}\pi_1 + \delta_0 D_{i1} + \theta_1\alpha_i + \theta_2\eta_i + \varepsilon_{i1} \tag{6}$$

Similarly, the initial disability is captured by

$$D_{i1} = X'_{i1}\pi_2 + \theta_3\alpha_i + \theta_4\eta_i + \nu_{i1} \tag{7}$$

The error terms ε_{i1} and ν_{i1} are assumed to be uncorrelated with each other and anything else in the model. No restriction is imposed on the relationship between the parameters of the initial level equations and the parameters of the main equations.

The likelihood contribution for a given individual can be written as the expected value of the log likelihood contribution conditional on the random effects.

$$\begin{aligned} L_i = &\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \Phi\left[\left(x'_{i1}\pi + \delta_0 D_{i1} + \theta_1\alpha_i + \theta_2\eta_i\right)(2y_{i1}-1)\right] \\ &\times\Phi\left[\left(x'_{i1}\pi_2 + \theta_3\alpha_i + \theta_4\eta_i\right)(2D_{i1}-1)\right]\times\left\{\prod_{t=2}^{T}\Phi\left[\left(\gamma y_{it-1} + x'_{it}\beta_1 + \alpha_i\right)(2y_{it}-1)\right]\right\} \\ &\times\left\{\prod_{t=2}^{T}\Phi\left[\left(\gamma D_{it-1} + x'_{it}\beta_2 + \eta_i\right)(2y_{it}-1)\right]\right\} d\alpha\, d\eta \end{aligned} \tag{8}$$

Given the nature of the problem, the quadrature techniques to estimate the model are feasible but difficult. Instead, I use Maximum Simulated Likelihood estimation with 20 Halton draws[2].

The estimation process can be summarised as follows:

1) Generate 2R*N Halton draws (α^H, η^H), where R is the number of draws and N is the number of individuals. These draws remain fixed during estimation.

[2] It has been argued that Halton draws provide better coverage than pseudo-random numbers and therefore computationally they are up to 10 times more efficient than pseudo-random numbers. See Train (2003) for a detailed discussion. The results are not significantly different when 50 draws were used.

2) Transform the draws to standard normal by $\Phi^{-1}(\alpha^H, \eta^H) = (\alpha, \eta)$, where Φ^{-1} is the inverse of the Gaussian normal CDF. This provides 2R independent draws for each individual.

3) Convert (α, η) to a bivariate normal distribution by using a Choleski decomposition of Σ .

4) Insert (α^r, η^r) into the likelihood function (8) and average the results to obtain the simulated likelihood function.

5) Estimate the parameters of (1), (4), (6), (7) and the elements of Σ via maximum likelihood[3].

5. Results

Given that the focus of this paper is to control for the persistence and permanent unobserved factors that affect work and work-limitation simultaneously, I mainly focus on the results from the two-equation model. The estimates from the single equation model are presented in Table 8 and are briefly discussed at the end of this section.

The models' explanatory variables are a set of dummy variables indicating the work-limitation (both current and past), lagged employment status, level of education, marital and dependent children status, country of birth and location of residence. Additionally, the model is quadratic in age and includes a physical conditioning index. Table 5 presents a brief definition of the variables.

[3] The optimization is carried using GAUSS CML library and BFGS algorithm with user supplied numerical gradient. Variance of the time variant error terms are normalized to one.

Table 5: Variable Definitions

Variable	**Definition.**
CONST	*Constant*
WORK	*=1 if Currently employed*
DISAB	*=1 if Have a work-limitation*
LWORK	*Lagged work*
LDISAB	*Lagged work-limitation status*
BACHEP	*=1 if highest completed degree is B.A. or higher*
MARR	*=1 if Married or in a de facto relationship.*
CITY	*=1 if Lives in a major city*
AUST	*=1 if Australian born*
AGE	*(Current age -25)/10*
AGE2	*AGE squared*
KID04	*Youngest child is btw 0-4 yrs old*
KID514	*Youngest child is btw 5-14 yrs old*
PHIND	*SF-36 Physical functioning index /10*

Table 6 presents the results from dynamic two-equation model. I report estimated coefficients from the dynamic work equation in segment A of Table 6. Most of the control variables have the expected sign. For men, residing in a major city, having been born in Australia or having young children does not significantly contribute to working decisions. For women, the presence of young children decreases the likelihood of employment. As expected, education and being in better physical condition increase the likelihood of working for both sexes. Marriage affects men and women differently. Married men are more likely to be working, and this is exactly opposite for women.

For both men and women the lagged work variable is highly significant. People who are currently employed are very likely to be working in the next period. After controlling for the persistence in the work decisions, the work-limitation in the current period still significantly influences the probability of working, although this effect is smaller for women. The lagged disability is not significant in either of the samples. This does not mean that lagged disability has no effect on employment; the effect of past disability is indirect and works through the lagged work variable. Overall, the men's employment decision exhibits higher persistence than the women's. Self-reported work-limitation also has a larger effect on men's employment than on women's.

The results from the dynamic disability equation are presented in segment B. The results show that disability reporting is highly persistent for both samples. Reporting a work-limitation in a given period substantially increases the probability of a work-limitation being reported in the next period. This persistence is higher for women. Older men are more likely to report a work-disability, whereas being from a major city, marriage and education are associated with a lower probability of reporting a work-disability. Education does not play a significant role in work-disability reporting for women. On the other hand, having young children and being married significantly reduce the likelihood of a limitation being reported. For both men and women, poorer physical condition is associated with higher rates of work-limitation reporting.

Segment C of Table 6 presents the estimated parameters of the Σ matrix. Men and women differ in terms of the role that unobserved heterogeneity plays. After controlling for a lag effect of both work and disability, the unobserved effects do not significantly contribute to the employment decision for men. However, the random effects play an important role in the reporting of work-limitations. The implied standard deviation of the random effect is significant and explains about 48% of the unsystematic variation in disability reporting. The correlation between the two random effects has the expected sign but it is very small and statistically insignificant. For women unobserved heterogeneity has a substantial impact on the probability of employment. 49% of the variation due to unobserved factors in the work decision is captured by the random effects. The unobserved heterogeneity plays an important role in the prevalence of work-limitation reporting as well. The unsystematic variation that is explained by the unobserved heterogeneity is 28%. I found a strong and significant correlation between unobserved effects of work and disability equations. This suggest that constant personal unobserved characteristics that make women work less also increase their likelihood of reporting work-limitations. This makes disability endogenous in the work equation for women, a fact that is taken into account in my estimations.

Table 6. FIML Estimates of Dynamic Work and Disability Equation

A.	Work Equation, Waves 2-5					
	MEN			WOMEN		
	Parameters.	*S.E*	*Par/S.E*	*Parameters.*	*S.E*	*Par/S.E*
CONST	-1.2838	0.1994	-6.438	-1.5794	0.2043	-7.731
LWORK	2.1529	0.0467	46.124	1.2882	0.0646	19.932
DISAB	-0.7183	0.0745	-9.645	-0.2404	0.0823	-2.922
LDISAB	0.0021	0.0749	0.028	-0.1302	0.0818	-1.591
AGE	0.52	0.1216	4.275	0.9634	0.166	5.804
AGE2	-0.1789	0.0288	-6.209	-0.2958	0.0445	-6.654
AUS	0.065	0.0624	1.043	0.2279	0.0661	3.449
CITY	0.0569	0.0541	1.052	-0.041	0.0535	-0.766
MARR	0.3344	0.0669	5.001	-0.0285	0.0592	-0.482
K04	0.0031	0.0881	0.035	-0.7738	0.0719	-10.765
K514	-0.0289	0.0768	-0.376	-0.2662	0.0583	-4.569
BACHP	0.1473	0.0681	2.162	0.7173	0.0749	9.577
PINDX	0.0595	0.0143	4.15	0.1215	0.0145	8.396
B.	Disability Equation, Waves 2-5					
	Parameters.	*S.E*	*Par/S.E*	*Parameters.*	*S.E*	*Par/S.E*
CONST	0.8778	0.2199	3.992	0.6717	0.1652	4.067
LDISAB	0.9669	0.0715	13.524	1.4555	0.0505	28.834
AGE	0.4174	0.1697	2.46	0.2098	0.1399	1.5
AGE2	-0.048	0.0394	-1.219	-0.0392	0.0368	-1.068
AUS	0.0052	0.0826	0.062	0.1133	0.0569	1.989
CITY	-0.1939	0.0696	-2.785	0.0429	0.0504	0.851
MARR	-0.1935	0.0843	-2.294	-0.1727	0.0536	-3.223
K04	-0.1123	0.0978	-1.149	-0.2208	0.0827	-2.671
K514	-0.0925	0.0797	-1.161	-0.1225	0.0569	-2.152
BACHP	-0.2795	0.088	-3.176	-0.0556	0.0566	-0.982
PINDX	-0.3391	0.0163	-20.824	-0.2866	0.0117	-24.458
C.	***Auxiliary Parameters***					
σ_α	0.0292	0.0286	1.0218	0.9660	0.0809	11.9474
σ_η	0.9112	0.0815	11.1857	0.3934	0.0572	6.8776
ρ	-0.0238	0.0378	-0.6246	-0.5226	0.0821	-6.3695
Mean Log-Likelihood		-0.4584		-0.591277		
Number of Individuals		2200		2369		

Table 7 contains the results from the initial level equations. Here I only discuss the coefficients of the random effects that are presented in segment C. The coefficients of random effects in the initial equations are generally significant. Likelihood ratio tests reject the joint insignificance of the individual heterogeneity for both of these models. This indicates that the initial conditions are in fact endogenous. One important result is that the unobserved effect of disability has a significant effect on the initial work equation for men. That is, even though the correlation between unobserved characteristics across equations are not significant for men, the unobserved characteristics that drive disability prevalence make a significant contribution to the employment decision by affecting probability to work initially.

Table 7. FIML Results from Initial Level Equations

Initial Work Equation Wave=1						
A.	MEN			WOMEN		
	Parameters.	*S.E*	*Par/S.E*	*Parameter.*	*S.E*	*Par/S.E*
CONST	0.0205	0.2913	0.07	-0.4145	0.3399	-1.22
DISAB	-0.6511	0.1694	-3.843	-0.5451	0.2182	-2.498
AGE	0.062	0.1809	0.343	0.6231	0.2571	2.423
AGE2	-0.0958	0.0461	-2.079	-0.2436	0.0808	-3.014
AUS	0.1459	0.0977	1.494	0.3673	0.1238	2.967
CITY	0.1934	0.0896	2.16	-0.0013	0.1039	-0.013
MARR	0.5782	0.0964	6	0.1758	0.1213	1.449
K04	0.0053	0.1372	0.039	-1.5022	0.1499	-10.023
K514	0.1291	0.112	1.152	-0.397	0.1102	-3.603
BACHP	0.4101	0.1174	3.494	0.9961	0.1346	7.401
PINDX	0.1003	0.0235	4.272	0.1252	0.0297	4.219
Initial Disability Equation Wave=1						
B.	MEN			WOMEN		
	Parameters.	*S.E*	*Par/S.E*	*Parameters*	*S.E*	*Par/S.E*
CONST	1.1096	0.3574	3.104	1.3759	0.2613	5.266
AGE	0.6122	0.3051	2.007	0.5513	0.2438	2.261
AGE2	-0.0687	0.0786	-0.875	-0.144	0.076	-1.895
AUS	0.0291	0.1568	0.186	0.227	0.114	1.991
CITY	-0.488	0.1354	-3.604	-0.0597	0.0986	-0.605
MARR	-0.3695	0.1579	-2.341	-0.3613	0.1085	-3.329
K04	0.5396	0.1752	3.08	-0.1432	0.1446	-0.99
K514	-0.3655	0.1616	-2.262	-0.2393	0.1079	-2.217
BACHP	-0.5897	0.1829	-3.224	-0.0798	0.1192	-0.67
PINDX	-0.3814	0.0342	-11.147	-0.3634	0.0258	-14.067
C.	***Auxiliary Parameters***					
θ_1	-0.0456	0.0469	-0.974	1.5514	0.135	11.496
θ_2	-0.334	0.0998	-3.347	0.1436	0.1229	1.168
θ_3	0.0691	0.0679	1.017	-0.302	0.0728	-4.15
θ_4	1.3646	0.1725	7.91	0.6255	0.1292	4.841

I have also estimated a single equation dynamic model of work that is described in section 4.1. In this set up, unobserved factors that can influence both disability reporting and probability of work are ignored. The results are presented in Table 8. A major difference is the fact that the estimated coefficient of disability is larger, especially for women where we observed a significant correlation of random effects in the two-equation models. Additionally, unlike the complete model, the single equation produces a significant lag effect for disability which is absorbed by unobserved factors. This is an analogy of true versus spurious persistence where the omission of individual heterogeneity inflates the impact of the variable of interest.

Table 8. FIML Estimates from Single Equation Work Model, Wave 2-5

	MEN			WOMEN		
	Parameters.	*S.E*	*Par/S.E*	*Parameters.*	*S.E*	*Par/S.E*
CONST	-0.7543	0.2540	-2.9700	-1.4511	0.2075	-6.9900
LWORK	1.3660	0.1122	12.1700	1.1822	0.0710	16.6600
DISAB	-0.9407	0.0962	-9.7700	-0.4516	0.0816	-5.5400
LDISAB	-0.3016	0.0996	-3.0300	-0.3690	0.0832	-4.4300
AGE	0.0877	0.0178	4.9200	0.1080	0.0167	6.4800
AGE2	-0.0030	0.0005	-6.6700	-0.0032	0.0005	-6.9900
AUS	0.1045	0.0846	1.2400	0.3219	0.0783	4.1100
CITY	0.1031	0.0724	1.4200	-0.0290	0.0614	-0.4700
MARR	0.5816	0.0910	6.3900	-0.0629	0.0667	-0.9400
K04	0.0315	0.1127	0.2800	-0.8699	0.0788	-11.0400
K514	-0.0402	0.0903	-0.4400	-0.2918	0.0635	-4.6000
BACHP	0.3156	0.0990	3.1900	0.8075	0.0872	9.2600
PINDX	0.0866	0.0172	5.0400	0.1151	0.0151	7.6100
λ	0.4287	0.0644	6.6600	0.5181	0.0380	13.6200
θ	1.5433	0.2811	5.4900	1.4169	0.1694	8.3600
Log-likelihood	-2283.5727			-4197.5099		

Note: Dependent variable is probability to work.

λ represents equi-correlation between time variant disturbance ε_{it} in any two different time periods.

The results from initial level equations are available from the author upon request

Table 9 presents the Average Partial Effects (APE) for the variables of interest in the work equations. The estimates are readily interpretable as marginal effects. The effects are evaluated at individuals' wave 5 values[4]. Results re-emphasise discrepancies across gender and different model specifications. For men, the two-equation model suggests that being employed in one period increases the probability of work by 56% in the next period, whereas reporting a work-limitation reduces the likelihood of work by 9%. Single-equation values for these estimates are 23% and 11%, respectively. In other words, the effect of the work-limitation in the single equation is absorbed by the lag work variable in the two-equation model. For women, the average partial effect of persistence is very similar across models. However, work-limitation has a lower effect once the endogeneity of the work-limitation is controlled for in the two-equation setup. This suggests that, for women, the effect of a work-limitation is greatly absorbed by the unobservables that impact work and work-limitation simultaneously.

Table 9. Average Partial Effects

	MEN	
	Two-Equation Model	Single -Equation Model
LWORK	0.5638*	0.2371*
DISAB	-0.0991*	-0.1309*
LDISAB	0.0002	-0.0329*
	WOMEN	
	Two-Equation Model	Single -Equation Model
LWORK	0.3549*	0.3621*
DISAB	-0.0514*	-0.1181*
LDISAB	-0.0271	-0.0951*

Note: Above estimates are evaluated at Wave 5 values.

* indicates significance at 1%

[4] There was no significant difference when any other wave or individual means across waves were used. See Wooldridge (2002) for a detailed discussion of APE.

6. Conclusion

In this paper, I introduce a two-equation dynamic panel data model to analyse the effect of work-limiting disabilities on individuals' probability to work. The model controls for time invariant unobserved factors that influence disability prevalence and employment jointly. The persistence of employment and work-disability equations and endogeneity of initial conditions are also accounted for. It is shown that persistence plays a crucial role in the determination of employment and reporting of a work-disability. People who report work-limitations in one period are very likely to report work limiting disabilities in the next period. Similarly, current employment status is a driving factor of future employment. People employed in the current period, are much more likely to be employed in the next period, than people who are unemployed in the current period. However, in this paper, I show that the effect of self-reported work-disability, net of persistence of employment and unobserved heterogeneity, is still highly significant. A current report of work-limitation is strongly associated with being out of work. Given the dynamic nature of disability, a lag effect of work-limitation is then investigated. The two-equation model shows no significant impact of past limitations on current employment. This does not mean that past limitation has no effect on employment, but that this effect is indirect and works via lagged employment status. Simply put, while being disabled in the current period decreases the probability of being employed in that period, past periods of disability do not directly affect current employment status. However, being unemployed in past periods does decrease the probability of being employed in the current period, and so since having been disabled in the past also means a higher likelihood of having been unemployed in the past due to that disability, disability in the past has an indirect effect on current employment status.

For women, both work-disability and employment have a significant unobserved component, which are correlated with each other and captured by the model. For men the unobserved factors play a significant role only for the disability equation and the correlation between two individual effects were insignificant. Additionally, a single equation dynamic model demonstrates that ignoring correlation between unobserved heterogeneity across equations can overestimate the impact of past and current limitations on employment.

The results of this analysis have shown both a direct and indirect negative effect of self-reported work-disability on employment: being work-limited in the current period makes an individual less likely to be employed, and being unemployed makes an individual less likely to be employed in the future. Since the effect of past unemployment status is a much more important driver of current employment status than work-disability, an important implication of these results is that, regardless of how individuals became unemployed, it is difficult for them to get back into the labour force. Policies that aim at keeping disabled individuals in the work force one way or another, might address some of these problems.

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