Some Applications of Panel Data in Health Economics

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**Goal:** Study the effect of age and labour market status on changes in health

**Model:**

\[ h_{it} = \alpha_0 + \alpha_1 L_{it} + \alpha_2 S_{it} + \beta' x_{it} + \gamma_i + \varepsilon_{it} \]

- \( h_{it} \) = health status (a score)
- \( L_{it} \) = labour market status (= 1 if individual works)
- \( S_{it} \) = health shock (= 1 if a disease, accident ... in \((t-1, t))\)
- \( x_{it} \) = characteristics (age, education, marital status, ...)

**Data:** Dutch CERRA panel dataset, two waves: 1993, 1995
4727 individuals in 1993, about 70% responding in 1995
Table 1. First stage estimates: linear regression of change of HSCL score

<table>
<thead>
<tr>
<th>Variable</th>
<th>HSCl on 7-point scale</th>
<th>Total HSCl score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Estimate</td>
<td>t-value(^a)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.6245</td>
<td>2.27 (2.35)</td>
</tr>
<tr>
<td>Age in 1993(^b)</td>
<td>0.0146</td>
<td>2.83 (2.89)</td>
</tr>
<tr>
<td>Dummy female</td>
<td>-0.1052</td>
<td>1.48 (1.46)</td>
</tr>
<tr>
<td>First differences of:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dummy partner</td>
<td>-0.2907</td>
<td>1.52 (1.43)</td>
</tr>
<tr>
<td>Dummy work</td>
<td>0.2543</td>
<td>1.87 (1.77)</td>
</tr>
<tr>
<td>Dummy disabled 1st</td>
<td>0.2205</td>
<td>1.35 (1.00)</td>
</tr>
<tr>
<td>Dummy early retired</td>
<td>0.0840</td>
<td>0.79 (0.79)</td>
</tr>
<tr>
<td>Dummy self employed</td>
<td>0.4692</td>
<td>1.79 (1.77)</td>
</tr>
<tr>
<td>Dummy work (-2 yrs)</td>
<td>0.0987</td>
<td>0.60 (0.60)</td>
</tr>
<tr>
<td>Dummy disabled (-2)</td>
<td>0.3841</td>
<td>1.75 (1.55)</td>
</tr>
<tr>
<td>Dummy early ret (-2)</td>
<td>0.3396</td>
<td>2.20 (2.38)</td>
</tr>
<tr>
<td>Dummy self empl (-2)</td>
<td>-0.2587</td>
<td>0.75 (0.62)</td>
</tr>
<tr>
<td>Months worked in last:</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 years</td>
<td>0.0062</td>
<td>0.91 (0.86)</td>
</tr>
<tr>
<td>5 years</td>
<td>-0.0101</td>
<td>2.01 (1.97)</td>
</tr>
<tr>
<td>10 years</td>
<td>0.0101</td>
<td>2.72 (2.49)</td>
</tr>
<tr>
<td>Negative health shock</td>
<td>0.4040</td>
<td>3.49 (2.97)</td>
</tr>
<tr>
<td>Positive health shock</td>
<td>-0.3342</td>
<td>1.28 (1.43)</td>
</tr>
<tr>
<td>R(^2) Square</td>
<td>0.0231</td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>3.5595</td>
<td></td>
</tr>
</tbody>
</table>

\(^a\) Absolute t-values and White heteroscedasticity corrected t-values in parentheses.

\(^b\) Age in 1993 in the difference equation can be related to the effect of age squared in the health level equation.

Other work history variables (the lagged status variables and the number of months worked in the past two years and past 5 years). The F-statistics for the test of joint significance of the set of labour market variables (11 degrees of freedom) are 3.062 and 2.916 for the untransformed and the transformed HSCL score, respectively. The hypothesis that the 11 labour market variables do not matter is strongly rejected (the p-values are 0.00044 and 0.00079, respectively).

To illustrate the joint effect of the labour market variables, we will present some calculations for different types of working careers below. From a comparison of the results of Tables A3 and 1 it can be deduced that it may be hazardous to ignore the simultaneity between health and labour market status and labour market history variables. Using panel data rather than a cross section one can take account of that type of endogeneity and also distinguish cohort effects from pure age effects.

Two health shocks variables are included in Table 1 to assess the relative importance of positive and negative health shocks in explaining health changes. From Table 1 it is difficult to assess the relative importance of these effects directly. We therefore confronted the effect of a negative health shock in the equation for the untransformed HSCL score with a change in health due to a pure aging effect. The results on the age variables imply that 2 years of aging for a 55 year old male are equivalent to a deterioration of health of 1.22 on the HSCL score. The coefficient for the negative health shock implies that a negative shock for a 55 year old male is equivalent to the effect of 5.27 years of aging on health. A negative health shock causes large changes in health.

The model discussed in the previous section allows for direct effects of age and labour market variables on health. It is conceivable that these key variables may also indirectly influence health levels through their effect on $S_t$; the occurrence of a health shock. In that case the total effect of labour market variables on health outcomes consists of a effect through $S_t$ and a direct effect...

present in the second wave held in 1995. Our analyses are based on respondents who participated in both waves of the survey. The results may be biased if attrition is non random to the (health) variable of interest. We therefore performed some simple tests on the (non) randomness of attrition in our survey. It can be concluded from these tests that the hypothesis of random attrition cannot be rejected. We report on this in Appendix C.

The results from Tables 1 and 2 provide estimates of the effect of age and labour market status and labour market history on (changes in) health levels. From notably the results in Table 1, it is difficult to assess the effect of age on health as the first difference estimates need to be transformed first to make the results interpretable. For that purpose we used Tables 1 and 2 to perform two types of calculations with the model: first a calculation of age, gender and health profiles, then profiles of health for different labour market states and levels of work experience.

Calculations with the model: age and gender profiles for different cohorts

From the estimates in Tables 1 and 2, we can derive the following relationship between the untransformed HSCL score and age, sex and birth cohort (standard errors in parentheses):

\[
h = \gamma - 3.087 \text{Age} + 0.033 \text{Age}^2 - 0.418 \text{Age} \times \text{female} \\
\begin{array}{c}
(1.27) \\
(0.012) \\
(0.322)
\end{array}
\]

\[
\gamma = -54.30 + 6.698 \text{Birthyr} - 0.076 \text{Birthyr}^2 + 41.40 \text{Female} - 0.452 \text{Female} \times \text{Birthyr} \\
\begin{array}{c}
(23.05) \\
(1.19) \\
(0.015) \\
(33.36) \\
(0.128)
\end{array}
\]

For the transformed HSCL scores a similar relationship can be derived. The remaining regressors are taken as fixed at values for typical respondents. This implies that in Figs 1 and 2 attention should focus on the pattern of age over time and the distance between different lines in the figures rather than focusing on the level of health at specific ages.

The figures depict health profiles over age for different cohorts of males and females. The dotted line represents age health profiles for different cohorts of females and the solid lines is for males. The figures depicts large differences in health levels for different cohorts. Cohort effects are measured by a quadratic function with a ‘top’ of 1942 for males and 1944 for females. As a result, we find, on average, worse health levels for male and female cohorts born during the Second World War. This may be interpreted as indication that differences in the environment and nutrition intake in early childhood have long-term effects on health outcomes. For females, the 1950 cohort (the youngest cohort depicted in the figure) is the
most healthy. For males, the 1935 cohort (the oldest cohorts depicted in the figure) appears to be the most healthy. This effect for males is surprising. It may be the case that the quadratic specifications of age and cohort are too restrictive. We estimated alternative models with spline functions for age and cohorts. This did not alter the results. An alternative explanation is an effect that we denote as a ‘survivor’ effect. It could be the case that only respondents in good health remain as the population ages. Hence the oldest cohort may consist of a relatively homogeneous group of healthy survivors, whereas the subgroup of younger cohorts is more heterogeneous in the sense that they still consist of both healthy and less healthy individuals.

For males health deteriorates monotonically with age. For females, health improves up to roughly age 50 and deteriorates thereafter. This may reflect that health deteriorates faster with age at ages beyond the menopausal period. Alternatively, it may be the case that this pattern is due to the small number of females in the left tail of the age distribution. With respect to this, it should be noted that the sample only includes heads of households and that only 18% of the sample consists of females. At the start of the age range that we consider (43 years), females are less healthy than their male counterparts. The health deterioration rates of males are, however, larger than those of females, leading to better health conditions for females at more advanced ages. This is in line with results from published life tables. As a last remark on these figures, the points at which each cohort of males and females intersect seem to come at earlier ages for the youngest cohorts. This may imply that females become, relative to men, more healthy over time.

Calculations with model: the effect of labour market status and labour market history

Several variables relating to an individual's labour market history are included in the specification. To see how these effects operate on the transformed HSCL score health profiles are reported in Table A4 in Appendix A. In Fig. 3 we depict the calculations for the total HSCL scores. The table and the figure make a ceteris paribus comparison of the age-health profile of three different types of individuals. All three are male and have worked continuously until the age of 44. Type I continues to work until age 65. The type II individual continues to work and applies for an early retirement scheme at the age of 55. Type III immediately loses his job and stays out of work until he is 65. Comparison of the first and the third types of individual in Table A4 shows that working speeds up the process of health deterioration. The effect of retiring is also marked. The early retiree quickly gains on the worker and the
gap between him and the type III person decreases over the years.

A similar profile shows up in the estimates based on the total HSCL-score. In Fig. 3 we see that after an initial health improvement the retiree experiences a fall-back to almost the health level of the individual that continued to work. Only after 6 years retirement does his health improve relative to that of the worker and the unemployed. The estimates are based on biannual information on the respondents' labour market status. This may account for the abrupt turns in the age-health profile after retirement. With more detailed information, preferably month to month information, one would expect to find a more gradual deviation from the age-health profile of workers, implying that it takes several years before a retiree's health improves relative to what his or her health would have been if he or she had continued to work.

CONCLUSIONS

We have focused on aspects of health changes, the importance of cohort effects, age related health changes and the effect of labour market status and work history on health. We have moreover assessed the relative importance of gradual changes in and sudden shocks to health and the role of work status on the likelihood of experiencing a health shock. For that purpose we constructed a fixed effect panel data model that allows for the endogeneity of labour market behaviour and health. A simple two-stage regression procedure was proposed and applied to two waves of a survey of Dutch elderly. We find that it is important to correct for the endogenous interrelation of health and labour market behaviour in a (behavioural) model for health and that panel data are required to disentangle cohort effects from pure age effects. We find differences in health outcomes for different age cohorts and gender. Second World War cohorts have lower health levels that other cohorts. Health deteriorates with age. Health deterioration rates of males are larger than those of females, causing females to be healthier than males at advanced ages. We furthermore find that work affects health, i.e. health deteriorates with employment and labour market history.

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**Goal:** Estimate the price elasticities of insurers’ market shares

**Model:**

\[
\log(s_{it}) = \alpha \log(s_{i,t-1}) + \beta \log(p_{it}) + \delta_t + \gamma_i + \varepsilon_{it}
\]

- \(s_{it}\) = market share of insurer \(i\) at time \(t\)
- \(p_{it}\) = contribution rate (premium = contribution rate \(\times\) wage)

Short-run price elasticity = \(\beta\)

Long-run elasticity to permanent price shock = \(\frac{\beta}{1 - \alpha}\)

**Data:** Panel of 7 inequally spaced waves between 2001 and 2004 for German social health insurers
Static model

In the static panel data model, the market share of each individual company is solely determined by its current contribution rate and by company-specific individual effects. The company-specific effects represent unobservable factors of health insurers that influence consumers in their choice between companies and that might be correlated with the contribution rate. Examples for such factors not included in the data are: the number of branch offices, the quality of service the insurers provide, and any additional medical treatments that, although not compulsorily covered by the standard benefit package, are nevertheless covered by some of the companies.

Contrary to models analyzing individual consumer data, the contribution rate might not be exogenous at the level of company data, since price-setting insurers observe those insurance-specific effects that are unobservable to the researcher. Thus, we instrument contribution rates by their one-period lag and use a test for endogeneity as reported in Wooldridge (2002, pp.118–122). Equation (2) is estimated using the standard fixed-effects model. As can be seen in Table III, the contribution rate is insignificant if the contribution rate is not instrumented. Yet, in the instrumental variables model, it has a (nearly significant) negative effect on the market share of an insurer. Exogeneity of the contribution rate, however, is rejected at the 5% level but not at the 10% level.

Having said this, estimation results presented in subsequent sections strongly argue against the static model. It has to be regarded as misspecified rendering any results from the static model biased. Hence, any conclusions presented in the remainder of the paper rest on results obtained from dynamic model specifications rather than static ones.

Dynamic models

Generalized method of moments (GMM). The dynamic model is equivalent to a world in which only some consumers decide about staying with their health insurer or choosing a new one. Our estimation is based on Equation (3). We compare several specifications based on different moment conditions or sets of instruments.

The first two specifications in Table IV are based on an Arellano–Bond-type first-differenced GMM estimator. In column 1, we present the results for a specification in which the contribution rate is assumed to be predetermined, all available instruments are used, and the estimation is done by two-step GMM (GMM1). The contribution rate has a negative effect on the market share but is clearly insignificant, and the lagged market share has a coefficient (z) close to one. Furthermore, the statistic of the Sargan test is highly significant, indicating that some of our over-identifying restrictions are not valid. A test in which the matrix of possible instruments has been reduced to a minimum (Δlog(sit−1) and Δxit are instrumented by only one variable each), indicates that the additional restrictions are not valid, since the difference-Sargan test is significant (χ2(25) = 45.76).

<table>
<thead>
<tr>
<th>Table III. Fixed-effects estimates for static model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed-effects model</td>
</tr>
<tr>
<td>---------------------</td>
</tr>
<tr>
<td>Coefficient</td>
</tr>
<tr>
<td>Contribution rate</td>
</tr>
</tbody>
</table>

Notes: Regression includes time dummies for each wave. Huber–White robust standard errors given. *** indicates significance at the 1% level, ** at 5%, * at 10%.
Yet, when the contribution rate is treated as endogenous (GMM2), the Sargan statistic becomes insignificant at the 5% level. The difference-Sargan test between GMM1 and GMM2 is significant and clearly confirms these findings: \( \chi^2(5) = 17.38 \).

Therefore, we conclude that the contribution rate indeed is endogenous. In GMM2, the estimated coefficient for \( \alpha \) is lower than before, but still relatively close to unity, and the contribution rate is insignificant. Since the first-differenced GMM model is only weakly identified if \( \alpha \) is close to unity, we might favor the system GMM estimator in this case.

The Arellano–Bover-type system GMM estimator includes additional moment conditions, and therefore allows the identification of the model even if \( \alpha \) is close to unity, and the contribution rate is insignificant. Since the first-differenced GMM model is only weakly identified if \( \alpha \) is close to unity, we might favor the system GMM estimator in this case.

The Arellano–Bover-type system GMM estimator includes additional moment conditions, and therefore allows the identification of the model even if \( \alpha \) is close to unity. The estimates are also provided in Table IV. We see that in all of the system GMM models, the coefficient of the contribution rate is significant and of a much higher magnitude than in the first-differenced GMM models. Once more, we start with a specification in which the contribution rate is assumed to be predetermined (GMM3). These estimates show highly significant Sargan statistics. This Sargan statistic for invalid assumptions does not drop to an insignificant level if either (i) the matrix of possible instruments in reduced (not reported), or if (ii) the contribution rate is considered to be endogenous (GMM4). For GMM4, a comparison with GMM2 indicates that the additional moment conditions in the system GMM are not valid (i.e. are rejected at the 10% level; difference-Sargan test: \( \chi^2(10) = 17.07 \)). This might indicate that the market shares observed in the first period systematically deviate from equilibrium shares conditional on contribution rates and individual effects. Taking into account that changes between insurance companies were heavily restricted, if not impossible, for consumers prior to 1996, it is quite plausible that these market constraints led to strong deviations from equilibrium under market conditions that had not been neutralized until 2001, the beginning of our data sample. Hence, system GMM seems to rely on inappropriate assumptions in the case analyzed here.

Summing up, the Sargan tests tend to favor the first-differenced GMM specification that includes the contribution rate as an endogenous regressor (GMM2), although it is close to a unit-root process and, hence, poor precision of the estimates. Still, all variants of the GMM model strongly argue in favor of market shares being highly persistent, rendering any static specification inappropriate.

**Model in first differences.** In this subsection, we provide the results for a model that explains first differences of market shares \( \Delta \log(x_{it}) \), rather than levels; i.e. the restriction \( \alpha = 1 \) is imposed on

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**Table IV. GMM estimates for dynamic panel data model**

<table>
<thead>
<tr>
<th></th>
<th>First-differenced GMM</th>
<th></th>
<th>System GMM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( x_{it} ) predetermined</td>
<td>( x_{it} ) endogenous</td>
<td>( x_{it} ) predetermined</td>
</tr>
<tr>
<td></td>
<td>Coef.</td>
<td>Std. error</td>
<td>Coef.</td>
</tr>
<tr>
<td>Market share in ( t-1 )</td>
<td>0.9798***</td>
<td>0.0751</td>
<td>0.9525***</td>
</tr>
<tr>
<td>Contribution rate</td>
<td>-0.0034</td>
<td>0.0545</td>
<td>-0.0413</td>
</tr>
<tr>
<td>Observations</td>
<td>1221</td>
<td></td>
<td>1588</td>
</tr>
<tr>
<td>AR(1)</td>
<td>-3.32***</td>
<td></td>
<td>-4.16***</td>
</tr>
<tr>
<td>AR(2)</td>
<td>0.12</td>
<td></td>
<td>-0.05</td>
</tr>
<tr>
<td>Sargan statistic</td>
<td>57.65***</td>
<td></td>
<td>73.42***</td>
</tr>
<tr>
<td>Diff.-Sargan test (fewer instruments)</td>
<td>45.76*** (25)</td>
<td></td>
<td>32.12 (25)</td>
</tr>
<tr>
<td>Diff.-Sargan test (system vs first-dif. GMM)</td>
<td>15.77 (14)</td>
<td></td>
<td>17.07* (10)</td>
</tr>
</tbody>
</table>

*Note:* Regression includes time dummies for each wave. Two-step GMM estimates with corrected standard errors (Windmeijer 2005). AR(1) and AR(2) are tests for first- and second-order serial correlation in the first-differenced residuals (Arrelano and Bond 1991). (Difference) Sargan statistics are \( \chi^2 \) distributed; number in brackets behind difference Sargan test provides the number of restrictions/degrees of freedom. *** indicates significance at the 1% level, ** at 5%, * at 10%.

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CONCLUSIONS

This paper analyzes an important issue that advances insights into the dynamics of the German social health insurance market. Results indicate that consumers are sensitive to price differences, which might have severe consequences for health insurers charging higher premiums than their competitors. The analysis is based on two novel elements. First, it is based on a unique panel data set that covers the social health insurance market on the level of individual insurance companies. Prior to this study, only data aggregated over insurers or with very few individual insurers were available. Second, this paper uses an advanced econometric technique that takes into account the dynamics of the market. So far, studies on price elasticities in the German social health insurance market have been based on static models only.

The econometric analysis favors a dynamic model that uses the level of premiums to explain changes in market shares or, if specified in levels, displays high persistence. For this specification, we obtain a short-run premium elasticity of market shares of minus one-half to minus one. This indicates a moderate short-run sensitivity of consumers to differences in contribution rates. Compared to earlier analyses dealing with the German case, e.g. Schütz et al. (2003), our elasticity is smaller. Interestingly, our results are much closer to those obtained for other countries like Switzerland (Beck, 2004). From the point of view of economic theory, the estimated short-run price sensitivity appears to be rather small. In theory, the price elasticity should approach infinity, because consumers can choose between products that are almost perfect substitutes from an objective perspective. But since the estimated elasticity is relatively small, one might hypothesize that most consumers do not treat health insurers as perfect substitutes.

Another reason for the small short-run price sensitivity estimate could be that 55% of the respondents in a recent survey stated that their health insurer gave them a feeling of security and reliability. Besides, the costs incurred by switching companies were considered to be very high, and information about the differences between health insurers was perceived to be poor (Höppner et al., 2004). One instrument to enhance transparency for consumers and, thus, improve competition might for instance be a standardized reporting system.

In contrast to earlier analyses, our results are based on a dynamic specification. They indicate that market shares follow a unit-root process or are, at least, close to non-stationarity. That is, even if the price sensitivity might appear to be rather moderate in the short-term, permanent relative changes in contribution rates will have dramatic effects on the market shares of health insurers in the long-run. Insurers who permanently charge contribution rates that are higher than those of competitors and do not offset this by being attractive to consumers for other reasons than price will ultimately drop out of the market. However, this process might take some time.

Clearly, we have been able to show that consumers exert their right to choose among social health insurers, that the choice is sensitive to price, and that therefore major conditions for managed competition to work are fulfilled. Furthermore, our results show that this will – at least in the long-run – impose substantial pressure on health insurers. In other words, ‘the prospect of being hanged’ is real. Yet, it is less clear whether this will ultimately lead to enhanced efficiency as intended by the reform of 1996. Other – possibly more promising – strategies to reduce the premium are available.

Table VII. Estimates of short-run premium elasticity

<table>
<thead>
<tr>
<th></th>
<th>GMM2</th>
<th>UR2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean premium elasticity</td>
<td>−0.55</td>
<td>−1.09</td>
</tr>
<tr>
<td>95% confidence interval</td>
<td>−1.74</td>
<td>+0.64</td>
</tr>
<tr>
<td></td>
<td>−1.43</td>
<td>−0.75</td>
</tr>
</tbody>
</table>

Note: Elasticity estimated for sample mean. Estimates based on results from Tables IV and V.

**Goal:** Analyse the effect of disability on participation in the labour force

**Model:**

\[
y_{it} = 1\{\beta_0 + \beta_1 y_{i,t-1} + \beta_2 D_{it} + \beta_3 D_{i,t-1} + \beta_4' z_{it} + \alpha_i + \varepsilon_{it} \geq 0\}
\]

\(y_{it}\)=indicator of labour force participation (= 1 if \(i\) works at \(t\))

\(D_{it}\)=disability dummy

\(z_{it}\)=individual characteristics (age, education, unearned income, ...)

Distinguish state dependence (via \(y_{i,t-1}\)) vs. unobserved heterogeneity (via \(\alpha_i\))

**Data:** Living Ireland Survey, 1995-2000
Likelihood function from:

\[
f(y_{i,1}, \ldots, y_{i,T}|y_{i,0}, x_i) = \int \prod_{t=1}^{T} f(y_{i,t}|y_{i,t-1}, x_{i,t}, \alpha_i)f(\alpha_i|y_{i,0}, \bar{x}_i)\,d\alpha_i
\]

where:

\[
f(y_{i,t}|y_{i,t-1}, x_{i,t}, \alpha_i) = \begin{cases} \Phi(\beta_0 + \beta_1 y_{i,t-1} + \beta' x_{i,t} + \alpha_i) & y_{i,t} \\ 1 - \Phi(\beta_0 + \beta_1 y_{i,t-1} + \beta' x_{i,t} + \alpha_i) & 1 - y_{i,t} \end{cases}
\]

with \( x_{i,t} = (D_{it}, D_{i,t-1}, z_{i,t}) \) and:

\[
\alpha_i \sim N(\delta_0 + \delta_1 y_{i,0} + \delta' \bar{x}_i, \sigma^2_{\alpha})
\]

Account for correlation of random effects with initial observations and explanatory variables!
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. Only 2.2% of the panel is retired before the age of 65, with more men than women taking early retirement. For those who had a disability in the previous year, 1% changes from employment to retirement in the current year, and only 0.5% go from non-participation into retirement. Of all those currently with a disability, 2% of men leave employment for retirement and 4% retire following a spell of non-participation. While it would be interesting to analyse the effect of disability on early retirement, again the sample size does not allow such investigation. A more detailed survey of disability and retirement of older workers in Ireland would provide better data for this purpose.

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.

We should note that employers in Ireland as in many other industrialised countries are obliged by law to make ‘reasonable accommodation’ for those affected by disability, by changes in the work environment or in the way a job is performed to enable a person with a disability to fully do a job and enjoy equal employment opportunities. For this reason, in the survey a person may respond as not limited in daily activities, but without adaptation it is possible that they should be classified as severely limited. 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

| Table 1. Sample size and composition at each wave, age 15–64, Living in Ireland Survey 1995–2000 |
|-----------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Men                               | 50.4            | 50.5            | 50.4            | 49.8            | 49.9            | 49.1            |
| Women                             | 49.6            | 49.5            | 49.6            | 50.2            | 50.1            | 50.9            |
| Age 15–24                         | 24.9            | 24.7            | 24.2            | 23.7            | 22.8            | 23.1            |
| 24–34                             | 20.5            | 20.2            | 20.3            | 20.5            | 20.0            | 18.7            |
| 35–44                             | 20.6            | 20.7            | 21.1            | 20.9            | 21.4            | 21.3            |
| 45–54                             | 19.1            | 19.4            | 19.3            | 19.7            | 19.8            | 19.5            |
| 55–65                             | 14.8            | 14.9            | 15.0            | 15.2            | 15.9            | 17.4            |
| Education                         |                |                |                |                |                |                |
| Primary                           | 26.9            | 26.3            | 26.2            | 24.6            | 23.8            | 21.8            |
| Secondary                         | 59.8            | 60.7            | 60.7            | 58.7            | 58.3            | 60.7            |
| Third level                       | 13.2            | 13.1            | 13.1            | 16.6            | 17.9            | 17.6            |
| Married                           | 59.1            | 58.7            | 59.2            | 58.5            | 58.6            | 56.9            |
| N                                 | 7254            | 6337            | 5782            | 5273            | 4482            | 3670            |
We test this in our paper by explicitly modelling state-dependence in labour force participation and observing the resulting effect on lagged disability.

To provide some baseline estimates of disability we firstly estimate a static pooled model assuming that the errors are independent over time and uncorrelated with the explanatory variables. This model assumes that disability is exogenous (we relax this assumption later on) and provides us with base estimates, with which we can compare results from models that incorporate unobserved heterogeneity and state dependence. For notational purposes, we let $x_{it}$ include disability, lagged disability and other variables, for the remainder of the paper. The log likelihood function for the pooled panel data is similar to that of the cross-sectional probit:

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

and maximising this across all $i$ with respect to $\beta$, we obtain the pooled probit estimator. The standard errors have been adjusted to account for clustering at the level of the individual.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>LFP</td>
<td>$= 1$ if participating in the labour market, $= 0$ otherwise</td>
</tr>
<tr>
<td>Disabled with severe limitation</td>
<td>$= 1$ if disabled and severely limited in daily activities, $= 0$ otherwise</td>
</tr>
<tr>
<td>Disabled with some limitation</td>
<td>$= 1$ if disabled and limited to some extent in daily activities, $= 0$ otherwise</td>
</tr>
<tr>
<td>Disabled with no limitation</td>
<td>$= 1$ if disabled and not limited in daily activities, $= 0$ otherwise (Base category=no disability)</td>
</tr>
<tr>
<td>Age 15–24</td>
<td>$= 1$ if aged 15–24 years, $= 0$ otherwise</td>
</tr>
<tr>
<td>Age 25–34</td>
<td>$= 1$ if aged 25–34 years, $= 0$ otherwise</td>
</tr>
<tr>
<td>Age 35–44</td>
<td>$= 1$ if aged 35–44 years, $= 0$ otherwise</td>
</tr>
<tr>
<td>Age 45–54</td>
<td>$= 1$ if aged 45–54 years, $= 0$ otherwise (Base category=aged 55–64 years)</td>
</tr>
<tr>
<td>BMW</td>
<td>$= 1$ if living in border, midlands, west region, $= 0$ otherwise (Base category=rest of country)</td>
</tr>
<tr>
<td>Secondary education</td>
<td>$= 1$ if highest level of education completed is secondary, $= 0$ otherwise</td>
</tr>
<tr>
<td>Third level education</td>
<td>$= 1$ if highest level of education completed is third level, $= 0$ otherwise (Base category=no qualifications or highest level of education completed is primary)</td>
</tr>
<tr>
<td>Married</td>
<td>$= 1$ if married or living with a partner, $= 0$ otherwise</td>
</tr>
<tr>
<td>Age youngest child $&lt; 4$</td>
<td>$= 1$ if age of youngest child is less than 4, $= 0$ otherwise</td>
</tr>
<tr>
<td>Age youngest child $\geq 4$ and $&lt; 12$</td>
<td>$= 1$ if age of youngest child is greater than or equal to 4 and less than 12, $= 0$ otherwise</td>
</tr>
<tr>
<td>Age youngest child $\geq 12$ and $&lt; 18$</td>
<td>$= 1$ if age of youngest child is greater than or equal to 12 and less than 18, $= 0$ otherwise (Base category=no children)</td>
</tr>
<tr>
<td>Unearned income</td>
<td>$= \frac{\text{Net household income}}{\text{Net individual disposable income}}$ (Net individual disposable income includes net incomes from work, social welfare payments and child benefit. Net household income aggregates individual data to household level)</td>
</tr>
</tbody>
</table>

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

Table 6. Panel model results

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Lag LFP</td>
<td>0.7511***</td>
<td>1.687***</td>
<td>0.7494***</td>
<td>1.7974***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.1194)</td>
<td>(0.0918)</td>
<td>(0.0835)</td>
<td>(0.0623)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disabled with severe limitation</td>
<td>-1.2368***</td>
<td>-0.6639**</td>
<td>-0.9173**</td>
<td>-0.8256**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.1314)</td>
<td>(0.2218)</td>
<td>(0.1736)</td>
<td>(0.2827)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disabled with some limitation</td>
<td>-0.7886***</td>
<td>-0.5159**</td>
<td>-0.3296**</td>
<td>-0.3137**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0814)</td>
<td>(0.1285)</td>
<td>(0.0755)</td>
<td>(0.1283)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Disabled with no limitation</td>
<td>-0.2066**</td>
<td>-0.3464**</td>
<td>-0.0175</td>
<td>-0.1811**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.1042)</td>
<td>(0.1380)</td>
<td>(0.0928)</td>
<td>(0.1497)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Lagged disability**

Disability and Labour Force Participation in Ireland 933

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Health Econ. 14: 925–938 (2005)

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tion-averaged parameters $\beta_a = \hat{\beta}/\sqrt{1 + \sigma^2_a}$. 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 $N^{-1}\sum_{i=1}^N \Phi[\psi_a + x_i \hat{\beta}_a + \xi_i \hat{\xi}_a] = N^{-1}\sum_{i=1}^N \Phi[(\psi + x_i \beta_a + \xi_i \xi_a)(1 + \sigma^2_a)^{-1/2}]$ and for a discrete variable we evaluate this expression at different values for $x_{ij}$, i.e. 0 and 1, and form the difference to obtain the average partial effect. The average partial effect for a continuous variable $x_i$ is obtained by using the average across $i$ of $\beta_{ai}/\phi(\psi_a + x^0 \hat{\beta}_a + \xi_a \hat{\xi}_a)$.

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 7, 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 7, 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, [13] show that 50% of the difference in participation rates between disabled and non-disabled men is due to unexplained effects. Likewise, Kreider [3] uses US data and finds that the estimate of disability for men is overestimated by 17.2%. Lindeboom and Kerkhofs [2] use data from the

Table 7. Average partial effects

<table>
<thead>
<tr>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Disabled with severe limitation</td>
<td>-0.3346** (0.0504)</td>
<td>-0.1111** (0.0471)</td>
<td>-0.0865** (0.0230)</td>
<td>-0.3377** (0.0502)</td>
<td>-0.2557** (0.0295)</td>
<td>-0.3979** (0.0598)</td>
</tr>
<tr>
<td>Disabled with some limitation</td>
<td>-0.1680** (0.0238)</td>
<td>-0.0746** (0.0230)</td>
<td>-0.0654** (0.0295)</td>
<td>-0.1308** (0.0295)</td>
<td>-0.0787** (0.0295)</td>
<td>-0.1666** (0.0428)</td>
</tr>
<tr>
<td>Disabled with no limitation</td>
<td>-0.0330** (0.0187)</td>
<td>-0.0461** (0.0221)</td>
<td>-0.0438** (0.0369)</td>
<td>-0.0069 (0.0369)</td>
<td>-0.0435** (0.0504)</td>
<td>-0.1086** (0.0524)</td>
</tr>
<tr>
<td>Lag LFP*</td>
<td>0.1292**</td>
<td>0.3927**</td>
<td>0.1926**</td>
<td>0.1296**</td>
<td>0.6286**</td>
<td></td>
</tr>
</tbody>
</table>

**p \leq 0.05, *p \leq 0.10.
(Significance in random effects models are based on t-stats on base coefficients, not on the rescaled coefficients reported in this table). Estimation was carried out using the xtprobit command in Stata Version 7.0.
REFERENCES

Review articles


Papers using linear static panel data models


Papers using linear dynamic panel data models


Papers using discrete choice and sample selection panel models

