DOCTORAL THESIS

HEALTH, INFORMAL CARE AND LABOUR MARKET OUTCOMES IN EUROPE

Pilar García Gómez

Advisor: Ángel López Nicolás

April 2008

Universitat Pompeu Fabra

Department of Economics and Business

Contents

Acknowledgements

In Spanish

Todo aquel que me conoce sabe lo poco dada que suelo ser a extenderme por escrito en palabras, lo que me llevaría a decir: "¡Gracias a todos por todo!". No obstante, esta vez siento que debo dedicar algunas líneas a agradecer el apoyo y la ayuda recibidos en este largo proceso.

A Ángel López Nicolás, por su accesibilidad invariable al pasar de la puerta de al lado a las tierras de Levante; por su infinita paciencia en cada proyecto, así como cada una de las veces en las que redefinía el contenido de esta tesis; por haberse leído todas y cada una de las líneas de la misma y haberme ayudado a mejorarlas; por enseñarme a valorar el rigor y la econometría como instrumentos para avanzar en el conocimiento de las políticas públicas incluso antes de que siquiera considerase el realizar un doctorado. Y sobretodo, por la confianza mostrada desde el primer momento, sin la que difícilmente hubiese podido embarcarme en todo esto.

A Guillem López Casasnovas por ayudarme a encontrar el camino en tantas ocasiones; sin lugar a dudas esto no sería posible sin aquella conversación en su despacho con esquema incluido en cuarto de carrera en el que me animó a ir a York, sin que me hubiese ofrecido la posibilidad de formar parte del CRES a mi vuelta a Barcelona, así como tantas otras ocasiones en las que no tenía muy claro por dónde debía, e incluso quería, seguir. A Jaume Puig Junoy por tener siempre la puerta abierta dispuesto a escucharme por descalabradas que fueran mis ideas; por aceptar el "marrón" de tutorizarme en el último momento intentando siempre ayudar en lo máximo posible. A Vicente Ortún por mostrarme su apoyo y dejarme entrar de puntillas en otras áreas de la Economía de la Salud. A Sergi Jiménez por darme la posibilidad de dedicar más tiempo al trabajo necesario para mi Tesis al ofrecerme una beca FPI, así como por embaucarme en algún que otro proyecto.

A David Casado por tener una silla (o su mesa) siempre disponible para discusiones impertinentes a las siete de la tarde, por dejarme entrometer en cualquier momento en su agenda, por ser ese perfecto coautor y compañero de despacho. A Ana Tur por dejarse embaucar en la Operación Mallorca, y por estar siempre disponible a la hora de hacer una parada de emergencia en momentos de crisis y acompañarme a hacer una. A los demás compañeros del CRES, Biel Ferragut, Iván Moreno, Ivan Planas y Ruth Puig, por estar siempre ahí. A Juan Oliva por esas largas conversaciones.

A los compañeros del Centre for Health Economics en York por hacerme sentir en casa en mis seis meses de estancia. A Andrew Jones y Nigel Rice por facilitarme los trámites de la estancia, por acogerme en su grupo como a cualquier otro estudiante de doctorado, y por esas fructíferas discusiones entre el Café Barista y B Henry's.

A todas esas personas que han venido a alguno de mis Seminarios o han dedicado algo de su tiempo en el despacho o en un tren o en un avión a leer parte de este trabajo con la intención de hacerme llegar tanto preguntas como comentarios. Sin duda esta tesis se ha beneficiado de las aportaciones de todas ellas.

En último lugar, pero seguramente la parte más importante, no querría olvidarme de todas esas personas que fuera del ámbito académico me han ayudado a relativizar la importancia de las cosas. A mis padres, Margarita y Manolo, por haberme animado a hacer siempre lo que me gustase pese a que para ellos no fuera su mejor opción. A ellos debo darles las más sentidas gracias no sólo por apoyarme, sino por realizar el esfuerzo de entenderme. A mi hermano Alejandro; y a Ina por no permitir que en ningún momento me obsesionara con lo que tenía entre manos usando siempre su característico buen humor, por estar siempre a mi lado, incluso cuando ésta no era la opción más fácil.

In English

All who know me agree that I tend to be brief, and in other times I would probably just say "thanks to everyone for everything!". However, this time I feel that I should spend some lines acknowledging all the help I have received during this long process.

I am grateful to Ángel López Nicolás, for being always approachable both when he was in the next office and in Murcia; for being patient in every project, each time I decided to change the contents of this thesis; for having read every line of it and helped to improve them all; for showing me how to be rigorous and use econometrics as a tool for policy analysis even before I had even thought about enrolling in a PhD. Above all, I am thankful for the confidence he placed on me since the very beginning, without which I doubt I would have been able to embark on this project.

I want to thank Guillem López Casasnovas for always helping me to find my own way. Undoubtedly, this wouldn't be possible without the conversation we had when I was finishing my first degree in which he made one of his famous diagrams and encouraged me to go to York, or if he had not offered me the opportunity to join CRES once I came back to Barcelona. He has helped me to find the way during those many times when I didn't know which option I should, or even which option I wanted to, take. I am thankful to Jaume Puig-Junoy for having his door always open and being willing to listen to me independent of the rashness of my ideas; and for having accepted to be my tutor at the very end of the process with a thoroughly helpful attitude. I am also thankful to Vicente Ortún for all his support and letting me approach other areas of Health Economics. I am thankful to Sergi Jiménez for allowing me spend more time in research to improve this thesis, as well as encouraging me to participate in other interesting projects.

I want to thank David Casado for always having a seat (or table) ready for some discussion around seven in the evening; for letting me change (at any time) his agenda; for being the perfect co-author and office mate. I am indebted to Ana Tur for allowing herself be swindled into the *Operación Mallorca*, as well as being always ready to make an emergency stop when the crises were approaching and go to have some beers. To all the other CRES colleagues, Biel Ferragut, Iván Moreno, Ivan Planas and Ruth Puig, for always being there, and to Juan Oliva for all those long conversations.

I want to thank the colleagues from the Centre for Health Economics at York as they made me feel at home during my six months visiting. I want to thank Andrew Jones and Nigel Rice for making my visit possible, for welcoming me to their group as if I were one of their other PhD students, and for all those fruitful discussions between Café Barista and B Henry's.

I also want to mention all those people who have attended any of the Seminars I have given or have spent some time in their office, on a train, or on a plane reading part of this work with the intention to send me comments or questions. This thesis has undoubtedly benefited from all of them.

Last, but probably the most important part: I would like to remember all the friends from outside the Academic world that have helped me to put everything into perspective. I am thankful to my parents, Margarita and Manolo, for having always encouraged me to follow my first option, even if it wasn't theirs. I especially want to acknowledge their support, not only in encouraging me, but also for making the effort to understand my decissions. To my brother Alejandro and to Ina, whose characteristic good humour ensured that I was never too obsessed with this Thesis, for being always at my side even when this was the difficult option.

Foreword

There is abundant evidence on the relationship between socioeconomic conditions and health status (Acheson, 1998; Deaton, 2002 and 2003; van Doorslaer and Koolman, 2004). In particular, these studies show that the health of the population is relatively more concentrated at the top of the income distribution and that, other things being equal, income is positively and significantly associated with health. It is nevertheless difficult to extract policy recommendations from existing evidence. Health and income are related through mechanisms of direct and indirect causality. Are the less healthy relatively poorer because they are unable to work? Or is it a lower level of income that causes poor health? It is plain to see that, depending on which causal pathway is at work, policies are quite different. In the first case, measures aimed at increasing the supply of labour of the relatively unhealthy, be it through reducing the direct costs of working or (with the necessary caveats) the opportunity costs in terms of foregone benefits, might be considered. In the second case, tackling the income-to-health causal link calls for measures that focus on access to health care, poverty or the promotion of healthy lifestyles among particular groups in the population.

This thesis aims to contribute to the literature with an attempt to identify the causal effects of health on labour market outcomes and income in the working-age population. In order to achieve this aim, I analyse the effects of the onset of a health shock on the individuals' labour market outcomes, and also the effects of caregiving (which is often triggered by a health shock affecting another member of the household) on female labour participation. Notwithstanding the importance of the second causal pathway mentioned above, measuring the impact of health shocks on labour outcomes (of the suffering individual or of other members of the household) is policy-relevant. Most European countries face similar challenges in terms of ageing of their populations and reductions in the ratios of active to retired over the coming decades. Increasing labour force participation, especially among females, is a widely known policy goal (as established in the Lisbon Agenda). Delaying retirement is also often thought of as a plausible solution. The extent to which health affects participation and how different institutional settings modify this impact is well worth studying. I have used the techniques developed in the literature on non-experimental evaluation in combination with the best observational data available for this purpose. The results will be presented in the following three pieces of research.

The first chapter, "**Institutions, health shocks and labour market outcomes across Europe**", contributes to the knowledge of the relationship between health and labour outcomes for the working population using a homogeneous empirical framework for nine European countries. In order to control for the non-experimental nature of the data I use matching and matching combined with difference-in-differences techniques with the European Community Household Panel survey. This homogeneous framework allows me to relate the empirical estimates to differences in social security arrangements across these countries.

The results suggest that there is a significant effect running from health to the probability of employment and to income: individuals who suffer a health shock are significantly more likely to leave employment than those who do not. As expected, there are differences in the estimates across European countries, with the largest employment effects being found in the Netherlands, Denmark and Ireland, and the smallest in France, Italy and Greece. The reduction in the likelihood of employment is paralleled by an increase in the probability of inactivity. This should be a cause for concern, as the outflow from inactivity is known to be close to zero (OECD, 2003).

The second chapter, "**Health effects on labour market exits and entries**", extends the analysis on the causal relationship between health and labour market transitions. It analyses the role of health in exits out of and entries into employment using data from the first 12 waves of the British Household Panel Survey (1991-2002) using discrete-time duration models to estimate the effect of health on the hazard of becoming non-employed and on the hazard of becoming employed. The results show that general health, measured by a variable that captures health limitations and by a constructed latent health index, affects entries into and exits out of employment, the effects being stronger for males than for females. Moreover, the results suggest that changes in mental health status influences only the hazard of non-employment for the stock sample of workers. The results are robust to different definitions of employment, and to the exclusion of older workers from the analysis.

As mentioned earlier, a health shock or health deterioration can have effects not only at the level of the individual, but also on his/her relatives, who might have to adjust their labour supply in order to provide caregiving. Informal care is today the form of support most commonly used by those who need help to carry out certain basic activities (eating, dressing, taking a shower, etc.), in Spain and in most other countries in the region. The potential labour opportunity costs incurred by these informal carers, the vast majority of whom are middle-aged women, have not as yet been properly quantified. It is, however, crucially important to gauge these effects at a time when dependency is at the core of the policy-making agenda.

In this context, the third chapter, "**Informal care and labour force participation among middle-aged women in Spain**", examines the effects of various types of informal care on labour behaviour using the Spanish subsample of the European Community Household Panel (1994-2001) to estimate a dynamic model for labour force participation. The results suggest the existence of labour opportunity costs for those women who live with the dependent person they care for, but not for those who care for someone outside the household. Furthermore, whereas caregiving for more than a year has negative effects on labour force participation, the same cannot be said of those who "start caregiving" and "stop caregiving".

Chapter 1. Institutions, health shocks and labour market outcomes across Europe

1. Introduction

The increase in the rates of recipients of disability support observed during the 1990s in almost all OECD countries has raised concerns about the labour outcomes of people with adverse health (OECD, 2003). The relevant policies often try to satisfy two possibly contradictory goals. On one hand, they have to guarantee that individuals who are or become disabled do not endure economic hardship, and thus provide some insurance for the potential income losses. On the other hand, they also aim to avoid the exclusion of disabled individuals from the labour market by, among other measures, encouraging participation.

Previous literature seems to confirm the existence of an effect of health events on labour market outcomes, but there is a lack of consensus on their magnitude. Our contention here is that the international differences in estimated effects partly reflect the emphasis that each country places on the two potentially conflicting goals of protecting income and encouraging participation mentioned above. This chapter attempts to contribute to this area of research by estimating the effects of health shocks on a set of labour outcomes for different European countries, and subsequently relating the differences in estimates to variations in institutional factors across these countries.

It is well known that the use of observational data to estimate the causal effect of health events on labour outcomes is plagued with potential biases (Lindeboom, 2006). In terms of methodology, our strategy is motivated, among others, by Smith's (2004) use of longitudinal information for representative samples of the US population so as to be able to condition on past health shocks before evaluating current changes in labour status and income. So in this chapter we resort to the best source of longitudinal information on health and socioeconomic characteristics for the European population available to researchers: the European Community Household Panel (1994-2001, hereafter ECHP). We will condition on past health and labour status to evaluate the effects of changes in health.

While the spirit is the same as in Smith's study, our specific methodology consists in matching individuals who experience a health shock with identical individuals in a control group. In this respect we follow the recent use of propensity score matching methods in the context of health shocks by Lechner and Vázquez Álvarez (2004), Frölich et al (2004), Dano (2005) and García Gómez and López Nicolás (2006).

Therefore, this chapter contributes to the existing literature in several directions. First, it extends the knowledge of the relationship between health and labour outcomes on the working population, using a homogeneous empirical framework for nine European countries. Second, this homogeneous framework allows us to relate the empirical estimates to differences in social security arrangements across these countries. To the best of our knowledge there is no other work containing this type of comparative analysis for the countries concerned.

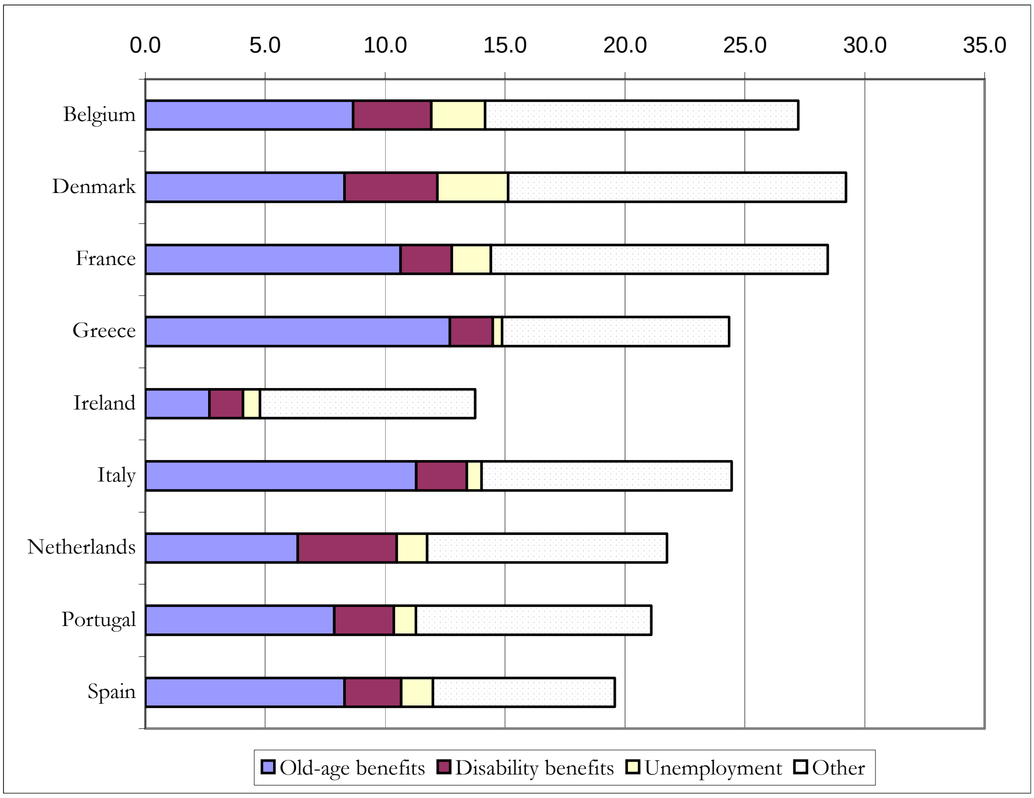
The results suggest that there is a significant effect running from health to the probability of employment and to income: individuals who suffer a health shock are significantly more likely to leave employment than those who do not, and in several countries this is associated with a significant reduction in some types of income. As expected, there are differences in the estimates across European countries, with the largest employment effects being found in the Netherlands, Denmark and Ireland, and the smallest in France, Italy and Greece. The reduction in the likelihood of employment is paralleled by an increase in the probability of inactivity. This should be a cause for concern, as the outflow from inactivity is known to be close to zero (OECD, 2003).

2. Institutional background

After the onset of a health condition, an individual can follow any of several routes (Aarts et al, 1996): i) work; ii) early retirement; iii) traditional disability insurance schemes (sickness, general disability and work injury); iv) unemployment; v) means-tested schemes for those not eligible for any other option. This implies that it is not only disability policies but also the set of incentives provided by the wider social security system that determine the labour consequences of a health shock.

Figure 1.1 gives a first glimpse of the differences between the countries under study, as it shows the fraction of social expenditures over GDP and their breakdown into four main chapters. Note that Ireland (Denmark) is the country with the lowest (highest) fraction of GDP devoted to social expenditures. In the case of Ireland, the difference with respect to the rest of the countries is mainly at the expense of old-age benefits.

Figure 1.1. Composition of social expenditure (as % GDP). 2001



Source: Compiled by the author using data from Eurostat (2007)

In order to obtain a closer picture of the relevant differences among countries, Table 1.1 summarises the main features of the social security system in the interrelated spheres of disability, unemployment and retirement. Note first the striking differences in the way in which countries establish eligibility criteria for disability benefits. Some countries define disability in terms of a reduction in the individual's work capacity (Denmark, Ireland, Italy and Spain), while others do so in terms of a reduction in earnings capacity (Belgium, France, Greece, the Netherlands and Portugal). But even among countries that use the same concept, the minimum level of disability that entitles individuals to receive benefits varies widely: from 15% in the Netherlands to being permanently incapable of work in Ireland (OECD, 2003; European Commission, 2004a). Table 1.1 also shows that some countries apply mandatory quotas obliging employers to have a certain proportion of disabled workers among their employees (7% Italy, 6% France, 2% Spain), or some sectors (3% in the public sector in Ireland and 5% for new recruitment in the public sector in Portugal). These quotas are absent in Denmark, the Netherlands and Belgium. Concerning measures aimed at integrating disabled individuals into the labour market, we can also observe in Table 1.1 that most countries allow a certain accumulation of disability benefits with earnings from work. The only exception is Ireland, where the invalidity pension requires permanent full incapacity (European Commission, 2004a).

Following the analysis in OECD (2003)[1], we can summarise the main components of the disability system into two dimensions. The "compensation" dimension reflects the characteristics of the main disability benefit scheme (coverage, minimum disability level, disability level for a full benefit, maximum benefit level, permanence of benefits, medical assessment, vocational assessment, sickness benefit level, sickness benefit duration and unemployment benefit level and duration). The second is the "integration" dimension, which reflects all the employment and rehabilitation measures (coverage consistency, assessment structure, employer responsibility for job retention and accommodation, supported employment programme, subsidised employment programme, sheltered employment sector, vocational rehabilitation programme, timing of rehabilitation, benefit suspension regulations and additional work incentives). Of the group of countries considered here (and included in the OECD study), Denmark would be the country in which the integration component is the highest, whereas the lowest levels are found in Italy and Portugal. The champions in the compensation dimension are Portugal, Spain and the Netherlands, while the laggards in this dimension are France, Belgium and Italy.

---

[1] In OECD (2003) the authors consider a different group of countries that did not include Ireland and Greece. For our purposes, we conjecture that these countries belong to the same cluster as the Mediterranean countries.

Table 1.1 Institutional features of the group of countries included

	Denmark	Netherlands	Belgium	France	Ireland	Italy	Greece	Portugal	Spain
Initial net unemployment replacement rate (as % of net earnings in work) (2004)	70	74	61	75	49	54	55	83	67
Average of net replacement rate over 60 months of unemployment (as % of net earnings in work) (2004)	70	66	61	57	64	22	35	68	49
Unemployment insurance benefit duration (months) (2004)	48	24	No limit	23	15	6	12	24	21
Average standardised unemployment rate (1994-2001)	5.6	4.5	8.7	10.6	8.7	10.7	10.3	5.7	15.2
Expenditure disability / Expenditure unemployment (2000)	1.13	2.29	0.79	0.81	0.55	3.55	0.78	3.42	0.66
Expenditure disability / Expenditure old-age benefits (2000)	0.31	0.32	0.28	0.15	0.27	0.11	0.10	0.34	0.18
Age of earliest retirement (2004)	50	60	60	60	55	60	50	55	60
Retirement net replacement rate for average earner, men (2007)	86.7	96.8	63.0	63.1	38.5	77.9	110.1	69.2	84.5
Disability is Work or Earn related	Work	Earn	Earn	Earn	Work	Earn	Earn	Earn	Work
Minimum level of incapacity for work to be entitled to disability benefits	50%	15%	66.6%	66.6%	Permanently incapable of work	66%	50%	Earnings capacity no more than 1/3 of normal occupation	33%
Disability benefits depend on previous earnings	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Disability benefits can be accumulated with earnings from work	Accumulation possible, but with benefit reduction.	Accumulation is possible, but the rate of benefit may be revised.	A professional activity during the period of disability may be authorised by the mutual insurance company's medical advisor. The amount of the daily benefit thus allocated may not exceed the daily amount that would be allocated if there	Suspension of the pension if the pension and the salary received during two consecutive quarters are greater than the average quarterly salary for the last calendar year before stopping work prior to invalidity.	Accumulation with earnings not possible. Invalidity requires permanent full incapacity.	No accumulation possible for incapacity pension; partial accumulation for partial pension.	Accumulation with earnings from a professional activity is possible, but the payment of the invalidity pension is interrupted when the earnings from the activity exceeds the earnings that a healthy worker can attain.	Accumulation possible up to the limit of the reference earnings.	Permanent incapacity pensions are compatible with earnings, provided the activity is consistent with the pensioner's physical condition and does not imply a change in his/her capacity to work.

	Denmark	Netherlands	Belgium	France	Ireland	Italy	Greece	Portugal	Spain
			were no accumulation.						
Preferential employment for handicapped persons	Public authorities have to give preference to handicapped persons who cannot get employment in private enterprises, but who are considered capable of working. The municipality provides subsidies to employers offering a job to the disabled.	No regulations.	No regulations.	Preferential employment of handicapped persons on staff up to 6% of total in firms with 20 or more employees.	Public authorities reserve up to 3% of suitable positions for disabled persons.	Persons disabled by industrial injuries are placed and employed in enterprises with a staff of 50 or over (one such person for each 50 workers).	For certain categories (e.g., the blind).	Firms employing a staff of at least 10 are obliged to employ handicapped persons incapacitated as a result of an accident occurring in the workplace.	Quotas may be established for the employment of handicapped workers (employers with a permanent workforce of over 50 to set aside 2% for handicapped workers). Also social security contributions relief.

Sources: Compiled by the author using data from OECD (2006), Eurostat (2007), OECD (2007), European Commission (2004a), Department of Social and Family Affairs (2003)

Concerning the characteristics of unemployment insurance, Table 1.1 shows that there are marked differences in i) the initial net unemployment replacement rate, ii) the duration of unemployment insurance, and iii) the average replacement rate over the course of the unemployment spell. Note that Denmark, the Netherlands and Portugal are the countries in which both the initial and the average replacement rate are highest. At the other end, Italy and Greece rank lowest in terms of initial and average net replacement rates. In the duration dimension, note that individuals are entitled to unemployment benefits from six months in Italy to an unlimited period of time in Belgium. It has been previously argued (OECD, 2003) that unemployment systems with long benefit payments are likely to reduce the pressure on the disability programme.

In several countries, (early) retirement benefits are as important as disability benefits for disabled persons of working age (OECD, 2003). In Portugal, for example, one third of non-employed disabled persons receive an early or regular retirement benefit. This is probably due to the fact that access to early retirement benefits is easy, as long as the contribution requirements are fulfilled, because there is no medical examination. An important element to determine the importance of (early) retirement as an incentive to withdraw from the labour force is the eligibility age. In only four of the countries considered (Denmark, Greece, Ireland and Portugal) are individuals younger than 60 able to take early retirement. In Ireland, unemployed persons aged 55 or over who have been receiving either Unemployment Benefits or Unemployment Assistance for 15 months or more may opt to apply for the Pre-Retirement Allowance (PRETA), which is a means-tested allowance that enables individuals aged 55 or over to retire from the labour force. In Portugal, 10 years of early retirement are available on the condition that there are either 30 years of registered earnings or else 20 years of registered earnings and the individual is in long-term unemployment. In Greece, mothers can retire at the age of 50 with a reduced pension if they have a dependent or disabled child and have worked for more than 5,500 days. Moreover, both men and women can retire with full pension at age 55 if they have worked at least 35 years. The route to early retirement available in Denmark for individuals aged 50 and over is based on grounds of social problems without any medical cause.

3. Empirical strategy

Outcomes of interest

In this chapter we investigate labour market outcomes potentially affected by an adverse health shock. We are particularly interested in labour market transitions that are not led by the availability of old-age retirement, so the population of interest is comprised of individuals below 60 years of age, as in most of the countries included in the analysis (early) retirement is not available for individuals younger than 60. The outcomes of interest are the probability of being in employment and the probability of being inactive or in other states, and the levels of income from work and other sources.

Identifying the causal effect

The fundamental difficulty for our purposes is how to adequately deal with the simultaneous determination of health and labour outcomes. One possible avenue would be to find instruments for health in a reduced form for labour outcomes. However, one source of potentially valid exclusion restrictions in this setting, i.e., detailed regional information, is absent from the ECHP due to the high level of aggregation employed for the regional markers.

Another option consists in conditioning on sufficient information to replicate random assignment to treatment (in this case suffering a health shock) and then using a parametric model where the treatment variable is one of the regressors. This is essentially the route taken by Smith (2004) in that the onset of a health shock is assumed to be exogenous (conditional on a set of observed covariates) in a labour outcomes equation. The approach of Lindeboom et al (2006) is similar in that the authors estimate multinomial logits for different transitions between work and disability states where having had an accident is one of the explanatory variables, but in this case the specification also allows for any remaining unobserved heterogeneity affecting health shocks and labour market/disability outcomes.

Our empirical strategy relies on the possibility of conditioning on sufficient observable information to obtain a credible counterfactual against which we may measure the impact of the health shock. Let T=1,0 indicate treatment (health shock) and lack of treatment respectively and let Y_{i1} and Y_{i0} denote the outcome of interest (labour status) for individual i with treatment and without treatment respectively. Since we will observe individual i either with treatment or without treatment, we cannot observe the causal effect of interest: Y_{i1}-Y_{i0}. Some features of this distribution are estimable, nevertheless. In particular, we may consider the Average Treatment Effect on the Treated (ATET):

$$ATET=E(Y_{i1}-Y_{i0}|T=1) \tag{1.1}$$

This magnitude measures how much the outcome of interest changes on average for those individuals who undergo the treatment (who suffer the health shock to be defined below). Clearly, simply computing the difference in the average outcomes of those under treatment and those not under treatment is open to bias, as there are observed and unobserved characteristics that determine whether the individual undergoes the treatment. That is,

$$\begin{gathered}E(Y_1|T=1)-E(Y_0|T=0)= \\ E(Y_1|T=1)-E(Y_0|T=1)+E(Y_0|T=1)-E(Y_0|T=0)= \\ E(Y_1-Y_o|T=1)+E(Y_0|T=1)-E(Y_0|T=0)= \\ ATET+BIAS\end{gathered} \tag{1.2}$$

Only if we can guarantee that the outcomes of the control group are equal on average to what the outcomes of the treatment group would have been in the absence of treatment does this consistently estimate the ATET. With non-random sorting into treatment and control this condition is rarely met.

Now suppose that by conditioning on an appropriate set of observables, X, the non-participation outcome Y_o is independent of the participation status T. This is the weak version of the unconfoundedness assumption, also called ignorable treatment assignment (Rosenbaum and Rubin, 1983) or conditional independence assumption (Lechner, 2000) or selection on the observables, which suffices when the parameter of interest is the ATET, as only assumptions about the potential outcomes of comparable individuals are needed to estimate counterfactuals.

$$Y_o \perp T \mid X \tag{1.3}$$

This implies that

$$E(Y_0|T=1, X)-E(Y_0|T=0, X)=0 \tag{1.4}$$

In order to identify the ATET, the overlap or common-support condition is also assumed. It ensures that, for each treated individual, there are control individuals with the same X.

$$Pr(T=1|X)<1 \tag{1.5}$$

Therefore, under the assumptions stated in Equations (1.3) and (1.5) above, we could estimate the ATET from the difference in outcomes between treated and controls within each cell defined by the conditioning variables X (see Blundell and Costa Dias, 2002). Using the law of iterated expectations and the conditional independence assumption, the ATET can be retrieved from observed data in the following way:

$$\begin{aligned} ATET&=E(Y_1 \mid T=1)- E(Y_0 \mid T=1)= \\ &=E_X[(E(Y_1 \mid X, T=1)- E(Y_0 \mid X, T=1)) \mid T=1]= \\ &=E_X[(E(Y_1 \mid X, T=1)- E(Y_0 \mid X, T=0)) \mid T=1] \end{aligned} \tag{1.6}$$

Defining health shocks and treatment and control groups

The measure of health shocks is based on the responses to the question on self-assessed health in the ECHP "How good is your health in general?". From the five possible responses (very good, good, fair, bad and very bad), we consider that the respondent has undergone an adverse health shock if he or she reports "fair", "bad" or "very bad" in any given period, with the timing of the shock occurring sometime between the last period when he or she recorded any of the other two alternatives.

Since we wish to evaluate whether suffering a health shock in these terms leads to any change in labour outcomes, we want to rule out the possibility that any potential anticipation of the change in labour status causes the change in self-reported health, therefore we adopt the following strategy – motivated by the procedures used by Lechner and Vázquez Álvarez (2004) and García Gómez and López Nicolás (2006) – in order to construct the treatment and control groups:

1) Consider a window of three years for each observed individual. This creates six possible sequences of three years over the time span covered by the data. We refer to these three years as $t=1$, $t=2$ and $t=3$, regardless of the sequence.
2) For each sequence, select individuals who are healthy (SAH good or very good) at $t=1$, the start of the sequence, and also are employed at $t=1$ and $t=2$.
3) The **treatment group** are individuals meeting selection criterion # 2 who report fair, bad or very bad health in $t=2$ and $t=3$. That is, those individuals who undergo a health shock after $t=1$ and for whom adverse health persists at least over $t=3$. The sequence of health states for these individuals is therefore GBB (Good, Bad, Bad).
4) The **control group** are individuals meeting selection criterion # 2 for whom we observe a GGG sequence of health states (Good, Good, Good).

It should be noted that by considering these sequences we disregard potential contemporaneous effects of health transitions on labour outcomes (and contemporaneous effects of employment transitions on health). However, this procedure ensures that the treatment occurs before the potential change in outcome, thus offering some guarantee that what we identify is not reverse causality. Moreover, as individuals suffer a health shock before leaving the labour force, we are also ruling out justification bias in the health responses, except in those cases where there are anticipation effects consisting in individuals who foresee a transition out of employment and report a change in self-assessed health one period in advance. It is not clear to what extent this anticipation effect might be empirically important, but in any case assuming it away is the price we have to pay in order to be able to rely on the timing of events as a source of identification.

Propensity score matching

The estimate of the ATET as shown in Equation (1.6) turns out to be prohibitive in terms of data when the set of conditioning variables X is large. An alternative is to use the results of Rosenbaum and Rubin (1983, 1984) and condition on the probability of treatment as a function of X, the propensity score P(X), since the conditional independence assumption also implies that

$$E(Y_0|T=1, P(X))-E(Y_0|T=0, P(X))=0 \tag{1.7}$$

Therefore, we could estimate the ATET from the differences in outcomes between treated and controls within each cell defined by values of P(X).

$$\begin{aligned} ATET&=E(Y_1 \mid T=1)- E(Y_0 \mid T=1)= \\ &= E_{P(X)}[(E(Y_1 \mid P(X), T=1)- E(Y_0 \mid P(X), T=1))\mid T=1]= \\ &= E_{P(X)} [(E(Y_1 \mid P(X), T=1)- E(Y_0 \mid P(X), T=0)) \mid T=1] \end{aligned} \tag{1.8}$$

Provided that the conditional participation probability can be estimated using a parametric method as a probit model, matching on the univariate propensity score reduces the dimensionality problem.

Moreover, it is worth mentioning that due to the strategy chosen to define the groups of treated and control individuals, we are using the propensity score as a "partial" balancing score, as it is complemented by an exact matching on pre-treatment health and labour status.

Once the propensity score is estimated, we calculate the ATET using the nearest neighbour algorithm (Becker and Ichino, 2002) with replacement, which matches each treated individual with the control unit that is closest in terms of propensity score. Notice that each control unit can be used more than once as a match, otherwise some individuals could be matched with substantially different control units. The general formula for the matching estimators can be written as follows:

$$ATET = \frac{1}{N^T} \sum_{i \in \{T=1\}} \left[Y_i^T - \sum_{j \in C(i)} w_{ij} Y_j \right] \tag{1.9}$$

where w_{ij} denotes the weight attributed to control individual *j* when comparing with treated individual *i*. In the case of the nearest neighbour algorithm, the weight is 1 if the control individual has the closest propensity score to that of individual *i* and 0 otherwise.

Abadie and Imbens (2006) show that the bootstrapped variance estimator is invalid for nearest neighbour matching. Therefore, we calculate analytical standard errors, assuming independent outcomes across units.

Plausibility of the conditional independence assumption

The identification of the ATET by matching methods relies on the unconfoundedness assumption, which may or not may be plausible depending on the particular context, and which is inherently untestable as the actual counterfactual cannot be observed.

Plausibility relies on the availability of a detailed group of characteristics that allow us to match treated and control units. The data used contains a rich set of pre-treatment variables on demographics, educational attainment, job characteristics, household composition and socioeconomic information. Moreover, the information for both treated and control individuals was collected with the same questionnaire, and individuals were drawn from the same local market. Heckman et al (1997) stressed the importance of satisfying these two conditions in order to reduce the bias when applying matching estimators.

Secondly, we include pre-treatment outcomes within the vector of conditioning variables, either by including these pre-treatment outcomes in the propensity score or restricting the sample of controls to individuals who are identical in terms of pre-treatment outcomes.

This procedure aims to include fixed unobserved factors in the outcomes of interest within the vector X of conditioning variables.

Imbens (2004) suggests that some support for the plausibility of the CIA can be obtained by estimating the ATET for the treatment of interest on a pre-treatment variable. This ATET should be null, so evidence suggesting otherwise will question the validity of the CIA. We will estimate the ATET of our measure of health shocks on all the pre-treatment outcomes[2].

Propensity score matching combined with difference-in-differences

Again, it is important to stress that the ability of the estimator shown in (1.9) to consistently retrieve the ATET relies crucially on the conditional independence assumption. That is, there are no unobserved variables that are correlated with both the exposure to treatment (the health shock) and the outcome. Therefore, if any systematic differences remain between the outcomes of treated and control individuals, matching estimation will not recover the parameter of interest. However, if we can assume that these differences are time-invariant the availability of panel data affords the possibility to correct for the hypothetical failure of this assumption. Letting the superscripts A and B denote the time periods before and after treatment occurs, the conditional independence assumption would now be stated in the following terms:

$$Y_0^A - Y_o^B \perp \mathrm{T} \mid \mathrm{X} \tag{1.10}$$

So that

$$\mathrm{E}(Y_0^A - Y_o^B \mid \mathrm{T}{=}1, \mathrm{X}) - \mathrm{E}(\mathrm{Y}^{\mathrm{A}}{}_0 - \mathrm{Y}^{\mathrm{B}}{}_0 \mid \mathrm{T}{=}0, \mathrm{X}) = 0 \tag{1.11}$$

2 Imbens (2004) also proposes a test based on the presence of multiple control groups (e.g., individuals who are eligible and individuals who are non-eligible for treatment), where one can estimate the ATET of interest considering one of these control groups as the “treated” sample. In that case, the treatment effect is known to be zero, thus the non-rejection of the null hypothesis of no treatment effect makes the satisfaction of the CIA more plausible. However, due to the characteristics of our setting, there are no different control groups to be used.

And therefore, the combined matching-differences-in-differences ATET can be estimated in the following way from observed data (Blundell and Costa Dias, 2002 and Blundell et al, 2004):

$$\text{ATET}_{\text{MDID}} = \frac{1}{N^T} \sum_{i \in \{T=1\}} \left\{ \left[Y_{i1}^{t+1} - Y_{i1}^{t} \right] - \sum_{j \in \{C(i)\}} W_{ij} \left[Y_{i1}^{t+1} - Y_{i1}^{t} \right] \right\} \tag{1.12}$$

where w_{ij} denotes the weight attributed to control individual *j* when comparing with treated individual *i*. Equation (1.12) shows that the estimate for the ATET is a weighted average of the differences in differences between each treated individual and his/her matched control.

We shall use $\text{ATET}_{\text{MDID}}$ in order to check the robustness of the results for the income outcomes. We do not estimate $\text{ATET}_{\text{MDID}}$ for the labour outcomes, as we have restricted all the individuals to being employed in the first and second period, thus the ATET estimates obtained are identical irrespective of whether we use matching or matching combined with difference-in-differences.

4. Data and descriptive statistics

The European Community Household Panel (ECHP) is an annual standardised longitudinal survey which provides eight waves of microdata about living conditions in most of the EU-15 member states. The survey is based on a standardised questionnaire given to individuals aged over 16 selected from a representative household panel. The survey covers a wide range of topics, including demographics, income, social transfers, individual health, education and labour. The information contained in the ECHP is comparable both across countries and over time.

The criteria used to select treatment and control groups meant that we could only use those countries for which information was available regarding all eight waves: Belgium, Denmark, France, Greece, Ireland, Italy, the Netherlands, Portugal and Spain. Table A1.1 in the Appendix shows the sample size for both treated and control groups, as means of the relevant variables, for each of the countries included in the study.

The outcome variables we consider are employment status and income from different sources. Information regarding employment status comes from the self-defined classification of main status, and we classify an individual as employed when he works part-time or full-time or is self-employed. The three non-employment categories that we will consider are unemployed, retired and inactive. Therefore, we will not look at other categories such as student, doing housework, looking after children or other persons, and in community or military service.

Table A1.1 shows that, in all countries, the percentage of individuals who work in the third period, without any restriction of the sample according to previous labour status, is clearly higher among the group of individuals who report being in good or very good health in all three periods. However, these differences are reduced when we select those individuals younger than 60. Moreover, in all countries the relative weight of the group of treated individuals with respect to the control group is reduced, as this profile (GBB) is more frequently found among the elderly. The largest decrease in sample size is observed when we restrict the sample to individuals working in the first period, as the percentage of individuals aged under 60 whose health profile is GBB or GGG that work in the first period varies between 53% in Spain and 81% in Denmark. The countries in which the percentage of individuals working in the first period is lowest are Spain, Italy, Ireland and Greece. On the other hand, once we have conditioned on working on the first period, the sample reduction when we condition on working also in the second period is small, as the remaining sample is around 95% of the previous one, which shows the importance of state dependence in labour market outcomes.

Table A1.1 also shows the demographic, socioeconomic and health status characteristics of both treated and controls in the working sample. We can observe that, with respect to the control group, individuals who suffer a health shock have, on average, lower equivalent household income, lower educational attainment, and are older. The health status in the third period is, as expected, worse for the treated than for the control group, although there are major differences across countries. The percentage of treated individuals who have been hospitalised in the last 12 months (inpaten) varies between 5.4% in Portugal and 26.1% in Ireland. This difference is also observed in the number of nights hospitalised (hospnight), as we can observe that the mean is less than 1 in Portugal, Denmark and the Netherlands, but greater than 2.5 in Belgium and Greece. On the other hand, while only 2.5% of the treated in Italy declare to be severely hampered by a chronic physical or mental problem in their daily activities (dchronsev), the percentage is 16.7% in the Netherlands.

5. Results

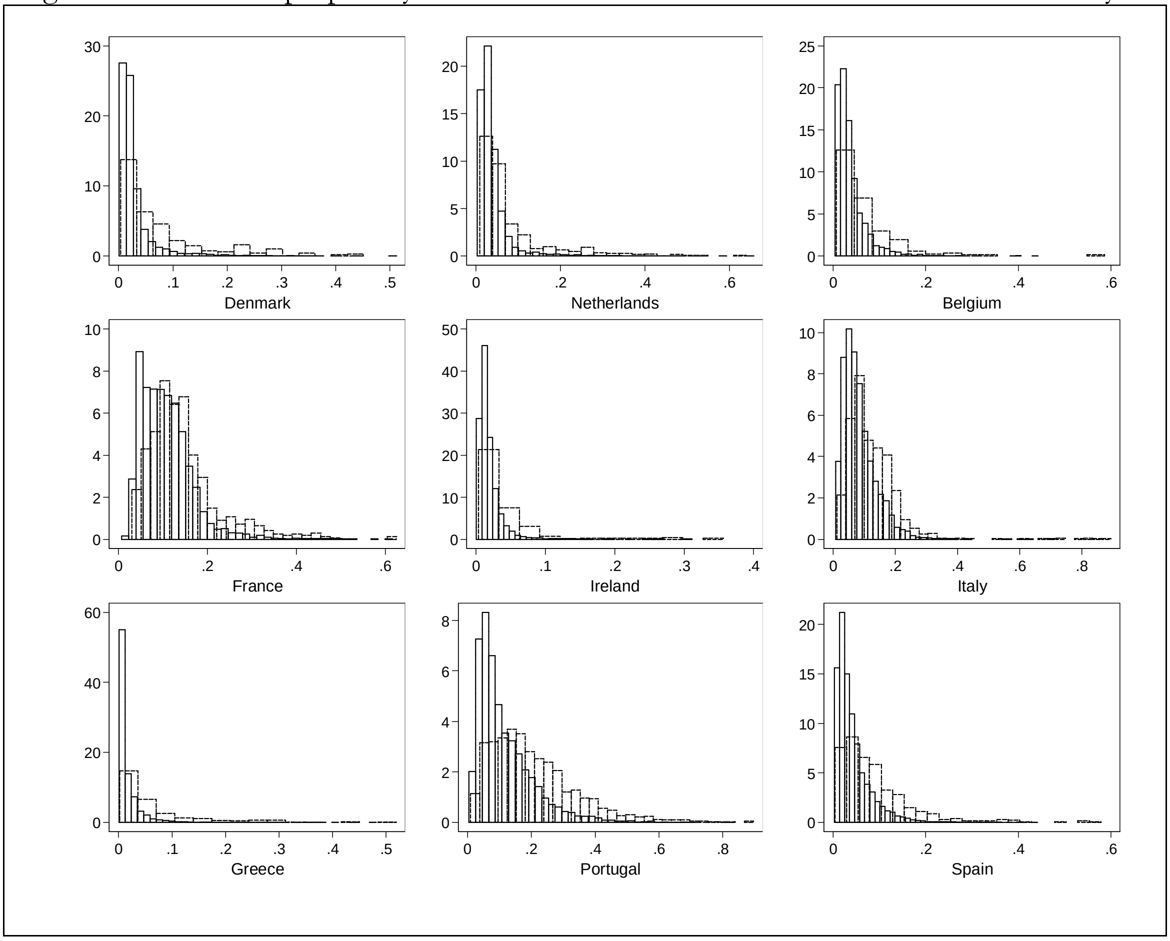
We construct the propensity score for suffering a health transition using a probit model in which the probability of belonging to the treated group is a flexible function of the following pre-treatment characteristics: age, gender, marital status, the logarithm of the household equivalent income, the number of children in the household, the percentage of total household income that comes from the individual's labour income, whether she works full-time, more than 10 years in the same firm, in the public sector, self-employed, the number of days lost because of illness in the last month, if she is severely limited by any chronic condition, limited by any illness, limited in daily activities by any illness or mental problem, indicators of health care utilisation and indicators of year. The propensity score estimates for each country are shown in Table A1.2 in the Appendix.

We have used a different specification for each country, ensuring in all cases the satisfaction of the balancing hypothesis. To test the latter, we have followed Dehejia and Wahba (1999, 2002). In particular, the observations are divided into strata until there are no statistically significant differences within strata in the mean estimated propensity scores between treated and controls. Subsequently, the null hypothesis of no significant differences in the means of each covariate between treated and controls is tested within each stratum.

Figure 1.2 presents histograms of the estimated propensity score for both treated and control individuals for each country. The distribution of scores among treated and controls in each country does not differ, giving support to the conditional independence assumption. In fact, when I restrict the sample to the common support I lose only a small percentage of individuals from the control group (from 0.23% in Portugal to 3.38% in

Denmark or 8.52% in Greece). In any event, all the estimates shown are obtained under the common support.

Figure 1.2 Estimated propensity score for treated and control individuals in each country



Note: ___ Treated --- Control

Effects on labour outcomes

Table 1.2 presents the nearest neighbour estimates of the ATET on the probability of employment, unemployment, inactivity, retirement, and a combined category of either retirement or inactivity. Although in most of the countries included in the analysis, individuals are not entitled to old-age retirement benefits before the age of 60, we have included this outcome because, as has been previously noted in the literature, retirement is not a well-defined state (Bardasi et al, 2002; Disney et al, 1994) and some individuals classify themselves as retired when they have permanently exited from the labour market, while others do so only if they receive a pension. Moreover, there can be cultural differences across countries, reinforced by the different routes available into retirement. For the sake of robustness analysis, we have estimated the same ATETs using a Gaussian kernel (reported in Table A1.3 in the Appendix) and the results are qualitatively indistinct from the ones obtained using nearest neighbour matching.

Table 1.2. Nearest neighbour ATET on the probability of several activity statuses

Country (#Treated, #Control)	Employment	Unemployment	Inactivity	Retirement	Retired+Inactive
Denmark (229, 207)	-0.0786 (0.0232)	0.0437 (0.0150)	0.0262 (0.0106)	0.0218 (0.0097)	0.0480 (0.0142)
Netherlands (476, 439)	-0.0756 (0.0163)	0.0315 (0.0101)	0.0126 (0.0060)	0.0000 (0.0000)	0.0126 (0.0060)
Belgium (226, 210)	-0.0221 (0.0186)	0.0000 (0.0131)	0.0177 (0.0088)	0.0088 (0.0062)	0.0265 (0.0107)
France (798, 704)	-0.0163 (0.0111)	0.0113 (0.0081)	0.0013 (0.0013)	0.0025 (0.0055)	0.0038 (0.0056)
Ireland (155, 152)	-0.0774 (0.0320)	0.0000 (0.0093)	0.0516 (0.0209)	0.0065 (0.0113)	0.0581 (0.0235)
Italy (1236, 1119)	-0.0016 (0.0085)	0.0000 (0.0045)	0.0040 (0.0031)	-0.0049 (0.0054)	-0.0008 (0.0062)
Greece (228, 216)	-0.0219 (0.0281)	0.0044 (0.0162)	0.0000 (0.0119)	0.0000 (0.0143)	0.0000 (0.0185)
Portugal (1441, 1200)	-0.0229 (0.0076)	0.0042 (0.0051)	0.0083 (0.0027)	0.0028 (0.0030)	0.0111 (0.0040)
Spain (556, 518)	-0.0306 (0.0165)	-0.0162 (0.0112)	0.0540 (0.0103)	-0.0018 (0.0020)	0.0522 (0.0105)

Note: Analytical standard errors in parentheses.

Table 1.2 shows that in most of the countries considered here, individuals who suffer a health shock are significantly more likely to transit to a non-employment status than those who do not. Ireland is among the countries in which the drop in the probability of remaining in employment is relatively high. This is consistent with the institutional feature mentioned in Section 2: disability benefits are not compatible with any kind of work. Therefore, individuals in Ireland who suffer even a partial disability are forced to leave the labour market in order to get any benefit from social security. This hypothesis is reinforced by the fact that the top six incapacity codes reported by individuals with any kind of disability benefits in Ireland are back/neck/rib/disc injury, anxiety/depression, other incapacity, arthritis/rheumatism/osteo-arthritis, nervous debility/bereavement, and hypertension (Department of Social and Family Affairs, 2003).

The other two countries where the effect is among the highest are Denmark and the Netherlands. They share with Ireland the non-existence of a quota regulation. This partly explains why in these two countries the drop in the chances of remaining in employment after a health shock is, like Ireland, relatively high. However, a concomitant factor is the fact that compensation policies in both Denmark and the Netherlands are among the most generous across Europe (OECD, 2003). Also, the comprehensiveness of integration policies is among the highest within the countries considered here. If individuals with a health shock can receive generous unemployment benefits in these two countries, they will tend to exit employment after a health shock, but if there are good integration policies they will not leave the labour market, unlike in Ireland, where they seem to remain in unemployment instead. However, another possible explanation comes through the unemployment replacement rate, as in Denmark and the Netherlands this is the highest. In order to disentangle whether the incentives come from the integration policies or the generosity of unemployment benefits (or both), I would need to be able to follow individuals through time to see whether they go back to work or transit to inactivity once the unemployment benefits expire. Unfortunately, the data at hand does not allow us to maintain a sample size large enough to perform this analysis.

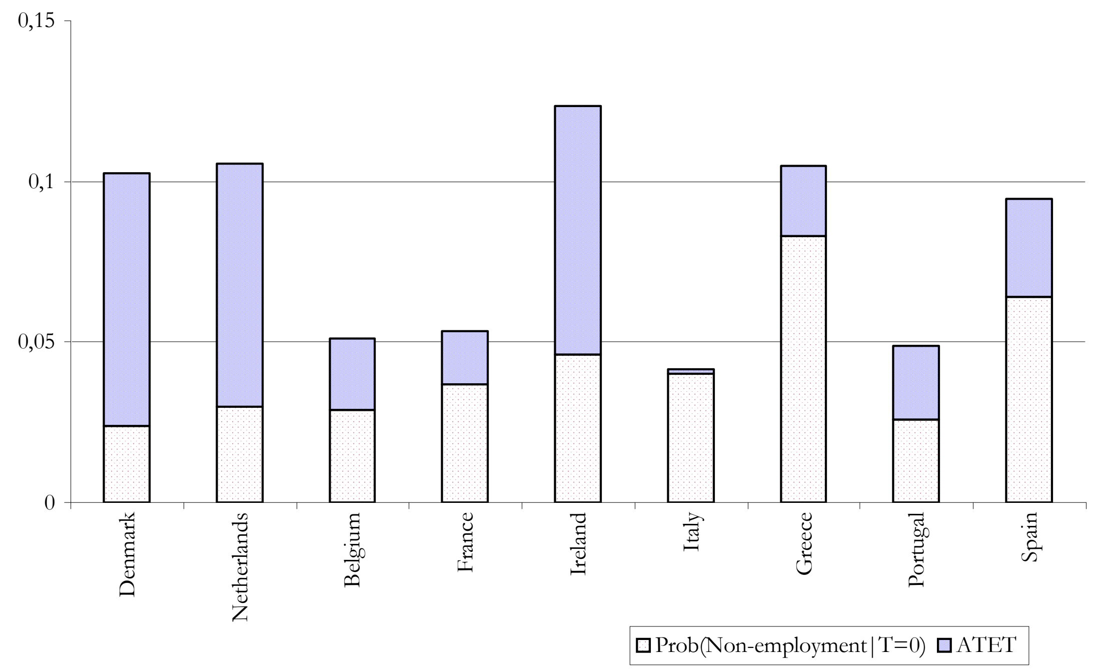
In Portugal and Spain, the estimates show that the reduction in the likelihood of employment, which is smaller than the corresponding figures for Ireland, Denmark and the Netherlands, is paralleled by an increase in the probability of entering inactivity. In France, Italy, Greece and Belgium, the estimated ATET is not statistically significant. However, in the case of Belgium, there is a significant increase in the ATET for the chances of reporting inactivity. In the cases of Italy and France, this may reflect the existence of mandatory employment quotas for disabled workers. These two countries have the highest quotas for disabled people in firms' workforce (7% in Italy and 6% in France). So this evidence is consistent with the perception that in countries in which the quotas are higher, individuals who become disabled are more likely to keep their jobs (OECD, 2003). Moreover, France is an exception as a country in which special employment programmes for people with disabilities seem to make an important contribution to the employment of severely disabled people and people with intellectual and mental disabilities.

The estimates do not suggest any impact for the possibility of early retirement before 60, because in only one of the countries where this is possible are the ATET estimates for entering retirement significant. The significant ATET for Denmark is consistent with the previously discussed arrangement whereby individuals can claim retirement benefits on grounds of an adverse social situation.

How important are these effects?

I have found that the size of the ATET estimates for the probability of being in employment varies from almost zero in Italy to –0.079 in Denmark. However, in order to gauge the relative importance of these effects, it is useful to compare them with the probability of non-employment that these individuals would have faced had they not suffered a health shock. This is shown in Figure 1.3. The figure shows that the relative magnitude of the effects of a health shock is not trivial, as in most cases it more than doubles the chances of leaving the labour market. Moreover, Figure 1.3 does not suggest a clear association between the probability of leaving the labour market for the matched non-treated and the estimated ATET. For example, the estimated ATET is similar in Denmark and Ireland, but while in Denmark the probability of leaving the labour market without having had a health shock is the smallest, in Ireland it is among the largest. Thus, in relative terms, Denmark is where the effect is largest.

Figure 1.3. Probability of non-employment for treated individuals if they had not suffered a health shock and estimated ATET



Note: Prob(non-employment|T=0) is the mean of prob(non-employment) at *t*=3 for matched control individuals. The ATET is the corresponding effect on the probability of being non-employed for treated individuals estimated by nearest neighbour matching.

Income security

Table 1.3 presents the nearest neighbour estimates of the ATET on different sources of income[3]. The results suggest that income seems to be insured against a health shock in most of the countries. Nevertheless, having a health shock significantly reduces household income in the case of Portugal and Spain.

[3] It should be noted that in the ECHP income data refers to the year prior to the date of the survey, therefore the sample size used to calculate these estimates is reduced, as we cannot use the data from the last wave of the survey.

Table 1.3 matching estimates of the ATET on different income measures

	Personal			Household		
	Total	Labour	Social transfers	Total	Labour	Social transfers
Denmark (166, 157)	-465.01 (749.14)	-745.39 (810.51)	297.18 (370.45)	-252.14 (675.60)	-384.20 (732.67)	299.47 (301.39)
Netherlands (347, 328)	715.75 (811.01)	44.07 (822.21)	633.22 (185.38)	304.13 (676.86)	-21.57 (706.31)	690.46 (159.98)
Belgium (195, 186)	-1339.98 (1071.47)	-1495.50 (1035.81)	655.97 (346.97)	-129.16 (1014.35)	-551.67 (738.25)	844.08 (744.56)
France (592, 533)	-915.65 (723.93)	-579.48 (673.61)	-200.67 (238.83)	-471.29 (653.00)	-633.50 (519.30)	15.18 (198.12)
Ireland (99, 95)	-589.85 (1813.80)	-694.19 (1684.68)	219.12 (308.50)	-60.52 (1235.46)	-470.03 (1190.35)	-80.03 (278.53)
Italy (950, 858)	-105.90 (520.72)	-479.35 (440.08)	78.30 (110.32)	210.19 (371.19)	239.94 (332.57)	-147.55 (113.82)
Greece (175, 171)	-45.79 (1213.66)	-62.28 (1185.54)	240.77 (173.83)	-344.45 (655.38)	-462.75 (616.74)	134.05 (185.60)
Portugal (1065, 904)	-587.46 (385.90)	-890.35 (311.49)	127.94 (78.72)	-524.69 (318.23)	-544.90 (255.15)	-76.12 (123.22)
Spain (390, 365)	-950.81 (762.15)	-1405.06 (755.20)	563.52 (206.49)	-897.68 (484.18)	-1399.48 (471.05)	450.49 (168.91)

Notes: Analytical standard errors in parentheses.
Income is annual € adjusted for PPP at 1994 prices. Household income is equivalised.

Heterogeneous effects

It has been argued (OECD, 2003) that educational attainment plays an important role in the incidence of disability, as it is considerably more prevalent among individuals with low educational attainments. In addition, individuals from different educational groups could respond differently to a health shock. It is useful to check (when the sample sizes allow) whether the results discussed above differ across educational groups.

The results show that although the probability of belonging to the treated group depends on educational attainment[4], as expected, the ATETs on the probability of the different

[4] The results of the propensity score estimates (Table A1.2 in the Appendix) show that educational attainment is negatively associated with the probability of belonging to the treated group in all the countries except Denmark and Ireland.

outcomes do not differ, as shown in Table A1.4 in the Appendix. This evidence suggests that, for labour outcomes, the ATETs are homogeneous across educational groups. We have carried out a similar test for gender, and the results shown in Table A1.5 in the Appendix again suggest homogeneous effects, despite the fact that the probability of belonging to the treatment group is higher for females, as can be seen in Table A1.2 in the Appendix.

Sensitivity analysis

As mentioned in Section 3, we have tested for any significant treatment effect in any of the pre-treatment outcomes. The results are shown in Table 1.4 below, which shows that the null hypothesis of no effect cannot be rejected for any of the pre-treatment outcomes in any of the countries studied. This provides evidence in favour of the conditional independence assumption that we have maintained throughout the analysis.

Table 1.4. ATET estimates on pre-treatment outcomes

	Personal income			Household income		
Country (#Treated, #Control)	Total	Labour	Social transfers	Total	Labour	Social transfers
Denmark	-584.59	-730.21	192.65	707.65	397.21	153.36
(229, 207)	(594.56)	(610.30)	(234.93)	(622.74)	(573.98)	(355.85)
Netherlands	-322.30	-382.92	47.81	-481.89	-162.92	-208.37
(476, 439)	(632.87)	(621.16)	(132.67)	(683.27)	(555.10)	(469.89)
Belgium	-1661.40	-632.60	-590.56	-648.66	-277.43	163.24
(226, 210)	(1286.46)	(1233.48)	(377.97)	(878.10)	(741.76)	(499.90)
France	181.84	228.06	38.63	209.14	194.69	131.38
(798, 704)	(621.15)	(592.61)	(122.45)	(456.69)	(518.28)	(105.32)
Ireland	822.59	602.11	-18.16	-120.89	-462.07	43.61
(155, 152)	(1187.89)	(1138.30)	(226.40)	(800.11)	(763.17)	(190.72)
Italy	15.16	-7.17	47.72	147.24	198.58	-70.04
(1236, 1119)	(340.77)	(321.80)	(52.29)	(282.24)	(261.95)	(93.05)
Greece	-1008.01	-880.52	-25.89	-511.81	-240.35	-165.76
(228, 216)	(926.20)	(870.82)	(105.89)	(527.27)	(468.31)	(160.62)
Portugal	-278.65	-293.37	7.05	-303.10	-119.62	-127.32
(1441, 1200)	(263.25)	(248.24)	(60.67)	(241.91)	(208.88)	(108.44)
Spain	424.40	263.51	93.01	-177.48	-316.36	78.70
(556, 518)	(605.61)	(592.90)	(65.42)	(428.43)	(422.20)	(105.30)

Notes: Analytical standard errors in parentheses.
Income is annual € adjusted for PPP at 1994 prices. Household income is equivalised.

As a further check on the robustness of the results, I have obtained the ATET of suffering a health shock on income outcomes using the matching combined with difference-in-differences algorithm, as described in Section 3. Recall that, should there be any fixed unobserved heterogeneity in income leading to a violation of the assumption of conditional independence, first-differencing income before and after the shock ($Y_{t=3}$-$Y_{t=1}$) would remove the resulting bias. Table 1.5 below shows the ATET estimates for the difference-in-differences matching. These figures suggest, despite a reduction in significance, changes along the same lines as the figures reported in Table 1.3.

Table 1.5. Matching and diff-in-diff estimates of ATET

	Personal income			Household income		
Country (#Treated, #Control)	Total	Labour	Social transfers	Total	Labour	Social transfers
Denmark (166, 157)	-698.84 (1707.96)	-658.98 (1711.94)	-353.25 (354.04)	-1418.70 (1331.13)	-1206.62 (1200.77)	-90.02 (470.80)
Netherlands (347, 328)	141.34 (930.48)	-133.64 (953.92)	119.57 (193.25)	66.64 (730.32)	108.89 (712.96)	175.50 (183.90)
Belgium (195, 181)	-938.31 (1452.14)	-201.96 (1268.20)	-811.00 (664.21)	102.27 (1524.10)	-778.84 (1190.10)	795.53 (1005.23)
France (592, 533)	10.07 (468.64)	295.52 (414.97)	-164.36 (254.35)	1000.74 (837.32)	514.82 (437.68)	73.50 (198.07)
Ireland (99, 95)	-1888.33 (1751.05)	-2855.50 (1644.72)	61.25 (359.49)	2.86 (1348.49)	-699.43 (1201.90)	-106.15 (292.06)
Italy (950, 858)	-181.59 (576.33)	-71.55 (464.04)	-266.04 (194.09)	197.73 (393.17)	152.25 (310.73)	-211.19 (137.19)
Greece (175, 171)	800.82 (1751.67)	905.12 (1800.17)	95.58 (186.72)	-123.31 (1022.92)	-8.55 (1027.66)	-64.92 (223.87)
Portugal (1065, 880)	397.71 (333.90)	120.38 (246.17)	5.27 (90.79)	54.96 (274.42)	148.57 (220.86)	-118.02 (76.67)
Spain (390, 365)	-2583.35 (1077.59)	-2168.71 (1103.68)	-369.04 (236.79)	-1073.87 (678.78)	-1071.05 (682.83)	-210.55 (177.48)

Notes: Analytical standard errors in parentheses.
Income is annual € adjusted for PPP at 1994 prices. Household income is equivalised.

6. Discussion and conclusion

In this chapter we have obtained evidence suggesting that health shocks have a causal effect on the probability of being in employment in nine European countries. However, the magnitude of the effect differs across countries. There are three countries (France, Italy and Greece) where the point estimate for this effect is not statistically significant. On the other hand, the largest effects exceed 7% in Denmark, the Netherlands and Ireland. In general, the magnitude of these effects is high in relative terms, because the chances of being non-employed are more than double the probability that treated individuals would have faced had they not suffered a health shock.

In one of the countries where the effect of a health shock on the probability of employment is highest, Ireland, individuals who experience a disability cannot even opt to work part-time if they want to be entitled to disability benefits. At the same time, the corresponding effect is not significantly different from zero in France and Italy. These two countries apply the highest mandatory quotas for disabled workers (7% Italy and 6% France). Therefore, the results suggest that the chances of an individual staying in employment after a health shock are affected by the disability policies in his country.

Concerning income adequacy after a health shock, it has been argued (OECD, 2003) that disabled individuals who are employed earn on average as much as non-disabled employed individuals, but they are better off than disabled individuals who do not work. In this context it is unfortunate that some countries have institutional arrangements that are relatively more conducive to withdrawal from the labour force after an individual suffers a health shock. Inevitably not all individuals who suffer a health shock could or should be employed. Many individuals with a short-term health problem may have jobs to return to once they recover from their illness. Other individuals, because of their illness, age or local market characteristics may not be in a position to work. However, these results are consistent with the idea that there are individuals whose incentives to remain in the labour market are affected by social security arrangements in a substantial way.

In addition, these results also point to the fact that a health shock tends to lead to inactivity in countries where the integration dimension of disability policies is lower (Ireland) to a greater extent than in countries that score high in this dimension (Denmark and the Netherlands). However, the transition to unemployment in Denmark and the Netherlands could also be the result of the higher unemployment replacement rate.

These results cast some doubt on the statement by the OECD (2003) to the effect that unemployment systems with long benefit periods are likely to reduce the pressure on disability programmes. In particular the results for Belgium are at odds with this notion. Belgians are entitled to an unlimited period of unemployment benefits, so according to the OECD's stylised fact, we should expect them to transit to unemployment after an adverse health shock. However, the estimates show that health shocks cause transitions to inactivity instead.

The results also show that income seems to be insured in most of the countries studied, except in Portugal and Spain, where equivalised household income is reduced by a health shock. However, in order to fully understand the income effects at the household level, future work should look into how individuals other than the one suffering the shock adjust their labour supply.

The results also show that, except in Denmark (where individuals can claim early retirement on grounds of an adverse social situation), a health shock has no effect on the probability of retirement. This is not an unexpected result in at least two of the four countries, Ireland and Portugal, where individuals need to be unemployed before being able to become early retirees. For these two countries, the significant increases in the probability of reporting inactivity after a health shock duly reflect this institutional feature.

The health status measure used here is based on subjective perceptions, and although the methods used are designed to minimise the problems of endogeneity, justification bias and unobserved heterogeneity, there could be some differences across countries in the objective health change associated with this measure of health shocks. However, these differences cannot completely explain the differences in the estimates across countries. An indirect test of the latter assertion is that there is no association between the proportion of treated individuals who report being hampered and the estimated causal effects. For example, in France and Ireland around 8% of the individuals in the treated group declare to be severely hampered in their daily activities by a chronic physical or mental health problem, illness or disability, but the employment effects discussed earlier are clearly different in these two countries (no effect for France and above 7% in Ireland).

The analysis also identifies lines for future research. Firstly, it would be of interest to analyse transitions from the different non-employment states. The specific aim would consist in testing whether individuals transit from unemployment to inactivity and/or to employment once unemployment benefits expire. Another useful avenue of research, in order to assess the role played by the integration policies across countries, would be to try to analyse differences in the outflow from inactivity after individuals recover from their adverse health episodes.

Notwithstanding these research needs, the results presented in this chapter show that disability policies across Europe generally satisfy their primary goal, i.e., to guarantee that individuals who suffer an adverse health shock do not endure economic hardship. However, more inspiration is needed in order to avoid the adverse employment effects detected in some countries.

Appendix

Table A1.1 Sample size and means of the relevant variables for each of the analysed countries

	Denmark			Netherlands			Belgium			France			Ireland		
	GGG	GBB	Total	GGG	GBB	Total	GGG	GBB	Total	GGG	GBB	Total	GGG	GBB	Total
Sample size															
All sample	94.77	5.23	15,401	93.83	6.17	28,111	93.79	6.21	17,896	86.25	13.75	27,964	95.8	4.2	22,736
Work	75.82	42.36		66.2	40.29		65.41	37.32		66.14	49.19		62.14	29.21	
<=59	96.33	3.67	12,898	95.41	4.59	23,650	95.64	4.36	14,726	89.15	10.85	23,812	97.34	2.66	18,654
Work	85.92	67.09		75.04	58.66		76.53	62.46		74.23	71.51		70.23	45.56	
if work at t=1	96.76	3.24	10,529	95.96	4.04	16,524	96.13	3.87	10,713	88.96	11.04	16,464	97.84	2.16	11,749
if work at=1 & t=2	96.95	3.05	9,974	96.11	3.89	15,741	96.22	3.78	10,366	89.12	10.88	15,611	98.18	1.82	10,944
Means															
hincome (t=1)	15,714.19	15,332.28		15,029.99	13,932.19		17,435.59	16,772.34		15,270.11	14,730.01		15,397.13	13,904.32	
Married (t=1)	0.590	0.655		0.666	0.658		0.713	0.668		0.615	0.667		0.612	0.698	
Never married (t=1)	0.316	0.204		0.276	0.221		0.205	0.171		0.313	0.220		0.364	0.251	
Widow (t=1)	0.009	0.013		0.004	0.007		0.008	0.013		0.011	0.016		0.006	0.005	
Sep/div (t=1)	0.084	0.128		0.054	0.114		0.074	0.148		0.061	0.097		0.018	0.045	
Isced2 (t=1)	0.088	0.158		0.186	0.237		0.097	0.162		0.231	0.309		0.209	0.302	
Isced3 (t=1)	0.382	0.395		0.527	0.551		0.370	0.413		0.432	0.412		0.480	0.472	
Isced7 (t=1)	0.530	0.447		0.287	0.212		0.533	0.426		0.338	0.278		0.312	0.226	
age (t=1)	38.618	42.632		37.922	40.900		37.566	40.648		37.026	40.768		36.055	41.025	
male (t=1)	0.546	0.474		0.630	0.518		0.570	0.490		0.574	0.554		0.643	0.628	
hh_size (t=1)	3.005	2.918		3.022	2.920		3.365	3.125		3.236	3.239		4.231	4.106	
children (t=1)	0.893	0.809		0.843	0.719		1.024	0.883		0.925	0.920		1.236	1.201	
full_time (t=1)	0.928	0.884		0.822	0.753		0.892	0.889		0.918	0.907		0.896	0.858	
start_working (t=1)	18.553	17.670		19.758	19.295		20.784	20.037		19.383	18.673		18.143	17.177	
public (t=1)	0.385	0.399		0.269	0.283		0.333	0.387		0.324	0.336		0.275	0.279	
number workers (t=1)	4.369	3.833		5.063	5.022		4.539	4.389		4.077	4.003		3.654	3.584	
inpaten (t=1)	0.047	0.095		0.035	0.049		0.061	0.110		0.041	0.061		0.051	0.095	
hospnight (t=1)	0.246	1.401		0.156	0.225		0.290	1.065		0.194	0.313		0.248	0.716	
dchronsev (t=1)	0.001	0.007		0.003	0.028		0.002	0.018		0.003	0.017		0.002	0.032	
dchronsome(t=1)	0.054	0.277		0.028	0.133		0.025	0.090		0.023	0.052		0.017	0.086	
inpaten (t=3)	0.052	0.145		0.037	0.103		0.060	0.207		0.040	0.138		0.051	0.261	

	Denmark			Netherlands			Belgium			France			Ireland		
	GGG	GBB	Total	GGG	GBB	Total	GGG	GBB	Total	GGG	GBB	Total	GGG	GBB	Total
hospnight (t=3)	0.268	0.668		0.163	0.824		0.291	2.676		0.165	1.284		0.247	1.980	
dchronsev (t=3)	0.002	0.099		0.005	0.167		0.002	0.069		0.003	0.077		0.002	0.080	
dchronsome(t=3)	0.052	0.447		0.031	0.452		0.023	0.182		0.024	0.192		0.019	0.412	
work (t=3)	0.967	0.885		0.975	0.897		0.978	0.944		0.962	0.945		0.961	0.889	
inactive (t=3)	0.32	2.960		0.19	1.47		0.14	1.28		0.14	0.41		0.13	5.53	
unemployed (t=3)	1.79	5.260		0.67	4.41		1.13	2.3		2.16	3.3		1.64	1.01	

Table A1.1. (cont)

	Italy			Greece			Spain			Portugal		
	GGG	GBB	Total	GGG	GBB	Total	GGG	GBB	Total	GGG	GBB	Total
Sample size												
All sample	88.54	11.46	41,719	93.87	6.13	35,044	91.88	8.12	37,910	82.84	17.16	22,917
Work	56.4	40.3		61.58	19.75		55.71	28.15		76.19	58.27	
<=59	91.67	8.33	37,556	97.61	2.39	29,119	95.43	4.57	32,806	86.99	13.01	20,777
Work	59.16	56.71		67.72	46.76		60.29	52.5		77.48	71.63	
if work at t=1	91.28	8.72	20,634	97.98	2.02	18,869	96	4.48	17,444	86.65	13.35	14,842
if work at=1 & t=2	91.43	8.57	19,360	98.27	1.73	17,580	95.64	4.00	15,830	87.24	12.76	14,194
Means												
hincome (t=1)	12,508.95	11,781.37		9,425.26	7,730.32		11,625.71	10,312.60		9,143.58	7,554.98	
Married (t=1)	0.641	0.802		0.720	0.807		0.641	0.774		0.634	0.753	
Never married (t=1)	0.332	0.165		0.250	0.105		0.326	0.178		0.328	0.186	
Widow (t=1)	0.003	0.008		0.009	0.052		0.008	0.014		0.007	0.023	
Sep/div (t=1)	0.023	0.026		0.020	0.036		0.025	0.033		0.031	0.039	
Isced2 (t=1)	0.328	0.437		0.324	0.639		0.335	0.546		0.667	0.815	
Isced3 (t=1)	0.535	0.470		0.353	0.210		0.249	0.186		0.189	0.117	
Isced7 (t=1)	0.137	0.094		0.323	0.151		0.416	0.268		0.144	0.068	
age (t=1)	36.090	41.222		37.687	45.682		35.971	42.259		33.390	40.094	
male (t=1)	0.654	0.623		0.661	0.600		0.674	0.651		0.628	0.559	
hh_size (t=1)	3.601	3.638		3.789	3.679		3.745	3.900		3.997	3.970	
children (t=1)	0.714	0.769		0.920	0.672		0.779	0.832		0.926	0.924	
full_time (t=1)	0.940	0.928		0.948	0.931		0.940	0.935		0.972	0.956	
start_working (t=1)	21.122	20.738		21.404	20.724		18.655	17.433		17.961	17.322	
public (t=1)	0.278	0.306		0.240	0.205		0.219	0.217		0.215	0.212	
number workers (t=1)	3.414	3.439		2.449	2.151		3.609	3.382		3.341	3.134	

	Italy			Greece			Spain			Portugal		
	GGG	GBB	Total	GGG	GBB	Total	GGG	GBB	Total	GGG	GBB	Total
inpaten (t=1)	0.034	0.057		0.017	0.083		0.037	0.093		0.016	0.027	
hospnight (t=1)	0.246	0.645		0.131	1.327		0.188	0.619		0.153	0.236	
dchronsev (t=1)	0.000	0.011		0.000	0.026		0.001	0.005		0.001	0.002	
dchronsome(t=1)	0.009	0.025		0.005	0.032		0.007	0.037		0.004	0.022	
inpaten (t=3)	0.035	0.128		0.018	0.151		0.038	0.170		0.015	0.054	
hospnight (t=3)	0.295	1.393		0.134	2.695		0.200	1.993		0.112	0.605	
dchronsev (t=3)	0.000	0.025		0.001	0.134		0.001	0.055		0.000	0.054	
dchronsome(t=3)	0.006	0.077		0.007	0.380		0.007	0.159		0.002	0.146	
work (t=3)	0.961	0.953		0.955	0.895		0.945	0.904		0.972	0.943	
inactive (t=3)	0.4	1.02		0.21	1.31		0.2	4.78		0.15	1.27	
unemployed (t=3)	1.67	1.21		2.16	3.16		3.96	3.33		1.52	2.21	

Note: GGG (health status: good, good, good)
GBB (health status: good, bad, bad)

Table A1.2. Propensity score estimates (probit models)

	Denmark		Netherlands		Belgium		France		Ireland		Italy		Greece		Portugal		Spain	
Variables	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
dF16_24	-0.21	0.26	-0.47	0.22			-0.55	0.22	-0.68	0.33	-0.27	0.15	-0.90	0.28	-1.30	0.16	-0.11	0.17
dF25_34	-0.45	0.22	-0.64	0.19			-0.65	0.19	-0.55	0.30	-0.27	0.11	-0.94	0.21	-0.94	0.15	-0.24	0.14
dF35_44	-0.27	0.21	-0.41	0.19			-0.44	0.18	-0.39	0.29	-0.11	0.11	-0.49	0.14	-0.62	0.15	0.20	0.13
dF45_54	-0.04	0.20	-0.36	0.19			-0.23	0.18	-0.39	0.29	0.22	0.11	-0.21	0.14	-0.16	0.15	0.54	0.14
dM16_24	-1.02	0.40	-0.96	0.25			-0.84	0.23	-0.75	0.32	0.49	0.16	0.46	0.18	-1.37	0.16	0.78	0.21
dM25_34	-0.41	0.23	-0.79	0.19			-0.76	0.19	-0.60	0.30	-0.60	0.14	-0.98	0.26	-1.08	0.15	-0.61	0.17
dM35_44	-0.19	0.21	-0.66	0.19			-0.37	0.18	-0.32	0.29	-0.34	0.10	-0.69	0.15	-0.73	0.15	-0.15	0.07
dM45_54	-0.06	0.20	-0.45	0.19			-0.12	0.18	-0.22	0.29	-0.23	0.10	-0.59	0.13	-0.45	0.15	0.32	0.14
dM55_60	0.31	0.23	-0.33	0.22			0.31	0.22	-0.10	0.31	0.12	0.10	-0.23	0.11	-0.29	0.17	0.53	0.15
age					0.03	0.03												
age^2					0.00	0.00												
male					-0.26	0.08												
married	0.20	0.33	-0.09	0.28	-0.22	0.25	0.05	0.16	0.16	0.42	-0.17	0.21	-0.72	0.16	-0.11	0.14	0.21	0.22
nvrmar	0.21	0.34	-0.09	0.29	-0.09	0.27	-0.04	0.17	0.23	0.42	-0.39	0.22	-0.65	0.19	-0.17	0.15	0.17	0.22
nvrmar*female											0.03	0.09						
sepdiv	0.27	0.34	0.10	0.29	0.03	0.27	0.14	0.17	0.27	0.46	-0.22	0.23	-0.49	0.25	-0.13	0.16	0.17	0.25
sepdiv*children													0.30	0.18				
isced3	0.15	0.23	-0.10	0.06	-0.21	0.10	-0.12	0.05	-0.02	0.09	-0.15	0.04	-0.29	0.08	-0.14	0.05	-0.26	0.06
isced7	-0.15	0.11	-0.20	0.07	-0.37	0.11	-0.12	0.07	-0.10	0.12			-0.43	0.09	-0.40	0.07	-0.29	0.06
isced7*female											-0.21	0.08						
isced7*male											-0.32	0.08						
lhincome	-0.21	0.08	-0.14	0.05	-0.06	0.08	-0.05	0.05	-0.08	0.08	-0.08	0.03	-0.10	0.05	-0.27	-0.03	-0.10	0.03
nch04	-0.07	0.10	-0.02	0.05	0.00	0.07	0.08	0.05	-0.07	0.08	0.01	0.04	-0.08	0.10	-0.05	0.05		
nch511	-0.01	0.05	-0.04	0.04	-0.08	0.05	0.12	0.03	-0.01	0.05	0.03	0.03	-0.06	0.06	-0.04	0.03	0.06	0.04
nch04*female	0.18	0.14					0.04	0.09					-0.18	0.24	0.02	0.08	0.09	0.09
nch04*male																	0.01	0.06
full_time	0.07	0.15	0.00	0.07	0.08	0.11	0.11	0.08	-0.04	0.12	-0.05	0.07	0.04	0.15	-0.11	0.09	0.05	0.10
startworkig	-0.02	0.01	0.00	0.00	0.00	0.01	0.00	0.01	-0.03	0.01	-0.01	0.00	0.00	0.00	-0.01	0.00	-0.01	0.00
dpublic	0.01	0.07	-0.05	0.05	0.15	0.07	0.01	0.05	0.00	0.09	0.02	0.04	0.11	0.09	0.12	0.04	0.04	0.06
selfemploy	0.26	0.19	0.13	0.11	0.07	0.11	-0.04	0.11	0.02	0.10	-0.07	0.04	-0.01	0.07	-0.08	0.04	-0.01	0.05
selfemploy*male	-0.10	0.24	-0.03	0.06														
perc_renta	-0.34	0.10	0.01	0.01	0.07	0.09	-0.19	0.05	-0.14	0.07	0.01	0.03	-0.01	0.05	-0.09	0.03		
perc_renta*M2544																	0.01	0.08

	Denmark		Netherlands		Belgium		France		Ireland		Italy		Greece		Portugal		Spain	
Variables	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
perc_renta*male																	-0.07	0.05
perc_renta*female																	-0.16	0.08
absence	0.01	0.01			0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00	0.01			0.01	0.01
absence*male															-0.02	0.01		
absence*female															-0.01	0.01		
absence*inpaten															0.01	0.02		
fulltime*illness	-0.30	0.22																
hospnight			0.00	0.01	0.02	0.01	0.00	0.01	0.02	0.01	0.01	0.00	0.01	0.01			0.01	0.01
hospnight*male	0.02	0.02													0.01	0.01		
hospnight*female	0.02	0.01													0.00	0.01		
dchronsev	-0.38	0.54	0.33	0.20	0.61	0.43	0.42	0.28	0.20	0.42	1.26	0.37	0.73	0.43	-0.66	0.58	-0.09	0.53
dchronsev*male					-0.66	0.76												
dchronsev*female							0.07	0.49										
dhamp	0.87	0.09	0.79	0.08	0.59	0.13	0.48	0.13	0.59	0.16	0.47	0.13	1.26	0.28	0.86	0.17	0.88	0.15
dhamp*female							0.00	0.22										
dhamp*male													-0.62	0.35				
illness	0.19	0.09	0.11	0.09	0.16	0.14			0.14	0.16	0.17	0.17	0.40	0.23	0.66	0.17	0.08	0.12
illness*male											0.08	0.21						
illness~*age1624	0.91	0.47																
illness*M1624			-0.22	0.56														
mentalprob	0.24	0.29	0.38	0.14	0.05	0.36					-0.16	0.56			0.55	0.13	0.12	0.43
spec	0.17	0.07	0.27	0.05	0.25	0.07			0.25	0.09			0.20	0.07	0.18	0.04	0.24	0.05
spec*male											0.25	0.05						
spec*female											0.12	0.05						
inpaten	0.06	0.25	-0.08	0.12	-0.02	0.14	0.20	0.10	-0.63	0.30	0.14	0.08	0.54	0.16	0.27	0.13	0.24	0.11
inpaten*nevermar	-0.27	0.27																
inpaten*female	0.18	0.28							0.90	0.32								
inpaten*hamp													-0.60	0.72				
dwave2	0.05	0.10			-0.12	0.19	-0.11	0.06	0.12	0.11	-0.04	0.05	-0.12	0.09	-0.10	0.05	-0.10	0.07
dwave3			0.14	0.07	-0.06	0.19												
dwave4	0.11	0.10	0.10	0.07	-0.17	0.20	-0.06	0.06	0.16	0.11	0.02	0.05	-0.09	0.09	-0.04	0.05	-0.14	0.07
dwave5	0.03	0.10	0.24	0.07	-0.19	0.20	-0.05	0.07	0.17	0.11	0.00	0.05	0.19	0.09	-0.16	0.05	-0.09	0.07
dwave6	0.07	0.10	0.05	0.07			-0.01	0.06	0.10	0.12	-0.19	0.05	-0.21	0.10	-0.12	0.05	-0.04	0.06
_cons	0.59	0.86	0.17	0.63	-1.86	1.05	-0.20	0.51	-0.49	0.93	-0.06	0.36	0.04	0.51	2.63	0.33	-0.72	0.36

	Denmark		Netherlands		Belgium		France		Ireland		Italy		Greece		Portugal		Spain	
Variables	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
N	7796		12064		6086		7271		8236		14326		13758		11449		12607	
Log-likelihood	-913.09		-1836.52		-896.99		-2389.81		-718.06		-3952.85		-985.27		-3877.71		-2070.93	

Table A1.3. ATET estimates using Gaussian kernel matching

	Labour outcomes					Personal income			Household income		
	Employed	Unemployed	Inactive	Retired	Retired+Inactive	Total	Labour	Social transfers	Total	Labour	Social transfers
Denmark	-0.0932	0.0268	0.0234	0.0212	0.0446	-1042.14	-1636.97	746.25	-867.65	-1221.74	498.86
	(0.0258)	(0.0156)	(0.0109)	(0.0102)	(0.0140)	(488.24)	(532.11)	(340.31)	(367.08)	(418.66)	(259.27)
Netherlands	-0.0667	0.0329	0.0121	-0.0004	0.0117	-898.35	-1522.93	633.32	-219.41	-667.37	658.20
	(0.0156)	(0.0092)	(0.0058)	(0.0002)	(0.0056)	(641.51)	(708.09)	(148.84)	(543.34)	(610.75)	(140.26)
Belgium	-0.0161	0.0058	0.0161	0.0046	0.0207	-1792.17	-2080.49	673.78	-417.84	-848.43	860.20
	(0.0200)	(0.0090)	(0.0085)	(0.0063)	(0.0108)	(639.58)	(638.02)	(276.21)	(852.72)	(504.87)	(725.05)
France	-0.0114	0.0042	0.0009	0.0026	0.0035	-575.71	-671.37	200.35	161.58	-472.55	392.86
	(0.0099)	(0.0069)	(0.0013)	(0.0038)	(0.0039)	(413.68)	(409.78)	(148.53)	(450.84)	(332.30)	(137.03)
Ireland	-0.1301	-0.0081	0.0606	0.0102	0.0708	-2638.62	-3228.88	400.40	-1448.31	-1832.46	-4.73
	(0.0367)	(0.0066)	(0.0204)	(0.0092)	(0.0207)	(1306.16)	(1175.64)	(184.89)	(888.04)	(782.02)	(159.60)
Italy	0.0018	-0.0033	0.0035	0.0045	0.0080	130.28	-400.96	224.65	-167.72	-89.13	-176.66
	(0.0103)	(0.0031)	(0.0025)	(0.0035)	(0.0042)	(364.14)	(266.23)	(86.91)	(256.60)	(231.71)	(82.93)
Greece	-0.1191	0.0116	0.0136	0.0142	0.0278	-835.06	-991.07	301.57	-771.13	-916.12	163.66
	(0.0264)	(0.0112)	(0.0103)	(0.0101)	(0.0133)	(956.62)	(981.45)	(157.54)	(459.27)	(455.50)	(147.43)
Portugal	-0.0342	0.0044	0.0082	0.0031	0.0113	-666.20	-937.16	120.85	-807.29	-818.65	-4.19
	(0.0088)	(0.0043)	(0.0026)	(0.0023)	(0.0034)	(250.03)	(145.57)	(64.08)	(190.28)	(131.77)	(54.03)
Spain	-0.0896	-0.0101	0.0547	-0.0005	0.0543	-1319.65	-1827.19	639.02	-1691.91	-1927.49	283.10
	(0.0178)	(0.0064)	(0.0095)	(0.0002)	(0.0099)	(443.52)	(444.42)	(168.33)	(261.82)	(260.43)	(120.62)

Notes: Bootstrapped standard errors in parentheses.
Income is annual € adjusted for PPP at 1994 prices. Household income is equivalised.

Table A1.4. ATETs by educational status

Country (#treated, #control)	Employed	Unemp.	Inactive	Retired	Retired+ Inactive	Employed	Unemp.	Inactive	Retired	Retired+ Inactive	Employed	Unemp.	Inactive	Retired	Retired+ Inactive
	Isced 2					Isced 3					Isced 7				
Denmark	-0.1481	0.0370	0.0370	0.0000	0.0370	0.0000	0.0538	0.0108	0.0108	0.0215	-0.1468	0.0275	0.0275	0.0367	0.0642
(27,24); (93,87); (100,93)	(0.0883)	(0.0370)	(0.0370)	(0.0000)	(0.0370)	(0.0615)	(0.0324)	(0.0194)	(0.0108)	(0.0221)	(0.0458)	(0.0157)	(0.0157)	(0.0181)	(0.0236)
Netherlands	-0.0783	0.0609	0.0174	0.0000	0.0174	-0.0661	0.0195	0.0156	0.0000	0.0156	0.0481	0.0385	-0.0288	0.0000	-0.0288
(115,109); (257,237); (104,97)	(0.0463)	(0.0256)	(0.0122)	(0.0000)	(0.0122)	(0.0275)	(0.0104)	(0.0097)	(0.0000)	(0.0097)	(0.0477)	(0.0236)	(0.0182)	(0.0000)	(0.0182)
Belgium	-0.1667	-0.0278	0.0833	0.0278	0.1111	0.0111	0.0444	0.0111	0.0000	0.0111	-0.0900	0.0000	0.0000	0.0100	0.0100
(36,31); (90,87); (100,93)	(0.0760)	(0.0360)	(0.0467)	(0.0278)	(0.0531)	(0.0480)	(0.0218)	(0.0111)	(0.0000)	(0.0111)	(0.0454)	(0.0000)	(0.0000)	(0.0100)	(0.0100)
France	0.0404	-0.0257	0.0000	0.0037	0.0037	-0.0366	0.0152	0.0000	0.0000	0.0000	-0.0253	0.0051	0.0051	0.0051	0.0101
(272,234); (328,293); (198,174)	(0.0308)	(0.0188)	(0.0000)	(0.0135)	(0.0135)	(0.0208)	(0.0124)	(0.0000)	(0.0067)	(0.0067)	(0.0286)	(0.0171)	(0.0051)	(0.0051)	(0.0071)
Ireland	-0.1111	0.0000	0.0889	0.0222	0.1111	-0.0395	-0.0263	0.0658	0.0000	0.0658	-0.0882	0.0000	0.0294	0.0000	0.0294
(45,45); (76,73); (34,34)	(0.1042)	(0.0314)	(0.0429)	(0.0222)	(0.0474)	(0.0777)	(0.0196)	(0.0286)	(0.0192)	(0.0341)	(0.0900)	(0.0000)	(0.0294)	(0.0000)	(0.0294)
Italy	0.0441	-0.0077	0.0115	0.0077	0.0192	0.0051	-0.0102	0.0017	-0.0085	-0.0068	0.0160	0.0080	0.0000	0.0000	0.0000
(522,458); (589,538); (125,115)	(0.0326)	(0.0094)	(0.0063)	(0.0099)	(0.0117)	(0.0249)	(0.0062)	(0.0017)	(0.0064)	(0.0066)	(0.0512)	(0.0144)	(0.0000)	(0.0000)	(0.0000)
Greece	0.0000	0.0138	0.0069	0.0069	0.0138	-0.0204	-0.0204	0.0204	0.0204	0.0408	-0.2647	0.0000	0.0000	0.0294	0.0294
(145,136); (49,47); (34,33)	(0.0567)	(0.0200)	(0.0141)	(0.0123)	(0.0186)	(0.1037)	(0.0465)	(0.0204)	(0.0204)	(0.0286)	(0.1107)	(0.0000)	(0.0000)	(0.0512)	(0.0512)
Portugal	-0.0052	0.0026	0.0086	0.0035	0.0121	0.0989	-0.0110	0.0055	0.0000	0.0055	-0.0588	0.0098	0.0098	0.0098	0.0196
(1157,943); (182,167); (102,90)	(0.0215)	(0.0062)	(0.0031)	(0.0032)	(0.0044)	(0.0428)	(0.0132)	(0.0055)	(0.0000)	(0.0055)	(0.0508)	(0.0098)	(0.0098)	(0.0181)	(0.0205)
Spain	-0.0268	0.0067	0.0671	0.0000	0.0671	-0.0288	-0.0288	0.0385	0.0000	0.0385	-0.0325	-0.0195	0.0260	-0.0065	0.0195
(298,275); (104,96); (154,153)	(0.0422)	(0.0157)	(0.0168)	(0.0000)	(0.0168)	(0.0665)	(0.0251)	(0.0189)	(0.0000)	(0.0189)	(0.0446)	(0.0113)	(0.0158)	(0.0066)	(0.0171)

Note: Analytical standard errors in parentheses.

Table A1.5. ATETs by gender

	Employed	Unemployed	Inactive	Retired	Retired+Inactive	Employed	Unemployed	Inactive	Retired	Retired+Inactive
Country (#treated, #control)	Men					Women				
Denmark	0.0190	0.0286	0.0095	0.0000	0.0095	-0.0726	0.0323	0.0403	0.0323	0.0726
(105,94); (124,113)	(0.0585)	(0.0221)	(0.0095)	(0.0150)	(0.0177)	(0.0495)	(0.0261)	(0.0177)	(0.0159)	(0.0234)
Netherlands	-0.0567	0.0202	0.0162	0.0000	0.0162	-0.0611	0.0349	0.0087	0.0000	0.0087
(247,228); (229, 212)	(0.0274)	(0.0124)	(0.0101)	(0.0000)	(0.0101)	(0.0316)	(0.0176)	(0.0062)	(0.0000)	(0.0062)
Belgium	-0.0755	0.0094	0.0000	0.0094	0.0094	-0.0417	0.0000	0.0333	0.0000	0.0333
(106,105); (120,107)	(0.0436)	(0.0164)	(0.0000)	(0.0164)	(0.0164)	(0.0441)	(0.0182)	(0.0165)	(0.0000)	(0.0165)
France	-0.0217	0.0174	0.0022	0.0043	0.0065	-0.0030	-0.0059	0.0000	-0.0030	-0.0030
(460,402); (338,304)	(0.0211)	(0.0105)	(0.0022)	(0.0082)	(0.0085)	(0.0218)	(0.0138)	(0.0000)	(0.0064)	(0.0064)
Ireland	-0.1354	-0.0208	0.0521	0.0104	0.0625	-0.0678	0.0000	0.0847	0.0000	0.0847
(96,92); (59,57)	(0.0693)	(0.0156)	(0.0228)	(0.0184)	(0.0289)	(0.0783)	(0.0246)	(0.0366)	(0.0000)	(0.0366)
Italy	0.0104	-0.0026	0.0039	0.0000	0.0039	-0.0194	0.0086	0.0022	-0.0043	-0.0022
(772,702); (464,422)	(0.0248)	(0.0054)	(0.0038)	(0.0073)	(0.0082)	(0.0280)	(0.0063)	(0.0051)	(0.0074)	(0.0090)
Greece	-0.0362	0.0000	0.0072	-0.0072	0.0000	-0.0333	0.0111	0.0111	0.0000	0.0111
(138,133); (90,81)	(0.0605)	(0.0181)	(0.0165)	(0.0196)	(0.0253)	(0.0777)	(0.0311)	(0.0111)	(0.0240)	(0.0263)
Portugal	-0.0049	0.0012	0.0074	0.0049	0.0123	-0.0351	0.0032	0.0096	0.0064	0.0160
(815,692); (626,501)	(0.0246)	(0.0065)	(0.0036)	(0.0037)	(0.0051)	(0.0272)	(0.0089)	(0.0039)	(0.0032)	(0.0050)
Spain	-0.0325	-0.0190	0.0623	0.0000	0.0623	0.0000	-0.0428	0.0321	0.0000	0.0321
(369,346); (187,177)	(0.0365)	(0.0147)	(0.0143)	(0.0000)	(0.0143)	(0.0478)	(0.0211)	(0.0129)	(0.0000)	(0.0129)

Note: Analytical standard errors in parentheses.

Chapter 2. Health effects on labour market exits and entries

1. Introduction

In many developed countries there is increasing concern about the fiscal implications of an ageing population. This has prompted discussion about potential changes in financial incentives geared towards discouraging early retirement and/or postponing the retirement age. In Spain, for example, the mechanisms implemented in the 2007 reform encourage employees to remain in employment after the retirement age of 65[5]. However, financial incentives may not be sufficient if individuals stop working due to shocks or deteriorations in health. The challenge can be exacerbated when individuals drop out of the labour force at younger ages, as they will not be affected by any of the policies that target individuals approaching retirement.

Most of the previous evidence on health and labour outcomes (Bound et al, 1999; Au et al, 2005; Disney et al, 2006; Hagan et al, 2006; Rice et al, 2006 and Zucchelli et al, 2007) has focused on the role played by health in retirement transitions. These studies show that decreases in health status have explanatory power for retirement decisions. In addition, results in the previous chapter show that the onset of a health shock decreases the probability of employment also for younger individuals, who mainly transit into inactivity. Therefore, the design of labour supply policies aimed at retaining workers within the labour force need to take into account the factors affecting labour supply, other than financial incentives, of younger individuals who have endured a health shock.

Moreover, in order to design integration policies that avoid the previously discussed possible adverse employment effects from disability benefits, more research is needed to understand the importance of health when individuals are deciding to either enter or re-enter the labour market. The limited evidence suggests that individuals with impaired health have longer unemployment spells (Stewart, 2001) and a higher probability of transiting from unemployment to economic inactivity (Böheim and Taylor, 2000).

[5] The pension fund will increase by 2% per full year of work after the age of 65 until the age of 70, and by 3% when the worker has contributed for 40 years.

However, there is a lack of evidence on the relative importance of health as a determinant of transitions into and out of employment.

So, in this chapter we contribute to the existing literature by analysing the effects that a health deterioration has on entries into and exits from employment. This is the first attempt, to the best of our knowledge, to analyse the relative role that health plays as a determinant of these two transitions. We use data from the British Household Panel Survey (BHPS) to analyse the effect that ill health has on exits out of and entries into employment using discrete-time hazard models. We use both psychological and physical measures of health. Moreover, we focus on the working-age population, rather than a more narrowly defined sample of individuals approaching retirement. In addition, we analyse whether individuals from different educational groups respond differently to the onset of a health shock by looking at the existence of heterogeneous effects.

Our empirical findings show that individuals' health is an important determinant for employment transitions, and the effects are greater for men than for women. However, there are some differences depending on the measure of health used. General health, measured by health limitations and a constructed latent health index, has a significant effect on exits from employment and entries into employment. Furthermore, a measure of psychological well-being appears to influence the hazard of becoming non-employed for the stock sample of workers, but it has no significant effect on the hazard of leaving the non-employment status. Surprisingly, the effects are robust to the exclusion of older workers from the sample of analysis.

2. Health and labour market outcomes

The expected relationship between health and labour market outcomes can be illustrated using the health production model (Grossman, 1972). Individuals are assumed to maximise an intertemporal utility function which depends on the stock of health, consumption of other goods, leisure and preferences. Labour supply will depend on the endogenous health variable (Currie and Madrian, 1999). Therefore, poorer health status may reduce the probability of work if it raises the disutility of work or reduces the return to work via lower wages (Disney et al, 2006), or by entitling the individual to disability benefits which would increase the reservation wage and thus the incentive to drop out of the labour market (Blundell et al, 2002).

Currie and Madrian (1999) stress that the empirical evidence suggests the existence of an effect from health to labour market participation, but that there is a lack of consensus on the magnitude of the effect and whether it is important when compared to other variables. Moreover, only a few studies use panel data to control for the presence of unobservable characteristics which influence both health and labour market participation. In addition, Currie and Madrian (1999) also highlight the lack of studies that analyse age groups other than elderly workers, and further, that investigate gender differences in labour market behaviour as a response to health shocks.

When studying the relationship between health and labour outcomes, the literature has traditionally focused on older workers and retirement transitions. Several studies (e.g., Bound et al, 1999; Au et al, 2005; Disney et al, 2006; Hagan et al, 2006 ; Rice et al, 2006; Zucchelli et al, 2007) focus on individuals older than 50 and show that decreases in health status have explanatory power for retirement decisions. Riphahn (1999) finds that health shocks increase the probability of unemployment by 84% and the probability of dropping out of the labour force by 200% for individuals aged 40 to 59 in Germany. Jiménez-Martín et al (2006) find that, for Spanish workers aged between 50 and 64, the probability of carrying on working decreases with the severity of the shock. Smith (2004) also finds that for individuals older than 50 who suffer a health shock there is a 15% decrease in the probability of working and, although this effect diminishes over time, it remains substantially high, at nearly 4% five years after the shock.

The number of studies that focus on the role played by health in labour market transitions for younger individuals is less extensive. Among these, Lindeboom et al (2006) estimate an event history model for transitions between work and disability states and find that the effects of health shocks on employment are not direct, but rather act through the onset of a disability, which increases by 138% after the onset of a health shock. At the same time, the onset of a disability at age 25 reduces the probability of employment at age 40 by 0.205.

Messer and Berger (2004) use the US Health and Retirement Survey and find that permanent adverse health conditions reduce both wages (8.4% for males and 4.2% for females) and hours worked (6.3% for males and 3.9% for females). Moreover, the largest effects of health on labour outcomes are found on prime-age individuals, as the peak of loss of wages after the onset of a permanent illness occurs at ages 40-49 for males (wages are 12.1% lower) and 30-39 for females (wages are 9.2% lower). Dano (2005) finds that there are both short and long-run effects on the probability of being employed for Danish males who have been injured in a road accident, and that this effect holds even when individuals receiving disability benefits are excluded from the analysis. García Gómez and López Nicolás (2006) analyse the effects of a health shock on the probability of leaving employment and transiting to unemployment or inactivity for the Spanish population. They find that suffering a health shock decreases the probability of remaining in employment by 5% and increases the probability of transiting into inactivity by 3.5%. Similar results are also found for other European countries (García-Gómez, 2008).

As stated before, there are very few studies that analyse the effect of ill health on transitions into employment. Stewart (2001) examines Canadian data on the effects of health limitations on the kind and amount of activity that individuals can do at work, and finds that individuals with impaired health have a lower probability of leaving unemployment and thus experience longer unemployment spells. Böheim and Taylor (2000) use calendar data from the first seven waves of the BHPS to analyse transitions from unemployment to part-time work, self-employment and economic inactivity. Their results show that the existence of a health condition that limits the type or amount of work observed before an unemployment spell doubles the exit rate from unemployment into economic inactivity.

So in this chapter we contribute with the analysis of the effects from health to labour market outcomes, looking at both entries into and exits from employment using a homogeneous framework (discrete-time duration models), which will allow us to state the relative importance of health in these two transitions. In addition, we do the analysis separately by gender and allow different measures of health (general or mental) to have different effects.

3. Econometric methods

Employment entries and exits

We are interested in the effect that ill health has on two different labour market transitions: employment entries and exits. We study these transitions separately. Thus, our first sample of interest are those individuals who are working (employed or self-employed) in the first wave of the survey and we follow these until they first become non-employed or are censored[6]. Secondly, we analyse the effect of ill health on leaving a jobless state. We pursue this by selecting two different samples of individuals. We first select the sample of non-working individuals in the first wave of the survey and we follow them until they first find a job or are censored. Next, we select the group of individuals for whom we observe a transition out of work, regardless of their working situation in the first wave of the survey, and follow these individuals until they return to work or are censored.

Duration in a labour market state, s, can be modelled using a hazard function representing the instantaneous probability of leaving the state at time t, conditional on survival in the state until time t. A discrete-time representation of the continuous-time hazard rate can be defined as:

$$h_{it}^{s} = \Pr[T_i = t \mid T_i \geq t, x_{it}] \qquad (2.1)$$

where x_{it} is a vector of covariates that may vary with time, t, and T_i is a discrete random variable representing the time at which the end of the spell occurs.

The sample log-likelihood function of the observed duration data can be simplified by defining a dummy variable $y_{it}=1$ if $t=T_i$ and the individual is non-censored; and $y_{it}=0$ otherwise. Accordingly, for individuals remaining in the labour market state of interest, $y_{it}=0$ for all periods, while for those who exit the state, $y_{it}=0$ for all periods except the period in which the exit occurs, when $y_{it}=1$. The log-likelihood can then be written in a

[6] Censoring occurs if an individual drops out of the survey or remains in the survey but fails to exit employment by the end of the survey period.

form familiar for the analysis of a binary variable y_{it}, where the unit of analysis is the spell period (e.g., Allison, 1982; Jenkins, 1995):

$$\log L = \sum_{i=1}^{n}\sum_{k=1}^{t_i} y_{it} \log\frac{h_{ik}}{1-h_{ik}} + \sum_{i=1}^{n}\sum_{k=1}^{t_i}\log(1-h_{ik}) \tag{2.2}$$

To complete the specification of the likelihood we need to choose the functional form for the hazard rate. We define a complementary log-log hazard rate, as it has the convenient property that it is the discrete counterpart of an underlying continuous-time proportional hazard model (Prentice and Gloecker, 1978) such that:

$$h_{it}=1-\exp\{-\exp[\theta(t)+\beta' X_{it}]\} \tag{2.3}$$

We model the baseline hazard rate ($\theta(t)$) as a step function, by specifying dummy variables to represent each period. This leads to a semi-parametric specification of the discrete-time duration model.

The empirical model presented here assumes that we observe the natural starting point of each episode. This holds for the third sample of individuals analysed, that is, those who we observe leaving employment and are followed until they become employed once again or are censored. But for the two stock samples consisting of either non-workers or workers in the first wave, we cannot assume that we observe the natural starting point for the duration episode. However, Jenkins (1995) shows that conditioning on a stock sample renders the contribution to the likelihood of individuals prior to selection into the sample ignorable. Accordingly, the likelihood can also be simplified to the likelihood suitable for the estimation of a binary response as expressed in (2.2).

Notice that the analysis here is based on a simplified division of the labour market, as it groups together in a single category all individuals in non-employment, regardless of the concerns discussed in the previous literature about the loss of information when non-employed individuals are grouped (Flinn and Heckman, 1983; Tano, 1991; Marzano, 2006).

Models for health

The use of subjective measures of health has been a major cause for concern in the analysis of the causal relationship between health and labour outcomes (Anderson and Burkhauser, 1985; Bazzoli, 1985; Stern, 1989; Bound, 1991; Kerkhofs and Lindeboom, 1995; Bound et al, 1999; Disney et al, 2006). First, individuals with the same level of underlying health may use different thresholds when providing categorical responses to questions on health status (Kerkhofs and Lindeboom, 1995; Lindeboom and van Doorslaer, 2004). Secondly, labour market status can affect health status (García Gómez and López Nicolás, 2006) and moreover, individuals who are not working may report being in worse health, as ill health is a legitimate reason to be out of employment (known as "justification bias").

We deal with the problems of reporting bias in the use of subjective measures of health following the approach suggested by Bound (1991) and implemented by Bound et al (1999), Au et al (2005), Disney et al (2006), and Rice et al (2006). Thus, we use a latent variable approach to predict an objective index of health.

Specifically, we consider the aspect of health that affects an individual's labour market transition, $h_{it}^{'}$, to be a function of a comprehensive set of objective measures of health, z_{it}:

$$h_{it}^{'} = z_{it}\beta + \varepsilon_{it} \qquad \text{i=1,2,…,n ; t=1,2,…T}_i \qquad (2.4)$$

We do not directly observe $h_{it}^{'}$ but instead observe a measure of self-assessed health (SAH), h_{it}^{S}. We can specify the latent counterpart to h_{it}^{S} as h_{it}^{*} such that:

$$h_{it}^{*} = h_{it}^{'} + \eta_{it} \qquad \text{i=1,2,…,n ; t=1,2,…T}_i \qquad (2.5)$$

where η_{it} represents measurement error in the mapping of h_{it}^{*} to $h_{it}^{'}$ and is uncorrelated with $h_{it}^{'}$. Substituting (2.4) into (2.5) gives:

$$h_{it}^{*} = z_{it}\beta + \varepsilon_{it} + \eta_{it} = z_{it}\beta + v_{it} \qquad \text{i=1,2,…,n ; t=1,2,…T}_{\text{i}} \qquad (2.6)$$

Combining (2.6) with the observation mechanism linking the categorical or dichotomous indicator of the categorical self-assessed measure of health to the latent measure of health, and assuming a distributional form for v_{it}, we can estimate the coefficients, β. Thus, if we express the observation mechanism as:

$$h_{it} = j \quad \text{if } \mu_{j-1} < h_{it}^{*} < \mu_{j} \qquad \text{, j=1,…, m} \qquad (2.7)$$

where $\mu_0 = -\infty, \mu_j \leq \mu_{j+1}, \mu_m = \infty$. Assuming v_{it} is normally distributed, and allowing that the threshold parameters, μ_j, depend on socioeconomic factors, model (2.6) can be estimated as a generalised ordered probit using full information maximum likelihood. We estimate separate models by gender and use the predicted values as our variable of health stock.

As an alternative to the predicted health stock we further use a measure of health limitations and a measure of psychological well-being. Both of these variables are described more fully in the next section.

We include in our duration models both initial period health and lagged health, which allows us to interpret the estimated coefficient on lagged health as a deviation from some underlying health stock that is captured through initial health. Moreover, the use of lags has the advantage of reducing fears of endogeneity bias by exploiting the "timing of events", as the change in health occurs before employment transitions are observed.

4. Data

We use the first 12 waves (1991-2002) of the British Household Panel Survey (BHPS). The BHPS is a longitudinal survey of private households in Great Britain designed as an annual survey of each adult (16+) member of a nationally representative sample of more than 5,000 households, with a total of approximately 10,000 individual interviews. The first wave of the survey was conducted between 1 September 1990 and 30 April 1991. The initial selection of households for inclusion in the survey was performed using a two-stage stratified systematic sampling procedure designed to give each address an approximately equal probability of selection. The same individuals are re-interviewed in successive waves and, if they split from their original households, are also re-interviewed along with all adult members of their new household. Moreover, children in the original households are interviewed when they reach the age of 16. Importantly, the BHPS contains a rich set of socioeconomic variables together with information on health status.

The samples

Our first sample of interest is defined by the group of workers in wave 1 who were at risk of becoming non-employed. The sample contains 2,954 men aged 16 to 64 and 2,672 women aged 16 to 59, who had provided a full interview and were in work (defined here as employed or self-employed) in the first wave of the survey. Similarly, we select 1,552 women and 892 men, who were non-workers in the first wave. Lastly, we select the group of individuals for whom we observe a transition out of work. This sample consists of 2,411 women and 1,523 men.

For all three samples our models are estimated on complete sequences of observations such that if an individual leaves the panel but then returns in a later wave, we only use the information up to the first exit wave. Moreover, for the analysis reported here we do not consider second or further spells, so our models focus on the first transition out of work or the first transition into work.

Variables

<u>Labour market status</u>

We use self-reported current economic activity to classify individuals as employed or non-employed. Individuals are classified as employed if they report to be either employed or self-employed. Non-employment covers individuals who report unemployment, retirement, maternity leave, family care duties, being a student, being long-term sick or being on a government training scheme. We also test the sensitivity of our results to the inclusion of being on maternity leave within the employment or the non-employment category.

Health variables

The BHPS includes a number of health and health-related variables. In order to build the stock measure of health discussed in Section 3, we use the five-point SAH variable. A continuity problem arises with this variable because in wave 9 there was a change in the question together with a modification to the available response categories. We follow the method of Hernández-Quevedo et al (2008) and recode SAH into four categories: 1 excellent health, 2 good or very good health, 3 fair health, 4 very poor or poor health. This ensures coverage of the categories of SAH used in both wave 9 and all other waves. The health indicators used to predict SAH are derived from self-reports of specific health problems associated with: arms, legs or hands, sight, hearing, skin conditions or allergies, chest/breathing, heart/blood pressure, stomach or digestion, diabetes, anxiety or depression, alcohol or drugs, epilepsy or migraine, or other. We create a dummy for the presence of each specific problem.

We also use a measure of self-reported functional limitations, based on the question "does your health in any way limit your daily activities compared to most people of your age?"[7]

The BHPS also includes information about mental health, and in particular, we use the General Health Questionnaire (GHQ). The GHQ (Goldberg and Williams, 1988; Bowling, 1991) was developed as a screening instrument for psychiatric illness and is often used as an indicator of psychological well-being (Weich, Lewis and Jenkins, 2001; Wildman, 2003; Jones and López Nicolás, 2004; Hauck and Rice, 2004; García-Gómez and López-Nicolás, 2005). The shortened GHQ includes 12 elements: concentration, sleep loss due to worry, perception of role, capability in decision making, whether constantly under strain, perception of problems in overcoming difficulties, enjoyment of day-to-day activities, ability to face problems, loss of confidence, self-worth, general happiness, and whether suffering depression or unhappiness. Responses are provided on a 4-point scale ranging

[7] This question is not asked in wave 9. In our analysis we assume that wave 8 values hold in wave 9.

from 0 to 3, with 0 being the best score. We use the Likert scale, which sums the individual components (Likert, 1952). This gives an overall scale that runs from 0 to 36, 0 being the best possible state of psychological well-being.

Income and socioeconomic characteristics

The income variable used is the individual specific mean of log equivalent household income[8] for all the periods the individual is observed before the transition, i.e., for the stock sample of workers it is the mean for all the periods the individuals are observed to be working, while for the samples of non-workers it is the mean for all the periods the individuals are observed to be out of employment. We follow this approach in order to minimise endogeneity problems, as labour market transitions are likely to affect disposable income.

Other covariates include age, gender, marital status, educational attainment, ethnicity and regional dummies. We also include variables that indicate the employment skills of the individual in wave 1 for the stock sample of workers, and in the last year before leaving their jobs for the last sample defined in Section 3.

Spousal/partner variables

The evidence on retirement decisions shows that there are complementarities in leisure among spouses (Michaud, 2003; Baker, 2002; Blau, 1997 and 1998), but as far as we know there is little evidence regarding these effects on decisions at younger ages. The health status of a spouse might have effects on an individual's employment transitions, due to caregiving within a household diminishing the probability of employment (Viitanen, 2005; Heitmuller, 2007; Heitmueller and Michaud, 2006; Casado-Marín et al, 2006). To investigate these effects we model the impact of health on labour market transitions separately for men and women. For both we include a variable representing the health status of the individual's spouse or partner (should they have one). For each model the health variable specified for the spouse corresponds to the health variable specified for the individual under analysis. We also include a variable representing whether a spouse or

---

[8] Equivalent household income consists of labour and non-labour equivalised real income, adjusted using the retail price index and equivalised with the McClements scale to adjust for household size and composition.

partner is employed, lagged one period to reduce endogeneity concerns. Variables names and definitions are summarised in Table 2.1.

Table 2.1. Variables names and definitions

Variable	Description
Work	Binary dependent variable, =1 if respondent states they are working, 0 otherwise
Nowork	Binary dependent variable, =1 if respondent states they are not working, 0 otherwise
hlltyes	Self-assessed health limitations: 1 if health limits daily activities, 0 otherwise
ghq	GHQ index
sah	Self-assessed health; 1: excellent, 2: good or very good, 3: fair, 4: very poor or poor
sahvpp	Self-assessed health: 1 if poor or very poor, 0 otherwise
sahfair	Self-assessed health: 1 if fair, 0 otherwise
sahgvg	Self-assessed health: 1 if good or very good, 0 otherwise
sahex	Self-assessed health: 1 if excellent, 0 otherwise
age1519	1 if respondent is aged 15 to 19 (inclusive), 0 otherwise (baseline category)
age20240	1 if respondent is aged 20 to 24 (inclusive), 0 otherwise
age25290	1 if respondent is aged 25 to 29 (inclusive), 0 otherwise
age30340	1 if respondent is aged 30 to 34 (inclusive), 0 otherwise
age35390	1 if respondent is aged 35 to 39 (inclusive), 0 otherwise
age40440	1 if respondent is aged 40 to 44 (inclusive), 0 otherwise
age45490	1 if respondent is aged 45 to 49 (inclusive), 0 otherwise
age50540	1 if respondent is aged 50 to 54 (inclusive), 0 otherwise
age55590	1 if respondent is aged 55 to 59 (inclusive), 0 otherwise
age60640	1 if respondent is aged 60 to 64 (inclusive), 0 otherwise
mlnhinc	Individual-specific mean of log equivalised real household labour and non-labour income
white	1 if respondent's race is white, 0 otherwise
male	1 if respondent is a man, 0 otherwise
marcoup	1 if married or living as a couple, 0 otherwise
divsep	1 if divorced or separated, 0 otherwise
nvrmar	1 if never married, 0 otherwise
widowed	1 if widowed, 0 otherwise (baseline category)
hhsize	Household size
NorthW	1 if respondent resides in North West, Merseyside or Greater Manchester, 0 otherwise
NorthE	1 if respondent resides in North, South Yorkshire, West Yorkshire, North Yorkshire, Humberside or Tyne & Wear, 0 otherwise
SouthE	1 if respondent resides in South East or East Anglia, 0 otherwise
SouthW	1 if respondent resides in South West, 0 otherwise
Midland	1 if respondent resides in East or West Midlands or West Midlands Conurb, 0 otherwise
Scot	1 if respondent resides in Scotland, 0 otherwise
Wales	1 if respondent resides in Wales, 0 otherwise
London	1 if respondent resides in Inner or Outer London, 0 otherwise (baseline category)
deghdeg	1 if highest educational attainment is degree or higher degree, 0 otherwise
hndalev	1 if highest educational attainment is HND or A level, 0 otherwise
ocse	1 if highest educational attainment is O level or CSE, 0 otherwise
noqual	1 if no qualifications, 0 otherwise (baseline category)
prof	1 if present job is professional, 0 otherwise
mantech	1 if present job is managerial or technical, 0 otherwise
Sknonm	1 if present job is skilled non-manual, 0 otherwise
Skmanar	1 if present job is skilled manual or in the armed forces, 0 otherwise
Ptskill	1 if present job is partly skilled, 0 otherwise
Unskill	1 if present job is unskilled, 0 otherwise (baseline category)

5. Results

Descriptive statistics

Descriptive statistics, by employment status, for the different samples of individuals used in our analysis are presented in Table 2.2. While most of the respondents classify themselves as having good or very good health, it is notable that the proportion of individuals reporting bad or very bad health is about 3.5 times higher within the group of non-employed individuals than for the employed, for all of the samples. The same result holds for the proportion of individuals that report being limited by a health condition. Moreover, the psychological health of individuals who work is also greater (lower values of the GHQ index) than for non-workers, although the differences are not so marked as for the general measures of health. Regarding partner's health status, it can be seen that the differences between individuals remaining in employment and those who leave employment are small for the stock sample of workers in wave 1. The differences between the employed and non-employed are more evident in the stock sample of non-workers in wave 1 and the flow sample of individuals who had a transition from employment to non-employment just prior to entering the sample. For the latter, the proportion of partners reporting having a health limitation or bad health is higher for the subsample remaining in non-employment.

There are also differences across employment status for some of the socioeconomic characteristics. Individuals who are non-employed have a slightly lower household income. The samples of non-employed are characterised by fewer men (around 35%) than the sample of employed. Moreover, within each sample the percentage of men in work is higher than the percentage of men out of work. This is due to the greater labour mobility among women. The data shows a slight educational gradient among individuals non-employed in the first wave, and an occupational gradient among individuals employed in wave 1. There appear to be job complementarities among partners, evidenced by the lower proportion of employed partners in the group of non-employed individuals compared to those with employment.

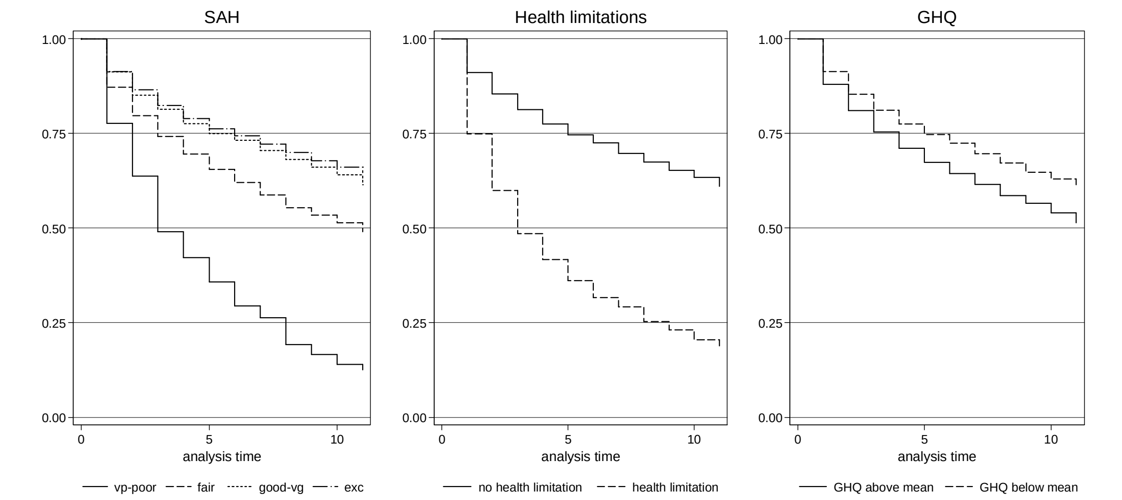
Table 2.2. Descriptive statistics

	IN WORK T=1		OUT OF WORK T=1		LEAVE WORK	
	Work	No work	Work	No work	Work	No work
Own health						
sahvpp	0.040	0.140	0.046	0.194	0.050	0.156
sahfair	0.158	0.197	0.168	0.263	0.190	0.250
sahgvg	0.525	0.441	0.528	0.379	0.520	0.428
sahex	0.277	0.222	0.257	0.164	0.240	0.166
hlltyes	0.061	0.187	0.073	0.328	0.092	0.287
ghq	10.83	12.35	10.48	12.55	10.69	12.20
Socioeconomic characteristics						
mlnhinc	9.880	9.721	9.188	9.142	9.544	9.362
white	0.971	0.969	0.938	0.937	0.959	0.966
male	0.551	0.393	0.370	0.307	0.365	0.346
marcoup	0.795	0.759	0.588	0.634	0.689	0.724
divsep	0.070	0.071	0.088	0.118	0.075	0.094
nvrmar	0.120	0.150	0.314	0.196	0.225	0.156
widowed	0.015	0.020	0.011	0.052	0.010	0.025
hhsize	2.950	2.924	3.493	3.120	3.260	2.866
deghdeg	0.142	0.133	0.187	0.094	0.171	0.111
hndalev	0.284	0.242	0.246	0.145	0.281	0.207
ocse	0.341	0.313	0.330	0.251	0.361	0.304
noqual	0.233	0.312	0.237	0.510	0.187	0.378
prof0	0.066	0.040			0.035	0.024
mantech0	0.310	0.251			0.239	0.216
sknonm0	0.241	0.285			0.265	0.260
skmanar0	0.220	0.195			0.184	0.185
ptskill0	0.129	0.164			0.206	0.216
unskill0	0.033	0.063			0.060	0.084
Spousal/Partner variables						
swork	0.635	0.499	0.434	0.309	0.553	0.389
ssahvpp	0.046	0.064	0.035	0.079	0.042	0.091
ssahfair	0.131	0.134	0.119	0.148	0.128	0.161
ssahgvg	0.407	0.368	0.261	0.262	0.337	0.319
ssahex	0.202	0.180	0.155	0.131	0.167	0.140
shlltyes	0.075	0.099	0.061	0.141	0.057	0.163
sghq	8.58	8.42	6.03	6.97	7.19	7.91

Figures 2.1 to 2.3 show Kaplan-Meier estimates of the probability of survival in the two labour market states (employment or non-employment depending on the sample used) together with the χ^2 values (and probabilities) of the log-rank and Peto-Peto-Prentice tests of equality of survivor functions by health status. We have defined two categories for the GHQ index: whether the individual's GHQ falls below or above the mean of her sample. We can see that individuals with better health, regardless of the measure of health

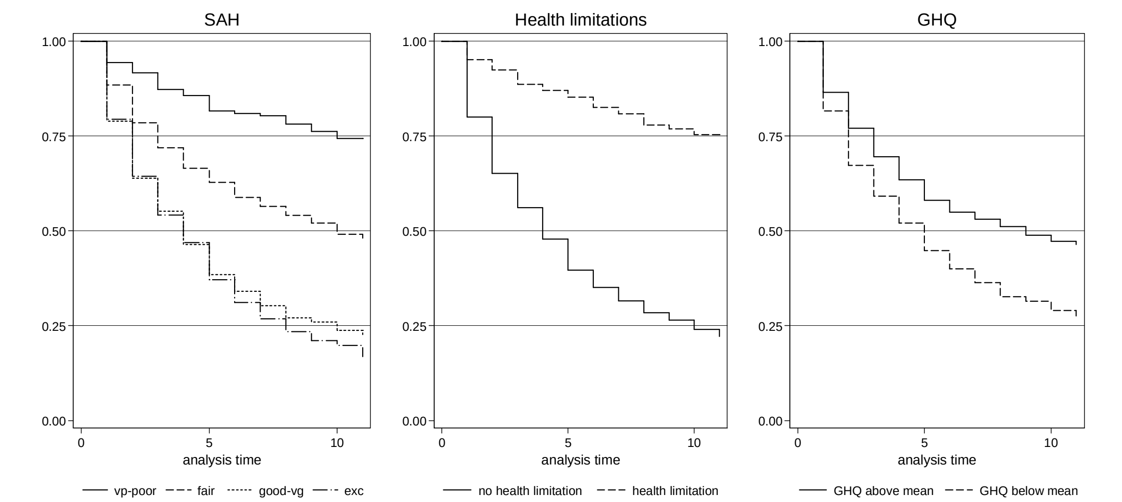
considered, are more (less) likely to remain employed (non-employed). Moreover, equality of survivor functions is always rejected.

Figure 2.1. Kaplan-Meier survival estimates and log-rank and Peto-Peto-Prentice tests of equality of survivor functions [χ^2 (Prob)] for workers in wave 1, by health status



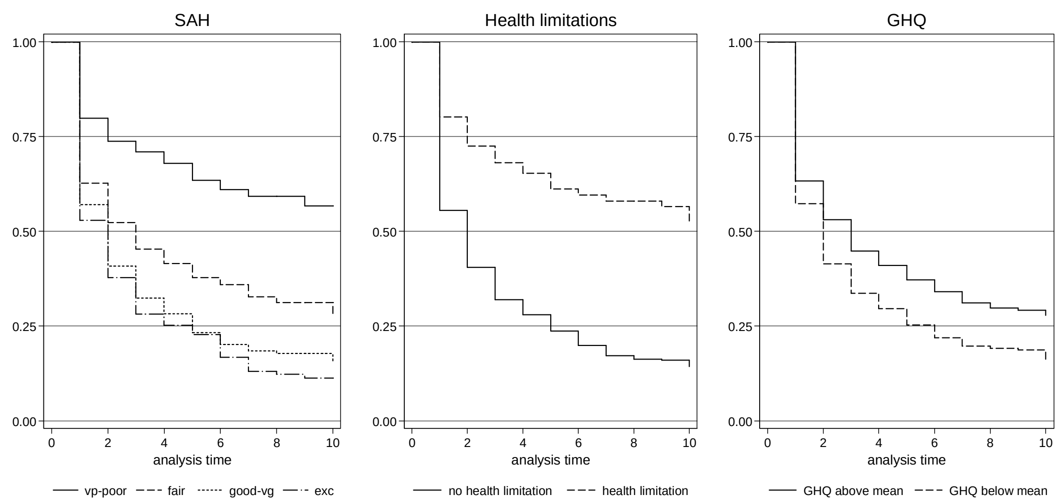
	SAH	Health limitations	GHQ
Log-rank	431.64 (0.000)	438.06 (0.000)	38.48 (0.000)
Peto-Peto-Prentice	397.86 (0.000)	429.45 (0.000)	38.35 (0.000)

Figure 2.2. Kaplan-Meier survival estimates and log-rank and Peto-Peto-Prentice tests of equality of survivor functions [χ^2 (Prob)] for non-workers in wave 1, by health status



	SAH	Health limitations	GHQ
Log-rank	206.82 (0.000)	243.37 (0.000)	40.67 (0.000)
Peto-Peto-Prentice	184.98 (0.000)	222.81 (0.000)	34.25 (0.000)

Figure 2.3. Kaplan-Meier survival estimates and log-rank and Peto-Peto-Prentice tests of equality of survivor functions [χ^2 (Prob)] for previously employed non-workers, by health status



Log-rank	165.83 (0.000)	220.32 (0.000)	37.13 (0.000)
Peto-Peto-Prentice	151.84 (0.000)	208.2 (0.000)	32.38 (0.000)

Empirical modelling results

We have estimated the health stock variable using generalised ordered probit models for men and women using the same specification as Rice et al (2006). The estimates are shown in Tables A2.1 and A2.2 in the Appendix. In order to be able to derive the latent health of a spouse we did not restrict the sample either by age or by labour status.

Results for the discrete-time hazard models are presented in Table 2.3 and Table A2.3 (see Appendix). Table 2.3 reports the effects of the health variables only, while all effects are shown in Table A2.3. For each sample and model, the results are presented as hazard ratios, which measure the proportional effect on the underlying (instantaneous) hazard of retiring of a one-unit change in that variable. All models were estimated defining the hazard ratio as a complementary log-log function. Further, all models were estimated including unobserved heterogeneity using a gamma mixture distribution (Meyer, 1990)[9]. The null hypothesis of no heterogeneity was only rejected in the stock sample of workers, and accordingly, the results shown here are for estimates including unobserved heterogeneity for the stock sample of workers and without unobserved heterogeneity for the two samples of non-workers.

The first column (1) reports results for the stock sample of individuals who work in the first period, where the hazard represents the transition to non-employment. The hazard ratios of becoming employed are shown in column (2) for the stock sample of non-workers, and in column (3) for the flow sample of non-workers.

We estimate three different models according to different measures of health. In the first model, we measure health using the information about whether the individual declares that health limits her daily activities. The second model includes the latent health measure and the third model focuses on mental health.

Table 2.3. Effects (hazard ratios) of health for different labour market states

		Stock sample **working** in the first wave. Hazard: not working (1)		Stock sample **not working** in the first wave. Hazard: working (2)		Individuals who **stop working**. Hazard: back to work (3)	
Model	Variable	Men	Women	Men	Women	Men	Women
Health limitations	lhlltyes	3.839***	2.202***	0.301***	0.511***	0.713	0.629**
	hlltyes0	0.802	1.063	0.656*	0.772	0.628**	0.784
Health stock	llatsah	1.874***	1.402***	0.495***	0.660***	0.700**	0.815**
	latsah0	1.009	1.096	0.992	1.023	0.829	0.946
GHQ	lghq	1.056***	1.025**	0.998	0.997	0.99	1.018**
	ghq0	1.006	1.034*	1.017	0.999	0.999	0.986*

Note: * p<.1; ** p<.05; *** p<.001

The results show that all measures of a negative change in health are associated with an increase in the hazard of non-employment for the stock sample of workers. The presence of limitations due to health increases the hazard of leaving employment, with a stronger effect for men (284%) than for women (120%). The effects of the lagged health stock and lagged psychological health are also greater for men than for women.

[9] These models can be estimated in Stata using the *pgmhaz8* routine (Jenkins, 1998).

For the samples of non-employed individuals, firstly, the presence of a health problem that limits daily activities in the first period diminishes the hazard of employment for men. Further, for all except men in the flow sample, a shock to health resulting in a limitation is also associated with a significant decrease in the hazard of returning to employment. For both men and women a decline in the health stock diminishes the hazard of returning to employment, while in general first period latent health has little effect on subsequent transitions. Psychological health appears to have a negligible effect on subsequent employment transitions.

The effects of other covariates are very stable across the different models, as can be seen in Table A2.3 in the Appendix. For example, the hazard of becoming non-employed for the employed stock sample initially diminishes with age and then increases. Further, the results show the expected gradient among the stock and flow sample of non-employed, that is, the hazard of employment becomes smaller as individuals age.

The hazard of employment (non-employment) increases (decreases) as mean household equivalent income increases. For the stock sample of workers, individuals with higher or first degree education have a hazard of non-employment of around 75% greater for men and 100% greater for women than workers without educational qualifications. At the same time, their hazard of employment is also higher, which suggests that they change jobs more frequently. Marital status only seems to have an effect on the hazard ratio of employment for the male flow sample, as compared to widowers (omitted category) the rest have a hazard ratio of employment at least 170% lower. Household size increases the hazard ratio of non-employment for female workers and decreases the hazard ratio of employment for the stock sample of female non-workers.

Concerning the relationship with the spouse's employment, we can observe that in general there are complementarities. The hazard ratio of non-employment for male workers is reduced by 37% when their partner or spouse works, and similarly the hazard of employment is increased among the non-employed (males and females) when their partner or spouse works. The effects regarding the health status of the spouse depend on the measure of health used. If the spouse has a health limitation, the hazard ratio of employment for non-working males is decreased by 95%. On the other hand, if we use our constructed measure of latent health, the hazard of leaving employment is increased and the hazard of employment is decreased when the health status of the partner is decreased for working and non-working males respectively. By contrast, the worse the mental health of the partner the higher the hazard ratio of non-employment is for working women.

Heterogeneous effects

It has been argued (OECD, 2003) that educational attainment plays an important role in the incidence of disability, as disability rates are observed to be considerably higher among individuals with low educational attainment. Moreover, education might influence the way in which individuals respond to a health shock. To investigate in more detail the role that education might play in determining the effect of a health shock on employment transitions, we re-estimate the models, allowing the effects of health to differ across groups defined by educational attainment[10]. The hazard ratios for each of the health measures by education are presented in the Appendix in Tables A2.4 and A2.5. Table 2.4 presents associated χ^2 values and probabilities of the test of equality of the coefficients on health across the educational groups. Rejection of the null hypothesis of equality of coefficients implies that the impact of health shocks on employment transitions varies with educational achievement.

In general we cannot reject the hypothesis that the effects are the same across the four educational groups. However, having a health limitation increases the hazard of non-employment for women without qualifications by 250%, while the increase is about 115% for women with a degree or higher. Similar results are found for the constructed latent health variable for women in the stock sample of both workers and non-workers; women without qualifications have a relatively higher hazard rate of non-employment when their latent health decreases, and a relatively lower hazard rate of re-employment.

[10] The educational groups represent: no qualification, O level or CSE, HND or A level, degree or higher degree.

Table 2.4. χ^2 (Prob>χ^2) of equality of coefficients across educational attainment groups

Health definition	Variable	Stock sample **working** in the first wave. Hazard: not working (1)		Stock sample **not working** in the first wave. Hazard: working (2)		Individuals who **stop working**. Hazard: back to work (3)	
		Men	Women	Men	Women	Men	Women
Health limitations	lagged	3.02 (0.39)	11.55 (0.01)	4.23 (0.24)	1.79 (0.62)	3.79 (0.28)	2.73 (0.44)
	initial	3.24 (0.36)	8.58 (0.04)	2.45 (0.48)	2.02 (0.57)	2.57 (0.46)	1.03 (0.79)
Latent health	lagged	3.00 (0.39)	9.02 (0.03)	1.27 (0.74)	6.74 (0.08)	7.86 (0.05)	2.45 (0.48)
	initial	2.01 (0.57)	2.06 (0.56)	3.94 (0.27)	1.27 (0.74)	7.59 (0.06)	4.43 (0.22)
GHQ	lagged	3.90 (0.27)	1.84 (0.61)	0.91 (0.82)	2.32 (0.51)	2.21 (0.53)	1.87 (0.60)
	initial	1.05 (0.79)	4.36 (0.23)	2.43 (0.49)	3.21 (0.36)	2.07 (0.56)	2.49 (0.48)

Sensitivity analysis

It could be argued that the above results were driven by the effects of health on labour market outcomes of older individuals. In order to rule out this hypothesis, we re-estimate the models excluding all individuals older than 50. The first quarter of Table 2.5 (A) shows that there are no noticeable differences in the results when older workers are excluded from the analysis[11].

In the analysis shown above we have included individuals who are on maternity leave in the non-employment category. However, these individuals can return to their previous jobs after maternity leave expires, and thus they might also be considered as employed. We re-estimate the previous models including maternity leave within the employment category. The second quarter of Table 2.5 (B) indicates that the results are robust to this change in the definition of employment[12].

[11] The full set of results is shown in the Appendix in Table A2.6.
[12] The full set of results is shown in the Appendix in Table A2.7.

The second half of Table 2.5 shows the hazard ratios when all models are first estimated without accounting for unobserved heterogeneity[13] (C), and secondly assuming that it is normally distributed and constant over time[14] (D). The results are robust to the assumptions about unobserved heterogeneity.

Table 2.5. Hazard ratios for health measures: individuals younger than 50, maternity leave within employment and different assumptions about unobserved heterogeneity

Sensitivity analysis	Health definition	Variable	Stock sample **working** in the first wave. Hazard: not working (1)		Stock sample **not working** in the first wave. Hazard: working (2)		Individuals who **stop working**. Hazard: back to work (3)	
			Men	Women	Men	Women	Men	Women
Individuals younger than 50 (A)	Health limitations	lhlltyes	4.083***	1.632**	0.290***	0.492***	0.777	0.775
		hlltyes0	0.578*	1.256	0.777	0.886	0.567**	0.649**
	Health stock	llatsah	1.793***	1.335**	0.511***	0.686**	0.800	0.840
		latsah0	1.004	1.094	1.103	0.972	0.727**	0.887
	GHQ	lghq	1.056***	1.021*	0.994	0.994	0.991	1.017*
		ghq0	1.004	1.040*	1.026**	1.003	0.998	0.982**
Maternity leave as employment (B)	Health limitations	lhlltyes	3.893***	2.114***	0.299***	0.433**	0.683*	0.622***
		hlltyes0	0.805	1.154	0.620*	0.499**	0.653**	0.795*
	Health stock	llatsah	1.887***	1.474***	0.493***	0.622**	0.687**	0.765**
		latsah0	1.036	1.095	0.977	0.879	0.847	1.006
	GHQ	lghq	1.057***	1.022**	0.995	1.013	0.992	1.008
		ghq0	1.008	1.02	1.018	0.987	0.998	0.995
No unobserved heterogeneity (C)	Health limitations	lhlltyes	3.441***	2.037***	0.301***	0.511***	0.713	0.629**
		hlltyes0	0.75	0.894	0.656*	0.772	0.628**	0.784
	Health stock	llatsah	1.746***	1.378***	0.495***	0.660***	0.700**	0.815**
		latsah0	0.908	1.018	0.992	1.023	0.829	0.946
	GHQ	lghq	1.054***	1.023**	0.998	0.997	0.99	1.018**
		ghq0	0.998	1.006	1.017	0.999	0.999	0.986*
Normal distributed unobserved heterogeneity (D)	Health limitations	lhlltyes	3.581***	2.071***	0.300***	0.509***	0.716	0.627**
		hlltyes0	0.768	0.913	0.645*	0.766	0.619**	0.772
	Health stock	llatsah	1.786***	1.387***	0.493***	0.656***	0.700**	0.813**
		latsah0	0.931	1.031	0.983	1.022	0.822	0.942
	GHQ	lghq	1.055***	1.023**	0.998	0.997	0.99	1.017**
		ghq0	1.000	1.008	1.017	0.999	0.999	0.986*

Note: * p<.1; ** p<.05; *** p<.001

[13] The full set of results is shown in the Appendix in Table A2.8.
[14] The full set of results is shown in the Appendix in Table A2.9.

6. Discussion and conclusion

This chapter analyses the role of health in exits out of and entries into employment using data from the British Household Panel Survey. We use a discrete-time hazard approach to model the hazard of non-employment for the stock sample of individuals employed in the first wave, and the hazard of employment for both the stock sample of individuals non-employed in the first wave and the flow sample of individuals who transit out of employment. We measure health using a measure of health limitations, a constructed latent health index, and the GHQ index to measure psychological well-being.

The results show that own health is an important determinant for employment transitions and the effects are greater for men than for women. However, there are some differences depending on the measure of health used. General health, measured by health limitations and the latent health index, has an effect on exits from employment and entries into employment. Moreover, the size of the effect of health is found to be symmetric, that is, the size of the effect of health on the hazard of non-employment is similar to the size of the effect of health on the hazard of employment. On the other hand, mental health seems to matter regarding the hazard of becoming non-employed for the stock sample of workers, but there is no significant effect on the hazard of leaving the non-employment status.

The previous related literature has mainly focused on the causal relationship between ill health and retirement among older workers. In contrast, we do not restrict our analysis to older workers, but focus on the entire working-age population, that is, men aged 16 to 64 and women aged 16 to 59. Our results, even when we exclude older individuals from the analysis, show that the effects running from health to employment transitions are qualitatively similar to the ones found in previous studies. In fact, the hazard ratios of non-employment for the stock sample of workers are higher than those found by Hagan et al (2006) or Zucchelli et al (2007) using the same empirical approach and definition of health limitations, but different definitions of exits from employment. Rice et al (2006) also use data from the BHPS to analyse the effect of health on retirement and found a slightly larger effect of health limitations on the retirement hazard. Our results emphasise that health shocks represent a non-negligible determinant of employment transitions, but moreover, that health is important not only for the employment transitions of older workers but also for younger individuals.

Appendix

Table A2.1 Generalised ordered probit: men

NT=64,802 N=12,631				Cut point 2		Cut point 3		Cut point 4	
Latent health index			Measurement model						
	Coef.	S.E.		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Health problems (HLTHPRB)			age1519	-0.124	0.073	-0.111	0.064	-0.129	0.090
Arms, legs or hands	0.640	0.017	age2024	-0.179	0.071	-0.395	0.061	-0.501	0.084
Sight	0.237	0.030	age2529	-0.151	0.070	-0.419	0.060	-0.530	0.084
Hearing	0.118	0.024	age3034	-0.167	0.070	-0.409	0.059	-0.564	0.082
Skin condition or allergies	0.075	0.023	age3539	-0.192	0.070	-0.416	0.058	-0.513	0.082
Chest / Breathing	0.641	0.022	age4044	-0.159	0.070	-0.354	0.059	-0.514	0.082
Heart / Blood pressure	0.597	0.023	age4549	-0.137	0.070	-0.328	0.058	-0.540	0.080
Stomach or digestion	0.679	0.027	age5054	-0.117	0.070	-0.302	0.057	-0.446	0.079
Diabetes	0.522	0.044	age5559	-0.112	0.068	-0.273	0.055	-0.281	0.078
Anxiety / Depression	0.754	0.032	age6064	-0.004	0.064	-0.167	0.052	-0.066	0.073
Alcohol or drugs	0.450	0.085	age6569	0.035	0.057	-0.114	0.045	0.005	0.059
Epilepsy	0.484	0.093	age7074	0.013	0.053	-0.090	0.042	0.035	0.054
Migraine	0.302	0.031	marcoup	-0.010	0.024	0.014	0.023	0.039	0.030
Others	0.743	0.033	deghdeg	0.287	0.035	0.444	0.036	0.372	0.055
			hndalev	0.183	0.029	0.321	0.028	0.170	0.038
			ocse	0.080	0.029	0.222	0.027	0.115	0.039
			selfemp	0.260	0.040	0.633	0.040	0.845	0.062
			emp	0.187	0.031	0.548	0.031	0.777	0.040
			unemp	0.053	0.039	0.291	0.036	0.507	0.048
			retired	0.099	0.053	0.375	0.046	0.382	0.061
			fammat	0.038	0.079	0.292	0.078	0.534	0.126
			matleave	-0.002	0.394	-0.019	0.326	-0.211	0.428
			lninc	0.082	0.012	0.092	0.012	0.059	0.018
			yr9293	-0.106	0.024	-0.034	0.027	-0.005	0.042
			yr9394	-0.138	0.026	-0.032	0.028	0.047	0.045
			yr9495	-0.168	0.027	-0.063	0.029	-0.012	0.045
			yr9596	-0.221	0.027	-0.093	0.029	0.007	0.046
			yr9697	-0.187	0.027	-0.076	0.029	0.012	0.045
			yr9798	-0.108	0.026	-0.086	0.029	0.041	0.044
			yr9899	-0.212	0.027	-0.111	0.029	-0.069	0.044
			yr9900	-0.500	0.027	0.269	0.029	0.466	0.046
			yr0001	-0.226	0.026	-0.131	0.027	0.002	0.041
			yr0102	-0.113	0.025	-0.063	0.027	0.089	0.041
			yr0203	-0.131	0.026	-0.058	0.028	0.086	0.042
			_cons	-1.064	0.133	-0.016	0.126	1.272	0.180
Likelihood: -66745.76									

Table A2.2. Generalised ordered probit: women

NT=75,980
N=14,490

Latent health index			Measurement model	Cut point 2		Cut point 3		Cut point 4	
	Coef.	S.E.		Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Health problems (HLTHPRB)	0.649	0.015	age1519	-0.251	0.060	-0.126	0.052	-0.094	0.066
Arms, legs or hands	0.193	0.026	age2024	-0.233	0.058	-0.316	0.049	-0.309	0.061
Sight	0.113	0.026	age2529	-0.152	0.058	-0.325	0.048	-0.408	0.061
Hearing	0.098	0.017	age3034	-0.102	0.057	-0.303	0.047	-0.385	0.059
Skin condition or allergies	0.594	0.020	age3539	-0.120	0.057	-0.249	0.048	-0.336	0.059
Chest / Breathing	0.482	0.019	age4044	-0.043	0.058	-0.192	0.048	-0.256	0.060
Heart / Blood pressure	0.617	0.024	age4549	-0.073	0.058	-0.213	0.047	-0.254	0.060
Stomach or digestion	0.630	0.044	age5054	-0.090	0.057	-0.109	0.047	-0.109	0.059
Diabetes	0.738	0.021	age5559	-0.008	0.056	-0.054	0.045	0.031	0.058
Anxiety / Depression	0.670	0.122	age6064	0.103	0.052	0.099	0.042	0.154	0.053
Alcohol or drugs	0.526	0.080	age6569	0.063	0.050	0.118	0.040	0.177	0.050
Epilepsy	0.252	0.019	age7074	0.025	0.049	0.069	0.036	0.099	0.044
Migraine	0.827	0.024	marcoup	-0.061	0.021	-0.041	0.019	-0.044	0.025
Others			deghdeg	0.304	0.036	0.465	0.033	0.409	0.044
			hndalev	0.217	0.030	0.351	0.027	0.228	0.036
			ocse	0.176	0.028	0.279	0.024	0.196	0.030
			selfemp	0.236	0.053	0.503	0.051	0.680	0.068
			emp	0.070	0.030	0.475	0.028	0.719	0.036
			unemp	-0.047	0.046	0.208	0.039	0.445	0.054
			retired	0.026	0.046	0.307	0.038	0.485	0.047
			fammat	0.002	0.036	0.274	0.031	0.494	0.039
			matleave	0.052	0.042	0.113	0.042	0.064	0.059
			lninc	0.105	0.012	0.091	0.011	0.040	0.015
			yr9293	-0.054	0.025	0.023	0.025	0.036	0.037
			yr9394	-0.125	0.027	0.002	0.027	0.096	0.039
			yr9495	-0.191	0.027	-0.024	0.027	0.137	0.041
			yr9596	-0.207	0.028	-0.051	0.027	0.112	0.040
			yr9697	-0.194	0.028	-0.049	0.028	0.105	0.041
			yr9798	-0.122	0.027	-0.056	0.027	0.069	0.039
			yr9899	-0.195	0.028	-0.044	0.027	0.067	0.039
			yr9900	-0.437	0.027	0.388	0.027	0.644	0.042
			yr0001	-0.185	0.026	-0.055	0.026	0.080	0.037
			yr0102	-0.059	0.025	-0.017	0.025	0.094	0.036
			yr0203	-0.070	0.026	-0.029	0.026	0.078	0.037
			_cons	-1.333	0.123	-0.098	0.109	1.205	0.150

Likelihood: -78,954.36

Table A2.3. Results for the baseline model

	HEALTH LIMITATIONS						LATENT HEALTH						GHQ					
	Stock sample workers		Stock sample non-workers		Transition out of employment		Stock sample workers		Stock sample non-workers		Transition out of employment		Stock sample workers		Stock sample non-workers		Transition out of employment	
Variable	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W
lhlltyes	**3.839**	**2.202**	**0.301**	**0.511**	0.713	**0.629**												
hlltyes0	0.802	1.063	*0.656*	0.772	**0.628**	0.784												
llatsah							**1.874**	**1.402**	**0.495**	**0.660**	**0.700**	**0.815**						
latsah0							1.009	1.096	0.992	1.023	0.829	0.946						
lghq													**1.056**	**1.025**	0.998	0.997	0.99	**1.018**
ghq0													1.006	*1.034*	1.017	0.999	0.999	*0.986*
age20240	**0.480**	0.555	1.259	0.947	*0.743*	0.982	**0.435**	0.621	1.221	0.879	0.768	0.977	**0.433**	0.425	1.167	0.873	0.756	0.949
age25290	**0.240**	0.618	1.405	0.743	0.979	0.866	**0.194**	0.602	1.287	0.738	1.005	0.83	**0.198**	0.508	1.089	0.737	0.904	0.802
age30340	**0.177**	**0.325**	1.127	**0.660**	0.722	0.907	**0.145**	**0.335**	1.058	**0.654**	0.705	0.898	**0.140**	**0.229**	0.67	**0.610**	0.753	0.894
age35390	**0.309**	**0.196**	0.812	**0.600**	0.697	1.011	**0.266**	**0.205**	0.848	**0.596**	0.706	0.975	**0.268**	**0.156**	0.671	**0.553**	*0.652*	0.941
age40440	**0.309**	**0.137**	0.843	**0.471**	0.693	0.927	**0.250**	**0.167**	0.797	**0.460**	0.758	0.886	**0.259**	**0.083**	*0.603*	**0.406**	**0.622**	0.872
age45490	**0.392**	**0.168**	**0.415**	**0.374**	*0.637*	0.798	**0.305**	**0.194**	**0.357**	**0.370**	*0.658*	0.75	**0.334**	**0.109**	**0.250**	**0.307**	**0.569**	*0.707*
age50540	0.965	**0.347**	0.612	**0.205**	**0.421**	**0.396**	0.763	**0.363**	**0.496**	**0.217**	**0.488**	**0.371**	0.835	**0.293**	**0.273**	**0.170**	**0.378**	**0.333**
age55590	1.268	0.511	**0.137**	**0.192**	**0.170**	**0.317**	1.008	**0.451**	**0.125**	**0.206**	**0.195**	**0.300**	1.179	0.458	**0.092**	**0.185**	**0.159**	**0.264**
age60640	**2.066**		**0.119**		**0.120**		1.532		**0.134**		**0.141**		*2.037*		**0.095**		**0.112**	
mlnhinc	**0.443**	**0.365**	**1.454**	**1.263**	**1.361**	**1.304**	**0.418**	**0.407**	**1.501**	**1.236**	**1.372**	**1.337**	**0.440**	**0.357**	**1.477**	*1.171*	**1.414**	**1.322**
white	1.25	0.83	1.057	**1.569**	*0.715*	1.024	1.274	0.779	1.013	**1.686**	**0.639**	1.081	1.282	0.783	1.044	**1.697**	**0.656**	1.064
marcoup	*0.440*	1.335	1.376	1.588	**0.337**	1.062	*0.415*	1.531	1.233	1.452	**0.290**	0.961	*0.424*	1.325	1.22	1.357	**0.260**	1.118
divsep	0.632	1.62	0.926	1.876	**0.361**	1.176	0.672	1.609	0.868	1.723	**0.314**	1.141	0.556	1.83	0.893	1.534	**0.300**	1.114
nvrmar	0.707	1.007	0.922	1.329	**0.335**	1.09	0.682	1.217	0.782	1.256	**0.275**	1.015	0.648	1.258	0.672	1.135	**0.285**	1.016
hhsize	0.965	**1.335**	0.986	**0.896**	1.023	0.979	0.969	**1.243**	0.989	**0.904**	1.017	0.976	0.968	**1.458**	0.987	**0.905**	1.041	0.994
deghdeg	**1.748**	**2.022**	*1.366*	**1.572**	0.994	**1.379**	**1.728**	**1.826**	**1.488**	**1.570**	1.052	**1.508**	**1.596**	**2.243**	**1.555**	**1.761**	1.077	**1.602**
hndalev	**1.338**	0.95	**1.985**	**1.696**	1.214	**1.297**	**1.413**	0.989	**2.088**	**1.657**	1.22	**1.322**	1.288	1.013	**2.152**	**1.816**	1.169	**1.376**
ocse	1.152	*0.729*	**1.730**	**1.401**	*1.247*	**1.248**	1.219	*0.750*	**1.735**	**1.457**	**1.289**	**1.262**	1.129	0.742	**1.678**	**1.490**	**1.281**	**1.286**
prof0	**0.329**	0.405			1.088	*1.596*	**0.293**	0.493			1.069	1.471	**0.296**	0.356			1.229	*1.570*
mantech0	**0.402**	0.767			1.168	1.153	**0.391**	0.772			1.194	1.113	**0.397**	0.71			1.249	1.092
sknonm0	**0.355**	1.05			1.179	0.984	**0.337**	1.042			1.163	0.996	**0.331**	0.981			1.222	0.960

	HEALTH LIMITATIONS						LATENT HEALTH						GHQ					
	Stock sample workers		Stock sample non-workers		Transition out of employment		Stock sample workers		Stock sample non-workers		Transition out of employment		Stock sample workers		Stock sample non-workers		Transition out of employment	
Variable	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W
skmanar0	**0.419**	0.855			*1.352*	1.194	**0.381**	0.861			*1.337*	1.176	**0.419**	0.782			*1.341*	1.160
ptskill0	**0.378**	1.003			1.279	1.060	**0.358**	0.943			1.315	1.079	**0.383**	0.917			1.281	1.032
lswork	**0.730**	1.197	*1.368*	*1.271*	**1.493**	*1.210*	**0.695**	1.172	*1.360*	**1.273**	**1.498**	**1.298**	**0.726**	1.175	**1.386**	**1.340**	**1.454**	**1.361**
lshealth	1.098	1.016	**0.515**	0.897	0.832	0.803	**1.209**	1.156	*0.777*	0.959	0.875	0.957	0.998	**1.029**	0.981	1.000	1.005	**0.979**
NorthE	0.957	0.946	0.94	1.014	0.954	0.862	0.96	1.067	0.943	1.008	0.987	0.833	0.92	1.055	0.819	1.031	0.983	0.848
SouthE	*0.697*	0.877	**1.580**	1.191	1.251	1.042	*0.708*	0.996	**1.590**	1.241	1.245	1.063	*0.679*	0.871	*1.454*	*1.380*	1.264	1.057
SouthW	*0.659*	1.138	**1.658**	1.057	**1.440**	0.858	*0.644*	1.251	**1.591**	1.111	1.303	0.862	**0.623**	1.333	*1.516*	1.144	*1.349*	0.871
Midland	0.759	0.967	*1.434*	1.001	0.944	1.039	0.755	1.029	*1.436*	0.983	0.928	1.047	*0.712*	1.068	1.296	1.046	0.931	1.053
Scot	0.832	1.164	1.049	0.924	0.96	0.938	0.827	1.274	1.028	0.895	1.029	0.939	0.791	1.23	0.868	0.905	0.971	0.955
Wales	0.973	1.377	1.317	1.175	0.978	0.997	0.967	1.367	1.123	1.141	1.008	0.977	0.937	1.504	0.723	1.253	0.983	1.029
t1	1.458	**0.216**	**4.411**	1.586	**11.015**	**5.422**	1.382	0.471	**4.648**	1.701	**10.927**	**5.508**	1.312	**0.097**	**6.559**	*1.793*	**12.381**	**4.964**
t2	1.293	**0.231**	**3.868**	1.646	**7.916**	3.021	1.282	0.433	**3.889**	*1.753*	**7.658**	3.023	1.199	**0.119**	**5.171**	*1.797*	**8.099**	2.721
t3	1.252	**0.232**	*2.958*	1.289	**5.235**	2.732	1.242	*0.407*	*2.920*	1.352	**5.081**	2.681	1.249	**0.138**	**3.800**	1.449	**5.423**	2.502
t4	0.979	**0.317**	**3.414**	1.307	**3.937**	1.465	0.961	*0.504*	**3.372**	1.371	**3.918**	1.432	0.885	**0.201**	**4.198**	1.486	**3.862**	1.35
t5	0.952	**0.365**	**5.815**	1.462	**4.576**	1.755	0.976	*0.532*	**5.415**	1.562	**4.591**	1.789	0.937	**0.221**	**6.964**	1.617	**4.019**	1.621
t6	0.843	**0.303**	**3.729**	1.109	1.821	2.164	0.855	*0.431*	**3.865**	1.218	1.918	2.317	0.799	**0.206**	**4.137**	1.211	1.759	2.092
t7	0.845	**0.435**	2.864	1.053	2.7	1.819	0.856	**0.553**	2.871	1.173	2.871	1.576	0.811	**0.338**	3.024	1.133	2.692	1.407
t8	1.032	**0.506**	**3.814**	0.986		0.793	1.058	**0.582**	**3.806**	1.096		0.929	1.078	**0.403**	4.118**	1.089		0.791
t9	0.778	**0.537**	1.149	0.721		0.281	0.802	**0.585**	1.149	0.729		0.292	0.797	**0.457**	1.127	0.687		0.288
t10	0.883	**0.576**		1.075			0.863	**0.613**		1.203			0.956	**0.521**		1.257		
Cons	**1480.653**	**14094.851**	**0.001**	**0.009**	**0.013**	**0.008**	**2962.10**	**1856.447**	**0.001**	**0.011**	**0.016**	**0.006**	**1377.309**	**19962.234**	**0.001**	**0.016**	**0.010**	**0.006**
N	17295	13401	2706	4731	2479	3782	17105	13081	2671	4634	2440	3683	16462	12630	2517	4379	2347	3541
ll	-2604.2	-3126.4	-877.4	-1652.0	-1144.6	-1971.9	-2580.5	-3049.9	-879.0	-1632.0	-1123.1	-1928.6	-2510.1	-2948.8	-867.3	-1572.5	-1111.5	-1875.8
aic	5300.4	6342.7	1832.8	3381.9	2373.2	4029.7	5253.1	6189.9	1835.9	3342.1	2330.1	3943.3	5112.2	5987.7	1812.6	3222.9	2307.0	3837.7
bic	5657.313	6680.341	2063.066	3633.944	2617.457	4297.939	5609.467	6526.425	2065.652	3593.304	2573.706	4210.379	5466.852	6322.643	2039.998	3471.935	2548.931	4103.1

Note: **P-value<0.05;** *P-value<0.10*

Table A2.4 Hazard ratio: differences by educational attainment

	HEALTH LIMITATIONS						LATENT HEALTH						MENTAL HEALTH					
	Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers	
Variable	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W
lhlltyes No qualification	**5.040**	**3.511**	**0.238**	**0.397**	0.692	**0.439**	**2.254**	**1.879**	**0.530**	**0.427**	**0.334**	0.836	**1.064**	*1.032*	0.982	0.975	0.974	1.024
lhlltyes Olevel or CSE	**2.420**	**2.502**	**0.290**	**0.464**	0.983	*0.598*	**1.975**	1.058	**0.359**	0.755	0.808	0.812	**1.055**	**1.040**	1.006	1.011	0.999	1.016
lhlltyes HND or A level	**4.179**	0.854	**0.339**	0.671	**0.387**	0.958	**1.670**	1.128	**0.595**	0.863	0.837	1.037	**1.073**	1.008	0.989	0.993	0.981	*1.026*
lhlltyes Degree or Higher Degree	**3.607**	*2.158*	1.095	0.659	1.265	0.776	1.336	**1.628**	0.489	0.816	1.058	*0.600*	1.012	1.019	1.011	1.001	1.026	0.99
hlltyes0 No qualification	0.698	0.646	0.504	0.592	*0.537*	0.774	0.973	0.983	0.585	1.159	*1.685*	0.883	0.985	1.024	0.993	0.989	0.987	0.993
hlltyes0 Olevel or CSE	1.213	0.721	*0.405*	0.836	0.538	0.73	0.786	1.387	0.94	0.927	0.738	0.868	1.006	0.993	1.021	0.988	1.001	*0.979*
hlltyes0 HND or A level	1.09	**3.420**	0.907	1.145	1.072	0.692	1.315	1.08	1.131	1.209	**0.606**	0.81	1.015	**1.096**	*1.042*	1.026	1.015	0.98
hlltyes0 Degree or Higher Degree	*0.334*	0.572	1.072	0.796	0.403	1.101	1.04	0.841	1.657	0.877	0.855	*1.510*	1.02	1.048	1.001	1.025	0.966	1.017
age20240	**0.484**	0.621	1.238	0.946	*0.742*	0.986	**0.434**	0.678	1.236	0.867	0.785	0.984	**0.448**	0.417	1.152	0.866	0.768	0.95
age25290	**0.240**	0.639	1.395	0.74	0.961	0.87	**0.194**	0.623	1.254	*0.716*	1.038	0.839	**0.209**	0.488	1.051	*0.721*	0.922	0.795
age30340	**0.179**	**0.353**	1.151	**0.656**	0.714	0.917	**0.147**	**0.361**	1.066	**0.634**	0.717	0.906	**0.149**	**0.219**	0.661	**0.593**	0.768	0.889
age35390	**0.309**	**0.211**	0.81	**0.601**	*0.695*	1.017	**0.270**	**0.226**	0.829	**0.575**	0.7	0.98	**0.280**	**0.143**	*0.636*	**0.525**	*0.660*	0.934
age40440	**0.312**	**0.165**	0.849	**0.465**	0.688	0.939	**0.255**	**0.196**	0.799	**0.453**	0.732	0.89	**0.273**	**0.078**	0.623	**0.402**	*0.638*	0.87
age45490	**0.396**	**0.202**	**0.422**	**0.379**	*0.632*	0.799	**0.310**	**0.221**	**0.378**	**0.381**	*0.654*	0.75	**0.347**	**0.101**	**0.252**	**0.301**	**0.564**	*0.693*
age50540	0.972	**0.388**	0.624	**0.206**	**0.423**	**0.399**	0.774	**0.396**	*0.519*	**0.216**	**0.489**	**0.372**	0.86	**0.275**	**0.280**	**0.161**	**0.386**	**0.333**
age55590	1.293	0.529	**0.136**	**0.194**	**0.167**	**0.319**	1.013	**0.465**	**0.136**	**0.202**	**0.194**	**0.301**	1.214	0.444	**0.091**	**0.172**	**0.160**	**0.261**
age60640	**2.175**		**0.120**		**0.120**		1.538		**0.143**		**0.139**		**2.086**		**0.093**		**0.113**	
mlnhinc	**0.439**	**0.391**	**1.462**	**1.281**	**1.363**	**1.308**	**0.419**	**0.421**	**1.473**	**1.264**	**1.376**	**1.333**	**0.447**	**0.346**	**1.465**	*1.181*	**1.427**	**1.314**
white	1.241	0.852	1.056	**1.557**	*0.712*	1.027	1.28	0.786	1.027	**1.675**	**0.632**	1.075	1.282	0.8	1.045	**1.753**	**0.636**	1.05
marcoup	*0.434*	1.384	1.453	1.574	**0.343**	1.073	*0.420*	1.506	1.167	1.449	**0.283**	0.949	*0.448*	1.347	1.332	1.39	**0.276**	1.145
divsep	0.624	1.516	0.966	1.869	**0.365**	1.191	0.679	1.504	0.872	1.76	**0.313**	1.122	0.585	1.868	1	1.61	**0.311**	1.132
nvrmar	0.707	1.016	0.989	1.319	**0.338**	1.121	0.687	1.195	0.768	1.261	**0.270**	1.01	0.686	1.278	0.749	1.154	**0.308**	1.042
hhsize	0.967	**1.272**	0.982	**0.898**	1.022	0.978	0.968	**1.198**	0.99	**0.905**	1.018	0.978	0.972	**1.465**	0.986	**0.904**	1.046	0.994
deghdeg	**1.918**	**2.003**	1.205	**1.433**	0.951	1.237	**2.124**	**2.016**	1.115	1.333	0.899	**1.402**	1.943	2.075	0.98	0.823	0.723	**1.860**
hndalev	*1.350*	0.954	**1.799**	**1.456**	1.181	1.189	**1.482**	1.209	**1.620**	1.239	1.251	*1.255*	0.85	0.638	1.12	0.919	0.75	**1.634**
ocse	1.217	0.775	**1.692**	**1.301**	1.178	1.185	*1.404*	0.892	**1.648**	1.253	1.24	*1.275*	0.986	0.934	0.891	0.925	0.78	**1.728**
prof0	**0.342**	0.466			1.09	*1.658*	**0.295**	0.528			1.102	1.52	**0.313**	0.346			1.2	*1.580*
mantech0	**0.405**	0.79			1.173	1.165	**0.385**	0.799			1.229	1.113	**0.411**	0.689			1.25	1.106

	HEALTH LIMITATIONS						LATENT HEALTH						MENTAL HEALTH					
	Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers	
Variable	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W
sknonm0	**0.355**	1.076			1.179	0.989	**0.329**	1.064			1.192	0.995	**0.342**	0.945			1.21	0.971
skmanar0	**0.420**	0.89			*1.362*	1.206	**0.376**	0.89			*1.358*	1.172	**0.431**	0.767			1.312	1.169
ptskill0	**0.375**	1.031			1.286	1.069	**0.353**	0.965			*1.359*	1.092	**0.389**	0.896			1.232	1.042
lswork	**0.738**	1.163	*1.368*	*1.256*	**1.487**	*1.214*	**0.696**	1.154	**1.378**	*1.269*	**1.486**	**1.296**	**0.731**	1.187	*1.371**	**1.329**	**1.457**	**1.358**
lshlltyes	1.101	1.012	**0.509**	0.891	0.841	0.805	**1.211**	*1.164*	0.792	0.959	0.883	0.956	0.998	**1.028**	0.982	1.000	1.005	**0.979**
NorthW	0.812	0.763	1.025	0.865	0.806	0.983	0.8	0.817	1.026	0.851	0.751	0.993	0.728	0.597	0.953	0.859	0.858	0.991
NorthE	0.961	0.963	0.931	1.02	0.954	0.887	0.955	1.05	0.933	1.024	0.975	0.858	0.949	1.049	0.832	1.011	0.996	0.844
SouthE	**0.690**	0.908	**1.579**	1.205	1.246	1.058	*0.698*	0.994	**1.558**	1.264	1.228	1.086	*0.696*	0.871	*1.426*	*1.362*	1.277	1.063
SouthW	*0.652*	1.149	*1.570*	1.061	**1.445**	0.863	**0.636**	1.215	*1.554*	1.128	1.303	0.879	*0.644*	1.318	*1.498*	1.133	*1.348*	0.875
Midland	0.759	0.971	*1.431*	0.995	0.941	1.056	0.749	1.023	*1.409*	1.002	0.929	1.078	0.732	1.069	1.296	1.045	0.943	1.051
Scot	0.828	1.176	0.961	0.907	0.953	0.957	0.823	1.241	0.975	0.916	1.026	0.962	0.811	1.212	0.851	0.908	0.989	0.959
Wales	0.969	1.381	1.282	1.224	0.983	1.012	0.976	1.339	1.073	1.171	0.995	1.008	0.955	1.452	0.664	1.223	0.982	1.039
t1	1.468	*0.354*	**4.245**	1.56	**11.123**	**5.272**	1.384	0.656	**4.411**	1.666	**10.435**	**5.165**	1.393	**0.090**	**6.237**	*1.759*	**12.560**	**4.917**
t2	1.303	**0.340**	**3.737**	1.615	**7.955**	2.952	1.277	0.561	**3.686**	1.716	**7.348**	2.821	1.252	**0.111**	**4.920**	*1.761*	**8.238**	2.69
t3	1.263	**0.320**	*2.879*	1.271	**5.215**	2.674	1.238	0.504	*2.792*	1.323	**4.893**	2.54	1.281	**0.131**	**3.670**	1.429	**5.515**	2.47
t4	0.986	**0.417**	**3.345**	1.291	**3.998**	1.442	0.96	0.604	*3.245*	1.338	**3.782**	1.349	0.904	**0.193**	**4.148**	1.464	**3.921**	1.338
t5	0.963	**0.458**	**5.772**	1.44	**4.528**	1.74	0.973	0.622	**5.214**	1.528	**4.555**	1.69	0.964	**0.213**	**6.750**	1.604	**4.091**	1.607
t6	0.85	**0.366**	**3.705**	1.092	1.8	2.14	0.855	**0.484**	**3.695**	1.18	1.877	2.183	0.814	**0.200**	**3.997**	1.205	1.794	2.101
t7	0.85	**0.502**	2.92	1.039	2.687	1.81	0.852	*0.611*	2.787	1.146	2.949	1.513	0.819	**0.331**	2.932	1.125	2.769	1.414
t8	1.047	**0.569**	**3.847**	0.968		0.792	1.054	*0.626*	**3.711**	1.068		0.896	1.087	**0.397**	**3.995**	1.075		0.793
t9	0.784	**0.583**	1.168	0.706		0.277	0.8	**0.609**	1.109	0.715		0.277	0.802	**0.451**	1.106	0.677		0.288
t10	0.886	**0.600**		1.06			0.864	*0.631*		1.183			0.957	**0.517**		1.254		
_cons	**1543.457**	**3970.579**	**0.001**	**0.009**	**0.013**	**0.008**	**2676.184**	**858.318**	**0.002**	**0.011**	**0.017**	**0.007**	**1075.456**	**30771.401**	**0.002**	**0.022**	**0.012**	**0.006**
ln_varg : _cons	0.991	**2.253**					1.253	1.356					1.128	**4.477**				
Statistics																		
N	17295	13401	2706	4731	2479	3782	17105	13081	2671	4634	2440	3683	16462	12630	2517	4379	2347	3541
Log-likelihood	-2600.494	-3118.839	-871.561	-1647.765	-1142.298	-1967.182	-2577.66	-3044.905	-873.255	-1626.324	-1115.883	-1925.356	-2507.258	-2946.2	-864.386	-1568.316	-1107.923	-1873.631
AIC	5304.989	6339.679	1833.122	3385.531	2380.595	4032.364	5259.32	6191.809	1836.511	3342.647	2327.767	3948.711	5118.517	5994.401	1818.771	3226.633	2311.847	3845.263
BIC	5708.414	6722.336	2098.768	3676.316	2659.745	4338.027	5662.17	6573.234	2101.57	3632.5	2606.155	4253.074	5519.375	6374.036	2081.158	3513.939	2588.37	4147.699

Note: **P-value<0.05**; *P-value<0.10*

Table A2.5 Hazard ratio (standard errors) for health measures by educational attainment

Health definition	Variable	Educational attainment	Stock sample **working** in the first wave. Hazard: not working (1)		Stock sample **not working** in the first wave. Hazard: working (2)		Individuals who **stop working**. Hazard: back to work (3)	
			Men	Women	Men	Women	Men	Women
HEALTH LIMITATIONS	lhlltyes	Noqual	5.04	3.511	0.238	0.397	0.692	0.439
			(1.341)	(0.897)	(0.102)	(0.127)	(0.237)	(0.159)
		Ocse	2.42	2.502	0.29	0.464	0.983	0.598
			(0.829)	(0.608)	(0.145)	(0.160)	(0.376)	(0.159)
		Hndalev	4.179	0.854	0.339	0.671	0.387	0.958
			(1.168)	(0.286)	(0.168)	(0.210)	(0.162)	(0.331)
		Deghdeg	3.607	2.158	1.095	0.659	1.265	0.776
			(1.587)	(0.870)	(0.689)	(0.295)	(0.753)	(0.305)
	hlltyes0	Noqual	0.698	0.646	0.504	0.592	0.537	0.774
			(0.269)	(0.298)	(0.238)	(0.189)	(0.196)	(0.271)
		Ocse	1.213	0.721	0.405	0.836	0.538	0.73
			(0.579)	(0.283)	(0.218)	(0.281)	(0.209)	(0.199)
		Hndalev	1.09	3.42	0.907	1.145	1.072	0.692
			(0.478)	(1.675)	(0.443)	(0.387)	(0.428)	(0.234)
		Deghdeg	0.334	0.572	1.072	0.796	0.403	1.101
			(0.215)	(0.435)	(0.566)	(0.363)	(0.274)	(0.411)
LATENT HEALTH	llatsah	Noqual	2.254	1.879	0.53	0.427	0.334	0.836
			(0.390)	(0.266)	(0.157)	(0.090)	(0.101)	(0.182)
		Ocse	1.975	1.058	0.359	0.755	0.808	0.812
			(0.402)	(0.176)	(0.139)	(0.133)	(0.205)	(0.129)
		Hndalev	1.67	1.128	0.595	0.863	0.837	1.037
			(0.323)	(0.216)	(0.144)	(0.201)	(0.206)	(0.229)
		Deghdeg	1.336	1.628	0.489	0.816	1.058	0.6
			(0.381)	(0.382)	(0.233)	(0.233)	(0.450)	(0.162)
	latsah0	Noqual	0.973	0.983	0.585	1.159	1.685	0.883
			(0.223)	(0.208)	(0.209)	(0.247)	(0.505)	(0.200)
		Ocse	0.786	1.387	0.94	0.927	0.738	0.868
			(0.211)	(0.317)	(0.379)	(0.172)	(0.199)	(0.144)
		Hndalev	1.315	1.08	1.131	1.209	0.606	0.81
			(0.337)	(0.274)	(0.303)	(0.317)	(0.141)	(0.174)
		Deghdeg	1.04	0.841	1.657	0.877	0.855	1.51
			(0.390)	(0.274)	(0.706)	(0.270)	(0.365)	(0.374)
GHQ	lghq	Noqual	1.064	1.032	0.982	0.975	0.974	1.024
			(0.021)	(0.019)	(0.025)	(0.020)	(0.027)	(0.017)
		Ocse	1.055	1.04	1.006	1.011	0.999	1.016
			(0.021)	(0.017)	(0.028)	(0.015)	(0.020)	(0.013)
		Hndalev	1.073	1.008	0.989	0.993	0.981	1.026
			(0.018)	(0.018)	(0.023)	(0.019)	(0.018)	(0.016)
		Deghdeg	1.012	1.019	1.011	1.001	1.026	0.99
			(0.026)	(0.023)	(0.024)	(0.021)	(0.030)	(0.023)
	ghq0	Noqual	0.985	1.024	0.993	0.989	0.987	0.993
			(0.024)	(0.033)	(0.026)	(0.020)	(0.026)	(0.017)
		Ocse	1.006	0.993	1.021	0.988	1.001	0.979
			(0.026)	(0.030)	(0.030)	(0.016)	(0.019)	(0.013)
		Hndalev	1.015	1.096	1.042	1.026	1.015	0.98
			(0.024)	(0.043)	(0.023)	(0.023)	(0.018)	(0.015)
		Deghdeg	1.02	1.048	1.001	1.025	0.966	1.017
			(0.036)	(0.050)	(0.026)	(0.025)	(0.031)	(0.023)

Table A2.6 Results for individuals younger than 50

	HEALTH LIMITATIONS						LATENT HEALTH						MENTAL HEALTH					
	Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers	
Variable	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W
lhlltyes	**4.083**	**1.632**	**0.290**	**0.492**	0.777	0.775	**1.793**	**1.335**	**0.511**	**0.686**	0.800	0.840	**1.056**	*1.021*	0.994	0.994	0.991	*1.017*
hlltyes0	*0.578*	1.256	0.777	0.886	**0.567**	**0.649**	1.004	1.094	1.103	0.972	**0.727**	0.887	1.004	*1.040*	**1.026**	1.003	0.998	**0.982**
age20240	*0.572*	0.541	1.283	0.975	*0.717*	0.991	**0.518**	0.582	1.224	0.91	0.747	0.992	*0.553*	0.434	1.16	0.891	0.74	0.972
age25290	**0.295**	0.575	*1.436*	0.775	0.931	0.869	**0.238**	0.559	1.301	0.77	0.98	0.834	**0.268**	0.464	1.065	0.763	0.861	0.803
age30340	**0.229**	**0.288**	1.05	*0.695*	0.724	0.91	**0.186**	**0.287**	0.978	*0.692*	0.711	0.907	**0.197**	**0.207**	*0.600*	**0.640**	0.764	0.904
age35390	**0.376**	**0.182**	0.781	**0.626**	*0.687*	1.038	**0.324**	**0.184**	0.813	**0.627**	0.715	1.001	**0.337**	**0.144**	*0.625*	**0.576**	*0.658*	0.973
age40440	**0.295**	**0.117**	0.935	**0.469**	*0.676*	0.974	**0.237**	**0.129**	0.867	**0.470**	0.747	0.941	**0.258**	**0.078**	0.626	**0.409**	*0.623*	0.926
age45490	**0.227**	**0.114**	0.788	0.717	0.684	0.859	**0.165**	**0.114**	0.669	0.706	0.732	0.8	**0.190**	**0.080**	**0.438**	*0.622*	*0.622*	0.753
mlnhinc	**0.308**	**0.335**	**1.635**	**1.297**	**1.536**	**1.346**	**0.280**	**0.354**	**1.645**	**1.265**	**1.518**	**1.371**	**0.323**	**0.336**	**1.630**	*1.200*	**1.572**	**1.346**
white	1.454	1.048	1.093	**1.540**	0.724	0.986	1.433	0.905	1.059	**1.657**	*0.653*	1.037	1.405	0.939	1.072	**1.663**	**0.612**	0.981
marcoup	0.889	1.358	**1.616**	3.009	1.09	0.807	1.092	1.379	**1.779**	2.842	1.109	0.683	1.001	1.223	**2.005**	2.793	1.007	0.736
divsep	2.042	2.416	1.006	*3.306*	0.922	0.769	2.798	2.205	1.145	3.035	0.997	0.699	2.337	2.289	1.336	2.906	0.904	0.651
nvrmar	1.473	1.061		2.607		0.789	1.864	1.166		2.475		0.688	1.803	1.144		2.322		0.646
hhsize	0.963	**1.472**	0.993	**0.896**	0.996	0.965	0.965	**1.376**	0.992	**0.901**	0.991	0.962	0.973	**1.571**	0.984	**0.898**	1.008	0.978
NorthW	**0.383**	*0.550*	1.187	0.925	0.85	0.998	**0.379**	0.618	1.3	0.887	0.849	1.008	**0.378**	**0.491**	1.14	0.917	0.944	1.012
NorthE	*0.641*	0.745	1.119	1.1	0.923	0.935	*0.648*	0.854	1.148	1.088	0.979	0.893	*0.639*	0.787	1.018	1.135	0.998	0.911
SouthE	**0.465**	0.844	**1.840**	1.21	1.3	1.062	**0.478**	0.955	**1.870**	1.244	*1.344*	1.083	**0.492**	0.832	**1.678**	*1.393*	*1.397*	1.066
SouthW	**0.422**	0.92	*1.590*	1.094	*1.422*	0.897	**0.395**	1.028	*1.566*	1.14	1.299	0.876	**0.424**	0.955	1.491	1.176	1.363	0.88
Midland	**0.440**	0.839	**1.663**	1.033	0.912	1.148	**0.418**	0.896	**1.663**	1.015	0.883	1.141	**0.432**	0.835	*1.472*	1.08	0.93	1.136
Scot	**0.568**	1.002	1.366	0.916	0.937	0.966	**0.539**	1.141	1.314	0.877	1.013	0.934	**0.574**	0.986	1.074	0.927	0.99	0.938
Wales	**0.475**	1.116	1.397	1.261	0.889	1.106	**0.422**	1.128	1.206	1.184	0.889	1.077	**0.428**	1.191	0.763	1.358	0.903	1.14
deghdeg	**1.780**	**2.746**	**1.579**	**1.531**	0.75	**1.544**	**1.758**	**2.466**	**1.671**	**1.520**	0.836	**1.667**	*1.554*	**3.004**	**1.670**	**1.699**	0.843	**1.773**
hndalev	1.066	1.024	**2.303**	**1.639**	1.121	**1.484**	1.139	1.056	**2.348**	**1.607**	1.198	**1.499**	0.991	1.101	**2.384**	**1.744**	1.102	**1.580**
ocse	0.889	0.836	**1.995**	**1.342**	1.191	**1.457**	0.952	0.823	**1.883**	**1.382**	*1.287*	**1.462**	0.852	0.873	**1.823**	**1.414**	1.242	**1.506**
prof0	**0.202**	*0.366*	*1.343*		1.411	1.515	**0.174**	0.423			1.379	1.391	**0.222**	0.352	1.317		1.491	1.43
mantech0	**0.236**	0.586	**0.520**		1.149	1.062	**0.241**	*0.573*			1.152	1.038	**0.283**	0.566	0.98		1.192	1.01
sknonm0	**0.193**	0.804	1.882		1.141	0.858	**0.180**	0.793			1.084	0.87	**0.222**	0.762	*2.841*		1.118	0.813
skmanar0	**0.297**	0.638	1.94		*1.350*	1.056	**0.273**	0.644			1.287	1.057	**0.348**	0.638	2.585		1.284	1.018
ptskill0	**0.298**	0.796	1.384		1.294	0.927	**0.278**	0.719			1.324	0.953	**0.324**	0.721	1.816		1.289	0.891

	HEALTH LIMITATIONS						LATENT HEALTH						MENTAL HEALTH					
	Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers	
Variable	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W
lswork	0.789	**1.607**	1.686	1.215	1.206	1.11	0.792	**1.617**	*1.349*	1.202	1.182	*1.206*	0.828	**1.512**	2.083	*1.272*	1.191	**1.294**
lshlltyes	0.81	*0.648*	**3.351**	0.925	0.866	*0.735*	1.099	1.093	**0.628**	0.921	0.966	0.945	1.01	**1.027**	**4.020**	0.998	1.003	**0.979**
t1	**3.294**	0.304	2.082	1.259	**5.382**	**5.797**	**2.892**	0.542	2.152	1.408	**5.521**	**5.766**	**4.088**	*0.204*	2.303	1.429	**7.193**	**5.021**
t2	**2.718**	*0.339*	1.886	1.35	**4.381**	**3.170**	**2.563**	0.535	2.081	1.491	**4.361**	*3.137*	**3.455**	**0.247**	2.062	1.488	**5.235**	*2.716*
t3	**2.326**	**0.338**	2.65	1.079	3.126	**3.182**	*2.183*	0.528	1.458	1.177	3.068	*3.069*	**2.990**	**0.277**	2.88	1.234	*3.732*	*2.756*
t4	1.405	**0.367**	1.081	1.076	2.935	1.644	1.272	0.521	1.856	1.195	2.993	1.566	1.553	**0.308**	1.091	1.249	*3.476*	1.411
t5	1.28	*0.470*	1.691	1.29	*4.156*	2.044	1.265	0.621	**3.371**	1.437	*4.294*	2.031	1.621	**0.359**		1.436	*4.116*	1.777
t6	0.828	**0.352**	**3.345**	0.997	1.462	*2.919*	0.819	*0.458*	2.361	1.143	1.58	*3.065*	1.073	**0.279**		1.093	1.636	2.671
t7	0.961	*0.509*	2.082	1.01	3.285	2.679	0.928	0.61	2.067	1.175	3.649	2.252	1.249	**0.454**		1.097	3.41	1.891
t8	1.049	**0.502**	1.888	0.909		1.406	1.026	0.58	2.819	1.052		1.708	1.361	**0.471**		1.01		1.348
t9	0.846	*0.551*	2.65	0.597			0.874	0.607	1.263	0.675			1.156	*0.528*		0.606		
t10	1.198	*0.514*	1.082	1.025			1.102	*0.559*		1.183			1.601	**0.488**		1.201		
_cons	**26856.555**	**16619.569**	**0.001**	**0.005**	**0.003**	**0.007**	**68039.672**	**5896.324**	**0.001**	**0.006**	**0.004**	**0.007**	**6414.350**	**14922.532**	**0.000**	**0.008**	**0.002**	**0.010**
ln_varg																		
_cons	0.991	**3.149**					1.322	2.326					0.919	**4.029**				
N	12556	10063	1593	3516	1324	2875	12419	9834	1576	3450	1307	2797	12006	9514	1504	3275	1270	2697
Log-likelihood	-1444.41	-2280.646	-733.647	-1447.573	-794.446	-1664.006	-1421.942	-2223.001	-734.958	-1428.583	-783.48	-1625.326	-1399.927	-2151.565	-717.634	-1378.914	-773.342	-1582.391
AIC	2974.821	4647.292	1537.295	2969.147	1664.893	3408.013	2929.885	4532.003	1539.917	2931.167	1642.96	3330.652	2885.854	4389.131	1505.268	2831.829	1622.685	3244.783
BIC	3294.653	4957.607	1725.363	3197.255	1862.053	3646.565	3249.245	4841.328	1727.609	3158.574	1839.629	3568.104	3203.76	4697.033	1691.324	3057.309	1818.262	3480.778

Note: **P-value<0.05**; *P-value<0.10*

Table A2.7 Hazard ratios when maternity is considered employment

	HEALTH LIMITATIONS						LATENT HEALTH						MENTAL HEALTH					
	Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers	
Variable	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W
lhlltyes	**3.893**	**2.114**	**0.299**	**0.433**	*0.683*	**0.622**	**1.887**	**1.474**	**0.493**	**0.622**	**0.687**	**0.765**	**1.057**	**1.022**	0.995	1.013	0.992	1.008
hlltyes0	0.805	1.154	*0.620*	**0.499**	**0.653**	*0.795*	1.036	1.095	0.977	0.879	0.847	1.006	1.008	1.02	1.018	0.987	0.998	0.995
age20240	**0.458**	0.772	1.253	1.365	*0.732*	0.951	**0.422**	0.747	1.215	1.267	0.757	0.945	**0.413**	0.723	1.165	1.255	*0.741*	0.887
age25290	**0.222**	*0.525*	*1.434*	1.377	0.96	0.775	**0.182**	*0.495*	1.301	1.424	0.988	0.758	**0.184**	**0.438**	1.11	1.363	0.882	*0.729*
age30340	**0.166**	0.55	1.184	0.921	0.712	0.833	**0.138**	*0.500*	1.111	0.885	*0.692*	0.833	**0.132**	*0.459*	0.707	0.702	0.723	0.786
age35390	**0.301**	**0.289**	0.921	1.797	*0.669*	0.872	**0.261**	**0.279**	0.973	1.591	*0.676*	0.855	**0.260**	**0.270**	0.745	1.65	**0.622**	0.802
age40440	**0.279**	**0.281**	0.837	1.379	0.691	0.728	**0.228**	**0.272**	0.788	1.005	0.751	*0.711*	**0.233**	**0.255**	*0.610*	0.73	**0.615**	**0.665**
age45490	**0.367**	**0.331**	**0.433**	0.918	**0.613**	**0.651**	**0.287**	**0.301**	**0.366**	0.612	*0.630*	**0.635**	**0.313**	**0.300**	**0.252**	*0.441*	**0.544**	**0.570**
age50540	0.919	0.617	0.584	*0.446*	**0.425**	**0.338**	0.734	0.556	**0.466**	**0.402**	**0.494**	**0.330**	0.8	0.63	**0.254**	**0.253**	**0.378**	**0.295**
age55590	1.211	0.922	**0.137**	**0.284**	**0.172**	**0.318**	0.971	0.775	**0.124**	**0.283**	**0.196**	**0.311**	1.126	0.909	**0.091**	**0.257**	**0.159**	**0.276**
age60640	*1.999*		**0.115**		**0.122**		1.492		**0.131**		**0.142**		*1.999*		**0.091**		**0.113**	
mlnhinc	**0.406**	**0.310**	**1.428**	**1.499**	**1.380**	**1.168**	**0.383**	**0.317**	**1.478**	**1.456**	**1.391**	**1.188**	**0.403**	**0.324**	**1.453**	**1.433**	**1.432**	**1.169**
white	1.300	0.879	1.068	**2.241**	*0.700*	1.211	1.325	0.814	1.027	**2.021**	**0.625**	1.269	1.339	0.831	1.057	**2.098**	**0.648**	1.24
marcoup	**0.372**	1.083	0.886	*5.824*	*0.437*	1.065	**0.347**	1.234	0.829	3.582	**0.393**	0.988	**0.352**	1.066	0.919	4.157	**0.337**	1.047
divsep	0.563	1.177	0.572	*5.640*	*0.468*	1.254	0.589	1.26	0.563	3.593	*0.424*	1.228	0.487	1.207	0.641	2.822	**0.387**	1.159
nvrmar	0.588	1.139	0.605	4.696	*0.441*	1.119	0.559	1.351	0.531	3.187	**0.378**	1.091	0.527	1.44	0.492	2.959	**0.375**	1.062
hhsize	0.961	**1.171**	0.987	0.943	1.025	**0.943**	0.965	**1.156**	0.99	0.954	1.018	**0.943**	0.963	**1.158**	0.988	0.969	1.042	0.958
NorthW	0.781	*0.617*	1.011	0.762	0.776	0.796	0.775	0.673	1.048	0.736	0.761	0.809	0.677	**0.582**	0.92	0.754	0.821	0.838
NorthE	0.925	0.75	0.922	1.272	0.972	0.815	0.934	0.878	0.92	1.226	1.004	0.838	0.892	0.833	0.819	1.124	0.986	0.843
SouthE	**0.671**	0.874	**1.569**	0.898	1.248	1.115	*0.685*	0.991	**1.565**	1.039	1.245	1.175	**0.653**	0.897	*1.460*	1.073	1.26	1.227
SouthW	**0.607**	1.154	**1.601**	0.872	**1.458**	0.988	**0.594**	1.301	*1.528*	0.934	1.321	1.035	**0.572**	1.236	*1.470*	1.057	*1.366*	1.044
Midland	*0.720*	0.912	*1.412*	0.868	0.943	1.044	0.718	1.005	*1.408*	0.855	0.927	1.076	*0.675*	0.971	1.272	0.825	0.932	1.098
Scot	0.818	0.908	1.052	0.767	0.96	0.9	0.807	1.047	0.991	0.767	1.036	0.912	0.777	1.002	0.848	0.76	0.97	0.94
Wales	0.928	1.234	1.316	1.456	0.984	0.959	0.925	1.375	1.099	1.38	1.021	0.947	0.894	1.414	0.726	1.31	0.973	1.036
deghdeg	**1.781**	**1.599**	1.274	**2.384**	1.022	**1.320**	**1.772**	**1.587**	*1.389*	**2.172**	1.084	**1.391**	**1.649**	*1.537*	**1.470**	**2.463**	1.105	**1.481**
hndalev	**1.359**	1.034	**1.865**	**3.196**	*1.260*	**1.246**	**1.445**	1.094	**1.954**	**2.812**	*1.267*	**1.270**	*1.319*	1.104	**2.037**	**2.824**	1.205	**1.317**
ocse	1.193	**0.716**	**1.708**	**2.473**	**1.271**	**1.240**	1.275	**0.715**	**1.687**	**2.295**	**1.315**	**1.257**	1.188	*0.745*	**1.643**	**2.309**	**1.294**	**1.288**
prof0	**0.206**	**0.003**			1.257	1.709	**0.179**	**0.004**			1.223	1.65	**0.173**	**0.003**			1.409	1.727
mantech0	**0.249**	**0.011**			*1.369*	**1.928**	**0.238**	**0.013**			*1.389*	**1.852**	**0.233**	**0.010**			**1.459**	**1.825**

	HEALTH LIMITATIONS						LATENT HEALTH						MENTAL HEALTH					
	Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers	
Variable	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W	M	W
sknonm0	**0.214**	**0.016**			*1.378*	**1.648**	**0.199**	**0.019**			1.347	**1.668**	**0.189**	**0.015**			*1.422*	**1.617**
skmanar0	**0.257**	**0.013**			**1.599**	**1.902**	**0.229**	**0.015**			**1.567**	**1.857**	**0.244**	**0.012**			**1.576**	**1.837**
ptskill0	**0.234**	**0.017**			**1.517**	**1.793**	**0.217**	**0.019**			**1.546**	**1.786**	**0.226**	**0.016**			**1.511**	**1.751**
lswork	**0.723**	1.045	**1.528**	1.18	**1.472**	**1.233**	**0.690**	1.077	**1.496**	1.187	**1.484**	**1.293**	**0.724**	1.007	**1.492**	1.245	**1.432**	**1.373**
lshlltyes	1.124	1.108	**0.499**	0.725	0.822	0.817	**1.212**	1.146	*0.754*	1.055	0.873	0.939	0.998	**1.032**	*0.978*	0.978	1.006	**0.984**
t1	1.419	**0.337**	**6.819**	3.553	**8.747**	**2.302**	1.342	**0.407**	**7.153**	3.769	**8.532**	**2.510**	1.272	**0.340**	**10.155**	4.712	**9.679**	**2.478**
t2	1.265	**0.294**	**6.125**	4.224	**6.238**	1.498	1.255	**0.341**	**6.063**	4.295	**5.914**	1.594	1.172	**0.292**	**8.138**	5.122	**6.275**	1.6
t3	1.247	**0.292**	**4.715**	3.702	**4.050**	1.334	1.236	**0.329**	**4.648**	3.62	**3.853**	1.388	1.245	**0.293**	**6.069**	4.573	**4.125**	1.435
t4	0.987	**0.339**	**5.580**	3.5	**3.326**	1.031	0.968	**0.375**	**5.443**	3.725	**3.250**	1.103	0.891	**0.340**	**6.715**	4.743	**3.110**	1.143
t5	0.968	**0.405**	**8.785**	4.453	**3.537**	0.946	0.992	**0.437**	**8.107**	4.733	**3.485**	1.038	0.952	**0.362**	**10.604**	5.142	**3.090**	1.045
t6	0.862	**0.361**	**5.988**	3.141	1.402	1.128	0.874	**0.394**	**6.162**	3.004	1.452	1.243	0.818	**0.317**	**6.430**	3.548	1.34	1.212
t7	0.866	**0.434**	*4.497*	3	*2.876*	1.039	0.878	**0.457**	*4.474*	2.931	*3.015*	1.034	0.833	**0.422**	*4.720*	3.362	*2.840*	1.004
t8	1.062	**0.461**	*4.685*	0.538		0.615	1.089	**0.446**	*4.540*	0.585		0.65	1.11	**0.440**	**4.915**	0.619		0.58
t9	0.807	**0.513**	1.813	1.26		0.839	0.829	**0.520**	1.739	1.251		0.911	0.825	**0.510**	1.71	1.335		0.892
t10	0.915	**0.550**		1.525			0.895	**0.546**		1.497			0.995	**0.523**		1.638		
_cons	**7272.027**	**3.55e+06**	**0.002**	**0.000**	**0.009**	**0.027**	**14678.629**	**1.59e+06**	**0.001**	**0.000**	**0.012**	**0.021**	**7061.171**	**1.43e+06**	**0.001**	**0.000**	**0.007**	**0.022**
ln_varg																		
_cons	1.239	**2.736**					1.498	**2.496**					1.525	**2.734**				
N	17307	14986	2617	1514	2555	5899	17117	14639	2583	1486	2515	5737	16474	14148	2439	1408	2405	5489
Log-likelihood	-2614.196	-3430.306	-854.287	-543.489	-1167.591	-2555.101	-2589.688	-3346.681	-856.845	-547.87	-1146.025	-2496.995	-2519.62	-3234.519	-847.458	-537.325	-1132.069	-2422.403
AIC	5320.391	6950.611	1786.574	1164.978	2419.182	5196.202	5271.376	6783.362	1791.691	1173.741	2376.051	5079.99	5131.24	6559.038	1772.916	1152.649	2348.138	4930.805
BIC	5677.299	7293.281	2015.495	1372.556	2664.706	5483.552	5627.776	7124.977	2020.103	1380.591	2620.912	5366.142	5485.879	6899.118	1999.091	1357.396	2591.121	5215.057

Note: **P-value<0.05**; *P-value<0.10*

Table A2.8 Hazard ratio for health limitations when we do not control for unobserved heterogeneity

	Stock sample workers		Stock sample non-workers		Flow sample non-workers	
Variable	M	W	M	W	M	W
lhlltyes	**3.441**	**2.037**	**0.301**	**0.511**	0.713	**0.629**
hlltyes0	0.75	0.894	*0.656*	0.772	**0.628**	0.784
age20240	**0.649**	0.901	1.259	0.947	*0.743*	0.982
age25290	**0.364**	*0.720*	1.405	0.743	0.979	0.866
age30340	**0.275**	**0.482**	1.127	**0.660**	0.722	0.907
age35390	**0.440**	**0.324**	0.812	**0.600**	0.697	1.011
age40440	**0.459**	**0.326**	0.843	**0.471**	0.693	0.927
age45490	**0.545**	**0.380**	**0.415**	**0.374**	*0.637*	0.798
age50540	1.222	**0.564**	0.612	**0.205**	**0.421**	**0.396**
age55590	*1.503*	*0.630*	0.137	**0.192**	**0.170**	**0.317**
age60640	**2.270**		**0.119**		**0.120**	
mlnhinc	**0.523**	**0.521**	**1.454**	**1.263**	**1.361**	**1.304**
white	1.199	0.796	1.057	**1.569**	*0.715*	1.024
marcoup	*0.541*	1.432	1.376	1.588	**0.337**	1.062
divsep	0.753	1.121	0.926	1.876	**0.361**	1.176
nvrmar	0.853	1.005	0.922	1.329	**0.335**	1.09
hhsize	0.982	**1.092**	0.986	**0.896**	1.023	0.979
NorthW	0.987	0.893	1.027	0.87	0.802	0.957
NorthE	1.103	0.985	0.94	1.014	0.954	0.862
SouthE	0.824	0.972	**1.580**	1.191	1.251	1.042
SouthW	0.817	1.057	**1.658**	1.057	**1.440**	0.858
Midland	0.907	0.988	*1.434*	1.001	0.944	1.039
Scot	0.935	1.076	1.049	0.924	0.96	0.938
Wales	1.169	1.133	1.317	1.175	0.978	0.997
deghdeg	**1.657**	**1.474**	*1.366*	**1.572**	0.994	**1.379**
hndalev	*1.228*	0.905	**1.985**	**1.696**	1.214	**1.297**
ocse	1.102	**0.804**	**1.730**	**1.401**	*1.247*	**1.248**
prof0	**0.459**	0.689			1.088	*1.596*
mantech0	**0.544**	0.906			1.168	1.153
sknonm0	**0.491**	1.123			1.179	0.984
skmanar0	**0.564**	1.055			*1.352*	1.194
ptskill0	**0.489**	1.079			1.279	1.06
lswork	**0.800**	1.001	*1.368*	*1.271*	**1.493**	*1.210*
lshlltyes	1.147	1.074	**0.515**	0.897	0.832	0.803
t1	**2.311**	**1.626**	**4.411**	1.586	**11.015**	**5.422**
t2	**1.764**	1.13	**3.868**	1.646	**7.916**	3.021
t3	**1.588**	0.876	*2.958*	1.289	**5.235**	2.732
t4	1.175	0.964	**3.414**	1.307	**3.937**	1.465
t5	1.097	0.895	**5.815**	1.462	**4.576**	1.755
t6	0.941	**0.648**	**3.729**	1.109	1.821	2.164
t7	0.926	0.793	2.864	1.053	2.7	1.819
t8	1.089	0.779	**3.814**	0.986		0.793
t9	0.794	0.705	1.149	0.721		0.281
t10	0.904	*0.667*		1.075		
_cons	**72.180**	**59.483**	**0.001**	**0.009**	**0.013**	**0.008**
N	17295	13401	2706	4731	2479	3782
Log-likelihood	-2607.777	-3133.268	-877.42	-1651.965	-1144.601	-1971.852
AIC	5305.554	6354.536	1832.841	3381.93	2373.201	4029.705
BIC	5654.672	6684.672	2063.066	3633.944	2617.457	4297.939

Note: **P-value<0.05**; *P-value<0.10*

Table A2.9. Hazard estimates with unobserved heterogeneity assuming that it is normally distributed and constant over time

	HEALTH LIMITATIONS						LATENT HEALTH						MENTAL HEALTH					
	Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers	
Variable	M	W	M	W	M	W	M	W	M	M	W	M	W	M	W	M	W	M
lhlltyes	**3.581**	**2.071**	**0.300**	**0.509**	0.716	**0.627**	**1.786**	**1.387**	**0.493**	**0.656**	**0.700**	**0.813**	**1.055**	**1.023**	0.998	0.997	0.99	**1.017**
hlltyes0	0.768	0.913	*0.645*	0.766	**0.619**	0.772	0.931	1.031	0.983	1.022	0.822	0.942	1.000	1.008	1.017	0.999	0.999	*0.986*
age20240	**0.601**	0.859	1.269	0.944	*0.739*	0.977	**0.557**	0.807	1.23	0.878	0.765	0.973	**0.588**	0.824	1.175	0.873	0.752	0.938
age25290	**0.326**	0.698	1.405	0.738	0.981	0.862	**0.289**	*0.653*	1.292	0.735	1.007	0.827	**0.303**	**0.628**	1.095	0.734	0.905	0.793
age30340	**0.244**	**0.453**	1.128	**0.654**	0.721	0.909	**0.219**	**0.416**	1.061	**0.650**	0.703	0.901	**0.220**	**0.407**	0.671	**0.607**	0.749	0.894
age35390	**0.401**	**0.294**	0.811	**0.597**	0.693	1.015	**0.369**	**0.278**	0.847	**0.594**	0.705	0.976	**0.382**	**0.277**	0.668	**0.551**	*0.650*	0.946
age40440	**0.413**	**0.289**	0.832	**0.463**	0.691	0.926	**0.370**	**0.270**	0.794	**0.453**	0.757	0.886	**0.392**	**0.268**	*0.601*	**0.401**	**0.619**	0.871
age45490	**0.501**	**0.341**	**0.413**	**0.370**	*0.634*	0.793	**0.428**	**0.302**	**0.353**	**0.367**	*0.657*	0.745	**0.475**	**0.311**	**0.246**	**0.304**	**0.564**	0.693
age50540	1.16	**0.526**	0.602	**0.200**	**0.417**	**0.388**	0.98	**0.468**	**0.489**	**0.212**	**0.483**	**0.365**	1.086	**0.520**	**0.268**	**0.166**	**0.373**	**0.316**
age55590	1.458	*0.603*	**0.134**	**0.188**	**0.166**	**0.310**	1.226	**0.513**	**0.122**	**0.203**	**0.190**	**0.294**	1.466	*0.589*	**0.090**	**0.183**	**0.154**	**0.249**
age60640	**2.251**		**0.116**		**0.118**		**1.745**		**0.131**		**0.138**		**2.284**		**0.093**		**0.109**	
mlnhinc	**0.495**	**0.494**	**1.467**	**1.274**	**1.372**	**1.318**	**0.492**	**0.494**	**1.515**	**1.246**	**1.386**	**1.352**	**0.502**	**0.512**	**1.495**	*1.180*	**1.429**	**1.357**
white	1.221	0.796	1.056	**1.578**	*0.710*	1.023	1.269	0.777	1.014	**1.697**	**0.633**	1.08	1.223	0.74	1.045	**1.708**	**0.651**	1.071
marcoup	*0.511*	1.431	1.362	1.607	**0.334**	1.079	0.555	1.45	1.225	1.47	**0.287**	0.976	0.552	1.337	1.214	1.369	**0.255**	1.155
divsep	0.722	1.179	0.913	1.902	**0.357**	1.188	0.867	1.267	0.856	1.748	**0.310**	1.152	0.701	1.229	0.885	1.552	**0.295**	1.136
nvrmar	0.814	1.01	0.904	1.335	**0.332**	1.102	0.899	1.104	0.772	1.263	**0.272**	1.025	0.833	1.128	0.665	1.138	**0.281**	1.038
hhsize	0.978	**1.114**	0.985	**0.895**	1.025	0.978	0.987	**1.121**	0.988	**0.903**	1.018	0.975	0.982	**1.104**	0.986	**0.904**	1.042	0.992
NorthW	0.932	0.875	1.019	0.866	0.796	0.955	0.927	0.882	1.062	0.828	0.784	0.971	0.828	0.823	0.935	0.86	0.838	0.986
NorthE	1.059	0.983	0.934	1.014	0.949	0.855	1.079	1.037	0.934	1.006	0.981	0.829	1.043	1.025	0.809	1.029	0.975	0.837
SouthE	0.782	0.965	**1.580**	1.194	1.25	1.043	0.791	1.002	**1.593**	1.246	1.244	1.067	0.776	0.955	*1.458*	*1.386*	1.266	1.07
SouthW	0.764	1.071	**1.671**	1.06	**1.445**	0.853	0.753	1.138	**1.600**	1.116	1.312	0.86	*0.729*	1.098	*1.518*	1.151	*1.357*	0.868
Midland	0.859	0.986	*1.430*	1.000	0.939	1.035	0.864	1.009	*1.432*	0.982	0.923	1.046	0.818	1.03	1.291	1.046	0.926	1.053
Scot	0.901	1.092	1.039	0.926	0.955	0.94	0.906	1.172	1.016	0.899	1.026	0.943	0.879	1.072	0.861	0.906	0.968	0.966
Wales	1.105	1.172	1.323	1.175	0.975	0.999	1.121	1.177	1.121	1.141	1.005	0.981	1.082	1.24	0.721	1.253	0.981	1.046
deghdeg	**1.691**	**1.524**	1.368	**1.580**	0.999	**1.388**	**1.611**	**1.526**	**1.488**	**1.578**	1.057	**1.515**	**1.498**	**1.525**	**1.557**	**1.772**	1.081	**1.625**
hndalev	*1.260*	0.905	**2.003**	**1.714**	1.219	**1.299**	*1.273*	0.94	**2.108**	**1.672**	1.226	**1.323**	1.18	0.938	**2.169**	**1.830**	1.174	**1.380**
ocse	1.116	**0.792**	**1.745**	**1.409**	*1.255*	**1.254**	1.146	**0.789**	**1.752**	**1.466**	**1.295**	**1.267**	1.071	**0.790**	**1.694**	**1.497**	**1.288**	**1.300**
prof0	**0.417**	0.654			1.086	*1.617*	**0.434**	0.651			1.065	1.489	**0.417**	0.691			1.226	1.628
mantech0	**0.499**	0.892			1.171	1.166	**0.545**	0.86			1.196	1.123	**0.526**	0.879			1.253	1.117

	HEALTH LIMITATIONS						LATENT HEALTH						MENTAL HEALTH					
	Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers		Stock sample workers		Stock sample non-workers		Flow sample non-workers	
Variable	M	W	M	W	M	W	M	W	M	M	W	M	W	M	W	M	W	M
sknonm0	**0.448**	1.12			1.181	0.989	**0.491**	1.092			1.165	1	**0.454**	1.116			1.224	0.973
skmanar0	**0.518**	1.033			*1.361*	1.205	**0.528**	0.968			*1.349*	1.186	**0.542**	0.972			*1.353*	1.189
ptskill0	**0.453**	1.078			1.285	1.062	**0.474**	1.006			1.324	1.082	**0.469**	1.053			1.288	1.041
lswork	**0.777**	1.027	**1.391**	**1.278**	**1.508**	*1.214*	**0.750**	1.069	**1.381**	**1.281**	**1.516**	**1.304**	**0.763**	0.967	**1.406**	**1.348**	**1.469**	**1.382**
lshlltyes	1.132	1.071	**0.516**	0.897	0.831	0.799	**1.201**	**1.190**	*0.780*	0.957	0.872	0.951	0.999	**1.025**	0.981	1	1.006	**0.978**
t1	**2.002**	1.303	**4.193**	1.494	**10.412**	**4.969**	**2.141**	*1.377*	**4.392**	1.601	**10.292**	**5.082**	**2.025**	1.294	**6.242**	1.698	**11.697**	*4.115*
t2	**1.603**	0.955	**3.733**	1.566	**7.637**	2.848	**1.730**	1.003	**3.732**	1.665	**7.379**	2.866	**1.623**	0.916	**4.992**	1.718	**7.825**	2.398
t3	*1.478*	0.764	*2.880*	1.237	**5.108**	2.618	*1.572*	0.818	*2.828*	1.296	**4.954**	2.579	*1.565*	0.772	**3.698**	1.396	**5.303**	2.281
t4	1.113	0.861	**3.347**	1.263	**3.867**	1.419	1.152	0.907	*3.284*	1.324	**3.847**	1.391	1.058	0.852	**4.113**	1.441	**3.798**	1.26
t5	1.052	0.819	**5.737**	1.423	**4.515**	1.715	1.126	0.861	**5.313**	1.517	**4.529**	1.751	1.088	0.731	**6.867**	1.579	**3.977**	1.532
t6	0.911	**0.601**	**3.700**	1.086	1.807	2.132	0.959	**0.640**	**3.820**	1.193	1.9	2.287	0.894	**0.568**	**4.101**	1.19	1.748	2.016
t7	0.902	0.748	2.85	1.037	2.684	1.806	0.936	0.752	2.844	1.155	2.852	1.564	0.892	0.754	3.007	1.117	2.677	1.381
t8	1.073	0.748	**3.803**	0.973		0.794	1.13	0.73	**3.785**	1.081		0.927	1.156	0.724	**4.100***	1.077		0.788
t9	0.79	0.689	1.148	0.714		0.282	0.833	*0.674*	1.14	0.722		0.291	0.828	*0.679*	1.124	0.681		0.287
t10	0.898	*0.658*		1.07			0.886	*0.662*		1.197			0.974	*0.644*		1.251		
_cons	**159.147**	**107.832**	**0.001**	**0.009**	**0.012**	**0.007**	**123.732**	**93.143**	**0.001**	**0.011**	**0.016**	**0.006**	**90.546**	**60.570**	**0.001**	**0.015**	**0.010**	**0.006**
lnsig2u																		
_cons	**0.298**	**0.310**	**0.040**	**0.042**	**0.040**	**0.054**	**0.310**	**0.297**	**0.041**	**0.043**	**0.042**	**0.051**	**0.294**	**0.317**	**0.041**	**0.042**	**0.043**	0.124
LR-test	3.23 (0.036)	3.26 (0.036)	4.30 (0.019)	2.15 (0.071)	2.56 (0.055)	3.38 (0.033)	1.42 (0.117)	1.07 (0.151)	1.06 (0.152)	0.88 (0.174)	1.09 (0.148)	1.20 (0.136)	1.55 (0.107)	0.01 (0.459)	1.17 (0.140)	0.12 (0.363)	0.84 (0.179)	0.28 (0.299)
N	17295	13401	2706	4731	2479	3782	17105	13081	2671	4634	2440	3683	16462	12630	2517	4379	2347	3541
Log-likelihood	-2606.163	-3131.639	-878.129	-1652.498	-1145.374	-1971.847	-2583.938	-3052.037	-879.496	-1632.49	-1123.642	-1928.704	-2512.275	-2957.078	-867.843	-1573.07	-1111.909	-1875.697
AIC	5304.326	6353.277	1836.258	3384.996	2376.749	4031.694	5259.875	6194.074	1838.992	3344.98	2333.284	3945.408	5116.551	6004.156	1815.686	3226.14	2309.818	3839.394
BIC	5661.202	6690.916	2072.387	3643.471	2626.82	4306.166	5616.243	6530.625	2074.6	3602.627	2582.673	4218.713	5471.156	6339.128	2048.918	3481.523	2557.537	4110.969

Note: **P-value<0.05**; *P-value<0.10*

Chapter 3. Informal care and labour force participation among middle-aged women in Spain

1. Introduction

The process of population ageing that developing countries are likely to undergo in the coming decades is one of the phenomena whose social and economic consequences cause most concern. The already classical debates on the future sustainability of the systems of public pensions (Jimeno et al, 2008) and health care (Ahn et al, 2005) have extended more recently to the discussion on how to provide and fund the care required by older people who cannot look after themselves.

To date, in Spain and throughout southern Europe, the family has characteristically been the main source of support to meet the needs of dependent people (OECD, 2005). Thus, in the particular case of Spain (Casado, 2006), the needs of 74% of all dependent people are met solely by informal carers, and the figure rises to 85% if we include those who combine informal care with some other source of support of a formal nature (for example, home care)[15]. The extraordinary vigour of this family model, undoubtedly made possible by the low labour force participation rates of current cohorts of middle-aged women and their predecessors, has until now enabled the public sector to take on a subsidiary role: only when the family is unable or unwilling to help or does not exist, and always depending on the economic capacity of the older person concerned, is the required care publicly funded (Edad & Vida, 2004).

Following the lead of other European countries, which have had universal public long-term care systems for some years, Spain is now developing a similar scheme known as the National Long-Term Care System (*Sistema para la Autonomía y Atención a la Dependencia* or SAAD) over the period 2007-2015[16]. One of the main goals pursued through the SAAD, in addition to eliminating means testing for access to public long-term care services, is to strike a new balance between formal and informal care that is compatible with the higher

[15] Carers are considered to be informal when they receive no financial remuneration for the help they give.
[16] See OECD (2005) for an up-to-date description of the long-term care systems of EU countries.

labour force participation rates of future cohorts of middle-aged women. Specifically, given that a steep rise is expected in the percentage of women that will be in employment when someone in their family becomes dependent, the development of community services (home care, day centres and so on) through the SAAD seeks to make providing a certain amount of informal care compatible with having a paid job. This would not only avoid the negative consequences at an individual level associated with leaving the labour market (loss of income, smaller future pension, etc.) but would also make it possible to take on family responsibilities without jeopardising the macroeconomic objective, enshrined in the Lisbon Agenda, of increasing the female labour force participation rate to 60% over the next decade.

However, if the SAAD is really to reach the goals that have been set, the design of the new benefits must be based on a profound knowledge of how today's middle-aged women combine (or fail to combine) informal caregiving with doing paid work. Although several studies have been published that examine the existence of labour opportunity costs associated with informal care in other countries, to our knowledge there is no specific study on this issue for the Spanish case.

Thus, in view of the above, the main aim of this chapter is to analyse to what extent women who give informal care today incur labour opportunity costs as a result of doing so. To this end, we use the eight waves of the European Community Household Panel (1994-2001) to estimate a dynamic ordered probit that enables us to examine the effects of various types of informal care on labour behaviour. The results obtained indicate the existence of labour opportunity costs for those women who live with the dependent person they care for, but not for those who care for someone outside the household. Furthermore, whereas caregiving for more than a year has negative effects on labour force participation, the same cannot be said of those who "start caregiving" and "stop caregiving".

2. Informal care and labour market outcomes

The main methodological challenge faced when analysing the relationship between informal care and labour behaviour is that informal care is usually endogenous to the process determining labour outcomes. This endogeneity may arise from either of two types of elements. First, considering that the two activities compete for the potential carer's time, allocations to one or the other will be the result of a simultaneous choice process in which other factors also come into play: the use of formal services, the previous employment status of the potential carer, the availability of other informal carers, etc. And second, even in the event of being able to model the simultaneity of the choices and the influence of the factors mentioned above, we may still be faced with a problem of endogeneity if the individuals possess unobserved characteristics correlated with both the propensity to care for a dependent relative and the propensity to participate in the labour market.

On the basis of the definition of the two problems described above, henceforth referred to as the *simultaneity problem* and the *unobserved individual heterogeneity problem*, previous studies examining the relationship between informal care and labour force participation can be classified according to whether they deal with both problems, only one of them, or neither. Starting with the last of these groups of studies, the two papers by Carmichael and Charles (1998 and 2003) analyse the relationship between informal care and labour behaviour in the UK, using cross-section data from the General Household Survey of 1985 and 1990 respectively. The results obtained by these authors, undoubtedly the least robust from a methodological point of view in that they assume informal care to be exogenous in both cases, show this variable to have negative effects on both the probability of being employed and the number of hours worked.

A second group of studies have attempted, despite their use of cross-section data, to tackle the possible endogeneity of informal care by estimating the labour equations of interest with instrumental variables (Wolf and Soldo, 1994; Ettner, 1995 and 1996; Heitmueller, 2007; Bolin et al, 2008). The instruments used in these studies typically include the health status of the parents of caregiving and non-caregiving women (as worse health status is assumed to require more intensive care) and the number of siblings these women have (as the intensity of the informal care to be given will be lower if there are alternative carers).

The results obtained by this second group of studies tend to confirm the existence of labour opportunity costs associated with informal care. Thus, with the exception of Wolf and Soldo (1994), who find no effect either on the probability of being employed or on the number of hours worked, the rest of the papers mentioned above point to the existence of considerable labour effects for women carers, despite using databases referring to different countries and different moments in time. Ettner (1995 and 1996) uses US data, as do Wolf and Soldo, yet obtains very different results: first, significant labour effects are detected when the woman providing informal care lives with the dependent person, basically in the form of a lower labour market participation; and second, although women caring for someone outside the household do not seem to participate less in the labour market, the number of hours worked is nevertheless lower than that of non-carers.

Ettner's results have been confirmed in part by more recent studies conducted using European data. Heitmueller (2007) uses instrumental variables to estimate, on the basis of the 2002 wave of the British Household Panel Survey (BHPS), the effect on labour force participation of caregiving both inside and outside the household; his results show that only the first case yields a statistically significant decrease in the probability of being employed. Within the same empirical framework, Bolin et al (2008) use data from the Survey of Health, Ageing and Retirement in Europe (SHARE) to analyse the respective association between hours of informal care provided and the following three labour market outcomes: i) the probability of employment, ii) hours worked, and iii) wages. Their results suggest that giving informal care to one's elderly parents is associated with significant costs in terms of foregone labour market opportunities and that these effects vary between European countries.

Crespo (2007) uses data from the first available wave (2004) of the SHARE to calculate the effects of informal care on female labour force participation in two triplets of countries in southern Europe (Spain, Italy and Greece) and northern Europe (Sweden, Denmark and the Netherlands), by estimating a bivariate probit model to control for the endogeneity of the caregiving decision. Her results indicate that women who provide an "intense" level of care – i.e., live in the same household as the dependent, or give daily care elsewhere – have less probability of participating in the labour force both in the three southern European countries and in the three northern ones.

A third group of studies is characterised by concentrating on unobserved individual heterogeneity using longitudinal data. In particular, using the first three waves of the European Community Household Panel (1994-1996), Spiess and Schneider (2003) employ a difference-in-difference model to examine the impact on number of hours worked of three "stages" of informal care: starting caregiving, continuing caregiving, and stopping caregiving. The results obtained, which cannot be broken down into countries due to the small sample size, show that in the southern European (Mediterranean) group of countries it is the fact of continuing to give care – not the fact of starting – that affects the number of hours worked, whereas in the rest of the countries analysed (non-Mediterranean Europe) the results show exactly the opposite.

In turn, Viitanen (2005) uses all eight waves of the ECHP (1994-2001) to examine the effects of informal care on the labour behaviour of women aged 20 to 59, with the aid of dynamic probit models that take into consideration unobserved individual heterogeneity (random effects), state dependence, and the attrition biases that tend to appear when working with panel data. The results obtained by this author, which unlike those of Spiess and Schneider are country-specific, indicate that informal caregiving only has a negative influence on the probability of being employed in the case of Germany. However, on replicating the study taking specific subgroups of women into consideration, Viitanen detects significant effects in several countries among middle-aged women (Belgium, Finland and Germany) and among single women (Greece, the Netherlands, Italy and Germany).

More recently, Heitmueller (2007) also analyses the relationship between caregiving and labour market participation by estimating fixed effects models using the first 12 waves of the BHPS (1991-2002). The results in this case are similar to the ones obtained using an instrumental variable approach using only data from 2002 (see above). However, now regardless of whether caregiving is co-residential or extra-residential, his results reveal that unobserved heterogeneity plays a role.

The last group of studies that have examined the relationship between informal care and labour behaviour have tackled the two issues of simultaneity and unobserved heterogeneity. Thus, on the basis of two waves of the Health and Retirement Study, Johnson and Lo Sasso (2000) estimate a simultaneous equation model with panel data to analyse the impact of caring for a dependent parent for more than 100 hours a year on the annual number of hours worked. The results obtained indicate that the annual labour supply of middle-aged (aged 53-63) carers is 23% and 28% lower (among men and women respectively) than that of non-carers. In a recent paper based on 13 waves of the British Household Panel Survey (1991-2003), Heitmueller and Michaud (2006) estimate a dynamic bivariate probit that adjusts for reverse causality, state dependence and individual heterogeneity. The model is estimated separately for two distinct samples of carers, which yield different results in each case: if we consider everyone who cares for another person, whether at home or elsewhere, labour force participation does not appear to be lower than that of non-carers; but when the model is estimated for the subsample of co-resident carers, the results show a lower labour force participation, both among women (-6%) and among men (-4.7%).

So, we contribute to the existing literature by looking at the effect of various characteristics of caregiving (where it is carried out and whether there is a transition into or out of caregiving or simply a continuation) on the probability of being employed full-time or part-time. We exploit the panel structure of the Spanish sample of the ECHP, thus allowing for the presence of individual specific unobserved heterogeneity and state dependence, in a dynamic ordered probit model. In this regard, we follow an approach similar to Viitanen (2005). However, our approach carefully considers different caregiving states, as we suspect that Viitanen's (2005) results suggesting that caregiving affects the probability of employment only in the case of German women can be explained by having considered co-residents and non-coresidents together. Thus, we consider caregiving at home or elsewhere as possibly having different effects, as the results obtained by Heitmueller (2007) and Heitmueller and Michaud (2006) for the UK suggest. In addition, we exploit the dynamics of caregiving, i.e., we allow the effects of caregiving to be different depending on whether it is a recent situation or a mere continuation (first years vs. subsequent years). Also we analyse the propensity to be employed once the individual stops giving care. One further distinguishing feature of our approach consists in testing for the assumption of (conditional) exogeneity of caregiving status in our equation for labour outcomes.

3. Econometric methods

Econometric model

The econometric model we use to estimate the impact of informal care is an ordered probit[17]. This model specifies the relationship between a latent index of linkage to the labour market, l_{it}^{*}, and the explanatory variables according to the following expression:

$$\begin{aligned} &l_{it}^{*} = \delta' C_{it} + \beta' X_{it} + \gamma' l_{it-1} + \alpha_i + \varepsilon_{it} \\ &i = 1 \ldots N \\ &t = 2 \ldots T \end{aligned} \qquad (3.1)$$

where i represents individuals and t years, C_{it} contains dummy variables denoting that woman i is engaged in caregiving in period t, X_{it} contains observable characteristics potentially associated with the decision to work, such as age, marital status, region of residence, etc., l_{it-1} contains dummy variables capturing the employment status in the previous period, α_i is an individual fixed effect denoting the effect of the unobserved systematic heterogeneity inherent in microeconomic data, and ε_{it} depicts the purely random variation around the expected value of l_{it}^{*} (conditioned by the value of the observed explanatory variables and the individual fixed effect). Furthermore, whereas α_i can be

[17] This is not the only possibility for modelling. For example, Bingley and Walker (1997) use a multinomial probit to assess the impact of a labour force participation incentive programme for single mothers. However, the identification of the multinomial probit requires the existence of variables with different values for each alternative. The obvious case is that of the variable "labour income", which habitually requires us to predict counterfactual values, as income is only observed in the declared employment status. Another possibility would be the multinomial logit model, which is identified even when its specification only includes variables that do not vary between alternatives. However, the clearly ordered nature of the three categories of employment status justifies our choice of the ordered probit, which has also been used in previous studies of the employment status of women (e.g., Ermisch and Wright, 1991). Furthermore, its simple structure facilitates the introduction of delayed employment status variables capturing state dependence in the labour supply.

correlated with the explanatory variables and generates intra-individual autocorrelation in the composite error term ($\alpha_i + \varepsilon_{it}$), ε_{it} is independent of the explanatory variables and is not autocorrelated.

In order to model the correlation between the observed variables and the unobserved individual fixed effect, we specify a parametric relationship between the latter and the former along the lines of those proposed by Mundlak (1978) and Chamberlain (1984). That is,

$$\begin{aligned} &\alpha_i = \eta' \overline{Z}_{i.} + \lambda' l_{i0} + u_i \\ &i = 1 \ldots N \end{aligned} \tag{3.2}$$

where $\overline{Z}_{i.}$ contains the mean of vector X_i and C_i over T time periods for individual i, l_{i0} contains the values of the employment status variables in the initial period, and u_i is an independent random term of the observed explanatory variables. Equation (3.2) also enables us to solve the initial conditions problem that arises in dynamic models for discrete dependent variables with unobserved heterogeneity (Heckman, 1981), as it incorporates the proposal made by Wooldridge (2005) which consists in conditioning α_i to the initial employment status values[18].

Thus, substituting (3.2) into (3.1), we get:

$$\begin{aligned} &l_{it}^* = \delta' C_{it} + \beta' X_{it} + \gamma' l_{it-1} + \eta' \overline{Z}_{i.} + \lambda' l_{i0} + u_i + \varepsilon_{it} \\ &i = 1 \ldots N \\ &t = 2 \ldots T \end{aligned} \tag{3.3}$$

where u_i is independent of the explanatory variables, but the composite error ($u_i + \varepsilon_{it}$) presents intra-individual temporal autocorrelation.

---

[18] See Contoyannis et al (2004) for an application of this solution in the context of a model for self-perceived health status.

The latent variable l_{it}^{*} is not observed, but we do observe whether woman *i* in period *t* falls into one of the three categories "no work", "part-time" or "full-time". The rule that governs the relationship between the latent variable and the information on employment status in models of the ordered multinomial family is that as l_{it}^{*} exceeds certain thresholds we observe alternatives in ascending order. That is, for the three possible ordered alternatives (for *k*=1,2,3), which in our case correspond to the employment statuses mentioned above, we observe $l_{it}=k$ if $\mu_{k-1} < l_{it}^{*} \le \mu_k$, where $\mu_0 = -\infty$ and $\mu_m = \infty$, with *m* being the number of alternatives. Therefore, the basis for the maximum likelihood estimation of the model is given by the expression:

$$\Pr_{itk} = \Pr(l_{it} = k) = \Pr\left(\mu_{k-1} < l_{it}^{*} \le \mu_k\right) \tag{3.4}$$

where Pr denotes probability.

There are two alternatives to consistently estimate the parameters of Equation (3.3). First, under the assumptions $u_i \sim N(0,\sigma_u^2)$ and $\varepsilon_{it} \sim N(0,1)$, it is possible to integrate (throughout the distribution of u_i) the probabilities of expression (3.4) conditioned in realisations of u_i. The log-likelihood function would be as follows:

$$\ln L = \sum_{i=1}^{N} \ln \int_{-\infty}^{\infty} \prod_{t=2}^{T} \left(\Pr_{itk} \mid C_{it}, X_{it}, l_{it-1}, \overline{Z}_{i.}, l_{i0}, u_i\right) du \tag{3.5}$$

Expression (3.5) is the log-likelihood function for the random effects ordered probit model. Thus, under the assumptions of the model, the maximisation of (3.5) yields consistent and efficient estimates.

Alternatively, we can consider the composite error $v_i = u_i + \varepsilon_{it}$, and make the assumptions $\mathbf{v} \sim N(\mathbf{0},\mathbf{I})$ so as to maximise the following function:

$$\ln L = \sum_{i=1}^{N} \sum_{t=2}^{T} \ln\left(\Pr_{itk} \mid C_{it}, X_{it}, l_{it-1}, \overline{Z}_{i.}, l_{i0}\right) \tag{3.6}$$

Expression (3.6) is the log-likelihood function for the pooled ordered probit model. Although expression (3.6) is an incorrect specification of the likelihood function of the model we are using, since the assumption $\mathbf{v}\sim N(\mathbf{0},\mathbf{I})$ ignores the existence of intra-individual correlation induced by u_i, its maximisation yields consistent but inefficient estimates of the parameters of interest. In fact, the estimate based on (3.6) corresponds to the estimate of the model by quasi-maximum likelihood (or partial maximum likelihood). As shown by Cameron and Trivedi (2005, p. 150), the consistency of quasi-maximum likelihood estimation does not require the correct specification of the joint density of the vector $\mathbf{l}_i=(l_{i2}, l_{i3}, \ldots, l_{iT})$ as performed in expression (3.5); it is sufficient to correctly specify the marginal density of each of its elements l_{it}. It is important to note, however, that the standard error estimate based on (3.6) is not consistent, and therefore we use an estimator of the matrix of variances and covariances that is robust to the autocorrelation in the composite error term v_i. Obviously, the preferred way to estimate the model is the one that uses expression (3.5), since it yields consistent and efficient estimates. However, for reasons associated with the problem of attrition bias which we will elucidate below, we will use expression (3.6) for the set of final results.

Treatment of attrition

In the ECHP, and habitually in household panels, we come up against the phenomenon of attrition (Peracchi, 2002). Insofar as this attrition is related to the event we are interested in, the parameters – estimated by means of one or other of the two methods described above – will be biased. With the aim of analysing the presence of attrition bias, we perform the variable addition test proposed by Verbeek and Nijman (1992), whereby we add one of the following variables to the estimated model: i) a dummy variable indicating whether the individual has responded in the following wave; ii) a dummy variable indicating whether the individual is in the balanced panel; iii) a variable with the number of waves in which the individual has responded. The null hypothesis of non-existence of bias is rejected when any of these variables is significant, or when all three of them together (or any combination of two of them) are significant.

In any event, when the results for the attrition contrasts do not enable us to accept the null hypothesis of absence of attrition, it is possible to obtain consistent estimates even in the presence of attrition using the inverse probability weighting estimator, as suggested by Wooldridge (2007).

In order to implement this estimator, first we use binomial probit models to estimate the probability of individual *i* being present in the sample in period *t*, $\hat{p}_{it}$, as a function of a set of characteristics. These models are estimated for each wave of the ECHP (2-8), using the whole sample of individuals observed in the first wave. Two different models are considered. The first includes the values in the first wave (1994) to estimate the response probabilities in the consecutive years. The second uses the values of the variables in *t-1* to estimate the response probability in *t*; in this case, given that the sample in *t-1* is potentially unrepresentative of the sample in the first year of the survey, it is necessary to update the predicted probability such that $\hat{p}_{it} = \hat{\Pi}_{i2}\hat{\Pi}_{i3}...\hat{\Pi}_{it}$, where $\hat{\Pi}_{it}$ represents the response probabilities estimated for each year (Wooldridge, 2007).

Lastly, we use the inverse of the predicted probabilities for each individual in each model $(1/\hat{p}_{it})$, or lacking that, the fitted probability in the second of the two models, to weight the contributions of each observation to the log-likelihood function. In this respect, as mentioned by Contoyannis et al (2004), the IPW estimator can be applied in situations where the objective function is additive in the contribution of each observation. This is why this estimator cannot be used in models such as the random effects ordered probit model, for which – as can be seen in expression (3.5) – there is a term consisting of the product of the contributions of the observations of any given individual for different time periods. This limitation does not affect the pooled ordered probit model, in which the log-likelihood function to maximise is:

$$\ln L = \sum_{i=1}^{N}\sum_{t=2}^{T}\left(\frac{R_{it}}{\hat{p}_{it}}\right)\ln\left(\Pr_{itk} \mid C_{it}, X_{it}, l_{it-1}, \overline{X}_{i}, l_{i0}\right) \tag{3.7}$$

where R_{it} is a dummy variable which takes the value 1 if individual *i* is present in the sample for period *t* and 0 otherwise.

3. Data and descriptive statistics

The ECHP has a series of characteristics that make it an interesting database for analysing possible relationships between informal care and labour behaviour. First of all, while subjects remain in the panel, the survey provides ample information on their labour behaviour (employment status, whether full or part-time, number of hours worked, wages, etc.). Also, the ECHP enables us to characterise informal care fairly precisely: subjects are asked not only whether they care for a dependent adult, but also how many hours of care they provide per week, whether or not the dependent lives in the same household, and so on. And lastly, with a view to controlling for the influence of other variables on the labour behaviour of carers and non-carers, the survey contains ample socioeconomic information (age, gender, educational attainment, health status, employment record, income from work and property, etc.).

Sample analysed and selection of variables

For our analysis we took the subsample of women residing in Spain and aged 30 to 60 who participated in at least three of the eight waves of the ECHP and supplied complete information on the variables that appear in Table 3.1 in all the waves in which they participated. This subsample contains a total of 15,200 observations.

As can be seen in Table 3.1, caregiving was characterised according to two alternative classifications: first, given that several research studies have detected different effects on employment depending whether or not the dependent co-resides with the carer (Heitmueller, 2007), we divided the women carers in our sample into those who provide care at home and those who do so elsewhere; and then, since there is also some evidence that the effects of informal care on labour behaviour change over time (Spiess and Schneider, 2003), the women in our sample were classified into four possible dynamic states between *t-1* and *t*: "starting caregiving", "continuing caregiving", "stopping caregiving" and "no caregiving in either period".

Table 3.1. Variables included in the analysis

Labour behaviour	
nowork	1 if not working, 0 otherwise
fulltime	1 if working part-time, 0 otherwise
parttime	1 if working full-time, 0 otherwise
Informal care	
carer	1 if engaged in unpaid care of an adult dependent, 0 otherwise
carer_household	1 if engaged in unpaid care of an adult dependent within the household, 0 otherwise
carer_elsewhere	1 if engaged in unpaid care of an adult dependent outside the household, 0 otherwise
starting caregiving	1 if starting unpaid care of an adult dependent, 0 otherwise
continuing caregiving	1 if this is at least the second consecutive year of unpaid care of an adult dependent, 0 otherwise
stopping caregiving	1 if engaged last year in unpaid care of an adult dependent to whom she no longer gives care this year, 0 otherwise
Sociodemographic	
d3539	1 if aged 35 to 39, 0 otherwise
d4044	1 if aged 40 to 44, 0 otherwise
d4549	1 if aged 45 to 49, 0 otherwise
d5054	1 if aged 50 to 54, 0 otherwise
d5560	1 if aged 55 to 60, 0 otherwise
single	1 if single, 0 otherwise
widow	1 if widowed, 0 otherwise
sepdiv	1 if separated or divorced, 0 otherwise
isced57	1 if highest completed educational level is tertiary, 0 otherwise
isced3	1 if highest completed educational level is secondary, 0 otherwise
nch04	number of children in household aged 0 to 4
nch511	number of children in household aged 5 to 11
sizehshd	size of household
Health status	
sahvgood	1 if self-assessed health status is very good, 0 otherwise
sahgood	1 if self-assessed health status is good, 0 otherwise
sahbad	1 if self-assessed health status is bad, 0 otherwise
sahvbad	1 if self-assessed health status is very bad, 0 otherwise
Regions	
Northwest	1 if region of residence is Northwest, 0 otherwise
Northeast	1 if region of residence is Northeast, 0 otherwise
Madrid	1 if region of residence is Madrid, 0 otherwise
Centre	1 if region of residence is Centre, 0 otherwise
South	1 if region of residence is South, 0 otherwise
Canaries	1 if region of residence is Canaries, 0 otherwise

Furthermore, although the ECHP contains information on the number of hours worked, the employment status of the women that make up the sample is coded by means of a categorical variable that takes three possible values: “no work”, “part-time” and “full-time”.

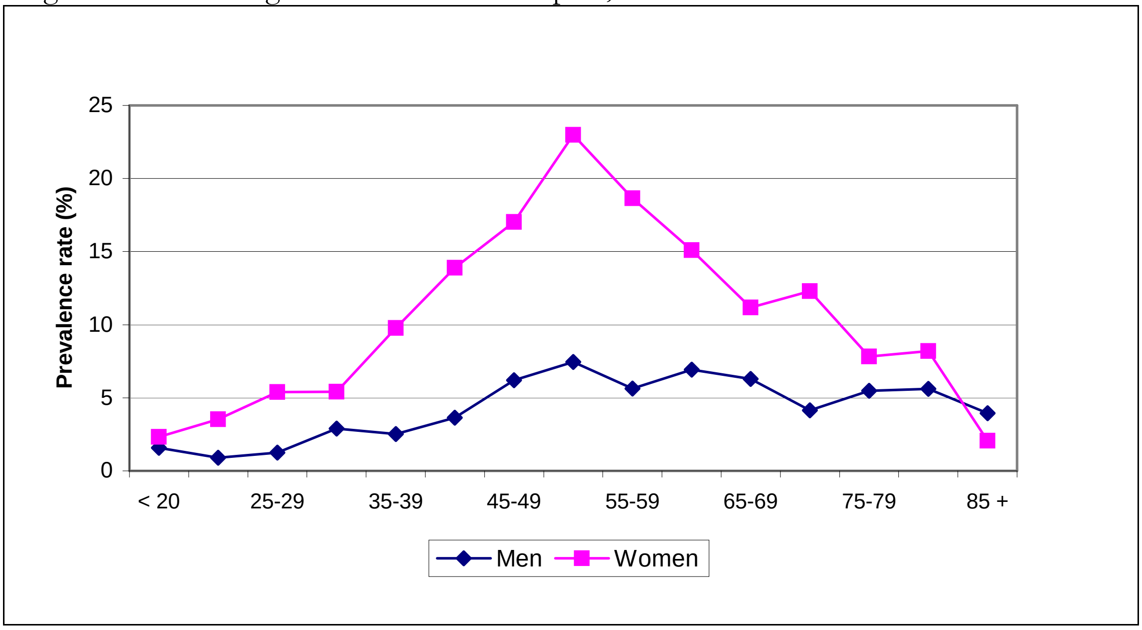
This is because we are interested in assessing the impact of caregiving on women's degree of integration into the labour market, and we believe that this impact – apart from the implicit change in hours worked – will tend to manifest itself as a transition between these three states. In addition, the number of hours worked in full-time employment tends to vary from job to job, and a woman will declare herself to be working part-time whenever her working day is shorter than the standard working day for that job. Therefore, using this categorisation enables us to work with a measure of employment status that implicitly takes into account the characteristics of the job as regards the length of the working day.

Descriptive analysis

The relevance of focusing on the subsample of women aged 30 to 60 is quite clear in view of the information contained in the graphs below. Specifically, on calculating the percentages of total men and women who stated that they were caring for an adult dependent in 1994 (Figure 3.1), we find that the average prevalence among women was three times that of men (12% vs. 4%). Furthermore, with regard to the age groups that concentrate the largest proportion of women carers, it should be noted that middle-aged cohorts show prevalence rates of above 15% in all cases. Thus, the exclusion from our analysis of women younger than 30 and older than 60 is justified not only because additional factors are involved in determining the labour behaviour of both these groups (uncompleted education, abandonment of the labour market due to retirement, etc.) but also because most carers are not to be found in these two age groups.

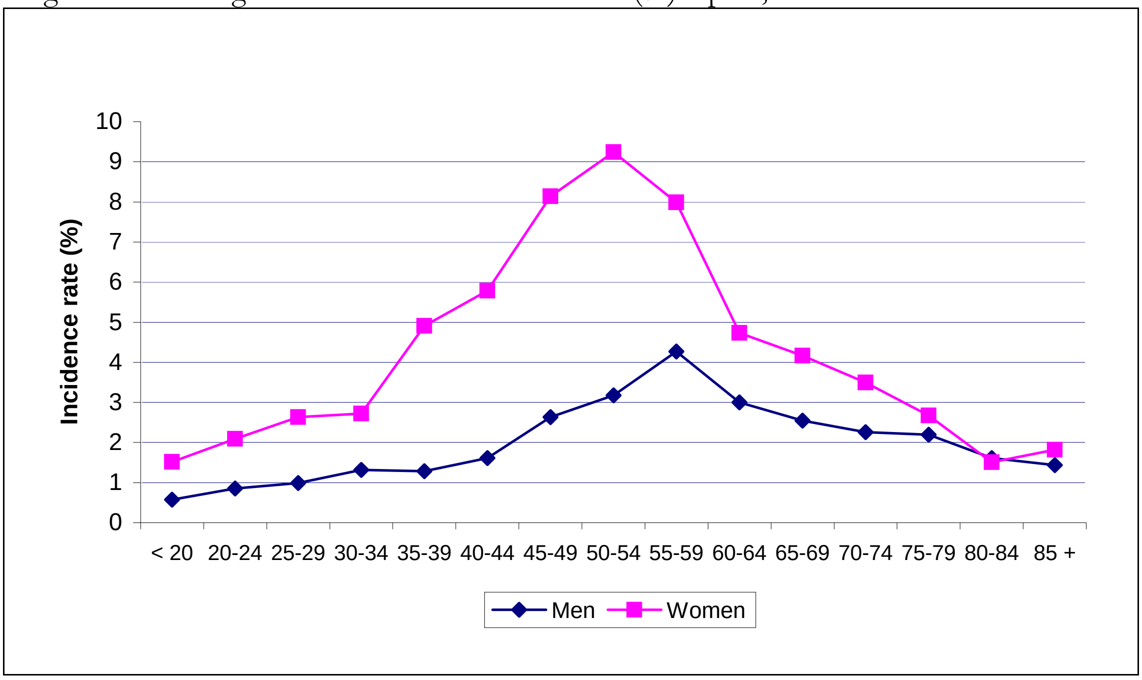
If we look at the dynamic incidence of the event "starting caregiving", again notable differences can be seen both between men and women and in terms of age groups (Figure 3.2). Specifically, the cohorts of middle-aged women display the highest incidence rates, for two reasons: first, since dependency problems are concentrated in older people, mostly widows, the cohorts of individuals with the greatest probability of having a dependent parent are precisely those aged between 45 and 65; and second, owing to the gender bias that characterises the adoption of a caregiving role, it is generally the daughters and daughters-in-law of these dependent people who provide the required help. However, when we come to consider older cohorts (65+), the differences between men and women narrow, as the carers that appear in these cases are usually the dependents' spouses.

Figure 3.1. Percentage of informal carers: Spain, 1994



Source: Compiled by the author using ECHP data

Figure 3.2. Average incidence rates of new carers (%): Spain, 1995-2001



Source: Compiled by the author using ECHP data

Table 3.2. Descriptive statistics of the variables included: mean and standard deviation (in parentheses)

	Non-carers		Carers	
nowork	0.60	(0.49)	0.73	(0.44)
fulltime	0.34	(0.47)	0.23	(0.42)
parttime	0.05	(0.23)	0.04	(0.20)
carer_household	-	-	0.64	(0.48)
carer_elsewhere	-	-	0.36	(0.48)
starting caregiving	-	-	0.48	(0.50)
continuing caregiving	-	-	0.52	(0.50)
stopping caregiving	0.06	(0.24)	0.00	(0.00)
d3539	0.19	(0.39)	0.11	(0.32)
d4044	0.17	(0.38)	0.16	(0.37)
d4549	0.15	(0.36)	0.20	(0.40)
d5054	0.13	(0.34)	0.23	(0.42)
d5560	0.15	(0.36)	0.22	(0.41)
single	0.11	(0.31)	0.11	(0.32)
widow	0.04	(0.19)	0.05	(0.22)
sepdiv	0.05	(0.22)	0.04	(0.19)
nch04	0.18	(0.45)	0.17	(0.44)
nch511	0.34	(0.63)	0.35	(0.64)
sizehshd	3.78	(1.35)	4.22	(1.44)
sahvgood	0.16	(0.36)	0.11	(0.31)
sahgood	0.55	(0.50)	0.47	(0.50)
sahbad	0.07	(0.26)	0.10	(0.30)
sahvbad	0.01	(0.12)	0.01	(0.11)
lincome_ot	13.57	(0.94)	13.56	(0.72)
isced57	0.24	(0.43)	0.12	(0.32)
isced3	0.18	(0.39)	0.15	(0.35)
Northwest	0.15	(0.35)	0.17	(0.38)
Northeast	0.16	(0.36)	0.13	(0.34)
Madrid	0.10	(0.30)	0.08	(0.27)
Centre	0.14	(0.35)	0.17	(0.38)
South	0.18	(0.39)	0.19	(0.40)
Canaries	0.06	(0.24)	0.06	(0.23)
Number of observations	24,469		3,151	

Table 3.2 shows the descriptive statistics of the variables used in the analysis, calculated separately for women who care for and who do not care for a dependent adult over the various waves of the ECHP. The main features characterising the carers are as follows: labour force participation rate 13 percentage points lower; greater relative importance of part-time jobs among those who work; larger proportion of middle-aged cohorts; and clearly lower educational levels. The purpose of our exercise, as we will explain below, is to

ascertain the extent to which this negative relationship between informal care and labour force participation is maintained when we control for: i) the differences between carers and non-carers as regards observable characteristics (age, marital status, educational attainment, etc.), ii) the existence of unobservable fixed factors (individual heterogeneity), iii) the state dependence that tends to characterise the labour behaviour of individuals over time, and iv) the attrition problems that tend to arise when working with panel data.

5. Results

We consider two different models to assess the impact of caregiving on employment status. In both models the dependent variable is the ordered categorical variable l_{it}=1, 2, 3, corresponding to whether the woman declares herself to be in "no work", "part-time" or "full-time" status respectively. The models differ, however, in the specification of caregiving. In Model 1 we use three categories which are intended to capture – in the event that the woman is giving care in the current period – whether the place in which the care is given is relevant: caregiving at home, caregiving elsewhere, and non-caregiving. In Model 2, however, we use four categories that are intended to capture whether the moment at which the transition to (or from) caregiving occurs is important: start caregiving (did not give care in *t-1* but does so in *t*), continue caregiving (gave care in *t-1* and also does so in *t*), stop caregiving (gave care in *t-1* but does not do so in *t*) and continue not caregiving (did not give care in *t-1* and does not do so in *t*). These four categories are parameterised with three dummy variables (one for each of the first three conditions). As mentioned earlier, both models include a broad set of control variables: age, educational level, marital status, etc. (see Table 3.1).

Attrition test

The results of the tests for attrition bias proposed by Verbeek and Nijman (1992), in which the null hypothesis is the non-existence of this bias, are shown in Table 3.3 both for random effects specification and for pool specification. In these comparisons we can see that, when we use the dummy variable that captures whether the individual is in the sample the following year, the null hypothesis of non-existence of bias is rejected for both models under both specifications. However, with the rest of the variables, the null hypothesis is not rejected at conventional significance levels.

Table 3.3 Attrition test results: χ^2 values and probabilities (in parentheses)

	Ordered probit		Ordered probit (random effects)	
	Model 1	Model 2	Model 1	Model 2
Following year	1.66 (0.1980)	2.97 (0.0849)	4.09 (0.0431)	3.96 (0.0467)
All years	0.31 (0.5787)	0.01 (0.9167)	2.44 (0.1182)	2.44 (0.1185)
Number of years	0.14 (0.7074)	0.10 (0.7515)	0.51 (0.4733)	0.64 (0.4224)
Joint test	2.67 (0.4449)	4.27 (0.2335)	9.46 (0.0237)	9.31 (0.0255)

Note: Model 1 refers to the specification in which the treatment distinguishes between caregiving at home and caregiving elsewhere. Model 2 refers to the specification in which the treatment distinguishes between starting, continuing and stopping caregiving.

Model estimates

The rejection of the null hypothesis when the dummy variable "following year" is used suggests that it is necessary to use the IPW estimator. However, for the reasons mentioned in Section 2, it can only be applied in the case of the pooled ordered probit model; hence the results we present below correspond to this specification. Furthermore, in order to calibrate the robustness of the estimates, in Table 3.4 we present the results with two different ways of computing the weights $\hat{p}_{it}$. In the first of them we use information for the initial period (1994), whereas in the second we use information for the period *t-1*[19]. Lastly, in the third column of Table 3.4 we present, for each model, unweighted estimates in order to be able to assess the potential impact of attrition bias.

Table 3.4 shows the results of the estimation of the various specified models. The first three columns of coefficients contain the results for the three models that distinguish between caregiving at home and caregiving elsewhere. Then the last three columns show the results of the three models estimated when we consider the dynamic behaviour of the carer; i.e., distinguishing between the effects in the first year, successive years and the year after caregiving stops.

[19] Probit estimates are shown in Table A3.1 (1994 values in the covariates) and Table A3.2 (*t-1* values in the covariates) in the Appendix.

Table 3.4. Dynamic ordered probit models for employment status

	Treatment: caregiving at home or elsewhere			Treatment: starting, continuing or stopping caregiving		
Variable	Ordered probit with IPW (1994 values)	Ordered probit with IPW (*t-1* values)	Ordered probit without IPW	Ordered probit with IPW (1994 values)	Ordered probit with IPW (*t-1* values)	Ordered probit without IPW
fulltime(1994)	**0.8449**	**0.8885**	**0.8503**	**0.8494**	**0.8878**	**0.8529**
parttime(1994)	**0.3495**	**0.3896**	**0.3428**	**0.3527**	**0.3875**	**0.3444**
fulltime(t-1)	**2.0445**	**2.0755**	**2.0352**	**2.0386**	**2.0758**	**2.0290**
parttime(t-1)	**1.3033**	**1.2344**	**1.2229**	**1.3039**	**1.2429**	**1.2235**
carer_household	**-0.2331**	-0.1583	-0.124			
carer_elsewhere	-0.2044	0.1223	0.0641			
starting caregiving				-0.0601	0.0224	0.0236
continuing caregiving				*-0.2081*	-0.1469	-0.1129
stopping caregiving				*0.1696*	-0.0298	0.0116
d3539	-0.0704	-0.0004	0.0144	-0.0691	0.0043	0.0195
d4044	-0.0205	0.1715	0.1497	-0.0217	0.1749	0.1535
d4549	0.0377	0.2213	0.1923	0.0296	0.224	0.188
d5054	-0.0163	0.1752	0.0889	-0.0303	0.1696	0.0767
d5560	-0.3515	0.0111	-0.1076	-0.3703	0.0003	-0.1204
single	**0.7900**	**0.7195**	**0.6000**	**0.8185**	**0.7124**	**0.6201**
widow	-0.3706	*-0.8120*	-0.3935	-0.3586	**-0.8055**	-0.3688
sepdiv	-0.114	0.0748	-0.082	-0.1092	0.0686	-0.0821
nch04	0.0934	0.0367	*0.0750*	0.0944	0.0455	*0.0791*
nch511	-0.0611	-0.0497	-0.0488	-0.0556	-0.0414	-0.042
sizehshd	-0.064	-0.0107	-0.0248	-0.064	-0.0131	-0.0268
isced57	**0.4111**	**0.3544**	**0.3643**	**0.4130**	**0.3566**	**0.3711**
isced3	**0.1684**	**0.1517**	**0.1800**	**0.1675**	**0.1486**	**0.1800**
sahvgood	**0.1659**	**0.1425**	**0.1248**	**0.1589**	**0.1385**	**0.1177**
sahgood	*0.1036*	-0.0095	0.0208	0.0986	-0.0109	0.0157
sahbad	**0.2318**	-0.0458	-0.0192	*0.2188*	-0.0467	-0.026
sahvbad	-0.1164	-0.1213	-0.0514	-0.1302	-0.1288	-0.0555
lincome_ot	0.0043	0.0254	0.0064	0.0042	0.0247	0.0066
Northwest	**0.1377**	0.0283	*0.0986*	**0.1384**	0.0301	*0.0924*
Northeast	-0.0185	-0.0913	-0.057	-0.021	-0.0945	-0.058
Madrid	-0.0586	-0.0852	-0.0858	-0.0609	-0.0887	-0.0876
Centre	**-0.1922**	**-0.1868**	**-0.1957**	**-0.1948**	**-0.1909**	**-0.1975**
South	**-0.1749**	**-0.2314**	**-0.2114**	**-0.1749**	**-0.2290**	**-0.2128**
Canaries	0.0039	-0.0352	-0.0043	0.0033	-0.0403	-0.0048
Means of variables:						
d3539	-0.0271	-0.1652	-0.0775	-0.022	-0.17	-0.0799
d4044	0.0796	*-0.3036*	-0.1914	0.0954	*-0.3013*	-0.1897
d4549	-0.3657	*-0.3759*	-0.2747	-0.3597	*-0.3799*	-0.2705
d5054	-0.0013	-0.3487	-0.2011	0.0337	-0.3519	-0.1865
d5560	-0.0764	*-0.4934*	-0.2874	-0.0512	*-0.4915*	-0.2758
single	-0.5764	-0.4418	-0.3622	*-0.5985*	-0.435	-0.3843
widow	0.352	0.7049	0.3428	0.3379	0.6877	0.3191
sepdiv	-0.0232	-0.0528	0.1331	-0.0228	-0.0578	0.131

Variable	Treatment: caregiving at home or elsewhere			Treatment: starting, continuing or stopping caregiving		
	Ordered probit with IPW (1994 values)	Ordered probit with IPW (*t-1* values)	Ordered probit without IPW	Ordered probit with IPW (1994 values)	Ordered probit with IPW (*t-1* values)	Ordered probit without IPW
nch04	-0.003	-0.0576	-0.035	0.000	-0.0535	-0.0362
nch511	0.0049	0.0168	0.0286	-0.0044	0.0068	0.019
sizehshd	*0.0728*	0.025	0.0338	*0.0737*	0.0239	0.0348
sahvgood	*-0.2537*	-0.1889	-0.1738	*-0.2460*	-0.1939	-0.1701
sahgood	-0.124	0.0585	-0.0295	-0.1244	0.0449	-0.0259
sahbad	**-0.5761**	-0.2881	**-0.3488**	**-0.5690**	-0.2953	**-0.3480**
sahvbad	-1.0452	*-0.8050*	**-0.8852**	-1.0503	*-0.8118*	**-0.8742**
lincome_ot	**-0.1054**	**-0.1334**	**-0.1226**	**-0.1044**	**-0.1307**	**-0.1233**
carer_household	-0.0695	-0.0707	-0.1302			
carer_elsewhere	-0.2325	-0.2925	-0.2694			
starting caregiving				*-0.5538*	-0.1506	-0.3549
continuing caregiving				-0.1398	-0.1097	-0.2005
stopping caregiving				0.0124	0.1044	0.2324
cut1	-0.1407	-0.176	-0.3158	-0.1313	-0.1694	-0.3259
cut2	0.194	0.1862	0.0251	0.2033	0.1913	0.0156
N	15200.00	12400.00	15200.00	15200.00	12500.00	15200.00
Log-likelihood	-6050.00	-4780.00	-6120.00	-6050.00	-4810.00	-6130.00

Note: **P-value<0.05**; *P-value<0.10*

For purposes of interpretation, although the scale of the ordered probit is arbitrary, the coefficients appearing in Table 3.4 enable us to know the direction of the effect of the different explanatory variables. The first outstanding feature is the importance of state dependence, as those women who work in the previous period, whether full-time or part-time, have a higher probability of working in the following period. Regarding the rest of the explanatory variables, note the positive effect on the probability of working of being single, having a higher educational attainment and having very good health status. Major regional differences are also found: women living in the autonomous communities of the centre and south have a lower probability of working than those living in the rest of Spain. Finally, we should mention the robustness of the results to the use of the different types of weights (IPW94 vs. IPW *t-1*) for both specifications considered.

Average treatment effect on the treated

As we mentioned earlier, the scale of the ordered probit model is arbitrary; therefore, in order to obtain an indicator of the magnitude of the relationship between the various caregiving conditions and employment status, we have calculated the average treatment effect on the treated (ATET). In other words, we have computed the extent to which the probability of being in each employment status changes for those individuals in each category in comparison with the same probability if they had not been carers.

Table 3.5 shows this average treatment effect on the treated for each of the models estimated. Figures 3.3 to 3.5 depict both the average treatment effect on the treated and also the confidence intervals obtained by bootstrapping with 500 replications of samples with the same number of individuals resampled with replacement.

The results show, first of all, that the effects of informal care on employment status are restricted to the decision between working full-time and not working, since the estimated effects on the probability of working part-time are in all cases lower than 0.5%. Secondly, we find that caring for someone at home reduces the probability of working full-time, yet caregiving elsewhere does not appear to have any effect.

Table 3.5. Average treatment effect on the treated

	Prob(no work)			Prob(part-time)			Prob(full-time)		
	IPW	IPW-2	NoIPW	IPW	IPW-2	NoIPW	IPW	IPW-2	NoIPW
At home	**0.030**	*0.020*	0.017	**-0.004**	*-0.003*	-0.002	**-0.027**	-0.017	-0.014
Elsewhere	0.026	-0.016	-0.009	-0.004	0.003	0.001	-0.022	0.013	0.007
Starting caregiving	0.008	-0.003	-0.003	-0.001	0.0004	0.0004	-0.007	0.003	0.003
Continuing caregiving	*0.026*	0.018	0.014	*-0.004*	-0.004	-0.003	*-0.022*	-0.015	-0.012
Stopping caregiving	*-0.025*	0.004	-0.002	*0.003*	0.003	0.0002	*0.022*	-0.004	0.001

Note: **P-value<0.05**; *P-value<0.10*

However, if we ask ourselves at what moment the possible change in employment status occurs, we find that it is as of the second year that the probability of working full-time diminishes. This is not surprising, in view of the number of hours dedicated to caregiving in each case. Lastly, the probability of being in one of the employment statuses considered is in most cases not significantly different between women who have stopped caregiving and women who have provided care neither in the current year nor in the previous year.

Figure 3.3. Average treatment effect on the treated: results with weights that consider the characteristics of the individual in the first period (IPW1) in order to correct possible attrition bias

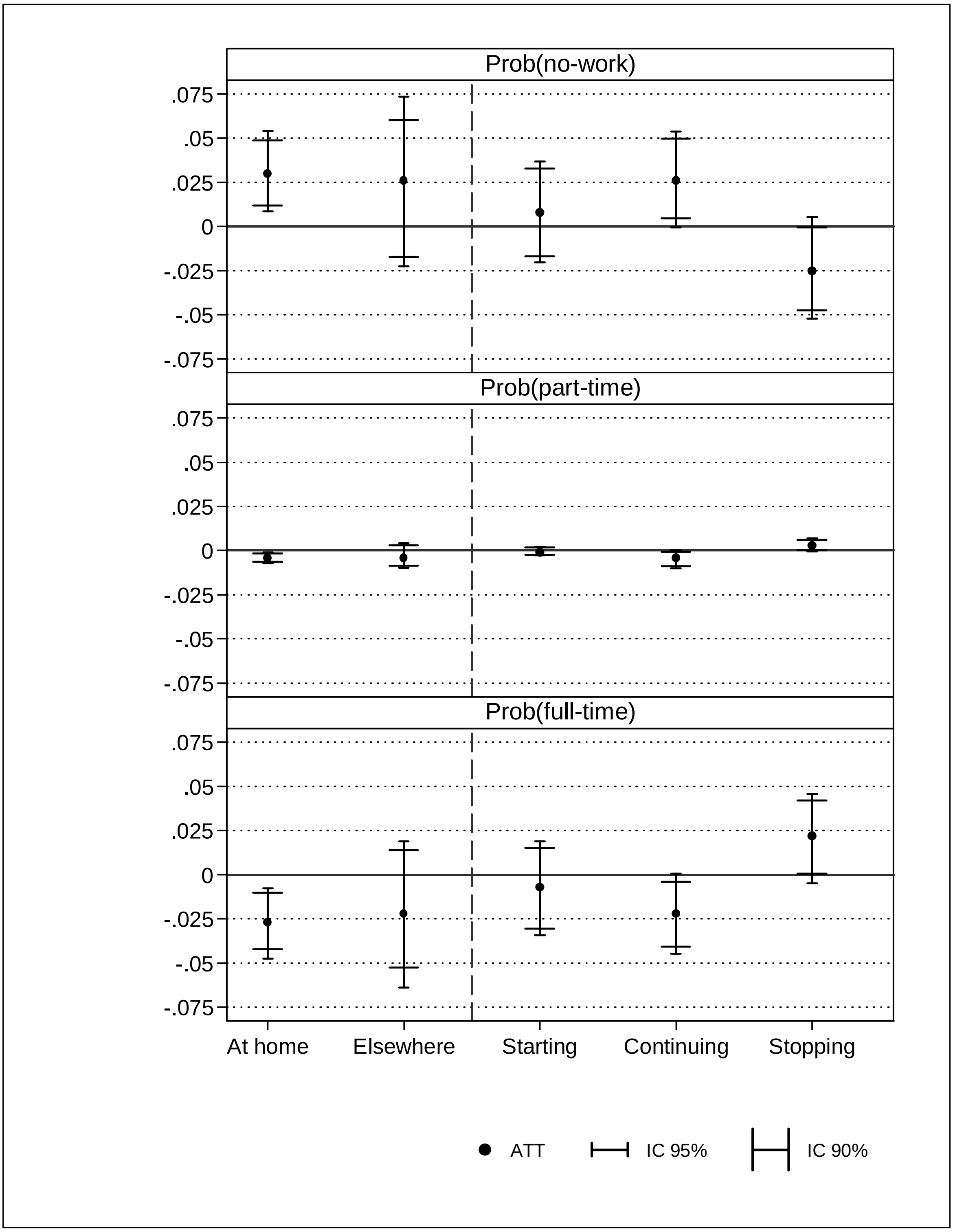


Figure 3.4. Average treatment effect on the treated: results with weights that consider the characteristics of the individual in the previous period (IPW-2) in order to correct possible attrition bias

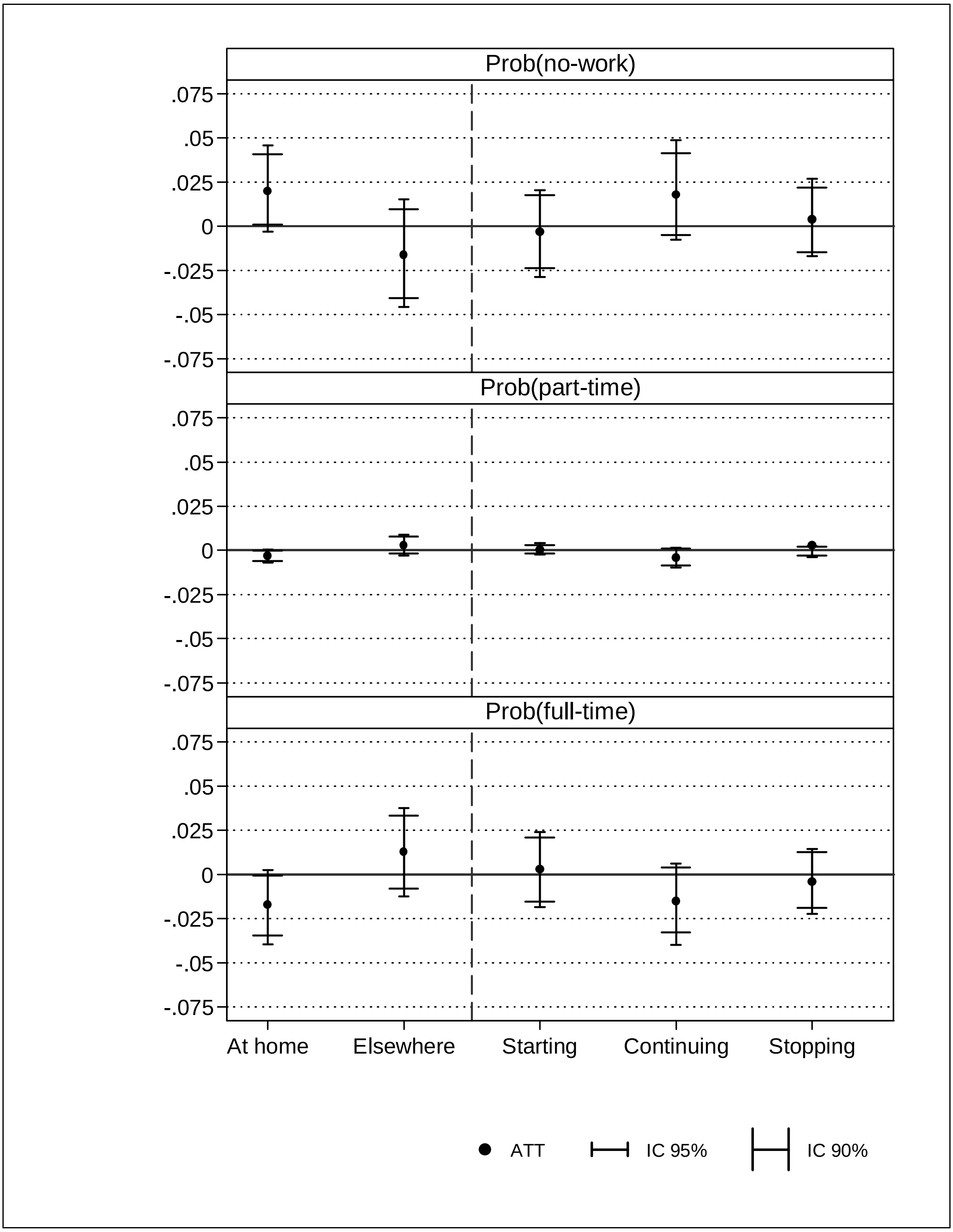
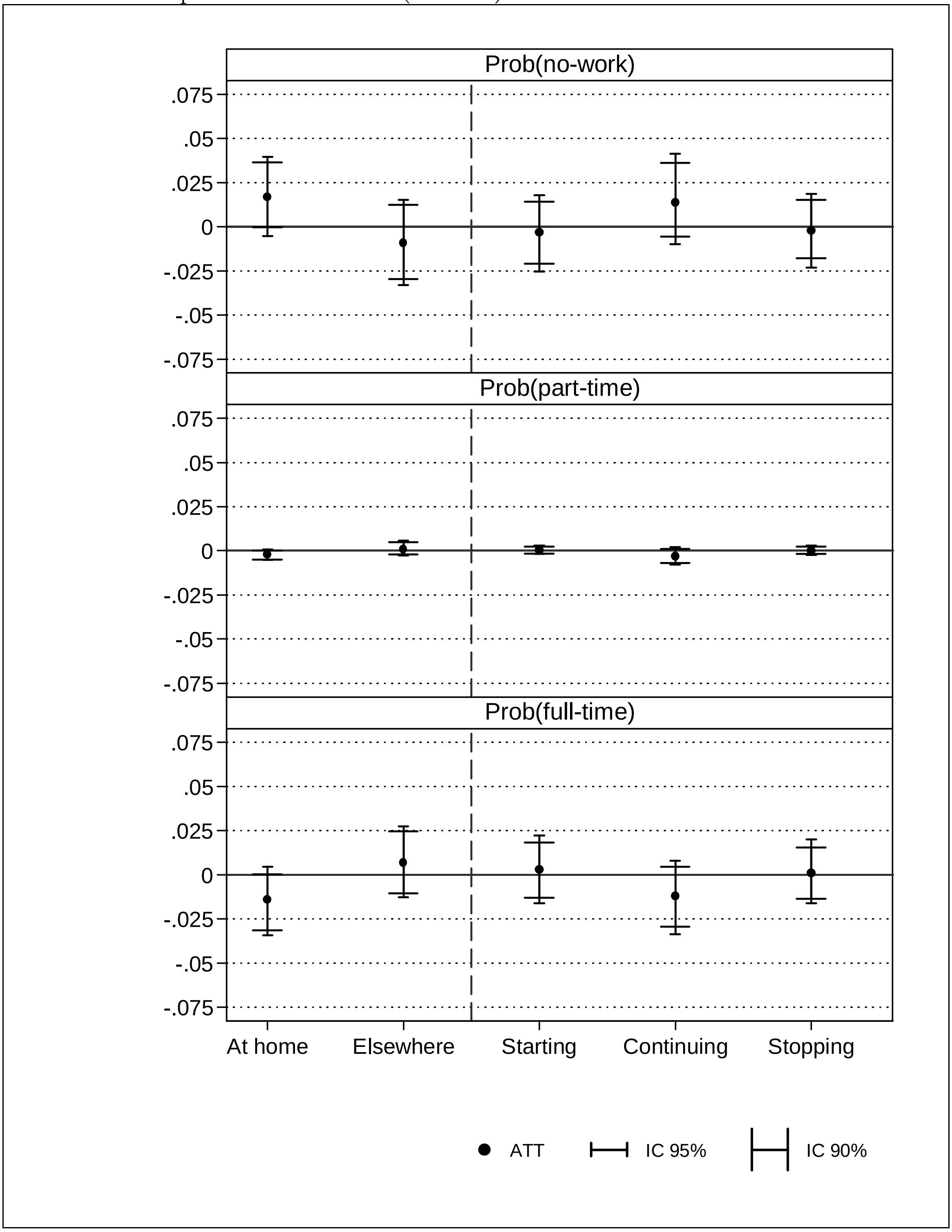


Figure 3.5. Average treatment effect on the treated: results without including weights in order to correct possible attrition bias (No IPW)



In this section we carry out a test on the adequacy of our modelling assumption regarding the conditional exogeneity of the caregiver status. For this purpose we consider a model of two simultaneous equations with dynamics: a labour participation equation in which caregiving is one of the explanatory variables and a caregiving equation, allowing for dependence among their stochastic components.

Each individual *i* at each moment *t* decides whether he is going to provide care and participate in the labour market. Formally, we specify the following recursive bivariate dynamic model:

$$\begin{gathered} l_{it}^{*} = x_{it}^{l'}\beta_l + \delta_l C_{it} + \gamma_l l_{it-1} + v_{it}^{l} \\ c_{it}^{*} = x_{it}^{c'}\beta_c + \delta_c l_{it-1} + \gamma_c C_{lt-1} + v_{it}^{c} \\ c_{it} = I(c_{it}^{*} > 0), l_{it} = I(l_{it}^{*} > 0) \\ \text{i=1,...,N; t=1,...,T} \end{gathered} \tag{3.8 }$$

where c_{it} represents the decision to care and l_{it} the employment decision.

We specify composite error terms in the two equations, where *u* represents an individual fixed effect, possibly correlated with the explanatory variables, and ε is white noise.

$$\begin{aligned} v_{it}^{l} &= u_i^{l} + \varepsilon_{it}^{l} \\ v_{it}^{c} &= u_i^{c} + \varepsilon_{it}^{c} \end{aligned} \tag{3.9}$$

In parallel to our strategy in the previous section, we model the individual fixed effect as suggested by Mundlak (1978), Chamberlain (1984) and Wooldridge (2005), i.e., we have modelled the individual fixed effects as shown in Equation (3.10).

$$\begin{aligned} u_i^{l} &= \lambda_l l_{io} + \eta_l \overline{Z}_{i.} + \xi_i^{l} \\ u_i^{c} &= \lambda_c l_{io} + \phi_c C_{io} + \eta_c \overline{X}_{i.}^{c} + \xi_i^{c} \end{aligned} \tag{3.10}$$

where the random terms on the right hand side are white noise. We assume that the stochastic terms are normally distributed and therefore our model is a bivariate probit.

Note that this model explicitly specifies caregiving status as an endogenous variable. Note also that if the error terms in Equation (3.8) are independent then each equation can be consistently estimated by a univariate probit (Maddala, 1983). Our contention is that the modelling of the individual fixed effect according to Equation (3.10) suffices to account for the endogeneity of caregiving status in the labour participation equation. If this is the case, we should find that, while a model that imposes $u^l_i=\xi^l_i$ and $u^c_i=\xi^c_i$ might still show dependence between v^l_{it} and v^c_{it},, lifting this restriction would drive this correlation to zero (ρ_{cl}). In fact, Maddala (1983) and Knapp and Seaks (1998) propose that a test of H_0: $\rho_{cl}=0$ using a z-test and an LR test can act as an alternative to the Hausman test for exogeneity of the caregiving dummy variable in the labour participation equation.

Even if our model in the previous section is an ordered probit, the results for this test on the current model, where only the observability rule for the dependent variable changes with respect to the former model, are able to shed some light on the adequacy of our strategy. In particular, finding that the Mundlak representation of unobserved fixed heterogeneity renders the two error terms in Equation (3.8) independent, and therefore allows us to treat the caregiving dummy variable as exogenous in the labour equation, would lend support to our choice for the estimation of Equation (3.3) in the previous section as a univariate ordered probit.

We include the same covariates as in the previous models in the employment equation. In addition, in order to achieve the non-parametric identification of the model, we include a dummy variable that captures whether there was an individual older than 65 in the household in the previous period in the caregiving equation. This exclusion restriction is grounded on the idea that the presence of individuals aged 65+ among the rest of the members of the household will affect the chances of labour participation only via the potential need for caregiving.

We estimate the bivariate probit model shown in (3.8) by maximum likelihood and simulated maximum likelihood using the Geweke-Hajivassilou-Keane (GHK) simulator[20]. The full set of results is shown in Table A3.3 in the Appendix, and Table 3.6 shows the results of the endogeneity test. We first estimate the bivariate probit assuming that η_l and η_c are equal to zero, and thus that u_i^l and u_i^c are uncorrelated with the covariates. Secondly, we introduce the parameterisation of the unobserved fixed effect. The results regarding the endogeneity test suggest that the null hypothesis of no correlation between the random components of the error terms cannot be rejected in either case. This provides evidence regarding the consistency of the estimates obtained in the previous analysis.

Table 3.6. Results from the test of exogeneity of the caregiving variable

	Maximum likelihood		Maximum simulated likelihood	
	Rho (SE)	Wald test (prob>chi2)	Rho (SE)	LR test (prob>chi2)
Assume η_c and η_l in Equation (3.10) are equal to zero	0.0770 (0.0607)	1.5974 (0.2063)	0.0608 (0.0513)	1.5013 (0.2205)
Parameterisation of the unobserved fixed effect	-0.0490 (0.0879)	0.3092 (0.5782)	-0.0078 (0.0751)	0.0138 (0.9065)

These results are in line with those of Bolin et al (2007) and Heitmueller (2007), who are able to accept the exogeneity assumption.

20 We have used the bivariate command in Stata, and the command mvprobit created by Cappellari and Jenkins (Cappellari and Jenkins, 2003).

6. Discussion and conclusions

The results obtained indicate that the labour effects of informal care occur basically among those women who care for someone at home, and among those who continue to provide care for more than one period. Those who finish an episode of informal care do not appear to have problems re-entering the labour market. As regards the type of job change made by women carers, they seem to be at the extensive margin (labour force participation), but not the intensive margin (hours worked), of employment decisions (Heckman, 1993). In this respect, although these results have been confirmed in other research on informal care (Ettner, 1996), these phenomena are very probably more acute in the Spanish case owing to the relative scarcity of part-time contracts in Spain (European Commission, 2004b).

Our results have two types of implications for the design of public policies on long-term care. First, given that the labour effects appear to be concentrated in co-resident carers and those who provide care for long periods, the new SAAD benefits should be modulated according to the subjects' level of dependency; specifically, evidence exists for other countries to the effect that older people go to live with their adult children when dependency problems prevent them from continuing in their own homes (Pezzin and Schone, 1999), so co-residence of carer and dependent would be a proxy for serious dependency when the former is a middle-aged woman. In addition, since in most cases dependency problems get worse as time passes because they result from chronic processes of a degenerative nature (Alzheimer's, cancer, etc.), in many cases continuity of care is also very probably capturing the seriousness of the dependency.

As the effects on labour behaviour seem to be reduced to an all-or-nothing choice (work full-time or stop working), the labour opportunity costs could probably be mitigated by developing more flexible employment formulas, such as the reduction in working hours that already exists for maternity, duly incentivised economically so as to avoid perverse behaviour by employers.

A natural extension of our work, along the lines of that proposed by Viitanen (2005), would be to replicate the analysis for all the European countries for which the ECHP has data. Considering the great diversity that exists at European level as regards the flexibility of working hours (European Commission, 2004b) and the coverage provided by long-term care systems (OECD, 2005), this approach would reveal whether the results obtained for Spain are also forthcoming on examining other countries in the same region, and at the same time provide information as to what institutional factors lead to the largest reduction in the labour opportunity costs associated with informal care.

Appendix

Table A3.1. Probit models to estimate the probability of individual *i* being present in the sample in period *t* using 1994 values

	Sample of individuals in the first group of models (caregiving at home or elsewhere)						Sample of individuals in the second group of models (start caregiving, continue caregiving and stop caregiving)					
Variables	1995	1996	1997	1998	1999	2000	1995	1996	1997	1998	1999	2000
d3539	0.1331	*-0.1210*	**-0.1413**	**-0.2472**	**-0.2744**	**-0.3114**	0.1317	-0.102	**-0.1389**	**-0.2460**	**-0.2688**	**-0.3101**
d4044	0.1067	-0.0976	-0.073	*-0.1248*	**-0.1613**	**-0.2325**	0.1341	-0.0756	-0.068	*-0.1246*	**-0.1488**	**-0.2268**
d4549	0.0566	**-0.2195**	**-0.1981**	**-0.3163**	**-0.3201**	**-0.3708**	0.0676	**-0.2131**	**-0.1825**	**-0.3120**	**-0.3065**	**-0.3646**
d5054	0.0243	**-0.1905**	**-0.2370**	**-0.2548**	**-0.3379**	**-0.6547**	0.0264	**-0.1794**	**-0.2309**	**-0.2672**	**-0.3318**	**-0.6441**
d5560	**-0.6158**	**-1.1463**	**-1.4596**	**-1.8853**	-	-	**-0.6116**	**-1.1312**	**-1.4616**	**-1.8850**	-	-
Single	**-0.3001**	**-0.2892**	**-0.3022**	**-0.3684**	**-0.3268**	**-0.3636**	**-0.3018**	**-0.3040**	**-0.3187**	**-0.3752**	**-0.3271**	**-0.3669**
Widow	0.0586	*-0.1926*	-0.1478	**-0.2916**	*-0.2350*	**-0.3245**	0.0433	*-0.2251*	-0.1541	**-0.2875**	*-0.2368*	**-0.3323**
Sepdiv	-0.084	-0.09	-0.072	**-0.2336**	**-0.4253**	**-0.4523**	-0.0945	-0.1152	-0.0762	**-0.2322**	**-0.4273**	**-0.4562**
nch04	0.002	*-0.0799*	**-0.0876**	**-0.0915**	*-0.0881*	-0.0635	0.0034	-0.0739	*-0.0863*	**-0.0902**	*-0.0845*	-0.0592
nch511	0.0105	-0.047	-0.0063	-0.0092	-0.0324	*-0.0588*	0.013	-0.0466	-0.0118	-0.0077	-0.0267	*-0.0581*
Household size	**0.0563**	0.0096	-0.011	**-0.0451**	**-0.0943**	**-0.1069**	**0.0539**	0.0049	-0.0088	**-0.0438**	**-0.0976**	**-0.1091**
Sahvgood	-0.0118	-0.1058	-0.0931	**-0.1344**	**-0.2411**	**-0.2963**	-0.0192	-0.0927	-0.0942	**-0.1330**	**-0.2238**	**-0.3000**
Sahgood	0.025	**-0.1178**	**-0.1497**	**-0.1965**	**-0.3058**	**-0.3792**	0.0162	**-0.1098**	**-0.1560**	**-0.1986**	**-0.2938**	**-0.3877**
Sahbad	0.072	-0.0096	-0.0939	**-0.1799**	**-0.2388**	**-0.3650**	0.0548	-0.0159	-0.0858	**-0.1855**	**-0.2294**	**-0.3749**
Sahvbad	-0.0095	*-0.2717*	-0.1833	-0.2182	-0.0971	-0.1548	-0.0238	*-0.2684*	-0.1908	-0.1773	-0.0868	-0.1641
lincome_ot	**0.1997**	**0.1469**	**0.1017**	**0.0871**	**0.0757**	**0.0633**	**0.2004**	**0.1479**	**0.1016**	**0.0875**	**0.0755**	**0.0638**
Northwest	**0.2441**	0.0656	-0.0534	-0.0193	0.0126	-0.0462	**0.2484**	0.0469	-0.0605	-0.03	0.0192	-0.0392
Northeast	0.124	0.0298	*-0.1284*	**-0.1409**	**-0.1700**	**-0.2027**	0.1287	0.0217	*-0.1202*	**-0.1499**	**-0.1745**	**-0.1928**
Madrid	0.1207	0.029	0.0176	0.0439	-0.0661	-0.0924	0.1108	0.0207	0.0185	0.0441	-0.067	-0.0905
Centre	**0.5085**	**0.3444**	**0.1878**	**0.1777**	**0.2384**	**0.1783**	**0.5076**	**0.3515**	**0.1968**	**0.1840**	**0.2270**	**0.1807**
South	0.1232	*0.1248*	-0.0138	0.015	0.0324	-0.0185	0.1135	*0.1137*	-0.005	0.0139	0.0341	-0.012
Canaries	**0.3166**	0.1137	-0.0427	-0.0399	-0.0815	**-0.2683**	**0.3259**	0.1099	-0.0577	-0.0404	-0.0779	**-0.2651**
isced57	*0.1512*	0.0455	**0.1233**	**0.1396**	0.0795	0.0446	**0.1521**	0.0336	*0.1220*	**0.1359**	0.0747	0.0418
isced3	*0.1312*	0.1048	**0.1316**	0.0906	-0.0077	-0.0292	**0.1306**	*0.1056*	**0.1299**	0.0915	-0.007	-0.0275
informal carer	*-0.1217*	-0.0859	-0.0696	0.0025	0.0759	0.0445	-0.0734	-0.067	-0.0587	0.0045	0.0855	0.04
fulltime	0.069	-0.0472	**-0.0922**	**-0.1456**	**-0.2143**	**-0.2564**	0.0724	-0.0397	*-0.0981*	**-0.1387**	**-0.2123**	**-0.2541**
parttime	0.0404	-0.0004	-0.0169	-0.0759	-0.1443	-0.0932	0.0313	0.0189	-0.0079	-0.0575	-0.1425	-0.0805

Note: **P-value<0.05**; *P-value<0.10*

Table A3.2. Probit models to estimate the probability of individual *i* being present in the sample in period *t* using *t-1* values

	Sample of individuals in the first group of models (caregiving at home or elsewhere)						Sample of individuals in the second group of models (start caregiving, continue caregiving and stop caregiving)					
Variables	1995	1996	1997	1998	1999	2000	1995	1996	1997	1998	1999	2000
d3539	0.0518	0.0462	-0.1459	0.0531	-0.1195	-0.0621	0.0479	0.0622	-0.1347	0.0517	-0.0953	-0.0373
d4044	0.0753	0.0219	0.0672	0.019	-0.1166	-0.1128	0.1087	0.0454	0.0724	0.0163	-0.0809	-0.1088
d4549	-0.0116	0.1102	0.0957	0.0905	-0.1507	-0.0803	0.0001	0.1407	0.0964	0.1005	-0.094	-0.0702
d5054	-0.0178	0.0842	0.0431	0.0124	0.0098	-0.0426	-0.0165	0.096	0.0941	0.011	0.0466	-0.0386
d5560	**-0.7093**	**-0.4983**	**-0.5787**	**-0.3777**	**-0.7503**	**-0.7767**	**-0.7073**	**-0.4856**	**-0.5681**	**-0.3975**	**-0.7376**	**-0.7862**
Single	**-0.3756**	0.1061	0.0987	-0.1047	-0.1692	*-0.2314*	**-0.3795**	0.1178	0.0934	-0.1031	-0.161	*-0.2126*
Widow	-0.1666	**-0.3901**	-0.0754	-0.1129	-0.0736	-0.2689	-0.1935	**-0.3761**	-0.1315	-0.1264	-0.0877	*-0.3006*
Sepdiv	**-0.3680**	-0.2364	*-0.3024*	-0.2557	**-0.5005**	-0.2287	**-0.3892**	*-0.2545*	*-0.3053*	*-0.2705*	**-0.5235**	-0.2771
nch04	0.0123	-0.052	*-0.1227*	-0.0523	*0.1392*	0.0533	0.0137	-0.0556	*-0.1115*	-0.0653	*0.1308*	0.0484
nch511	-0.0202	0.0184	0.0213	0.0269	-0.0111	0.0175	-0.0181	0.024	0.0148	0.0212	-0.0047	0.0208
Household size	*0.0423*	**0.0938**	0.0333	**0.0526**	-0.0172	0.0369	*0.0387*	**0.0921**	0.0362	**0.0569**	-0.0244	0.0363
Sahvgood	-0.0327	0.0604	0.0221	0.0189	0.0165	-0.1905	-0.0433	0.0454	0.0175	0.0119	-0.0022	-0.2125
Sahgood	-0.0749	-0.0049	-0.0741	-0.0292	-0.0364	-0.11	-0.0876	0.0045	-0.0641	-0.0454	-0.025	-0.1152
Sahbad	0.0092	-0.0666	*-0.2102*	**-0.3066**	-0.1143	-0.0683	-0.0126	-0.0628	*-0.2060*	**-0.3024**	-0.1263	-0.0113
Sahvbad	-0.0224	0.1001	-0.2401	*-0.4854*	-0.3175	-0.1631	-0.041	0.0951	-0.2836	*-0.4741*	-0.3057	-0.1719
lincome_ot	**0.1210**	**0.0693**	-0.0198	**0.0786**	*0.0593*	0.0126	**0.1166**	**0.0733**	-0.0118	**0.0773**	*0.0581*	0.0294
Northwest	0.039	0.0254	-0.085	**0.2335**	*0.1904*	-0.0499	0.0387	0.0073	-0.0688	**0.2178**	*0.2112*	-0.0486
Northeast	-0.0129	0.071	-0.1246	**0.2228**	0.091	-0.13	-0.0113	0.061	-0.112	**0.2314**	0.1035	-0.0414
Madrid	0.0145	0.1346	0.1636	**0.2980**	0.0066	0.1396	0.0002	0.1111	0.168	**0.2924**	0.005	0.1381
Centre	**0.3208**	**0.2065**	-0.037	**0.3340**	**0.4430**	0.0633	**0.3161**	**0.2376**	-0.0333	**0.3743**	**0.4391**	0.0717
South	-0.1039	**0.2877**	-0.0274	**0.2855**	**0.3380**	-0.0892	-0.1207	**0.2818**	0.0179	**0.2865**	**0.3383**	-0.076
Canaries	0.1489	-0.0011	*-0.2504*	0.1721	0.1509	**-0.5087**	0.1543	-0.0137	*-0.2386*	0.1573	0.1495	**-0.5004**
isced57	**0.1935**	0.0479	**0.1993**	0.0864	-0.0502	-0.0439	**0.1960**	0.0446	**0.2082**	0.1004	-0.0665	-0.0886
isced3	0.0464	**0.1876**	0.1377	0.0554	-0.1375	0.0137	0.0455	**0.1831**	0.1371	0.0443	-0.1381	0.015
informal carer	-0.0903	-0.014	0.0858	0.0509	*0.2149*	-0.0863	-0.0309	0.004	0.0916	0.1076	**0.2353**	-0.0263
fulltime	0.0179	-0.0464	-0.0288	-0.1189	*-0.1339*	0.0719	0.0201	-0.0292	-0.0477	-0.1197	-0.1278	0.0794
parttime	-0.0407	-0.0243	-0.0499	-0.0643	-0.1208	0.0666	-0.0529	0.038	-0.0576	-0.0726	-0.1215	0.0648

Note: **P-value<0.05**; *P-value<0.10*

Table A3.3. Bivariate probit estimates

	Exclude Mundlak specification of the unobserved heterogeneity								Include Mundlak specification of the unobserved heterogeneity							
	Maximum likelihood				Maximum simulated likelihood				Maximum likelihood				Maximum simulated likelihood			
	Work		Caregiving		Work		Caregiving		Work		Caregiving		Work		Caregiving	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
informal carer	-0.213	0.104			-0.189	0.092			0.069	0.178			-0.011	0.157		
informal carer (t-1)			1.296	0.044			1.296	0.044			1.080	0.049			1.081	0.049
fulltime (t-1)	2.424	0.042	-0.087	0.040	2.425	0.042	-0.087	0.040	1.902	0.049	-0.187	0.058	1.901	0.049	-0.186	0.058
parttime (t-1)	1.975	0.065	-0.166	0.083	1.976	0.065	-0.166	0.083	1.670	0.071	-0.197	0.091	1.669	0.071	-0.196	0.090
informal carer (1994)											0.460	0.049			0.459	0.049
fulltime (1994)									0.781	0.050	0.142	0.061	0.782	0.050	0.140	0.061
parttime (1994)									0.559	0.073	0.035	0.089	0.560	0.073	0.034	0.089
older65 (t-1)			0.660	0.041			0.661	0.041			0.390	0.208			0.388	0.209
d3539	0.006	0.045	0.156	0.064	0.006	0.045	0.156	0.064	0.039	0.073	-0.189	0.098	0.037	0.073	-0.189	0.098
d4044	0.020	0.048	0.371	0.066	0.018	0.048	0.371	0.066	0.145	0.117	-0.156	0.143	0.143	0.117	-0.156	0.143
d4549	-0.019	0.049	0.395	0.065	-0.021	0.049	0.396	0.065	0.182	0.157	-0.273	0.177	0.178	0.157	-0.272	0.177
d5054	-0.118	0.056	0.448	0.068	-0.121	0.056	0.448	0.068	0.091	0.190	-0.275	0.213	0.086	0.191	-0.275	0.213
d5560	-0.325	0.057	0.230	0.073	-0.327	0.057	0.230	0.073	-0.087	0.228	-0.327	0.246	-0.095	0.228	-0.327	0.246
single	0.241	0.052	-0.089	0.071	0.239	0.052	-0.089	0.071	0.725	0.272	-0.639	0.343	0.721	0.271	-0.638	0.345
widow	0.085	0.092	0.100	0.082	0.084	0.092	0.099	0.082	-0.518	0.339	-0.307	0.271	-0.522	0.341	-0.303	0.270
sepdiv	0.117	0.075	-0.008	0.086	0.118	0.075	-0.008	0.086	-0.036	0.173	-0.104	0.209	-0.036	0.173	-0.101	0.208
nch04	0.052	0.032	-0.059	0.039	0.052	0.032	-0.059	0.039	0.076	0.046	-0.043	0.054	0.075	0.046	-0.043	0.054
nch511	-0.028	0.022	0.012	0.025	-0.028	0.022	0.012	0.025	-0.061	0.037	0.014	0.039	-0.061	0.037	0.014	0.039
sizehshd	-0.015	0.013	0.043	0.012	-0.015	0.013	0.043	0.012	-0.039	0.039	0.282	0.043	-0.035	0.039	0.282	0.043
sahvgood	0.101	0.049	-0.205	0.057	0.102	0.049	-0.204	0.057	0.084	0.061	-0.176	0.070	0.083	0.061	-0.176	0.070
sahgood	0.016	0.036	-0.165	0.038	0.017	0.036	-0.164	0.038	-0.020	0.045	-0.122	0.048	-0.022	0.045	-0.121	0.048
sahbad	-0.221	0.062	-0.130	0.064	-0.220	0.062	-0.129	0.064	-0.042	0.079	-0.025	0.078	-0.042	0.079	-0.026	0.078
sahvbad	-0.364	0.181	-0.452	0.150	-0.362	0.181	-0.452	0.150	-0.057	0.212	-0.270	0.169	-0.058	0.212	-0.270	0.169
lincome_ot	-0.064	0.018	0.017	0.019	-0.065	0.018	0.017	0.019	-0.001	0.027	0.010	0.026	-0.001	0.027	0.010	0.026
Northwest	0.036	0.049	-0.051	0.059	0.035	0.049	-0.051	0.059	0.053	0.057	-0.017	0.063	0.054	0.057	-0.016	0.063
Northeast	-0.065	0.049	-0.061	0.058	-0.065	0.049	-0.061	0.058	-0.065	0.055	-0.034	0.061	-0.065	0.055	-0.033	0.061
Madrid	-0.116	0.057	0.002	0.066	-0.115	0.057	0.002	0.066	-0.111	0.066	0.014	0.071	-0.111	0.066	0.014	0.071
Centre	-0.185	0.053	0.107	0.057	-0.185	0.053	0.107	0.057	-0.176	0.061	0.126	0.061	-0.175	0.061	0.127	0.061
South	-0.243	0.050	0.059	0.056	-0.243	0.050	0.058	0.056	-0.240	0.057	0.088	0.060	-0.239	0.057	0.089	0.060

	Exclude Mundlak specification of the unobserved heterogeneity								Include Mundlak specification of the unobserved heterogeneity							
	Maximum likelihood				Maximum simulated likelihood				Maximum likelihood				Maximum simulated likelihood			
	Work		Caregiving		Work		Caregiving		Work		Caregiving		Work		Caregiving	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Canaries	-0.115	0.067	-0.072	0.083	-0.114	0.067	-0.072	0.083	-0.064	0.076	-0.061	0.088	-0.065	0.076	-0.061	0.088
isced57	0.434	0.041	-0.146	0.053	0.435	0.041	-0.146	0.053	0.407	0.048	-0.162	0.059	0.405	0.048	-0.162	0.059
isced3	0.113	0.039	-0.037	0.046	0.114	0.039	-0.037	0.046	0.114	0.045	-0.049	0.050	0.113	0.045	-0.049	0.050
dwave2	-0.202	0.047	0.095	0.055	-0.202	0.047	0.095	0.055	-0.210	0.063	-0.074	0.074	-0.211	0.063	-0.075	0.074
dwave3	-0.279	0.049	0.109	0.056	-0.279	0.049	0.109	0.056	-0.278	0.060	-0.033	0.068	-0.278	0.060	-0.033	0.068
dwave4	-0.117	0.048	0.212	0.055	-0.118	0.048	0.212	0.055	-0.139	0.053	0.103	0.062	-0.138	0.053	0.103	0.062
dwave5	-0.061	0.048	0.085	0.055	-0.062	0.048	0.085	0.055	-0.084	0.050	0.018	0.059	-0.083	0.050	0.017	0.059
dwave6	-0.044	0.051	0.105	0.061	-0.044	0.051	0.106	0.061	-0.058	0.049	0.068	0.061	-0.058	0.049	0.067	0.061
md3539									-0.055	0.140	0.663	0.183	-0.051	0.140	0.663	0.183
md4044									-0.182	0.152	0.695	0.193	-0.177	0.152	0.694	0.193
md4549									-0.274	0.200	0.859	0.229	-0.265	0.200	0.859	0.229
md5054									-0.193	0.221	0.936	0.249	-0.184	0.221	0.935	0.249
md5560									-0.281	0.265	0.667	0.294	-0.269	0.265	0.667	0.294
msingle									-0.555	0.281	0.513	0.352	-0.548	0.281	0.513	0.353
mwidow									0.590	0.359	0.425	0.288	0.596	0.360	0.423	0.288
msepdiv									0.079	0.192	0.080	0.230	0.079	0.192	0.080	0.229
mnch04									-0.049	0.071	-0.052	0.079	-0.049	0.071	-0.052	0.079
mnch511									0.038	0.052	-0.007	0.056	0.038	0.052	-0.008	0.056
msizehsd									0.033	0.042	-0.275	0.047	0.029	0.042	-0.275	0.047
msahvgood									-0.073	0.118	-0.086	0.132	-0.075	0.118	-0.087	0.132
msahgood									0.015	0.090	-0.179	0.090	0.013	0.090	-0.180	0.090
msahbad									-0.451	0.171	-0.329	0.162	-0.456	0.171	-0.327	0.162
msahvbad									-0.952	0.411	-0.465	0.404	-0.952	0.411	-0.468	0.405
mlincome_ot									-0.138	0.038	0.028	0.039	-0.138	0.039	0.028	0.039
minformalcare									-0.251	0.133			-0.208	0.128		
older65(1994)											0.246	0.210			0.248	0.210
_cons	-0.193	0.266	-2.358	0.290	-0.191	0.266	-2.355	0.290	0.795	0.402	-2.532	0.428	0.788	0.402	-2.539	0.429
N	15202				15202				15199				15199			
Likelihood	-8721.5				-8721.6				-8428.9				-8429.1			

Concluding remarks

The aim of this thesis has been to contribute to the knowledge of the causal relationship between health and socioeconomic status. I have chosen to focus on the effect running from health to labour market outcomes, as job status appeared to be one of the main contributors to the observed income-related health inequality in European countries (van Doorslaer and Koolman, 2004; García-Gómez and López-Nicolás, 2005), and knowledge of the magnitude of different causal pathways that link health and labour can help in the design of policies to tackle these observed inequalities.

I have dealt with this research objective by looking at three related questions. In the first chapter, I have analysed the effects that the onset of a health shock or health depreciation have on the probability of remaining in employment among European workers (16-59), as well as the effects on other labour market states such as unemployment or economic inactivity. The evidence shows that workers in good health more than double their probability of being non-employed after the onset of a health shock in most of the countries analysed. The absolute sizes of the effects vary to a large extent across countries, and I am able to relate this variation to differences in institutional settings.

One of the main results in the first chapter is that individuals with a health deterioration transit not only towards economic inactivity, but also to unemployment, in Denmark and the Netherlands, where both replacement rates and integration policies are most generous. This result raises an important question: if we want to design integration policies to keep individuals at work, it is important to understand the role that health plays when individuals are deciding whether to go back to work. Thus, in the second chapter I have analysed the effect of health on employment entries and exits using a homogeneous framework. The evidence shows that the effects are symmetric as regards physical measures of health such as the existence of health limitations; i.e., with the onset of a health limitation, the increase in the hazard of becoming non-employed for workers is quantitatively similar to the decrease in the hazard of becoming employed for non-workers (this effect is greater for men than for women). On the other hand, when we look at the effects of mental health we find that it only plays a role in explaining exits out of employment.

In addition, health can affect not only an individual's labour choices but also the decisions taken by his/her relatives whenever informal care is needed. I indirectly test this hypothesis in the third chapter, where I analyse whether middle-aged Spanish women have lower probabilities of being in a full-time or part-time job as a result of having caregiving responsibilities. The results show that the labour market effects of caregiving are most apparent among women who care at home or who have been caring for more than one year.

The above paragraphs highlight the main results of this thesis. I would like to point out some of their implications and future lines of research. First of all, the results show that health is a non-trivial determinant of labour market transitions of young individuals (i.e., not only individuals close to retirement), who, after a health shock, mainly transit from employment to economic inactivity, from where the outflow back to employment is close to zero (OECD, 2003). Thus, in order to attain higher participation rates at older ages, policies should not only target early retirement incentives or the postponement of the retirement age, but also attempt to keep younger individuals at work. If they leave employment at younger ages, they will not be affected by any of the policies that target individuals approaching retirement.

In the first chapter, the evidence on the differences in the magnitude of the effects of health shocks, as well as on the transitions followed by the individuals, suggests that there is some room to improve the institutional setting, by learning from international experiences. In this respect, one of the stylised empirical results is that higher quotas[21] are associated with lower labour market effects after the onset of a health shock. This prompts new research priorities. For instance, this hypothesis could be tested by exploiting the different quota percentage applicable to firms according to their size in countries with a policy of quotas. For example, in Spain only firms with a permanent workforce over 50 people are obliged to set aside 2% of posts for handicapped workers. In France firms with at least 20 employees are obliged to employ disabled workers to account for at least 6% of their workforce (European Commission, 2007). Moreover, legislation is currently being

---

21 The quota is the percentage of the permanent workforce that employers are obliged to set aside for disabled individuals.

drafted in the Netherlands to govern quota policy. Its future implementation will generate an opportunity to evaluate the effects of this policy.

Another cross-country dissimilarity worth exploring in the future is the differences in the types of transitions following a health shock; only in Denmark and the Netherlands are individuals observed to move into unemployment after the onset of a health shock, while the predominant state in other countries is economic activity. In this situation, it would be of interest to follow these individuals in order to find out to which state they transit once the unemployment benefits expire. This would provide evidence regarding whether the greater effort towards integration policies is working in any of these two countries, or whether on the contrary individuals are moving into unemployment due to the relative generosity of the benefits.

In the last chapter of my thesis I have focused on the effect that an individual's health can have on other individuals' labour market status, via informal caregiving. Thus, the main aim has been to analyse to what extent middle-aged Spanish women who give informal care bear labour opportunity costs as a result of doing so. As stated before, the main result shows that caregiving affects women's chances of employment when they care at home or for more than one period. Unfortunately, with the data at hand it has not been possible to tease out the effect of the intensity with which care is given with finer measures. But there are reasons to believe that these results are in line with what would be expected had we better proxies for the intensity of caring activities. On one hand, old parents can move in with their adult children when dependency problems prevent them from continuing in their own homes (Pezzin and Schone, 1999). On the other, we know that dependency problems get worse as time passes because they result from chronic processes of a degenerative nature.

These results prompt some caveats about the likely effects of the new Long-Term Care System in Spain. On one hand, the gradual implementation of the system (individuals in worse health are being covered first) would in theory allow the effects on women's participation to diminish in the short run. However, the design of the different in-kind and monetary benefits suggests that some confronting effects could ensue. The provision of up to 20 weekly hours of formal care and the provision of subsidised day-care centres and residences should work in the direction of favouring women's labour participation. In contrast, the availability of monetary transfers (up to €500/month if severely disabled or €320/month if moderately disabled) for women acting as the main informal carer will decrease the opportunity costs of leaving the labour market. The net effect on the labour supply of co-resident carers is difficult to predict, but most likely it will depend on each woman's labour opportunity costs. Thus, women with low earnings will probably be induced to drop out of the labour force, while high earners are likely to be encouraged to remain at work.

The answer to all these questions is undoubtedly an empirical issue to be solved in future research. This research should focus on understanding the mechanisms that drive families to choose different combinations of informal and formal care, and how these decisions are related to women's labour participation. Moreover, these questions should be answered as an evaluation of the new measures being implemented in Spain, in order to learn about the satisfaction of the main goals of the system, but also from an international perspective, in order to understand how different institutional arrangements affect the phenomenon. Regarding this research desideratum, the gradual implementation of the programme can provide us with some valuable variation to be used to evaluate its effects. In addition, the co-payment scheme is defined at the regional level. Thus, if the autonomous communities finally choose different percentages of co-payment, we will be able to learn about the role played by formal care prices in a society with strong family networks.

Another conclusion from the third chapter that is worth emphasising is the fact that the effects on labour behaviour seem to be reduced to an all-or-nothing choice (work full-time or stop working). There is evidence that while more flexible hours do not diminish caregivers' propensity to be employed, there are some positive effects when caregivers work for a firm with unpaid family leaves (Pavalko and Henderson, 2006). Thus, a comprehensive reform to diminish the costs paid by informal carers should also include some more flexible employment formulas.

I would like now to draw attention to some long-run implications of the empirical effects identified in this thesis. The propensity of young individuals to be employed is reduced when their health decreases, and middle-aged women decrease their labour supply if they give care. These are short-run effects whose long-run reflection will probably be lower future earnings due to the depreciation of human capital and qualifications during periods out of the labour force (Mincer and Polachek, 1974), together with reduced pension claims due to poorer contributions to social security and/or private pension schemes. There are, nevertheless, several compensatory mechanisms. First, individuals may receive social security benefits to compensate for the loss of income from work up to the retirement age. Secondly, caregivers can be privately compensated via inter vivo transfers or bequests. These long-run effects are very relevant questions for further research. The empirical techniques used in this thesis are expected to yield useful results with new and developing longitudinal data sources such as the British Cohort Study, the German Socioeconomic Panel and the US Panel Study of Income Dynamics.

References

Aarts L, Burkhauser R and de Jong P (1996) *Curing the Dutch Disease: An International Perspective on Disability Policy Reform*. Aldershot, Avebury.

Abadie A and Imbens GW (2006) Large sample properties of matching estimators for average treatment effects. *Econometrica*, 74: 235-67.

Acheson D (chairman) (1998) *Independent Inquiry into Inequalities in Health Report*. The Stationery Office, London, 1998.

Ahn N, García J and Herce J (2005) Demographic uncertainty and health care expenditure in Spain. Documento de Trabajo 2005-07, FEDEA, Madrid.

Allison P (1982) Discrete-time methods for the analysis of event histories. *Sociological Methodology*, 13: 61-98.

Anderson KH and Burkhauser RV (1985) The retirement-health nexus: a new measure of an old puzzle. *Journal of Human Resources*, 20: 315-330.

Au D, Crossley TF and Schellhorn M (2005) The effects of health shocks and long-term health on the work activity of older Canadians. *Health Economics*, 14: 999-1018.

Baker M (2002) The retirement behaviour of married couples: evidence from the Spouse's Allowance. *Journal of Human Resources*, 37(1): 1-34.

Banks J, Emmerson C and Tetlow G (2007) Healthy retirement or unhealthy inactivity: how important are financial incentives in explaining retirement? Institute for Fiscal Studies WP.

Bardasi E, Jenkins SP and Rigg JA (2002) Retirement and the income of older people: a British perspective. *Ageing and Society*, 22: 131-159.

Bazzoli G (1985) The early retirement decision: New empirical evidence on the influence of health. *Journal of Human Resources*, 20: 214-234.

Becker S and Ichino A (2002) Estimation of average treatment effects based on propensity scores. *The Stata Journal*, 2(4): 358-377.

Bingley P and Walter I (1997) The labour supply, unemployment and participation of lone mothers in in-work transfer programmes. *The Economic Journal*, 107: 1375-1390.

Blau DM (1997) Social security and labour supply of older married couples. *Labour Economics*, 4: 373-418.

Blau DM (1998) Labor force dynamics of older married couples. *Journal of Labor Economics*, 16(3): 595-629.

Blundell R and Costa Dias M (2002) Alternative approaches to evaluation in empirical microeconomics. *Portuguese Economic Journal*, 1: 91-115.

Blundell R, Costa Dias M, Meghir C and van Reenen J (2004) Evaluating the employment impact of a mandatory job search program. *Journal of the European Economic Association*, 2: 569-606.

Blundell R, Meghir C and Smith S (2002) Pension incentives and the pattern of early retirement. *Economic Journal*, 112: 153-170.

Böheim R and Taylor M (2000) Unemployment duration and exit rates in Britain. CEPR discussion paper No. 2500.

Bolin K, Lindgren B and Lundborg P (2008) Your next of kin or your own carer? Caring and working among the 50+ of Europe. *Journal of Health Economics* (in press). doi:10.1016/j.jhealeco.2007.10.004.

Bound J (1991) Self-reported versus objective measures of health in retirement models. *Journal of Human Resources*, 26(1): 106-138.

Bound J, Schoenbaum M, Stinebrickner T and Waidmann T (1999) The dynamic effects of health on the labor force transitions of older workers. *Labour Economics*, 6: 179-202.

Bowling A (1991) *Measuring Health: A Review of Quality of Life Measurement Scales*. Milton Keynes: Open University Press.

Cameron AC and Trivedi PK (2005) *Microeconometrics: Methods and Applications*, Cambridge University Press, New York.

Cappellari L and Jenkins SP (2003) Multivariate probit regression using simulated maximum likelihood. *The Stata Journal*, 3(3): 278-294.

Carmichael F and Charles S (1998) The labour market costs of community care. *Journal of Health Economics*, 17: 747-765.

Carmichael F and Charles S (2003) The opportunity costs of informal care: does gender matter? *Journal of Health Economics*, 22: 781-803.

Casado D (2006) La atención a la dependencia en España. *Gaceta Sanitaria*, 20(S1): 135-142.

Casado-Marín D, García-Gómez P and López-Nicolás A (2006) Informal care and labour force participation among middle-aged women in Spain. Working paper 1023. Department of Economics and Business. Universitat Pompeu Fabra.

Chamberlain G (1984) Panel data. In Z Griliches and MD Intriligator (eds) *Handbook of Econometrics*, Vol 1, Amsterdam, North Holland: 1247-1318.

Contoyannis P, Jones AM and Rice N (2004) The dynamics of health in the British Household Panel Survey. *Journal of Applied Econometrics*, 19: 473-503.

Crespo L (2007) Caring for parents and employment status of European mid-life women. Documento de trabajo CEMFI No. 6015.

Currie J and Madrian BC (1999) Health, health insurance and the labour market. In O Ashenfelter and D Card (eds) *Handbook of Labour Economics*, Vol 3, Amsterdam, North Holland: 3309-3416.

Dano AM (2005) Road injuries and long-run effects on income and employment. *Health Economics*, 14: 955-970.

Deaton A (2002) Policy implications of the gradient of health and wealth. *Health Affairs*, 21(2): 13-30.

Deaton A (2003) Health, inequality and economic development. *Journal Economic Literature*, 41: 113-158.

Dehejia RH and Wahba S (1999) Causal effects in non-experimental studies: Re-evaluating the evaluation of training programs. *Journal of the American Statistical Association*, 94: 1053-62.

Dehejia RH and Wahba S (2002) Propensity score-matching methods for nonexperimental causal studies. *The Review of Economics and Statistics*, 84: 151-161.

Disney R, Meghir C and Whitehouse E (1994) Retirement behaviour in Britain. *Fiscal Studies*, 15: 24-43.

Disney R, Emmerson C and Wakefield M (2006) Ill health and retirement in Britain: A panel data-based analysis. *Journal of Health Economics*, 25: 621-649.

Department of Social and Family Affairs (2003) Report of the Working Group on the Review of the Illness and Disability Payment Schemes. Department of Social and Family Affairs, Dublin.

Edad & Vida (2004) *Estudio del modelo de atención a las personas mayores con dependencia en España*, Barcelona: Edad & Vida.

Ermisch JF and Wright RE (1993) Wage offers and full-time and part-time employment by British women. *Journal of Human Resources*, 28: 111-133.

Ettner SL (1995) The impact of parent care on female labor supply decisions. *Demography*, 32(1): 63-79.

Ettner SL (1996) The opportunity costs of elder care. *Journal of Human Resources*, 31(1): 189-205.

European Commission (2004a) Mutual Information System on Social Protection in the EU Member States and the EEA. Comparative Tables on Social Protection. Situation on 01/05/2004.

European Commission (2004b) Employment in Europe 2004: Recent trends and prospects, Employment and Social Affairs, European Commission, Brussels.

European Commission (2007) Comparative tables on social protection in the 27 Member States of the European Union, in the European Economic Area and in Switzerland – Situation on 1 January 2007. Mutual Information System on Social Protection in the EU Member States and the EEA. Employment and Social Affairs.

Eurostat (2007) European social statistics. Social protection, expenditure and receipts. Data 1996-2004. Eurostat Statistical Book. Luxembourg.

Flinn CJ and Heckmann JJ (1983) Are unemployment and out of the labour force behaviorally distinct labor force states? *Journal of Labor Economics*, 1: 28-42.

Frölich M, Hesmati A and Lechner M (2004) A microeconometric evaluation of rehabilitation of long-term sickness in Sweden. *Journal of Applied Econometrics*, 19: 375-396.

García-Gómez P (2008) Institutions, health shocks and labour outcomes across Europe. Documento de Trabajo 2008-01, FEDEA.

García-Gómez P and López-Nicolás A (2005) Socio-economic inequalities in health in Catalonia. *Hacienda Pública Española*, 175: 103-122.

García Gómez P and López Nicolás A (2006) Health shocks, employment and income in the Spanish labour market. *Health Economics*, 15: 997-1009.

Goldberg D and Williams P (1988) *A User's Guide to the General Health Questionnaire*. Windsor: NFER-Nelson.

Grossman M (1972) On the concept of health capital and the demand for health. *Journal of Political Economy*, 80: 223-255.

Hagan R, Jones A and Rice N (2006) Health and retirement in Europe. Health and Econometrics Data Group Working Paper 06/10. York.

Hauk K and Rice N (2004) A longitudinal analysis of mental health mobility in Britain. *Health Economics*, 13: 981-1001.

Heckman JJ (1981) The incidental parameters problem and the problem of initial conditions in estimating a discrete time-discrete data stochastic process. In CF Manski and D McFadden (eds) *Structural Analysis of Discrete Data with Econometric Applications*, Cambridge MA: MIT Press.

Heckman JJ (1993) What has been learned about labor supply in the past twenty years? *American Economic Review*, 83: 116-121.

Heckman J, Ichimura H and Todd P (1997) Matching as an econometric evaluation estimator. *Review of Economic Studies*, 64: 605-654.

Heitmueller A (2007) The chicken or the egg? Endogeneity in labour market participation of informal carers in England. *Journal of Health Economics*, 26(3): 536-559.

Heitmueller A and Michaud PC (2006) Informal care and employment in England: Evidence from the British Household Panel Survey. IZA Discussion Paper No. 2010, IZA, Bonn.

Hernández-Quevedo C, Jones AM and Rice N (2008) Reporting bias and heterogeneity in self-assessed health. Evidence from the British Household Panel Survey. Cuadernos económicos del ICE, forthcoming.

Imbens GW (2004) Nonparametric estimation of average treatment effects under exogeneity: A review. *The Review of Economics and Statistics*, 86: 4-29.

Jenkins SP (1995) Easy estimation methods for discrete-time duration models. *Oxford Bulletin of Economics and Statistics*, 57(1): 129-138.

Jenkins SP (1998) Discrete time proportional hazard regressions. *STATA Technical Bulletin*, STB-39: 22-32.

Jiménez-Martín S, Labeaga JM and Vilaplana Prieto C (2006) A sequential model of older workers' labor force transitions after a health shock. *Health Economics*, 15: 1033-1054.

Jimeno JF, Rojas SA and Puente S (2008) Modelling the impact of ageing on social security expenditures. *Economic Modelling*, 25(2): 201-224.

Johnson RW and Lo Sasso AT (2000) The Trade-Off between Hours of Paid Employment and Time Assistance to Elderly Parents at Midlife, report from the Urban Institute, Washington D.C.

Jones AM and López Nicolás A (2004) Measurement and explanation of socioeconomic inequality in health with longitudinal data. *Health Economics*, 13(10): 1015-1030.

Kerkhofs M and Lindeboom M (1995) Subjective health measures and state dependent reporting errors. *Health Economics*, 4: 221-235.

Knapp LG and Seaks TG (1998) A Hausman test for a dummy variable in probit. *Applied Economic Letters*, 5: 321-323.

Lechner M (2000) An evaluation of public-sector-sponsored continuous vocational training programs in East Germany. *The Journal of Human Resources*, 35: 347-375.

Lechner M and Vázquez Álvarez R (2004) The effect of disability on labour outcomes in Germany: evidence from matching. Discussion Paper #4223. Centre for Economic Policy Research, London.

Likert R (1952) A technique for the development of attitude scales. *Educational and Psychological Measurement*, 12: 313-315.

Lindeboom M (2006) Health and work of older workers. In AM Jones (ed) *Elgar Companion to Health Economics*, Edward Elgar: Aldershot.

Lindeboom M, Llena-Nozal A and van der Klaauw B (2006) Disability and work: the role of health shocks and childhood circumstances. IZA Discussion Paper No. 2096. Bonn.

Lindeboom M and van Doorslaer E (2004) Cut-point shift and index shift in self-reported health. *Journal of Health Economics*, 23(6): 1083-1099.

Maddala GS (1983) *Limited-Dependent and Qualitative Variables in Econometrics*. Cambridge University Press.

Marzano E (2006) How many labour force states? An analysis based on the British Household Panel Survey (BHPS). *Labour*, 20(2): 237-254.

Messer Pelkowski J and Berger MC (2004) The impact of health on employment, wages, and hours worked over the life cycle. *The Quarterly Review of Economics and Finance*, 44: 102-121.

Meyer BD (1990) Unemployment insurance and unemployment spells. *Econometrica*, 58: 757-782.

Michaud PC (2003) Joint labour supply dynamics of older couples. Tilburg University. Center for Economic Research, Discussion Paper No. 2003-69.

Mincer J and Polachek S (1974) Family investments in human capital: earnings of women. *Journal of Political Economy*, 82: 576-608.

Mundlak Y (1978) On the pooling of time series and cross-section data. *Econometrica*, 46(1): 69-85.

OECD (2003) *Transforming Disability into Ability: Policies to Promote Work and Income Security for Disabled People*. OECD: Paris.

OECD (2005) *Long-term Care for Older People*. OECD: Paris.

OECD (2006) *Employment Outlook 2006: Boosting Jobs and Incomes*. OECD: Paris.

OECD (2007) *Pensions at a Glance 2007: Public Policies across OECD Countries*. OECD: Paris.

Pavalko E and Henderson K (2006) Combining care work and paid work: Do workplace policies make a difference? *Research on Aging*, 28(3): 359-374.

Peracchi F (2002) The European Community Household Panel: A review. *Empirical Economics*, 27: 63-90.

Pezzin LE and Schone B (1999) Intergenerational household formation, female labor supply and informal caregiving: A bargaining approach. *The Journal of Human Resources*, 34(3): 475-503.

Prentice R and Gloecker L (1978) Regression analysis of grouped survival data with applications to breast cancer data. *Biometrics*, 34: 57-67.

Rice N, Roberts J and Jones A (2006) Sick of work or too sick to work? Evidence on health shocks and early retirement from the BHPS. Health, Econometrics and Data Group Working Paper 06/13. York.

Riphahn R (1999) Income and employment effects of health shocks. A test case for the German welfare state. *Journal of Population Economics*, 12: 363-389.

Rosenbaum P and Rubin DB (1983) The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70: 41-55.

Rosenbaum P and Rubin DB (1984) Reducing bias in observational studies using subclassification on the propensity score. *Journal of the American Statistical Association*, 79: 516-524.

Smith JP (2004) Unraveling the SES-Health Connection. The Institute for Fiscal Studies. Working Paper WP04/02. London.

Spiess CK and Schneider AU (2003) Interactions between care-giving and paid work hours among European midlife women. *Ageing and Society*, 23(1): 41-68.

Stern S (1989) Measuring the effect of disability on labour force participation. *Journal of Human Resources*, 24: 361-395.

Stewart JM (2001) The impact of health status on the duration of unemployment spells and the implications for studies of the impact of unemployment on health status. *Journal of Health Economics*, 20: 781-796.

Tano DK (1991) Are unemployment and out of the labor force behaviorally distinct labor force states? New evidence from the gross change data. *Economics Letters*, 36: 113-117.

Van Doorslaer E and Koolman X (2004) Explaining the differences in income-related health inequalities across European countries. *Health Economics*, 13: 609-628.

Verbeek M and Nijman T (1992) Testing for selectivity bias in panel data models. *International Economic Review*, 33(3): 681-703.

Viitanen TK (2005) *Informal Elderly Care and Female Labour Force Participation across Europe*, ENEPRI Research Report No. 13.

Weich S, Lewis G and Jenkins SP (2001) Income inequality and the prevalence of common mental disorders in Britain. *British Journal of Psychiatry*, 178: 222-227.

Wildman J (2003) Income related inequalities in mental health in Great Britain: analysing the causes of health inequality over time. *Journal of Health Economics*, 22: 61-87.

Wolf DA and Soldo B (1994) Married women's allocation of time to employment and care of elderly parents. *Journal of Human Resources*, 29(3): 1259-1276.

Wooldridge JM (2005) Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics,* 20(1): 39-54.

Wooldridge JM (2007) Inverse probability weighted estimation for general missing data problems. *Journal of Econometrics*, 141(2): 1281-1301.

Zucchelli E, Harris A, Jones A and Rice N (2007) Health and retirement among older workers. Health, Econometrics and Data Group Working Paper 07/19. University of York.