The impact of providing informal care on carer well-being, retirement, and health.

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Abstract

This thesis includes a series of case studies exploring the impact of providing informal (unpaid) care on the well-being, retirement decisions, and physical and mental health outcomes of carers. We use a representative sample of the UK population and informal carers from eighteen waves of the British Household Survey (BHPS). Analysis is undertaken from an economic and micro-econometrics perspective, using a variety of econometric techniques tailored to the specific questions and data in each study. The first chapter introduces the topics and provides descriptive statistics of the sample of carers in BHPS. In the second chapter, we study the impact of providing informal care on happiness and life satisfaction and calculate monetary values for informal care for each of these subjective well-being measures and by gender. We find monetary values of around £18 per extra hour of informal care provided per week for men and women in our preferred model, although values vary with the well-being measure, the measure of informal care, and the estimation method used. In chapter three we study whether the decision to retire before the State Pension Age is affected by the intensity of the informal care provided by men and women. We find that the probability of retirement is around twice as high for carers than for non-carers. Chapter 4 analyses the impact of providing informal care on caregiver´s health, using a variety of health measures: GHQ, SF-6D, health conditions and self-assessed health. We find a small but negative effect of providing informal care on both the physical and mental health of informal carers. With these analyses, we aim to contribute to the literature by providing evidence on the impact of informal caring on carers to inform policy towards them and those they care for.

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I would like to dedicate my thesis to my mum, dad, and my sister. *Mama, papa: Moltíssimes gràcies per creure en mi, per donar-me forces i estar sempre al meu costat. Arribar fins aquí no hauria sigut possible sense vosaltres, m'heu ensenyat sempre a lluitar i aspirar al màxim. Andreita, gràcies per sempre fer-me riure*. An especial mention to my best friend Alba who has always accompanied me in this long journey: *Mil gracias, de todo corazón, por siempre estar tan cerca y por todo lo que haces por mí*. And to Víctor, to bring dragons when I much needed.

Declaration

I declare that this thesis is a presentation of original work and I am the sole author. Contributions from my supervisors were made and are detailed below.

Chapter 2 was first supervised by Professor Bernard van den Berg who contributed to the original topic of research and gave useful comments on the first draft. Afterwards, I received expert advice and suggestions from Professors Hugh Gravelle and Nigel Rice. I prepared the data and carried out the empirical analysis, wrote the chapter and made revisions.

The topic for chapter 3 was suggested by Professors Gravelle and Rice. The topic for chapter 4 was suggested by me and refined by Professor Gravelle. For both chapters, I prepared the data, formulated the econometric approach, carried out the empirical analysis, wrote the chapters and made revisions following suggestions by Professors Gravelle and Rice. Papers based on chapters 2, 3, and 4, on which I am the lead author, are in preparation for submission to refereed journals.

Finally, I confirm that this work has not previously been presented for an award at this, or any other, University. All sources are acknowledged as References.

Chapter 1. Introduction

This thesis analyses four aspects of the provision of informal care in the UK: the cost of informal care and its impact on carer's well-being, their early retirement decisions and on their mental and physical health.

Informal care is generally defined as the care an individual provides to family members, friends, or close relatives, without receiving any financial payment in exchange. However, this definition is very broad and there is not consensus among the existing literature (Borgermans and Nolan, 2001). van den Berg et al. (2004) emphasises the heterogeneity of informal care and the need to take into account the time spent caring, the duration of the care provision, and the type and number of care tasks. These latter might include help with a wide range of activities of daily living, such as housework, personal care, or mobility, as well as administrative tasks, socializing or providing comfort to the receiver by for instance, listening to them. It is also difficult to disentangle which housework is associated with informal care especially if the caregiver and the care-receiver live in the same household.

In the UK there are currently 6.5 million people who are carers[1]. Yet, comparing the number of carers for the UK in the 2011 Census with the number in 2001, there has been an 11% increase on people providing informal care. Projections for the UK suggest that the number of carers will keep increasing with an estimation of a 40% rise by 2037[2].

This increment in informal care is usually attributed to an increase in life expectancy and to most individuals preferring personal and family care to formal care (Pickard et al., 2001). In 2016 the unpaid home care provided in the UK was estimated to cost £132 billion per year, almost doubling the cost since 2001 (£68 billion). That value approaches the total annual cost of health spending in the UK for the period 2014-2015 (£134 billion)[3].

The importance of informal care is evident in the number of hours that individuals spend caring. In the UK, 13.5% of carers provide care for between 1 to 19 hours per

[1] *Facts about carers*. Carers UK, making life better for carers. Policy Briefing, October 2015. *www.carersuk.org*.
[2] *Facts about carers*. Carers UK, making life better for carers. Policy Briefing, October 2015.
[3] *Valuing Carers 2015. The rising value of carers' support*. Buckner, L. Yeandle, S. Carers UK, University of Leeds, and University of Sheffield 2015

week, 15% of them care for 20 to 49 hours a week and almost 14% care for 50 or more than 50 hours weekly. The number of carers providing care for more than 50 hours a week has increased by 25% in the last ten years which is far more than the 11% increase in the overall number of carers.

Providing care can have a big impact on informal carers' life regarding their well-being, health, their labour market activities, social life and leisure. In the 2011 UK Census, approximately half of the carers reported working in the labour market while also providing unpaid informal care. Over 2 million had to stop working at the labour market at some point because of their caring responsibilities, and 3 million had to reduce their working hours. This tendency is of particular importance at the peak age for caring when individuals are between 40 and 60 years old, as individuals at these ages that provide care are more likely to take a decision on their labour market activities towards giving up their job, or reduce their working hours.

Furthermore, informal care can have a detrimental impact on physical and mental health. 54% of carers reported feeling depressed due to their caring responsibilities, while 60% reported to have a long-standing health condition where this percentage increased up to 70% for those providing care for more than 50 hours per week[4].

Those facts, together with the concern of carers of feeling socially excluded (61%)[5], and the financial impact of providing care, might have a negative impact on their overall perception of their well-being and life satisfaction.

In order to contribute to the evidence on the effects of informal carer on carers we examine the cost of informal care and its impact on the well-being, early retirement decisions, and mental and physical health outcomes of informal carers. Concretely our research questions are:

- What is the monetary value of informal care according with different well-being measures? What effects does informal care have on carer's well-being outcomes and what is the monetary value of these effects?

[4] *Sick tired, and caring: the impact of unpaid caring on health and long term conditions*. Carers Scotland (2011).

[5] *Facts about carers. Carers UK, making life better for carers*. Policy Briefing, October 2015.

- Are informal carers in their middle ages more likely to retire before the UK State Pension Age than non-carers due to their caring responsibilities?
- Is there a negative impact of informal care provision on the physical and mental health of carers?

We examine those questions in the three core chapters. In chapter two, we calculate monetary values for informal care using the well-being valuation method. We do so using two well-being outcomes, happiness and life-satisfaction, in order to see whether money values for that commodity are sensitive to the well-being measure used. For both happiness and life satisfaction models we calculate monetary values for informal care by gender and we also explore whether results are sensitive to the way in which hours providing care enters into the well-being function (linear or non-linear). We find the intensity of the informal care provision has a negative impact on well-being. Monetary values are contingent to the well-being measure used, the estimation method, and to the specification of the number of hours providing care. Men and women require similar compensations.

In chapter three, we use a discrete-time duration model to analyse the impact of providing informal care on the probability of early retirement decisions of individuals who work at the labour market and are aged 50 or over. We follow those individuals over time up until a year before the State Pension Age and analyse whether the likelihood to retire before that age is influenced by individuals' last year number of hours providing care and whether this probability varies for men and women. We find that the probability of early retirement for males and females providing care for 20 or more hours a week last period is higher than for non-carers and slightly bigger for males.

In the fourth chapter, we look at the impact of the care intensity on caregivers' health using a variety of mental and physical health measures: GHQ, SF-6D, health conditions, and self-assessed health. We use dynamic panel data models where current health depends on past health, and estimate Generalized Methods of Moments IV models and 2-Stage Residual Inclusion random effects ordered probit models depending on whether the health outcome is continuous or ordered categorical. We then analyse whether the intensity of care has detrimental effects on informal carer's health compared with the health of non-carers for each health outcome and discuss the performance of the models using different health measures. Overall, we find a negative and small effect of informal care on health across all measures, where the negative impact is higher when caring for 20 or more hours per week compared with non-carers.

The Department of Health's Demonstration Sites programme showed that more support for carers can be a cost-saving for the government and would keep carers in better health and overall satisfaction with their life (Yeandle and Wigfield, 2011). Government policy has promised to give more personalised support to carers in response to their demands for a better work-life balance, health, and financial situation in England[6]. Policy priorities include supporting people with caring responsibilities to identify themselves as carers so they can access advice and support; helping carers to keep their jobs and avoid drop outs from the labour market due to caring activities, as well as to engage them in educational programmes and labour market activities; ensuring they are and keep mentally and physically healthy; and providing personalised support for them and their families to reduce the financial hardship they might suffer. The Department of Health is also exploring the evidence on the impact of providing informal care on broader aspects of individuals' lives, including those we study in the present thesis[7].

This thesis does not attempt to evaluate the impact of policies towards carers. Rather, it aims to produce evidence on the impact of caring on carers. This is essential to inform policy towards asserting on the relevant issues to address when working on informal care policies. This thesis provides such evidence and quantifies the impact of the provision of informal care on carers. We have chosen to analyse the impact of informal care on well-being, labour market, and health as we believe those are the most immediate and relevant aspects for informal carers.

Knowledge of the impact of caring on carers is required not just to inform policy towards carers, but as an input in evaluation of other policies, especially the evaluation of healthcare technologies and practices affecting health (Bond et al., Getsios et al., Reed et al., 2017). Policies which change the health of individuals will affect the amount of informal care they require. These effects need to quantified and including in the evaluation of the overall effects of policies. Such evaluations will need to know both

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[6] *Carers at the heart of 21st century families and communities.* Department of Health Government, 2008.
[7] *Carers Strategy: Second National Action Plan 2014-2016*. Department of Health, October 2014.

how changes in health of those who care for affects the amount of informal care provided and the effects of informal care on carers. This thesis provides some initial evidence on the effects of informal care on carers as to contribute to steps to incorporate wider impacts into healthcare economic evaluations.

1.1 British Household Panel Dataset

We perform our analyses using the British Household Panel Dataset (BHPS) and use it through all chapters. The BHPS is an annual longitudinal survey of a sample of private households in Great Britain: England, Wales, and Scotland south of the Caledonian Canal. In 1991, the first households were recruited using a stratified sampling procedure (250 sampling units). As a consequence each address had an approximately equal probability of being selected. The chosen households were then followed over time and re-interviewed every subsequent year until 2008. This resulted in a sample of 5,050 households and approximately 10,000 interviewed individuals. In the late 1990s an additional sample of 1,500 households in each Wales and Scotland were added and, in 2001, a sample of 1,900 households for Northern Ireland was included. In wave one, in 74% of the households there was at least one individual interviewed and in 65% of the households all individuals answered the questionnaires[8].

The BHPS data is collected at individual and household level. The individual questionnaires are in principle answered by all household members aged 15 and above, and the household questionnaires are just answered by one member of the household on behalf of the others. If a household splits off, all the members are followed to the new household and interviewed along with all adult members of that new household. The BHPS selects only private households. Individuals residing in institutions such as nursing homes or military barracks, and people without a residential address are therefore excluded.

The BHPS has information on quite a broad range of topics including the organisation of the household, demographic characteristics, labour market characteristics, income and wealth, health, and information on child care, leisure, and life events of the interviewed individuals.

[8] More details can be found in BHPS User Documentation. Volume A: Introduction, Technical Report and Appendices – Sampling and Survey Methods. Table 17 “Wave One Household Outcomes and Response Rates”. Page A4-28.

Since our main objective is to study informal carers, in this chapter we present detailed descriptive statistics of this sample of individuals in the BHPS. Afterwards, each of the subsequent chapters presents its own descriptive section according.

1.2 Describing informal carers using BHPS

In BHPS, there are 12,433 individuals who look after someone else who is handicapped, sick, or elderly during the 18 waves of BHPS. As **Table 1.1** shows this corresponds to almost 16% of the total number of individual-wave observations and to 29% of the total number of individuals in our sample. **Table 1.2** shows that among the 16% of carers in BHPS, 10.14% provide care for someone who is not living with them, and therefore, the care-receiver(s) is someone outside the household where the carer lives. 5% provides care for only care-receiver(s) who live with them in the same household, and the remaining 0.81% provide both types of care at the same time; this is, they care for one or more individuals living with them and for one or more individuals outside their household.

Comparing the characteristics between carers and non-carers, **Table 1.3** shows that almost 18% of females in BHPS provide informal care and 14% among males in BHPS do so. **Table 1.4** compares the mean values for a set of variables for carers and non-carers and shows either T-statistics for discrete variables and Chi-squared test for categorical variables to assess whether the difference in means for carers and non-carers is significant[9]. Among the total number of individuals who provide care, more than half of them are female (60.20%) and about 40% are males. Carers are, in average, almost 5 years older than non-carers. The majority of carers have a low education, where around 40% of them have not acquired any qualification, more than 50% has an O or and A level, and less than 10% has a higher degree. Non-carers tend to be slightly more educated than carers as the proportion of individuals with no education (31.5%) is lower than for carers (almost 40%), and the proportion of individuals with A level, O level and with a degree or higher degree is higher for non-carers than for carers. 73.2% of carers are married or living with the couple, 14% are single, and the rest are widowed (5.4%) and divorced (7.4%). Comparing carers with non-carers, the proportion of widowed and single tend to be higher when not providing any care than when providing it and the proportion of divorces are slightly higher among carers than non-carers. Both carers and

[9] Since the BHPS sample is large, we expect even small differences in mean values for carers and non-carers to be significant.

non-carers in BHPS have in average one child. Carers earn on average £1,480 less than non-carers per year. Regarding the employment status, less than half of carers are employed (43%) contrary with non-carers where more than half of them are (51%); about the same percentage of carers and non-carers is self-employed (7% in both samples); 26% of carers are retired against the 19% of non- carers. The proportion of carers who are housework[10] (11.4%) is much higher than for non-carers (6.7%). All the difference in means by carers and non-carers for each variable are statistically different from zero at 1% significance level.

Focussing only on carers, **Table 1.5** shows that more than half of them provide care for one or more individuals living outside their household, while 31% provide care for care-receiver(s) living in the same household as the carer, and the remaining 5% provides both types of care at the same time. Regarding the number of hours providing care, 40% of the total number of carers provides care between 0 to 4 hours per week, while 19.4% provides informal care between 5 to 9 hours per week and around 13% of carers due so for between 10 to 19 hours a week. Almost 10% of carers say to provide informal care for more than 100 hours a week. Those carers who could not answer a specific number of hours providing care, reported to provide care for under 20 hours a week and for above 20 hours a week. In order to provide a better variable for the number of hours providing care, we collapse the categories above in “not providing informal care”, “providing informal care for less than 20 hours per week”, and “providing informal care for more than 20 hours per week”. Similar as explained above, the majority of the carers (76.2%) provides care for less than 20 hours a week, while almost 24% of them provides care for more than 20 hours a week.

Figure 1-1 shows the proportion of individuals not providing informal care, providing informal care for less than 20 hours per week, and providing informal care for more than 20 hours a week by age ranges on the sample of individual-year observations. The proportion of individuals providing less than 20 hours a week increases with age and it reaches its peak for individuals between 45 to 64 years old, where around 18% of individuals in each of the age ranges 45-54 and 55-64 provide that amount of informal care per week. The proportion of individuals providing more than 20 hours per week of care also increases by age where the highest proportion of individuals providing that

[10] House work is defined as individuals who do not work at the labour market. Instead, they do housing activities such that the housework, picking up the children from school, among others.

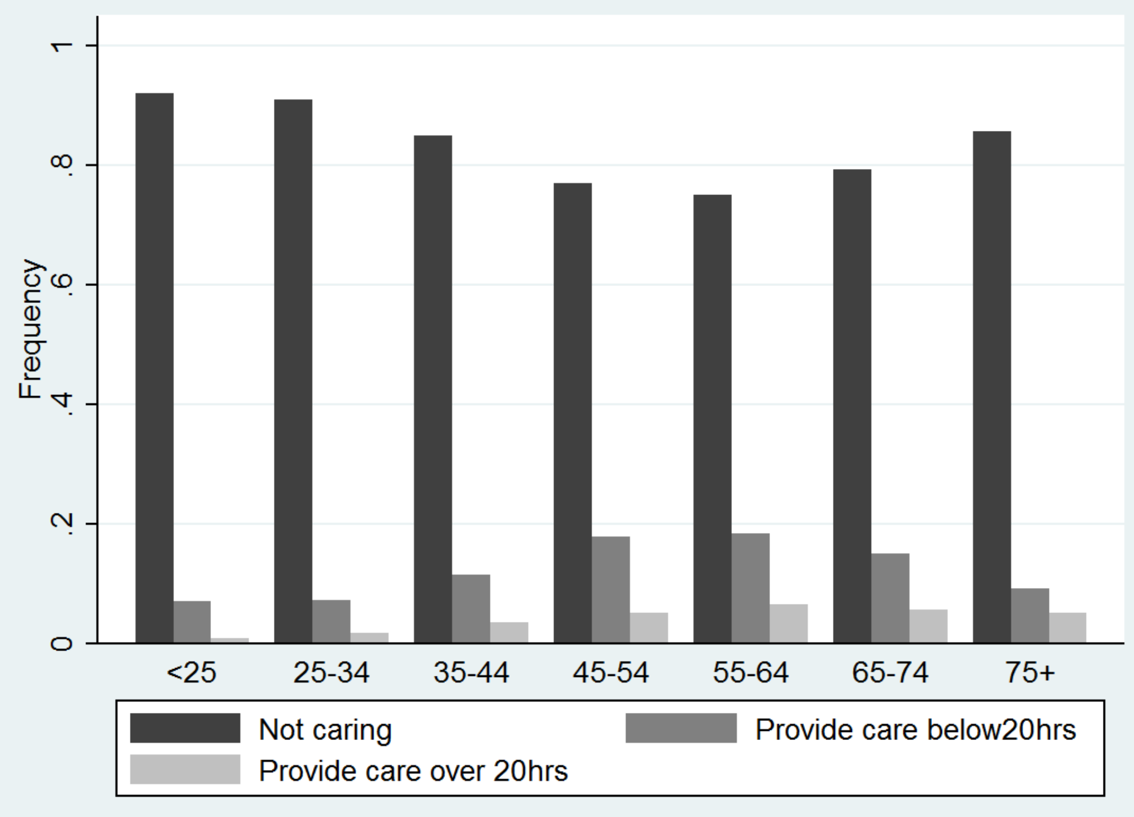
amount of care is for those in the age ranges 55-64, 65-74 and more than 75 years old with, respectively 6.5%, 6%, and 5% of individuals of those ages.

Overall, there are more female than male carers in BHPS. Carers provide in average less than 20 hours of care per week where the majority of carers do so for care-recipients living outside their households. The proportion of individuals providing any amount of care increases with age. And, in general, carers are more disadvantage than non-carers with respect to education achievements, employment status, and income.

The rest of the thesis is structured as follows. Chapter 2 presents the monetary value of informal care; chapter 3 studies the impact of providing informal care on early retirement decisions; chapter 4 analyses the impact of providing informal care on physical and mental health; and chapter 5 provides an overall conclusion of the thesis.

FIGURE

Figure 1-1 Distribution of weekly number of hours providing care by age



Note: NxT= 227, 684 individual-year observations.

TABLES

Table 1.1 Number and proportion of individuals providing care

Care	Frequency NxT	Percent NxT	Frequency N	Percent N
Never provided informal care	191,338	84.04%	30,138	70.795%
Ever provided informal care	36,346	15.96%	12,433	29.205%
Total	227,684	100%	42,571	100%

Note: NxT refers to the number of individual-year observations. N refers to the total number of people.

Table 1.2 Number of individual-year observations and proportion of carers by care type

Type care	Frequency NxT	Percent NxT
nocare	191,338	84.04%
careinonly	11,404	5.01%
careoutonly	23,097	10.14%
careinoutd	1,845	0.81%
Total NxT	227,684	100%

Table 1.3 Proportion of individual-year observation providing care by gender

Care	Female	Male
Never provided informal care	82.32%	86.08%
Ever provided informal care	17.68%	13.92%
Total NxT	100%	100%

Table 1.4 Mean values for carer vs non-carers by different characteristics

	Mean		Difference between means by carers vs non-carers
Variables	**Carers NxT=36,346**	**Non-carers NxT=191,338**	**T-test or Pearson's chi2**
Male	0.398	0.468	ttest = 24.452***
Age	50.403	44.297	ttest = -57.607***
no qualification	0.397	0.315	Chi2 = 1.1e+03***
O level	0.297	0.309	
A level	0.216	0.252	
Degree	0.090	0.124	
Married	0.732	0.624	Chi2 = 1.9e+03***
Widowed	0.054	0.081	
Divorced	0.074	0.070	
Single	0.140	0.225	
White	0.982	0.972	ttest = -10.407***
Number children	0.523	0.609	15.232***
Income	17,027.870	18,506.660	17.988***
self-employed	0.065	0.069	Chi2 = 2.8e+03***
employed	0.431	0.513	
unemployed	0.038	0.038	
Retired	0.256	0.193	
maternity leave	0.007	0.009	
Housework	0.114	0.067	
Student	0.029	0.065	
long term sick	0.049	0.039	
Gov.-training	0.002	0.003	
job other	0.008	0.003	

Notes**:** Mean values are calculated on the sample of individuals by wave observation i.e. NxT=36,346 carers and NxT=191,338 non-carers.

To assess whether the difference between means for each variable by carers and non-carers is statistically significant from zero we compute t-statistic for discrete variables and Pearson's Chi-squared for categorical variables. *** P-value<0.001

Table 1.5 Type and amount of informal care

Variable	Carers NxT=36,346 Mean	Std. Dev
careinonly	0.314	0.464
careoutonly	0.635	0.481
careinoutd	0.051	0.220
hours 0-4	0.402	0.490
hours 5-9	0.194	0.396
hours 10-19	0.128	0.334
hours 20-34	0.065	0.246
hours 35-49	0.028	0.166
hours 50-99	0.018	0.131
hours 100more	0.094	0.292
under 20hours	0.037	0.188
above 20hours	0.034	0.181
below20hrs	0.762	0.426
more20hrs	0.238	0.426

Chapter 2. The monetary value of informal care

2.1 Introduction

In this chapter, we study the impact of providing informal care on an individual's well-being for the UK and calculate the change in income required to compensate for providing an additional hour of informal care to maintain constant well-being.

Informal care is the care provided to family members, close relatives and friends without any payment (van den Berg et al., 2004). Informal carers not only care for sick and disabled family members, but also for those with chronic diseases and the terminally ill (Norton, 2000). The number of individuals providing care in the UK increased by 11% from the 2001 to the 2011 UK Census. 38% of informal carers provide care for more than 100 hours per week, and the number of carers caring for more than 50 hours a week has increased by 25% in the last ten years.[11] Informal care has an opportunity cost in terms of leisure and work and may adversely affect the health and financial status of carers. Therefore, we believe it is important to study the effect of informal care provision on a carer's well-being.

The sign of the effects on well-being is ambiguous. The time invested in the provision of care can be considerable (van den Berg and Spauwen, 2006) and can negatively affect labour market participation (Carmichael and Charles, 1998, Carmichael and Charles, 2003, Ettner, 1995, Ettner, 1996, Heitmueller and Michaud, 2006). Carers who do paid work usually receive lower wages than non-carers (Heitmueller and Inglis, 2007). However, satisfaction from providing care to others could increase well-being (Andren and Elmstahl, 2005, Jacobi et al., 2003, Zapart et al., 2007).

Informal care is often ignored in policy evaluations, possibly because as a non-market commodity it is difficult to measure and there is no consensus on how to value it (Francis and McDaid, 2009, van den Berg et al., 2004). Valuation is difficult because it may depend on the time invested, the duration of care, the type of care provided, and the relationship with the care-recipient (van den Berg et al., 2004).

We apply the well-being valuation method to value informal care. This method provides a monetary value for non-market commodities such as informal care by looking at their

[11] *Facts about carers*. Carers UK, making life better for carers. Policy Briefing, October 2015.

impact on an individual’s well-being. Individuals are not asked directly for the effect of informal care on well-being, but for their general well-being, considering all aspects of their life: personal, job, health, family, income, etc. The impact of informal care and these other factors on well-being is then estimated. The monetary value of informal care or other non-market commodity is calculated as the additional income individuals would need to maintain the same level of well-being when the amount of the commodity of interest changes (Clark and Oswald, 2002, Ferrer-i-Carbonell and van Praag, 2002, Fujiwara and Campbell, 2011, Kehl and Stahlschmidt, 2013, Powdthavee and van den Berg, 2011, van den Berg and Ferrer-i-Carbonell, 2007).

Other methods for the evaluation for informal care use individuals’ revealed preferences or their stated preferences (Koopmanschap et al., 2008, van den Berg et al., 2005a, van den Berg et al., 2005b, van den Berg et al., 2005c). The revealed preference methods value the time spent on informal care either by calculating the time forgone in the labour market assuming all informal carers are engaged in waged labour (Ettner, 1996, O'Shea and Blackwell, 1993, van den Berg et al., 2006); or by using the price of a market substitute for informal care, for instance the wage of a nurse, assuming formal and informal care to be perfect substitutes (van den Berg et al., 2006). However, these methods only consider the potential cost and not the utility of informal care and so do not fully reflect preferences. Stated preference methods examine an individual’s utility and disutility of providing care by asking how much carers would be willing to pay or accept in different hypothetical situations (van den Berg et al., 2005a, van den Berg et al., 2005b, van den Berg et al., 2005c). These methods, although accounting for different dimensions of informal care use individuals’ anticipated utilities in situations that they may not have experienced (Mitchell and Carson, 1989, van den Berg et al., 2006).

2.1.1 Literature

The well-being valuation method has been applied in many areas to value non-market commodities such as airport traffic noise (Van Praag and Baarsma, 2005), lasting marriage (Blanchflower and Oswald, 2004), divorce (Clark and Oswald, 2002), crime (Moore and Shepherd, 2007, Powdthavee, 2005), terrorism (Frey et al., 2009), environment (Frey et al., 2010), and health (Brown, 2015, Ferrer-i-Carbonell and van Praag, 2002). **Table 2.1** summarizes the main literature on the impact of informal care on well-being and its valuation.

The first application of this method to informal care was by van den Berg and Ferrer-i-Carbonell (2007) to analyse how much an individual must be compensated for providing an extra hour of informal care to maintain constant well-being. Individual's well-being is measured using two happiness questions: a categorical variable from 1 (in general I feel very happy) to 5 (not happy) and a happiness question scale from 0 (completely unhappy) to 10 (completely happy). Happiness is modelled as a function of the logarithm of income, the logarithm of hours providing care per week, and demographic factors using cross-section data from Dutch regional support centres for informal caregivers. They estimate the effect of hours providing care on happiness using ordinary least squares (OLS) and ordered probit and calculate compensating income variations distinguishing between whether the care recipient is a family member of the caregiver. Results show a negative effect of the logarithm of hours providing care on the informal caregivers' happiness. They find monetary compensations between 9€ and 10€ per extra hour of informal care when providing care for an average of 49 hours per week. The logarithmic specification implies that monetary values per hour decrease when the average number of hours providing care increases. The monetary value for caregivers not living in the same household as the receiver is slightly lower than for caregivers who live with the care-recipient (around 7-8€ and 9-10€ per extra hour of care, respectively). Limitations of this paper are the use of cross-section data and the fact that the data comes from carer support centres which might lead to sample selection bias. Also, no standard errors for monetary values are reported so it is not clear if the monetary values are statistically significant different from zero at the conventional levels.

Van den Berg et al. (2014) use the Household Income and Labour Dynamics in Australia (HILDA) panel dataset and find a negative effect of caregiving on life satisfaction (LS) but different money valuations according to the estimation method used. They estimate a fixed effects (FE) ordered logit model that allows for individual specific characteristics and the ordered nature of the life satisfaction variable and compare these results with pooled OLS and linear FE. Informal care is measured both as the logarithm of weekly number of hours providing care and as categorical variable. They also control for whether the care recipient lives inside or outside the informal caregiver's household. Using the logarithm of weekly number of hours providing care they find that the money value in Australian dollars when using FE ordered logit is \$115.20 per hour of care, \$78.12 when using pooled OLS, and \$105.20 when using linear FE. The authors do not indicate if these are statistically significantly different from zero at the conventional level of significance.

Mentzakis et al. (2012) use 12 waves of the British Household Panel Data Survey (BHPS), which has data on LS and General Health Questionnaire (GHQ) to calculate compensated income variations for informal care. They estimate linear FE for LS and GHQ. Informal care has a negative effect on LS and GHQ though effects on LS are much less precisely estimated. Estimated compensated variations ranged from £700 to £9,070 per week depending on the well-being measure used and the hours category, but not all of them are significant. For instance, the compensating variation is £3,132 per week for individuals caring 100 or more hours when using LS and £9,064 when using GHQ. The authors argue that compensating variations are higher than in van den Berg and Ferrer-i-Carbonell (2007) due to the use of cross-sectional data in that study which did not allow for unobserved individual heterogeneity.

Bobinac et al. (2010) study the effect of several caregiving tasks on happiness but do not calculate monetary values. Using a cross-sectional dataset collected in the Netherlands, they estimate OLS and ordered probit models of the effect of different caregiving tasks on happiness and find a negative effect of informal care. Niimi (2016) studies the effect of being a parental informal caregiver on caregiver's happiness on a cross-section from Japan using OLS regressions for married and unmarried caregivers. Results show a negative effect of informal care only for unmarried caregivers who care for parents or parents-in-law not living with the carer.

Overall, the existing literature finds a negative effect of informal care on well-being and a range of different compensations. The monetary values are sensitive to the well-being measure analysed, the estimation method, and the specification of the number of hours providing care.

2.1.2 This study

In this chapter, we further examine these issues combining in a single study the use of a UK longitudinal panel dataset, the use of two different measures of subjective well-being (life satisfaction and happiness), and the use of two different methods of estimation: linear FE estimation and FE ordered logit. We explore the implications of different ways to specify the number of hours providing care: linear, logarithmic, categorical, and as a polynomial.

We also examine how sensitive the valuation of informal care is to the well-being measure, to the method of estimation, and to individual gender and income.

Only Van den Berg et al. (2014) use FE ordered logit estimation but with an Australian dataset. Mentzakis et al. (2012) has UK data and two subjective well-being measures but does not take into account the ordered nature of those variables and only perform the analysis using linear FE. Moreover, none of the papers described in the literature section above have robustness checks around the computed monetary compensations

The rest of the paper is structured as follows. Section 2.2 presents the well-being valuation method in more detail. Section 2.3 explains the methodology used for estimating the impact of informal care on well-being. Section 2.4 describes the data used for the analysis. Section 2.5 presents the results and section 2.6 concludes.

2.2 The well-being model

In the well-being method, the answers to the happiness or life satisfaction questions are used as proxies for experienced utility. We assume this utility is

$$SWB_{it} = f\left(hcare_{it}, Inc_{it}, \boldsymbol{IC_{it}}, \boldsymbol{X_{it}}\right) \quad i = 1, \dots, N \text{ and } T = 1, \dots, T \qquad (1)$$

SWB_{it} denotes the subjective well-being of individual i at time t; $hcare_{it}$ is the number of hours providing informal care per week; Inc_{it} is household weekly income; $\boldsymbol{IC_{it}}$ a vector of characteristics of the care provided, such as the type of care, or the relationship between the carer and the care-recipient; and $\boldsymbol{X_{it}}$ denotes a set of socio-economic variables. We expect the relationship between subjective well-being and income to be positive (Easterlin, 2001, Ferrer-i-Carbonell, 2005, Frey and Stutzer, 2002), and the relation between hours providing care per week and subjective well-being to be negative (Bobinac et al., 2010, Kramer, 1997, Mentzakis et al., 2012, van den Berg and Ferrer-i-Carbonell, 2007, Van den Berg et al., 2014).

2.2.1 Monetary value of informal care

We measure the monetary value of informal care as the compensating variation: the change in income needed to maintain the same utility or subjective well-being level if their supply of informal care changes. Formally, let i have well-being

$$SWB_{it}^{0} = f\left(hcare_{it}, Inc_{it}, \boldsymbol{IC_{it}}, \boldsymbol{X_{it}}\right) \qquad (2)$$

when she is providing $hcare_{it}$ hours of care per week. If the number of hours providing care changes, her well-being is

$$SWB_{it}^{1} = f\left(hcare_{it} + \Delta hcare_{it}, Inc_{it}, \boldsymbol{IC_{it}}, \boldsymbol{X_{it}}\right) \tag{3}$$

where $\Delta hcare_{it}$ is an increase in the number of hours providing care per week for the caregiver i in a given year t. The compensating variation in income is the change in income ΔInc_{it} required in order to maintain the same level of well-being she had before in (2):

$$f\left(hcare_{it}, Inc_{it}, \boldsymbol{IC_{it}}, \boldsymbol{X_{it}}\right) = f\left(hcare_{it} + \Delta hcare_{it}, Inc_{it} + \Delta Inc_{it}, \boldsymbol{IC_{it}}, \boldsymbol{X_{it}}\right) \tag{4}$$

Suppose that subjective well-being is specified as

$$SWB_{it} = \alpha + \beta_1 hcare_{it} + \beta_2 \ln(Inc_{it}) + \boldsymbol{IC_{it}}\gamma + \boldsymbol{X_{it}}\delta \tag{5}$$

where $\ln(Inc_{it})$ is the logarithm of weekly household income, and β_1, β_2, γ, and δ are coefficients to be estimated. Using (5) in (4) we obtain

$$\beta_1 hcare_{it} + \beta_2 \ln(Inc_{it}) = \beta_1(hcare_{it} + \Delta hcare_{it}) + \beta_2 \ln(Inc_{it} + \Delta Inc_{it})$$

$$\Leftrightarrow \beta_2[\ln(Inc_{it} + \Delta Inc_{it}) - \ln(Inc_{it})] = -\beta_1 \Delta hcare_{it}$$

$$\Leftrightarrow \exp\left[\beta_2 \frac{\ln(Inc_{it} + \Delta Inc_{it})}{\ln(Inc_{it})}\right] = -\exp\left[\beta_1 \Delta hcare_{it}\right]$$

$$\frac{\Delta Inc_{it}}{Inc_{it}} = \exp\left[-\frac{\beta_1}{\beta_2}\Delta hcare_{it}\right] - 1 \tag{6}$$

where $\dfrac{\Delta Inc_{it}}{Inc_{it}}$ is the percentage of current income needed to maintain the individual's well-being constant for a given change in the hours of care provided.

In our case subjective well-being (happiness and life satisfaction) SWBit are reported in ordered categories. These reports are based on a latent utility function, which in our main model, is non-linear in income and linear in hours of care as shown in (5). The CV is defined in terms of the subjective well-being function, which is continuous in income and hours. With a linear relationship between hours of care and subjective well-being, we assuming that the marginal change in subjective well-being from a one hour increase in hours of care is the same for all individuals whatever their intensity of care. The required CV will vary with the income of the carer because income has a non-linear effect on subjective well-being. However, a non-carer who starts providing an hour of care per week will receive the same compensation as an individual with the same income who is already caring and increases their provision by an additional hour.

In other specifications, the number of hours providing care enters into the subjective well-being function in (5) as non-linear. There, monetary compensations vary according with the intensity of care, as well as income, and there are different compensations for carers and non-carers, as well as for carers providing different intensities of care.

2.2.2 Well-being measures

In the subjective well-being literature there is debate on which measures best proxy experienced utility (Kahneman and Krueger, 2006). The idea is to find a measure that captures individual's perception of their life experiences (pleasures, pains, etc.) through data on individual's physical and psychological characteristics. Although there is a wide range of measures and no consensus on which is the best proxy for experienced utility in the well-being valuation approach (Decancq and Neuman, 2014, Powdthavee and van den Berg, 2011), the most commonly asked questions in subjective well-being surveys refer to overall life satisfaction and happiness. The literature has studied the reliability of those questions to capture subjective well-being and finds that they correlate well and are in concordance with the answers that individuals respond to other characteristics such as income, self-reported health, quality of sleep, marriage, etc. (Layard, 2005, Frey and Stutzer, 2002, Diener *et al.*, 1999) .

We, therefore, use two measures of subjective well-being: self-assessed happiness and life satisfaction. Both measures are ordered categorical variables. Happiness ranges from 1 (much less happy) to 4 (more happy than usual); and life satisfaction ranges from 1 (not satisfied at all) to 7 (being completely satisfied). Previous studies have used both happiness (Bobinac et al., 2010, Brown, 2015, Niimi, 2016, Powdthavee, 2005, Van Praag and Baarsma, 2005) and life satisfaction measures (Frey et al., 2010, Leigh, 2010, Luechinger, 2009, Mentzakis et al., 2012, Powdthavee and van den Berg, 2011, Van den Berg et al., 2014) as good proxies for an individual's utility (Ferrer-i-Carbonell and Frijters, 2004, Frey, 2008, Frey and Stutzer, 2002, Hansen et al., 2013, Layard, 2005).

2.3 Model and estimation method

To estimate the subjective well-being function in (1) we use two main estimation methods: FE ordered logit which allows for the ordered categorical nature of the happiness and life satisfaction measures, and linear FE which assumes cardinality of the well-being measures.

2.3.1 Fixed effect ordered logit

We use fixed effects to allow for time invariant unobserved variables that might be correlated with some of the variables determining well-being. For instance, the number of hours an individual devotes to informal care might be correlated with the attitude towards care, or attributes such as patience and devotion which cannot be observed. Other forms of endogeneity in this model could come from the fact that self-reported well-being might suffer from reporting bias if different individuals have different perceptions of the levels of their subjective well-being. Our model is:

$$SWB_{it}^{*} = \alpha + hcare_{it}\beta_1 + \ln(Inc_{it})\beta_2 + \boldsymbol{IC_{it}}\gamma + \boldsymbol{X_{it}}\delta + c_i + \varepsilon_{it} \tag{7}$$

SWB_{it}^{*} is the latent construction of the subjective well-being of individual i in period t. The weekly number of hours providing care is $hcare_{it}$ and $\ln(Inc_{it})$ is the logarithm of weekly household income. $\boldsymbol{IC_{it}}$ is a set of informal care indicators such as the type of informal care provided, the relationship between the carer and the care-recipient and the number of years providing care. $\mathbf{X_{it}}$ is a vector of control variables such as respondent's marital status, job, and health status. c_i is an unobserved individual-specific time invariant variable and ε_{it} represents an idiosyncratic time varying error term.

Reported subjective well-being variable is related with the latent variable by the following observation rule:

$$SWB_{it} = j \text{ } if \, \tau_{j-1} \leq SWB_{it}^{*} < \tau_j \, ; \tau_0 = -\infty \, , \tau_{j-1} < \tau_j \forall j \text{ and } \tau_m = +\infty \tag{8}$$

We aim to estimate the impact of informal care on the probability of observing a category of subjective wellbeing. From equation (7) and (8) this probability depends on the weekly household income and hours providing care, the informal care indicators, the control variables, the individual's specific effect, c_i, and the thresholds, τ_{j-1} and τ_j. We assume that the error term ε_{it}, is not serially correlated, is strictly exogenous, and is independent identically distributed (IID) and follows a logistic distribution function (Cameron and Trivedi, 2005, Wooldridge, 2005). Then:

$$\Pr\left[SWB_{it} = j \mid hcare_{it}, \ln(Inc_{it}), \boldsymbol{IC_{it}}, \boldsymbol{X_{it}}, c_i\right] = \Pr\left[\tau_{j-1} < SWB_{it}^{*} \leq \tau_j\right]$$

$$= \Lambda\left(\tau_j - hcare_{it}\beta_1 - \ln(Inc_{it})\beta_2 - \boldsymbol{IC_{it}}\gamma - \boldsymbol{X_{it}}\delta - c_i\right)$$

$$-\Lambda\left(\tau_{j-1} - hcare_{it}\beta_1 - \ln(Inc_{it})\beta_2 - \boldsymbol{IC_{it}}\gamma - \boldsymbol{X_{it}}\delta - c\right) \qquad (9)$$

where $\Lambda(.) = \exp(\varepsilon_{it}) / \left[1 + \exp\left(\varepsilon_{it}\right)\right]$ is the logistic cumulative distribution function.

To estimate (9) we follow Baetschmann et al. (2015). We need to control for the individual specific fixed effects, c_i. This would be straightforward in linear panel data models using first differences or mean deviations of the model (Wooldridge, 2005). This, however, is a non-linear model and so we cannot control for c_i in the same way for two reasons. The first is that the thresholds τ_j cannot be distinguished from the individual fixed effect c_i and therefore, only the difference between those parameters $\tau_j - \alpha_i \equiv \alpha_{ij}$ can be identified.

The second reason is the incidental parameters problem (Lancaster, 2000, Neyman and Scott, 1948). As the number of individuals increases, the number of parameters to be estimated also grows. In linear models, we can control for c_i by taking mean deviations or differencing the model. This allows the derivation of estimators for β_1, β_2, γ, and δ that do not depend on c_i. However, since this is not possible in non-linear models we cannot find a consistent estimator for c_i and this will also affect the consistency of the other estimators.

As Baetschmann et al. (2015) explains, in order to control for c_i and find a consistent estimator for β_1, β_2, γ, and δ, Chamberlain (1980) finds a sufficient statistic for c_i

by collapsing the multinomial dependent variable into a binary one and applying Conditional Maximum Likelihood (CML) estimation.

The dependent ordered and multinomial variable can be collapsed into a binary variable using a cut-off point k

$$SWB_{it} = \begin{matrix} 1 & if & SWB_{it}^{*} \geq k \in 2,...,K \\ 0 & if & SWB_{it}^{*} < k \in 2,...,K \end{matrix} \quad (10)$$

Chamberlain (1980) showed that, conditioning the probability of observing a particular category of the outcome of interest on the sum over time of all the individual outcomes, is enough to construct a probability that does not depend on c_i. Formally, equation (10) is equivalent to defining an indicator function which equals 1 if the well-being response is bigger or equal than the cut-off point, k :

$$d_{it}^{k} = 1\left(SWB_{it}^{*} \geq k\right) \tag{11}$$

In this framework, the joint probability of observing a particular sequence of outcomes over time $d_i^k = \left(d_{i1}^k,...,d_{it}^k\right)' = \left(j_{i1},...,j_{iT}\right)' = j_i$ where $j_{it} \in \{0,1\}$ is given by

$$\Pr\left(d_i^k = j_i \mid \sum_{t=1}^{T} d_{it}^k = a_i \right) = \frac{\exp\left(j_i' Z_i \theta\right)}{\sum_{j \in B_i} \exp\left(j' Z_i \theta\right)} = P_i^k\left(\theta\right) \tag{12}$$

where $j_i = \left(j_{i1},...,j_{iT}\right)$; $a_i = \sum_{t=1}^{T} j_{it}$; Z_i is a T x L matrix of regressors, $Z_i = [hcare_{it}, \ln(Inc_{it}), \boldsymbol{IC_{it}}, \boldsymbol{X_{it}}]$; θ is a 1 x L vector, $\theta = [\beta_1, \beta_2, \gamma, \delta]$; L is the number of regressors; and the sum on the denominator is over all vectors j which belong to the set B_i.

Notice that equation (12) does not depend on c_i or on the thresholds. Therefore, the sum of all individual outcomes over time $\sum_{t=1}^{T} d_{it}^k = a_i$, constitutes a sufficient statistic for c_i. Chamberlain (1980) shows that maximizing the conditional log likelihood

$$LogL^k = \sum_{i=1}^{N} \ln\left[\Pr\left(d_i^k = j_i \mid \sum_{t=1}^{T} d_{it}^k = a_i \right)\right] = \sum_{i=1}^{N} \ln\left[P_i^k\left(\theta\right)\right] \tag{13}$$

gives a consistent estimation for θ.

Conditioning on a_i, causes all the time-invariant elements to cancel. Those are c_i, τ_k, τ_{k+1}, and all the variables that do not change over time. Moreover, apart from the fact that the threshold k in Chamberlain (1980) is arbitrary, using a unique cut-off point has the disadvantage that it does not use all the variation of the ordered dependent variable. An individual will not be included in the log likelihood if after having dichotomized his responses, his outcome d_{it}^k is constant over all t, even if the original responses were different over time. Consequently, when computing the likelihood function, those observations will be lost.

Subsequent papers (Baetschmann et al., 2015, Das and van Soest, 1999, Ferrer-i-Carbonell and Frijters, 2004) proposed extensions to Chamberlain's approach aiming to use more observations contributing to the likelihood function by using all the possible dichotomizations.

Ferrer-i-Carbonell and Frijters (2004) uses different dichotomizations based on a single and optimal cut-off point for each individual in the sample. Baetschmann et al. (2015) shows this method gives inconsistent estimators as the process to determine the optimal dichotomization is endogenous because the dependent variable is part of the cut-off.

Das and van Soest (1999) propose a two-step estimation. In the first step $K-1$ Chamberlain estimators are calculated, one for each possible cut-off point. In the second step, it applies the Minimum Distance (MD) procedure to obtain an efficient estimator as the matrix weighted average of all the Chamberlain estimators calculated in the first step. If there are enough observations in every threshold, this method uses all the variation in the ordered dependent variable because it combines all possible dichotomizations. However, in practice, this is not always the case since some of the cut-off points might contain very few observations or no observations (Baetschmann et al., 2015).

In order to avoid the problem of small sample size, Baetschmann et al. (2015) suggest using all the cut-off points simultaneously to estimate a single θ. That is, instead of computing a different estimator θ for every cut-off point as in Dan and Van Soest

(1999), this estimator sums all the log likelihood functions of all the possible $K-1$ Chamberlain estimators:

$$Log\pounds^{k} = \sum_{k=2}^{K}\sum_{i=1}^{N}\log P_i^k\left(\theta\right) \tag{14}$$

Notice that the only difference between equation (13) and (14) is that the likelihood in equation (14) sums over all the thresholds $\sum_{k=2}^{K}(.)$.

Baetschmann et al. (2015) call this estimator the "Blow-Up and Cluster" (BUC) estimator, because each individual is used $k-1$ times with different cut-off points to collapse the dependent variable. The model is then estimated on the blow-up sample using Chamberlain's CML where, the probabilities of the likelihood function are joint probabilities of observing a particular sequence of outcomes for each threshold k.[12] Since observations will now contribute several terms in the log-likelihood function in (14), it is necessary to cluster the standard errors at the individual level.

We use the BUC estimator to estimate the SWB equation presented in (7). As Baetschmann et al. (2015) argue, the BUC estimator has several good properties. First, even though it is asymptotically less efficient than Generalized Method of Moments (GMM), Empirical Likelihood (EL), and Minimum Distance (MD) models[13], by conducting a Monte Carlo simulation, the authors show that the actual loss of efficiency in BUC is very modest. Moreover, GMM, MD, and EL might not perform very well in empirical settings where the sample size is small and the number of categories is large, because the number of individuals in each category will be low. The authors show this in another Monte Carlo Simulation where GMM and MD do not perform very well in small sample size settings. Moreover, this method is less parametric than correlated random effects for instance, so it requires fewer assumptions to make when estimating the model.

However, the BUC method has some disadvantages. The number of cut off points and the blowing up increase more than in proportion to the number of categories of the dependant variable so it becomes computationally disadvantageous. Also, we lose

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[12] See appendix A2. for a simple example of this method.

[13] See Baetschmann *et al*. (2015) for a detailed demonstration.

individuals that remain in the same category of the dependant variable over time. Further, as with the linear fixed effects model, we cannot estimate the effects of time invariant variables such as gender. However, the effects of gender and other time invariant variables on subjective well-being are not the primary focus. Moreover, we estimate separate models for men and women to investigate the effects of gender.

2.3.2 Linear Fixed effects

We also estimate our subjective well-being model using a linear fixed effects specification which does not consider the ordered categorical nature of the happiness and life satisfaction measures and treats them as if they were cardinal and continuous outcomes. Although some of the predicted values of SWB_{it} might lie outside the range of numbers allocated to the categories, the estimated coefficients are good approximations of the partial effects (Wooldridge, 2010). The BUC estimator also requires an arbitrary assumption, namely, a logit distribution of the error term. Moreover, it takes longer to estimate.

Linear fixed effects have been extensively used to model ordered happiness and life satisfaction (Mentzakis et al., 2012, Powdthavee and van den Berg, 2011, van den Berg and Ferrer-i-Carbonell, 2007). Some of the papers suggest that results are not sensitive to whether ordered categorical or linear models are used and that it is more important to account for fixed effects (Ferrer-i-Carbonell and Frijters, 2004, Frey and Stutzer, 2000). However, Mentzakis (2011) finds that results are sensitive to the estimation method used.

2.4 Data

2.4.1 Sample and variables

We use the following variables in BHPS for our analysis. **Table A.18** in appendix A.1 summarises the definitions.

Subjective well-being measures

We use two subjective well-being measures from BHPS: self-assessed happiness and life satisfaction.

The happiness survey question in BHPS is:

“Have you recently been feeling reasonably happy, all things considered?”

The response categories are 1 if the individual answered “much less”, 2 if answered “less so”, 3 if “same as usual”, and 4 if the interviewed person responded “more than usual”. Respondents provide only one category of the four possible categories in the happiness question. The question is available on the 18 waves of BHPS and it is one of the dimensions of the GHQ, a mental health measure. Clark and Oswald (2002) also, use the GHQ happiness value (and the full GHQ) as a well-being outcome.

It is worth noting that the response categories on the happiness scale are formulated to a give a relative measure of happiness instead of an absolute one: individuals are expected to compare their current happiness against the one they usually feel. Therefore, every response on the happiness question scale corresponds to the difference in happiness between now and a conception of the norm. In this question, individuals compare with their own usual utility or happiness. However, the use of individual fixed effects should remove any ambiguity in interpreting estimated coefficients.

We also perform our analysis using a life satisfaction variable. The life satisfaction question in the BHPS is:

“How dissatisfied or satisfied are you with your life overall”.

The possible answers range from 1 being “not satisfied at all” to 7 being “completely satisfied”. This question is asked in waves 6 to 10 and 12 to 18.

We only include individuals with complete information on the subjective well-being variables. Consequently, the analysis when using the happiness variable is based on 220,417 observations and 27,527 individuals out of the 238,996 observations and 32,380 individuals in the BHPS. When using the life satisfaction variable, the analysis is based on 159,577 observations and 23,279 individuals.

Informal care indicators

Our first and main indicator of informal care is the number of hours per week caregivers spend looking after or helping someone else. Intensity of informal care time is measured in the BHPS as 10 categories: 0-4 informal care hours per week, 5-9 hours per week, 10-19, 20-34, 35-49, 50-99, 100 or more hours per week, varies under 20 hours, varies 20 hours or more, and some other times[14]. We classify individuals reporting no care as

[14] We drop 326 individual-wave observations in the “some other times” category.

providing zero hours of care and those reporting providing 0-4 category hours as providing some care[15].

We analyze different specifications of the number of hours providing care. First, we construct a continuous variable (*hourscare*) by taking the midpoint in each interval, as in van den Berg and Ferrer-i-Carbonell (2007). It takes the values 0 if individuals report providing zero hours of care, 2 if individuals answer caring for 0-4 hours in the original variable, 7 if individuals answer caring for 5-9 hours, 14.5 for the category of 10-19 hours, and so on. We assign 100 for the category "100 or more than 100", and 10 and 20 hours for the categories "varies under 20", and "varies 20 hours or more, respectively. Second, to allow for non-linearities, we enter hours as logarithms, and as up to a quintic order polynomial. Finally, we use the hours' categories.

We also distinguish between informal care provided to someone inside the same household, informal care provided to someone outside of the household, and both types of care provided at the same time. We construct the variables, *careinonly,* that takes value one if an individual only cares for someone who lives in the same household as the carer, *careoutonly* if the only care provided by the caregiver is to someone outside the household and *careinout* if an individual does both types of care, inside and outside the household.

The third indicator of informal care captures the social relation between the carer and the care recipient. Individuals providing informal care for someone outside the household are asked to indicate the social relation of up to three care recipients. The questions in BHPS are: "Who is the first (second or third) person you care for?" The answer categories are: partner, parent(s), or friends and other relatives. Subsequently, those who provide informal care to someone inside their household are asked to provide the BHPS person identifier of up to three care-recipients. We use this information together with the person identifier and create three new variables: *partner* if the caregiver cares for the partner (always inside the household), *parents* if caregivers care for either their mother or father (living inside or outside the household), and *friends* if caregivers provide informal care to other relatives or friends living inside or outside their household.

[15] Individuals in the 0-4 hour's category classify themselves as carers as they report to provide informal care. Then, when they are asked how many hours per week they provide care they report to do so between 0 and 4 hours without specifying the exact number of hours.

Our fourth indicator of informal care is *yearscaring* which is a time varying measure of the total number of years (not consecutive) to date in which the individual has provided informal care.

Control variables

We control for socio-economic, demographic and health variables.

Income (*lnhhincomeweek*) is a continuous variable indicating the inflation adjusted weekly household income using the Consumer Price Index[16] (base year 2005). BHPS provides an annual measure for household income. We convert it into a weekly measure to ensure consistency with the number of hours providing care variable. We assume well-being depends on the natural logarithm of weekly income implying diminishing marginal effects of income on well-being.

Household size, number of children and age are included as second order polynomials to account for potential non-linear associations between these variables and wellbeing. We also control for job status, education, and whether individuals are married or living as a couple, or not married.

Health is captured by three dummy variables: whether the individuals have one (*morbidity*) or more (*comorbidity*) health problems, or no health problem (*nomorbidity*). This variable is constructed from 13 dummy variables each of which accounts for different health conditions: arm, sight, hearing, skin, chest, heart, stomach, diabetes, depression, alcohol, epilepsy, migraine, and other health problems.

We also include the health of other members in the household since this might affect well-being and also might be correlated with informal care either because the individual may be providing care to them, or because the other household members are potential carers able to provide care to other individuals.

We create two variables, *hlthlimits_others* and *hlthconditions_others*. The first is the sum of daily limitations of other household members due to health: health limits housework, health limits climbing stairs, health limits dressing, health limits walking, work, and other activities. The second variable is the sum of the health conditions that

[16] Consumer Price Indices - CPI indices: 1988 to 2014: 2005=100: http://www.ons.gov.uk/ons/datasets-and-tables/data-selector.html?cdid=D7BT&dataset=mm23&table-id=1.1

other household members experience: arm, sight, hearing, skin, chest, heart, stomach, diabetes, alcohol, epilepsy, migraine, and other health problems. We make the distinction between health limitations and conditions because we believe they capture different health problems. Health limitations refer to basic daily activities such as walking or getting dressed that get inhibited due to a health issue(s). Health conditions, instead, refer to more physical problems and illnesses. Since these variables are only defined for those individuals living with at least one other person in the household we restrict the sample and the analysis to households with more than one member.

2.4.2 Sample characteristics

We expect our two well-being variables to capture similar aspects of individual preferences. For instance, we would expect that individuals answering "more happy than usual" to also have an answer among the higher categories of the life satisfaction variable, and individuals responding "much less happy than usual" to be in the lower categories of the life satisfaction scale.

Table 2.2 presents a cross-tabulation between the happiness and the life satisfaction variables showing the number of individuals answering those questions in every category. As expected, we observe that individuals who report being in a higher life satisfaction category are more likely to report being in a higher happiness category.

We carry out the analysis using the separate samples who reply to each well-being question to boost sample size. However, we also perform the analysis on the sample of 23,265 individuals who answered both the life satisfaction and the happiness question to compare results for individuals with the same preferences.[17]

Table 2.3 has summary statistics for the sample that answered both the happiness and the life satisfaction question. For those who provide informal care, the mean hours per week is 19 hours, 43% provide care to parents, 41% to friends and 20% to the partner. More than half of carers provide care for someone living in another household. Almost 42% do not have any health problems, and around 29% have morbidity or comorbidities. Other household members seem to experience more health conditions

[17] See appendix A.3.

than limitations with daily activities. Also, 65% of the sample is married or living as a couple, 56% has studied up to secondary school, and 60% are employed.

Males are slightly happier than females with similar levels of LS as females. Women provide on average two more hours of care per week and this care is mainly devoted to parents (44.8%) and friends (42.5%). Male carers also mainly provide care to parents (40.6%) and friends (32.7%). More than half of male and female carers provide care for someone not living in the same household than them. Weekly income is about £64 higher for males than for females. All the differences in means between males and females are statistically significant at 5% level of significance.

2.5 Regression Results

2.5.1 Full sample results

Estimation results

Table 2.4 has the estimation results of the well-being model (7). Columns 1 and 2 present the linear FE and the FE ordered logit estimated coefficient results for the happiness model and columns 3 and 4 for the life satisfaction model. The happiness sample has 27,527 individuals and information is available in the 18 waves. For the life satisfaction sample, there are 23,279 individuals in 12 waves.

Overall, coefficients are generally greater in absolute value in the linear life satisfaction models than in the linear happiness models because life satisfaction is measured on a larger scale (1 to 7 vs 1-4) in the linear models. The pattern of coefficients is very similar in the happiness and life satisfaction models suggesting that they are modelling the same underlying preferences.

The number of hours providing care per week has a negative and statistically significant impact on both happiness and life satisfaction variables and weekly household income has a positive impact.

The type of care (*careinonly*, *careoutonly* and *careinout*) is not significant in any of the four models at the 5% level of significance. The number of years providing care has a negative but decreasing effect on well-being, although the relationship is significant only for the happiness model. This might be due to adaptation into caregiving. The care-recipient (partner, parents or friends) has no impact on well-being.

Morbidity and co-morbidity reduce happiness and life satisfaction. Health limitations and health conditions of other household members also have a negative impact on well-being. Age has a convex relationship with well-being, showing a diminishing negative impact of age on happiness and life satisfaction. Household size has a concave and significant effect, with a positive and diminishing impact on well-being. Being married has a positive and significant impact on well-being. Well-being is smaller for individuals who are unemployed or disabled. Well-being is higher for retired individuals, and students (through only in the life satisfaction models). We find no significant effects of education or the number of children under 16 in the household on well-being.

If happiness and life satisfaction elicit the same preferences, then life satisfaction is a better measure because it has a wider scale (7 vs 4 categories). Also, the happiness question is being compared with being relative to “usual” whereas life satisfaction is an absolute measure, and therefore, easier to interpret. The linear model may perform better with more categories of the well-being measure (Rhemtulla et al., 2012) and therefore, might be better to use with life satisfaction rather than happiness. Therefore, our base case model uses life satisfaction with linear fixed effects.

Compensating variations

Table 2.5 shows the compensating variations for informal care following the formula presented in equation (6). As shown in the formula, compensating variation depends on current income, the change in the care provision of hours, and the estimated coefficients for both hours and income. We calculate the compensation for an extra hour per week providing care, using the median weekly household income (£553.12), and the estimated coefficients for weekly number of hours of care provided and the log of household income shown in Table 2.4.

For the FE ordered logit, compensating variations are defined in terms of the latent subjective well-being functions as the actual measures of subjective well-being are ordered categories. That makes no difference when using the formula in as the subjective well-being function is not assumed to be a cardinal utility function, but describes indifference curves, such that, any monotonic transformation to it will give the same monetary compensations (Ferrer-i-Carbonell and van Praag, 2002).

Table 2.5 presents the compensating variations together with standard errors (calculated using the delta method) and confidence intervals. Money values from the happiness model are higher than for the life satisfaction model. They are statistically significant at 1% when using the results from the linear FE estimations and statistically significant at 5% when using the coefficient results from the FE ordered logit.

According to the linear happiness model, individuals would demand £21.22 per extra weekly hour of care, or £24.30 if using the results of the FE ordered logit estimation. For the life satisfaction model, the monetary value of informal care is around £18 per extra hour of informal care provision per week.

2.5.2 Results by gender

Estimation results

Table 2.6 and **Table 2.7** present the happiness and life satisfaction estimation results for males and females for the coefficients of the main variables of interest (hours care and income). The number of hours providing care has a negative impact on happiness and life satisfaction for both males and females. The marginal rate of substitution between informal care and income is $-(\beta_1 / \beta_2)Inc$ so we can compare estimated marginal rates of substitution for men and women with a given Inc by comparing $(-\beta_1 / \beta_2)$ for each of the four types of models. We find that $-(\beta_1 / \beta_2)Inc$ is greater for men than for women for the happiness models but greater for women for the life satisfaction models.

Regarding the rest of the coefficients, the pattern of results is very similar to the full sample results in terms of coefficient signs and significance.

Compensating variations

Table 2.8 and **Table 2.9** show the compensating variations for males and females by each estimation method and well-being measure but using the median male and female income of £587.43 and £520.58 and the coefficient results from Table 2.6 and Table 2.7. Monetary values from the happiness model are approximately three times higher for males than for females when using the coefficient results from the linear FE, and almost 6 times higher if using the results from the FE ordered logit. However, these male money values are statistically significant at 5% only for the happiness linear FE model. The CV results for males and females differ so much for the happiness model but not for life satisfaction due to the poor performance of both the linear and FE ordered logit estimation results for males for happiness: the calculated CVs are not significantly different from zero at 5%.

The compensating variations from the life satisfaction model show that males and females would require similar compensations for an extra hour of informal care. When using the estimation results from the linear FE, males would demand a compensation of £18.02 per extra hour of informal care provided per week while females would demand a similar amount (£18.03). These results are statistically significant at 5% for both men and women. When using the coefficient results from the FE ordered logit model the money value for males is smaller (£14.77) than for females (£21.72) but those compensations are not significant at the 5% level.

Only the life satisfaction linear FE model provides statistically significant CV for both males and females. According to this model, males and females would demand very similar compensations (£18) for an extra hour of care per week considering differences in males and female incomes.

2.5.3 Robustness to income level

Table 2.10 shows CV's calculated from the linear FE life satisfaction model first using the coefficient results from the full sample in Table 2.4 and evaluated at the sample median income of £561.46 for non-carers, £519.41 for carers, and £553.12 for all. Then, we use the coefficient results in Table 2.4 evaluated at the median income of £597.47 for male non-carers, £5,425.41 for male carers, and £587.43 for all men, and compare them with compensating variations obtained using the coefficient results of the male sample in Table 2.6 to study whether they vary when assigning different preferences. We do the same for women where median incomes are £525.71 for female non-carers, £501.34 for female carers, and £520.58 for all female and using the estimated coefficients from Table 2.7.

Overall, compensating variations are not very sensitive to the small differences in incomes for the median carer and non-carer and are around £17 to £20 per extra hour of informal care per week.

2.5.4 Robustness to informal care measure

Next, we explore whether results are sensitive to how we measure informal care. We transform the number of hours providing care into logarithms, we allow for polynomials in hours, and we also measure hours of care as a categorical variable. We perform these robustness checks using the life satisfaction model estimated by linear FE.

Hours in logarithms

The literature suggests that carers increasingly overstate the number of hours providing care as hours increase and this is used to justify the use of log income (van den Berg and Ferrer-i-Carbonell, 2007, Van den Berg et al., 2014). **Table 2.11** shows the linear FE life satisfaction estimation results with the number of hours providing care in logarithms[18] and compares it with the results obtained when using the linear specification of hours providing care. The logarithm of hours of care has a negative and significant effect on life satisfaction. The R-squared and the AIC suggest the linear hours model has better fit but BIC suggests that the logarithmic specification is better.

Table 2.12 provides the compensating variation for informal care when treating hours of care in logarithms using the life satisfaction linear FE model and compares it with the compensating variation found when using the linear specification for hours of care. When using the log form, the formula to calculate the compensating variation is

$$\Delta Inc_{it} = Inc_{it}\left\{\left(\frac{hcare_{it}}{hcare_{it}+\Delta hcare_{it}}\right)^{\frac{\beta_1}{\beta_2}}-1\right\} \tag{15}$$

(See Appendix A.4). We use the median value for the number of hours providing care which is 7 hours of care and, as before, we set the change in care to one extra hour per week and use the median income of £553.12.

The monetary value for informal care is £51.67 per extra hour of care per week when using the log form for hours. It is statistically significant at 1%, and almost three times higher than the monetary value found when using the linear specification for hours. The compensating variation is thus sensitive to how we measure of number of hours providing care.

We also calculate compensating variations by gender using the log of hours, and evaluating them at the median number of hours providing care of 7, and at the median income for non-carers (£561.46), carers (£519.41), and the full sample (£553.12). We

[18] We use the inverse hyperbolic sine transformation (z = ln(x+(x2+1)0.5) which is a close approximation of the logarithm but allows for zero values (Burbidge et al., 1988).

also check whether compensating variations vary by gender using their respective median incomes: £597.47 for men non-carers, £5425.41 for men carers, and £587.43 for all men; and £525.71 for female non-carers, £501.34 for female carers, and £520.58 for all females. The median number of hours of informal care by gender is the same (7 hours). **Table 2.13** shows these results. Monetary compensations do not vary much either by carers, non-carers income, or by gender, and remain between £47 to £56 per extra hour of care a week when already caring for 7 hours a week.

Since the formula in (15) depends on the number of hours providing care, in **Table 2.14** we calculate different compensating variations varying the number of hours providing care at the median income for all the sample, non-carers, and carers. Results show that monetary compensations decrease when the number of hours providing care increases due to the assumption of diminishing marginal effects on the care intensity. The CVs evaluated at mean hours are similar to those from the linear hours models.

Thus, results are very sensitive to the assumed number of hours providing care and not so much for the median income by carers and non-carers.

Polynomials in hours

We next estimate life satisfaction linear FE models using hours of care entered as a polynomial up to order 5. Estimation results for each model are presented in **Table 2.15.** Coefficients for the powers of hours of care are not significant in any of the models, but we cannot reject the null hypothesis of joint significance of the coefficients. The R-squared is the same over the models. The BIC favors the quadratic over the linear specification and the AIC favors the linear.

We calculate the compensating variation for the quadratic hours specification as

$$\Delta Inc_{it} = Inc_{it}\left\{\exp\left(\frac{-\beta_1\Delta hcare - \delta[(\Delta hcare)^2 + 2hcare * \Delta hcare]}{\beta_2}\right) - 1\right\} \qquad (16)$$

(see Appendix A.5). This gives a compensating variation of £28.68 per extra hour of informal care provided per week with standard error of £15.54 [95% CI: -31.79, £59.15]. This is around £10 higher than the compensating variation for the linear case.

Categories for hours

We estimate models with all the hour categories that are provided in BHPS (*Hourscare 0-4*, *hourscare* 5-9, *hourscare* 10-19, *hourscare* 20-34, *hourscare* 35-49, *hourscare 50-99, hourscare 100+*, *hourscare<20, hourscare>20*) and with these categories collapsed to: providing no care, providing care below 20 hours a week and providing care for 20 or above 20 hours. Results for the life satisfaction linear FE estimations for each of the specifications[19] for hours are provided in **Table 2.16**. There are no significant effects of providing less than 100 hours per week of care, but well-being is reduced when the number of hours exceeds 100. Column 2 shows the estimation results when using the below and above 20 hours of care categories and shows a negative effect of providing informal care for those who care for at least 20 hours.

The within R-squareds for these models are smaller than in the main model in Table 2.4 for the linear FE life satisfaction estimation. However, both AICs and BICs in columns 1 and 2 of Table 2.16 are smaller than in the main model.

Table 2.17 provides the compensating variations for informal care for each hour category. The monetary values are very high compared with the ones for the main model, but are not statistically significant. The money values are similar to those in Mentzakis et al. (2012). Assuming that the mean number of hours in the 10-19 category is 14, the implied average compensating variation per hour is £51.25 compared to £18.69 in the main model. Similarly, assuming the mean hours in the category 35-49 is 41 the implied average hourly compensating variation is £80.84.

[19] Estimating a model including both categories of hours providing care and the dummies for the type of care (careinonly, careoutonly, and careinout) creates collinearity problems. This is because the individuals in the reference category of the "number of hours providing care" and the "type of care" are, respectively, providing zero hours of care and not providing care. Mentzakis, et al. (2012) suggest changing the reference category of the "type of care" variable to include both "individuals providing no-care" and "respondent provides care in and outside the household (careinout)" to avoid collinearity with the number of hours providing care variable, but this combines two disparate types of care. We prefer the approach of dropping the types of care variable as it is not statistically significant in the main model (Table 2.4).

2.6 Conclusion

In this paper, we use the well-being valuation method to analyze the impact of informal care on well-being and to calculate monetary values for informal care for two different measures of well-being and two different methods of estimation.

First, we find a significant and negative impact of informal care on happiness and life satisfaction, and find that the negative effect of informal care on well-being is mainly driven through the intensity of the care provided.

Second, the type of well-being measure and the estimation method matter when calculating compensating variations. Monetary values for an extra hour of informal care provision per week to maintain well-being constant for the happiness model are higher for both linear FE (£21.22) and ordered logit (£24.30) models than for the life satisfaction model (£18.02 and £18.03). Those monetary values are statistically significant and, overall, lower than the ones previous literature has found. Males and females would require similar compensations. We prefer the model which uses life satisfaction, since it has a more sensitive scale (seven rather than four categories), and which treats it as a linear measure of utility since estimation requires fewer assumptions about the distribution of errors and has a more straightforward handling of individual heterogeneity.

Our preferred estimate of a monetary value for informal care of £18.00 per an additional hour provided per week is similar to the one suggested by the UK Health and Social Care Information Centre. They estimate the average unit cost of home care provided by Local Authorities to adults aged 18 and over in 2013-2014 to be £17.20 per hour.[20]

We believe our results can enable policy makers to get an estimate of what informal care costs. Although our finding show similar compensations for males and females, providing monetary values for different groups of individuals, especially those with different incomes, might be useful from a policy perspective as targeting informal care policies according with individuals needs and preferences may be useful.

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[20] This is calculated using social care activity data and data on expenditure from the Personal Social Services: Expenditure and Unit Cost return (PSS-EX1). Health and Social Care Information Centre. 2013-2014 Final release. No details of the calculation are provided.

Compensating variations are robust to the median income by carer vs non-carer and to gender. However, the marginal valuations of an hour of care are contingent on the number of hours if we use assume a logarithmic specification. At the mean number of hours provided by carers the estimates from the logarithmic model are similar to those from the linear model but at the median hours they are around three times higher (£51.67).

Using the full sample as a comparator for our results allow us to study the differences for carers and non-carers and to provide evidence that carers have different characteristics that non carers and need to be compensated accordingly for the informal care provision. Restricting the sample to only carers could lead to sample selection bias.

Further work could look at other estimation methods. For instance, to avoid the complexities of the methods used to allow for fixed effects in models where well-being is treated as an ordinal measure we could use a Mundlak model (Mundlak, 1978) with random effects. Other questions for future research are reporting bias where reporting levels of the well-being measures can be differently assessed for different groups (gender, carers/non-carers, income, etc.) using different cut points for different subgroups in the population.

TABLES

Table 2.1 Existing literature: impact of informal care on well-being and valuation

Existing literature	Van den Berg and Ferrer-i-Carbonell (2007).	Van den Berg, Fiebig, and Hall (2014).	Mentzakis, McNamee, Ryan, and Sutton, (2012)
Data	Dutch regional support centres for informal caregivers 2001-2002. Cross-section.	Household Income and Labour Dynamics in Australia (HILDA) 2001-2011.	British Household Panel Dataset. Waves 6-18 and 12-15.
Objective	Analyse how much an individual must be compensated for providing an extra-hour of informal care.	Study the effect of providing informal care on subjective well-being	Calculate compensate income variations (CV) to value the utility of providing informal care for the UK. Study if CV vary for different well-being measures
Well-being measure	Two Happiness measures: Categorical from 1 (very happy) to 5 (not happy); Continuous happiness scale from 0 (completely unhappy) to 10.	Life Satisfaction from 0 (not satisfied) to 10.	Overall Life Satisfaction (LS) from 0 (not satisfied at all) to 7 (completely satisfied) and GHQ.
Informal care measure	Weekly number of hours providing care.	Weekly number of hours providing care (in logarithms). Providing care below or above 20 hours per week.	Weekly number of hours providing care (in hours intervals).
Econometric method	OLS and ordered probit	FE ordered logit model vs pooled OLS and linear FE.	Linear FE model.
Results	Negative effect of the hours providing care on happiness. CV for the average carer providing 49 hours of care per week is between 9-10€ per extra hour. Monetary compensation decreases as weekly number of hours providing care increases. If recipient is not a family member CV= 7 or 8 € per extra hour. If carer lives with care-recipient CV= 9 or 10€.	Negative effect of the number of hours providing care on life satisfaction. Money value when using FE ordered logit is \$A115.20 per hour of care, \$A78.12 when using pooled OLS, and \$A105.20 when using linear FE.	Negative effect of hours providing care on LS and GHQ. It is statistically significant when providing 100+ hours of care per week and for the category "varies under 20" for LS and in all the hours categories from more than 10 hours a week onwards when using GHQ. CV is £3,132 per week for individuals caring 100+ hours when using LS and £9,064 when using GHQ. CV in other categories of hours care vary from £700 to £9,070 per week.

Table 2.2 Life Satisfaction and happiness individuals' responses

Happiness	Life Satisfaction							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**Total**
1	825	698	695	540	320	127	99	3,304
2	661	1,463	3,756	5,083	4,602	1,746	408	17,719
3	721	1,122	4,670	15,042	35,727	39,649	17,387	114,318
4	127	161	404	1,336	5,425	9,687	4,822	21,962
Total	2,334	3,444	9,525	22,001	46,074	51,209	22,716	157,303

Note: Sample is individuals answering both the life satisfaction and happiness question for waves 6 to 10 and 12 to 18.

Table 2.3 Summary statistics

Variables	Full Sample NxT = 144,765	Females NxT = 78,453	Males NxT = 66,312	Difference between means by males vs females
happiness	2.99 (0.002)	2.966	3.018	Chi2 = 667.562***
Life Satisfaction	5.24 (0.003)	5.235	5.245	Chi2 = 521.672***
hourscare	18.637 (28.869)	19.482	17.363	T-test = 17.86***
hhincomeweek	676.168 (1.387)	646.752	710.969	T-test = -27.958***
care for partner	0.202 (0.402)	0.175	0.244	T-test = -2.904***
care for parents	0.431 (0.495)	0.448	0.406	T-test = 20.035***
care for friends	0.414 (0.492)	0.425	0.397	T-test = 18.245***
carein	0.321 (0.467)	0.289	0.369	Chi2 = 178.871***
careout	0.625 (0.484)	0.656	0.579	
carexhh	0.053 (0.225)	0.0542	0.052	
yearscaring	4.254 (3.338)	4.343	4.119	T-test = 30.819***
morbidity	0.287 (0.001)	0.288	0.285	Chi2 = 1500***
comorbidity	0.296 (0.001)	0.332	0.253	
nonmorbidity	0.417 (0.001)	0.379	0.462	
health limits_others	0.418 (0.003)	0.375	0.468	T-test = -17.913***
health cond_others	1.181 (0.004)	1.055	1.331	T-test = -35.822***
male	0.458 (0.001)	-	-	-
age	44.61 (0.047)	44.9	44.266	T-test = 14.182***
nchilds	0.613 (0.003)	0.645	0.576	T-test = 10.779***
hhsize	2.895 (0.004)	2.872	2.921	T-test = -12.391***
married	0.654 (0.001)	0.627	0.685	T-test = -26.056***
educ_secondary	0.558 (0.001)	0.582	0.531	Chi2 = 451.398***
educ_highsch	0.311 (0.001)	0.297	0.329	
educ_degree	0.13 (0.001)	0.122	0.141	
employed	0.604 (0.001)	0.541	0.678	Chi2 = 10000***
unemployed	0.034 (0.000)	0.026	0.044	
retired	0.182 (0.001)	0.192	0.169	
house work	0.073 (0.001)	0.131	0.005	
student	0.055 (0.001)	0.056	0.053	
disabled	0.04 (0.001)	0.037	0.043	
jobother	0.013 (0.000)	0.017	0.008	

Notes: Sample of individuals answering both happiness and life satisfaction (from wave 6-10 and 12-18). Means for the informal care indicators are performed on the sample of carers (NxT = 36,279). To assess whether the difference between means for each variable by males and females is statistically significant different from zero we compute t-statistic for discrete variables and Pearson's Chi-squared for categorical variables. *** P-value<0.001. Standard errors in parenthesis.

Table 2.4 Estimation results for the well-being variables

Dependent variable	Happiness		Happiness		Life Satisfaction		Life Satisfaction	
Estimation method	**Linear FE**		**FE ordered logit**		**Linear FE**		**FE ordered logit**	
	1		**2**		**3**		**4**	
Hourscare	-0.000832***	(0.000174)	-0.00371***	(0.00110)	-0.00172***	(0.000407)	-0.00336***	(0.00114)
Lnhhincomeweek	0.0221***	(0.00378)	0.0862***	(0.0217)	0.0519***	(0.00798)	0.103***	(0.0256)
Yearscaring	-0.00690**	(0.00290)	-0.0311*	(0.0165)	-0.00561	(0.00686)	-0.0380*	(0.0223)
Yearscaring2	0.000508**	(0.000225)	0.00222*	(0.00119)	0.000652	(0.000499)	0.00206	(0.00137)
Careinonly	0.0176	(0.0367)	0.0451	(0.185)	-0.126	(0.0784)	-0.361	(0.225)
Careoutonly	0.0228	(0.0353)	0.113	(0.179)	-0.0682	(0.0718)	-0.181	(0.208)
Careinout	0.00963	(0.0657)	0.127	(0.325)	-0.165	(0.137)	-0.488	(0.387)
Partner	-0.0481	(0.0371)	-0.355*	(0.187)	0.0523	(0.0817)	0.164	(0.234)
Parents	-0.0226	(0.0354)	-0.0957	(0.180)	0.102	(0.0717)	0.293	(0.209)
Friends	-0.0104	(0.0351)	-0.0162	(0.178)	0.109	(0.0723)	0.371*	(0.210)
Morbidity	-0.0508***	(0.00419)	-0.231***	(0.0252)	-0.102***	(0.00861)	-0.248***	(0.0300)
Comorbidity	-0.123***	(0.00590)	-0.573***	(0.0335)	-0.247***	(0.0121)	-0.592***	(0.0396)
Hlthlimits_others	-0.00353*	(0.00187)	-0.0102	(0.0121)	-0.0147***	(0.00380)	-0.0322**	(0.0128)
Hlthcond_others	-0.00260*	(0.00156)	-0.0151*	(0.00875)	-0.00619*	(0.00340)	-0.0128	(0.0104)
Age	-0.0103***	(0.00138)	-0.0275***	(0.00786)	-0.0208***	(0.00367)	-0.0316***	(0.0112)
Age2	7.48e-05***	(1.41e-05)	0.000153*	(9.09e-05)	0.000104***	(4.00e-05)	0.000137	(0.000123)
Nchilds	0.00494	(0.00693)	0.00798	(0.0369)	0.0270*	(0.0162)	0.0929**	(0.0469)
Nchilds2	-0.00251	(0.00212)	-0.00760	(0.0110)	-0.00334	(0.00528)	-0.0207	(0.0141)
Hhsize	0.0694***	(0.0213)	0.379***	(0.111)	0.166***	(0.0529)	0.738***	(0.144)

Hhsize2	-0.309***	(0.0784)	-1.638***	(0.411)	-0.755***	(0.194)	-3.025***	(0.537)
Marital	0.0292***	(0.00890)	0.0821**	(0.0387)	0.205***	(0.0202)	0.433***	(0.0546)
Educ_high	0.0175	(0.0121)	0.0512	(0.0550)	0.0195	(0.0280)	0.0706	(0.0887)
Educ_degree	-0.00118	(0.0196)	-0.0103	(0.0878)	-0.0578	(0.0415)	-0.220*	(0.131)
Unemployed	-0.103***	(0.0106)	-0.455***	(0.0534)	-0.227***	(0.0240)	-0.434***	(0.0651)
Retired	0.0128	(0.00858)	0.168***	(0.0621)	0.0430*	(0.0220)	0.201***	(0.0703)
House work	-0.0293***	(0.00846)	-0.0750*	(0.0437)	-0.0628***	(0.0197)	-0.100*	(0.0579)
Student	0.0145	(0.0112)	0.0819	(0.0537)	0.0891***	(0.0226)	0.261***	(0.0711)
Disabled	-0.160***	(0.0161)	-0.583***	(0.0797)	-0.425***	(0.0372)	-0.709***	(0.0925)
Jobother	0.115***	(0.0145)	0.579***	(0.0773)	0.114***	(0.0255)	0.395***	(0.0909)
Constant	3.498***	(0.0764)			6.359***	(0.186)		
N individuals	27,527		27,527		23,279		23,279	
T	18		18		12		12	
R-squared	0.0124		0.0101		0.0174		0.0162	
BIC	238,840		97,650		293,019		100,637	
AIC	238,547		97,364		292,737		100,353	

Notes: Happiness scale is from 1 to 4, life satisfaction scale from 1 to 7 (higher is happier and more satisfied, respectively). *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. For the linear FE estimations we show the within R-squared and for the fixed effects ordered logit the pseudo R-squared.

Table 2.5 Compensating variations (CV) for informal care

Y= Happiness	CV	Std. Errors	95% Conf. Interval
Linear FE	21.22***	5.795	(9.864 32.579)
FE ordered logit	24.30**	9.562	(5.562 43.043)
Y= Life Satisfaction			
Linear FE	18.69***	5.335	(8.237 29.149)
FE ordered logit	18.23**	7.680	(3.178 33.285)

Notes: Compensating variation is income for one additional hours of informal care calculated following the formula in (6) using the sample median weekly income of £553.12 and the coefficient results for the number of hours providing care and weekly household income in Table 2.4. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.6 Estimation results. Males sample

Dependent variable	**Happiness**	**Happiness**	**Life Satisfaction**	**Life Satisfaction**
Estimation method	**Linear FE**	**FE OL**	**Linear FE**	**FE OL**
	1	**2**	**3**	**4**
Hourscare	-0.000821***	-0.00402**	-0.00162**	-0.00308*
	(0.000267)	(0.00191)	(0.000634)	(0.00179)
Lnhhincomeweek	0.0120**	0.0303	0.0537***	0.124***
	(0.00543)	(0.0356)	(0.0119)	(0.0411)
N individuals	13,169	13,169	11,046	11,046
T	18	18	12	12
R-squared	0.0089	0.0122	0.0189	0.0191
BIC	99,477	40,489	131,554	131,294
AIC	99,206	40,228	43,647	43,386

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. For the linear FE estimations we show the within R-squared and for the fixed effects ordered logit the pseudo R-squared.

Table 2.7 Estimation results. Females sample

Dependent variable	Happiness	Happiness	Life Satisfaction	Life Satisfaction
Estimation method	**Linear FE**	**FE OL**	**Linear FE**	**FE OL**
	1	**2**	**3**	**4**
Hourscare	-0.000771***	-0.00345**	-0.00166***	-0.00366**
	(0.00023)	(0.00135)	(0.000535)	(0.0015)
Lnhhincomeweek	0.0302***	0.127***	0.0486***	0.0895***
	(0.00526)	(0.0277)	(0.0108)	(0.0327)
N individuals	14,358	14,358	12,233	12,233
T	18	18	12	12
R-squared	0.0122	0.0145	0.0178	0.0161
BIC	138,075	57,349	16,1306	57,167
AIC	137,801	57,079	16,1042	56,899

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. For the linear FE estimations we show the within R-squared and for the fixed effects ordered logit the pseudo R-squared.

Table 2.8 Compensating variation for males

Happiness	CV	Std. Errors	95% Conf. Interval
Linear FE	41.625*	23.844	(-5.109 88.359)
FE ordered logit	83.465	112.164	(-136.371 303.303)
Life Satisfaction			
Linear FE	18.019**	8.220	(1.908 34.131)
FE ordered logit	14.774	9.983	(-4.793 34.339)

Notes: Monetary values are calculated following the formula in (6) using the sample median weekly income for males of £587.43 and the coefficient results for the number of hours providing care and weekly household income in Table 2.6. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.9 Compensating variation for females

Happiness	CV	Std. Errors	95% Conf. Interval
Linear FE	13.453***	4.669	(4.302 22.605)
FE ordered logit	14.38**	6.462	(1.724 27.055)
Life Satisfaction			
Linear FE	18.031**	7.130	(4.056 32.007)
FE ordered logit	21.717*	11.885	(-1.576 45.010)

Notes: Monetary values are calculated following the formula in (6) using the sample median weekly income for females of £520.58 and the coefficient results for the number of hours providing care and weekly household income in Table 2.7. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.10 Compensating variations by median carer/non-carer income

	Full sample	Males		Females	
Median income		**Coefficients full sample**	**Coefficients male sample**	**Coefficients full sample**	**Coefficients female sample**
Non-carer	18.97***	20.19***	18.33**	17.77***	18.21**
	(5.42)	(5.76)	(8.36)	(5.07)	(7.20)
Carer	17.55***	18.33***	16.64**	16.94***	17.36**
	(5.00)	(5.23)	(7.59)	(4.84)	(6.87)
All	18.69***	19.85***	18.019**	17.59***	18.031**
	(5.33)	(5.67)	(8.22)	(5.02)	(7.13)

Note: Monetary values are calculated following the formula in (6) using the coefficient results from Table 2.4 (full sample), Table 2.6 (male sample), and Table 2.7 (female sample) and evaluated at sample median income of £553.12 for all, £561.46 for non-carers, and £519.41 for carers. For the male sample compensations are evaluated at the median income of £587.43 for all men, £597.47 for men non-carers, and £5425.41 for men cares. For women, these median incomes are, respectively, £520.58, £525.71, and £501.34. Standard errors are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.11 Life Satisfaction linear FE estimation results. Log of hours providing care

	Linear FE estimations for Life Satisfaction.			
	1		2	
Hourscare	-0.00172***	(0.000407)		
Log hourscare			-0.0346***	(0.00725)
Lnhhincomeweek	0.0519***	(0.00798)	0.0518***	(0.00798)
Individuals	23,279		23,279	
Within R-squared	0.0174		0.0173	
BIC	293,019		293,002	
AIC	292,737		292,749	

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Table 2.12 Compensating variation. Hours providing care in logarithms

Y= Life Satisfaction	CV	Std. Errors	95% Conf. Interval
Hourscare	18.69***	5.335	(8.237 29.149)
Log hourscare	51.67***	13.895	(24.438 78.905)

Notes: Monetary values are calculated following the formula in (15) and using the sample median weekly income of £553.12, the median hours of informal care of 7, and the coefficient results for the number of hours providing care in logarithms and weekly household income in table 2.10 column 2. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.13 Compensating variation by median income and gender evaluated at the median income. Hours providing care in logarithms

	Full sample	Males	Females
Median income			
Non-carer	52.45***	55.82***	49.11***
	(14.10)	(15.01)	(13.21)
Carer	48.52***	50.67***	46.83***
	(13.05)	(13.63)	(12.59)
All	51.67***	54.88***	48.63***
	(13.89)	(14.76)	(13.08)

Notes: Monetary values are calculated following the formula in (15) using the coefficient results for the number of hours providing care in logarithms and weekly household income in table 2.10 column 2, the median hours of informal care of 7, and the sample median weekly income of £553.12 for all the full sample, £561.46 for non-carers, and £519.41 for carers. For males those values are £587.43 for all men, £597.47 for men non-carers, and £5425.41 for men cares. For women, these median incomes are, respectively, £520.58, £525.71, and £501.34. Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.14 Compensating variation with log hours for different assumptions on hours of care

	7 hours (median)	5 hours	19 hours (mean)	25 hours
Median income				
Non-carer	52.45***	72.81***	19.60***	14.92***
	(14.10)	(19.90)	(5.13)	(3.88)
Carer	48.52***	67.36***	18.13***	13.81***
	(13.05)	(18.41)	(4.74)	(3.60)
All	51.67***	71.73***	19.30***	14.70***
	(13.89)	(19.60)	(5.05)	(3.83)

Notes: Monetary values are calculated following the formula in (15) using the coefficient results for the number of hours providing care in logarithms and weekly household income in table 2.10 column 2, and the sample median weekly income of £553.12 for all the full sample, £561.46 for non-carers, and £519.41 for carers. They are calculated at the median of 7 hours, at 5 hours, 19, and 25 hours. Standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.15 Life Satisfaction linear FE estimation results. Polynomials for informal care hours

Variables	1	2	3	4	5
Hourscare	-0.00172***	-0.00262*	-0.00596**	-0.00306	-0.000871
	(0.000407)	(0.00134)	(0.00239)	(0.00417)	(0.00792)
Hourscare2		6.89e-06	0.000132*	-5.87e-05	-0.000292
		(1.30e-05)	(7.68e-05)	(0.000241)	(0.000766)
Hourscare3			-9.38e-07	2.60e-06	1.09e-05
			(5.71e-07)	(4.30e-06)	(2.61e-05)
Hourscare4				-1.91e-08	-1.30e-07
				(2.31e-08)	(3.47e-07)
Hourscare5					4.97e-10
					(1.55e-09)
Lnhhincomeweek	0.0519***	0.0518***	0.0518***	0.0517***	0.0517***
	(0.00798)	(0.00798)	(0.00798)	(0.00798)	-0.00798
Individuals	23,279	23,279	23,279	23,279	23,279
R-squared	0.0174	0.0173	0.0174	0.0174	0.0174
BIC	293,019	293004	293011	293022	293034
AIC	292,737	292,741	292,739	29,274	292,742

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.

Table 2.16 Life Satisfaction linear FE estimation results using categories for informal care

	Linear FE estimations for Life Satisfaction. Different categories for informal care hours			
	1		**2**	
Hourscare0-4	-0.0287	(0.0414)		
Hourscare5-9	-0.0491	(0.0425)		
Hourscare10-19	-0.0419	(0.0461)		
Hourscare20-34	-0.120**	(0.0506)		
Hourscare35-49	-0.101	(0.0618)		
Hourscare50-99	-0.0979	(0.0726)		
Hourscare100+	-0.235***	(0.0531)		
Hourscare<20	-0.0822	(0.0542)		
Hourscare>20	-0.126**	(0.0580)		
Below 20 hrs			-0.044	(0.0406)
Above 20 hrs			-0.151***	(0.0443)
Lnhhincomeweek	0.0503***	(0.00806)	0.0503***	(0.00806)
N individuals	23,279		23,279	
R-squared	0.017		0.0169	
BIC	286,645.70		286585.2	
AIC	286,315.20		286322.7	

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses.
The categories for the number of hours providing care in the question in BHPS (column 1) include two categories for whether caring for less than 20 hours (hourscare<20) or caring for 20 hours or above (hourscare>20). In column 2 we collapse all the categories to three: in caring below 20 hours, caring 20 hours or above and no caring (reference category).

Table 2.17 Compensating variation for informal care when hours providing care is categorical.

Life Satisfaction	CV	Std. Errors	95% Conf. Interval	
Hourscare0-4	425.868	808.436	(-1158.721	2010.456)
Hourscare5-9	914.011	1255.326	(-1546.512	3374.535)
Hourscare10-19	717.494	1171.558	(-1578.839	3013.826)
Hourscare20-34	5,499.311	6470.161	(-7182.636	18181.26)
Hourscare35-49	3,536.299	5165.389	(-6588.207	13660.8)
Hourscare50-99	3,314.641	5686.249	(-7830.786	14460.07)
Hourscare100+	5,7902.92	74757.89	(-88627.52	204433.4)
Varies under 20	2,281.00	3146.989	(-3886.989	8448.981)
Varies above 20	6,265.87	8276.616	(-9955.997	22487.74)
Below 20 hrs	774.2813	1084.438	(-1351.178	2899.74)
Above 20 hrs	10,612.38	11085.92	(-11115.63	32340.38)

Notes: Monetary values are calculated following the formula in (6) using the sample median weekly income for females of £520.58 and the coefficient results for the number of hours providing care and weekly household income in table 2.12.

Appendices

A1. Variable definitions

Table A.18 Variable definitions

Dependant variables	
Happiness	Self-assessed happiness: 1 if much less, 2 if less so, 3 if same as usual, 4 if more than usual
Satoverall	Satisfaction with life overall: from 1 if not satisfied at all to 7 if completely satisfied
Indicators of informal care	
Hourscare	Number of hours per week spent caring for someone else.
Yearscaring	Number of years providing care
Yearscaring2	Number of years providing care (squared)
Careinonly	1 if caring for someone inside household, 0 otherwise
Careoutonly	1 if caring for someone outside household, 0 otherwise
Careinout	1 if caring for someone in and outside household, 0 otherwise
Partner	1 if caring for the partner, 0 otherwise
Parents	1 if caring for parent(s), 0 otherwise
Friends	1 if caring for a friend, 0 otherwise
Controls	
Lnhhincomeweek	Weekly deflated household income in pounds (logarithms)
Morbidity	1 if one health problem, 0 otherwise
Comorbidity	1 if several health problems, 0 otherwise
Nomorbidity	1 if no health problems, 0 otherwise
Age	Age in years at the day of the interview
Age2	Age in years at the day of the interview (squared)
Nchilds	Number of children in the household
Nchilds2	Number of children in the household (squared)
Hhsize	Number of individuals inside the household
Hhsize2	Number of individuals inside the household (squared)
Marital	1 if married or living with the partner, 0 otherwise
Educ_secondary	1 if highest qualification is secondary education, 0 otherwise
Educ_high	1 if highest qualification is high school, 0 otherwise
Educ_degree	1 if highest qualification is (higher) degree, 0 otherwise
Employed	1 if employed, 0 otherwise (baseline category)
Unemployed	1 if unemployed, 0 otherwise

Retired	1 if retired, 0 otherwise
House work	1 if house work activities, 0 otherwise
Student	1 if student, 0 otherwise
Disabled	1 if disabled, 0 otherwise
Jobother	1 if other job, 0 otherwise
Male	1 if male, 0 if female

A2. BUC estimator (Baetschmann et al. 2015)

To better understand the BUC estimator, **Table A.19** and **Table A.20** provide an intuitive example of our estimation method. The example involves two hypothetical survey respondents (N=2), three time periods or waves (T=3), and a subjective wellbeing answering scale of four possible responses (SWB=1, 2, 3, or 4). The first column is called ID. It gives the identifier of the two survey respondents. Both people (number 1 and number 2) have responded to the survey at three time periods: waves 1, 2 and 3. The subjective wellbeing responses of person 1 and 2 are presented in the third column called SWB. In wave 1 respondent 1 subjective wellbeing score was 3, in wave 2 it was 1 and in wave 3 it was 4. Respondent 2's answers are respectively: 2, 1 and 3.

Since the subjective wellbeing scores range from 1 to 4, there are three subjective wellbeing thresholds, k=2, k=3 and k=4. They are presented in columns 4, 5 and 6. Following the observation rule in equation (10), if the well-being outcome for a given individual at a given wave is greater or equal than the threshold number k, the value for the new discrete outcome will be 1; otherwise the value will be 0. In Table A.20 we see the "blow up" procedure: for each individual, a new outcome SWB_1 is constructed which is formed by the combination of all responses at every threshold. The example provides the "blow up" for individual 1: since there are 3 thresholds, for each year, there are now 3 different observations (N) of the well-being outcome. For instance, for year one, the outcome is 1 for k=2, 1 for k=3, and 0 for k=4.

Table A.19 BUC performance

N = 2; T=3; SWB=1, 2, 3, or 4; K=3

ID	T	SWB	k=2	k=3	k=4	n
1	1	3	1	1	0	1
1	2	1	0	0	0	2
1	3	4	1	1	1	3
2	1	2	1	0	0	4
2	2	1	0	0	0	5
2	3	3	1	1	0	6

Table A.20 BUC performance data reorganization

ID	T	SWB_1	K	N
1	1	1	2	1
1	1	1	3	1
1	1	0	4	1
1	2	0	2	2
1	2	0	3	2
1	2	0	4	2
1	3	1	2	3
1	3	1	3	3
1	3	1	4	3

A3. Analysis on the sample of individuals who answered both well-being questions

Regression results on columns 1 and 2 in Table 2.4 are estimated on the sample of individuals who responded to the happiness question and results on columns 3 and 4 on the sample of individuals who have a positive value on the life satisfaction scale. It is interesting to estimate those regressions on the sample of individuals who answered both the life satisfaction and the happiness question to compare individuals with the same preferences. In this case, the number of observations is 125,178 and the number of individuals is 23,265 and the analysis is made using 12 waves of the 18 in BHPS as the life satisfaction question is asked from wave 6 to 10 and from 12 to 18.

Table A.21 presents those results. Columns 1 and 2 present the results for the linear fixed effects and ordered logit estimations for happiness and columns 3 and 4 show the estimation results for the life satisfaction for the main variables of interest. The main result to highlight is the poor performance of the linear FE and the ordered logit estimations for happiness compared with the results in Table 2.4. Although the coefficients for the number of hours providing care and weekly household income are significant in the linear FE, the within R-squared is low, and the coefficient for hours in the ordered logit is not significant. Therefore, it seems that the happiness models are sensitive to the number of observations. The life satisfaction models have a very similar performance to the main models in Table 2.4 because the number of observations remains almost the same.

Hence, given the loss of observations and the poor performance of the happiness models when using an equal sample size for happiness and life satisfaction, we estimate our main analysis on different sample sizes for each well-being measure. Ideally, having the same sample size would be a better approach if one wants to study if individuals have same preferences when they are measured using different well-being variables.

Table A.21 Estimation results on the same sample for happiness and life satisfaction

Dependent variable	**Happiness**	**Happiness**	**Life Satisfaction**	**Life Satisfaction**
Estimation method	**Linear FE**	**FE OL**	**Linear FE**	**FE OL**
	1	**2**	**3**	**4**
Hourscare	-0.000739***	-0.00186	-0.00170***	-0.00329***
	(0.0002)	(0.0015)	(0.0004)	(0.0011)
Lnhhincomeweek	0.0215***	0.0608**	0.0520***	0.103***
	(0.0046)	(0.0286)	(0.0080)	(0.026)
N individuals	23,265	23,265	23,265	23,265
T	12	12	12	12
R-squared	0.0099	0.0133	0.0174	0.0163
BIC	161,485	53,281	292,159	100,339
AIC	161,202	53,013	291,877	100,055

Note: Estimation results using the same sample of individuals for happiness and life satisfaction (wave 6 to 10 and 12 o 18). ** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses. For the linear FE estimations we show the within R-squared and for the fixed effects ordered logit the pseudo R-squared.

A4. Monetary value formula when hours care is in logarithms

If the number of hours providing care is transformed to logarithms, our equation of interest is

$$SWB_{it} = f\left(hcare_{it}, Inc_{it}, \boldsymbol{IC_{it}}, \boldsymbol{X_{it}}\right) = \alpha + \ln(hcare_{it})\beta_1 + \ln(Inc_{it})\beta_2 + \boldsymbol{IC_{it}}\gamma + \boldsymbol{X_{it}}\delta$$

where $\ln(hcare_{it})$ is the number of hours providing care in logarithms. The monetary compensation ΔInc_{it} for a change in the weekly number of hours providing care to keep the same level of well-being is defined implicitly by

$$\alpha + ln(hcare_{it})\beta_1 + ln(Inc_{it})\beta_2 + \boldsymbol{IC_{it}}\gamma + \boldsymbol{X_{it}}\delta$$

$$= \alpha + ln(hcare_{it} + \Delta hcare_{it})\beta_1 + ln(Inc_{it} + \Delta Inc_{it})\beta_2 + \boldsymbol{IC_{it}}\gamma + \boldsymbol{X_{it}}\delta$$

Solving this equation for ΔInc_{it} we obtain the monetary compensation when the weekly number of hours providing care and the weekly household income are expressed in logarithms:

$$\ln(hcare_{it})\beta_1 + \ln(Inc_{it})\beta_2 = \ln(hcare_{it} + \Delta hcare_{it})\beta_1 + \ln(Inc_{it} + \Delta Inc_{it})\beta_2$$

$$\Leftrightarrow \beta_2 \left[\ln(Inc_{it} + \Delta Inc_{it}) - \ln(Inc_{it})\right] = \beta_1 \left[\ln(hcare_{it}) - \ln(hcare_{it} + \Delta hcare_{it}\right]$$

$$\Leftrightarrow \ln\left(\frac{(Inc_{it} + \Delta Inc_{it})}{Inc_{it}}\right) = \frac{\beta_1}{\beta_2}\ln\left(\frac{hcare_{it}}{(hcare_{it} + \Delta hcare_{it})}\right) = \ln\left(\left(\frac{hcare_{it}}{(hcare_{it} + \Delta hcare_{it})}\right)^{\frac{\beta_1}{\beta_2}}\right)$$

$$\Leftrightarrow \frac{(Inc_{it} + \Delta Inc_{it})}{Inc_{it}} = \left(\frac{hcare_{it}}{(hcare_{it} + \Delta hcare_{it})}\right)^{\frac{\beta_1}{\beta_2}}$$

$$\Leftrightarrow \Delta Inc_{it} = Inc_{it}\left\{\left(\frac{hcare_{it}}{hcare_{it} + \Delta hcare_{it}}\right)^{\frac{\beta_1}{\beta_2}} - 1\right\}$$

where $hcare_{it}$ is set to the median number of hours providing care (7 hours), $\Delta hcare_{it} = 1$, and Inc_{it} is set to the median household income.

A5. Monetary value formula when hours care is in quadratic form

If the number of hours providing care is in quadratic form, the SWB equation is

$$SWB_{it} = \alpha + hcare_{it}\beta_1 + hcare^2\delta + \ln(Inc_{it})\beta_2 + \boldsymbol{IC_{it}}\gamma + \boldsymbol{X_{it}}\delta$$

and the compensating variation is defined by

$$\beta_1 h_{it} + \delta h_{it}^{\ 2} + \beta_2 \ln Inc_{it} = \beta_1(h_{it} + \Delta h_{it}) + \delta(h_{it} + \Delta h_{it})^2 + \beta_2 \ln(Inc_{it} + \Delta Inc_{it})$$

$$= \beta_1(h_{it} + \Delta h_{it}) + \delta(h_{it}^{\ 2} + (\Delta h_{it})^2 + 2h_{it}\Delta h_{it}) + \beta_2 \ln(Inc_{it} + \Delta Inc_{it})$$

$$\Leftrightarrow \beta_2\left[\ln(Inc_{it} + \Delta Inc_{it}) - \ln Inc_{it}\right] = \beta_1\left[h_{it} - (h_{it} + \Delta h_{it})\right] + \delta[h_{it}^{\ 2} - (h_{it}^{\ 2} + (\Delta h_{it})^2 + 2h_{it}\Delta h_{it}))]$$

$$\Leftrightarrow \beta_2 \ln\left(1+\frac{\Delta Inc_{it}}{Inc_{it}}\right) = -\beta_1 \Delta h_{it} - \delta[(\Delta h_{it})^2 + 2h_{it}\Delta h_{it}]$$

$$\Leftrightarrow \Delta Inc_{it} = Inc_{it}\left\{\exp\left(\frac{-\beta_1 \Delta h_{it} - \delta[(\Delta h_{it})^2 + 2h_{it}\Delta h_{it}]}{\beta_2}\right) - 1\right\}$$

where $h_{it} = hcare_{it}$, $\Delta h_{it} = 1$, and Inc_{it} is set to the median household income.

Chapter 3. Informal care and early retirement decisions

3.1 Introduction

The objective of this chapter is to study the impact of providing informal care on individual early retirement decisions for the UK population using the British Household Panel Survey. A comparison between the 2001 and 2011[21] UK Census shows that the number of unpaid caregivers has increased and 10.3% of the UK population was providing some form of unpaid care in 2011. Furthermore, the peak age range for caring is 50 to 64, and 17% of men and 24% of women in this age interval provide informal care to a sick, disabled or elderly person.[22] The demand for carers in the UK society is and will keep increasing (Pickard, 2000), and the major part of this unpaid care will be more likely to be undertaken by those individuals aged 50 and over. This group of individuals is still undertaking labour market activities, so that they often need to combine both caregiving duties and work. Troubles in managing work and informal care simultaneously can lead individuals to retire earlier than the UK State Pension Age (SPA, 65 years for men and 60 years for women) which is the earliest age individuals become eligible to receive the State Pension[23].

Although the employment rate among people over 50 years old has increased in the UK in recent years, early labour market exits have also been on the rise.[24] In 2014, 28% of all people aged between 50 and the State Pension Age were out of the labour market. There were also lower employment rates (56.5% for males and 55.8% females) for individuals aged 50-64 that provide care for more than 10 hours per week than for individuals in this age range that do not provide informal care (74% for males and 64% for females).[25] The main factors that lead individuals to early retirement are age, financial situation, institutional regimes and health (Flippen and Tienda, 2000, Jones et

[21] Office for National Statistics Census 2011: Key Statistics for local authorities in England and Wales. London. The Stationery Office.
[22] Fuller Working Lives – Background Evidence. Department for Work & Pensions, Gov.uk. February 2017.

[23] The UK government defines the current State Retirement age as the earliest age you can start receiving your State Pension subject to having had National Insurance contributions. This age is worked out based on gender and date of birth and is currently set at 65 years old for men and 60 years old for women.
[24] Fuller Working Lives – Background Evidence. Department for Work & Pensions, Gov.uk. February 2017.
[25] Fuller Working Lives – Background Evidence. Department for Work & Pensions, Gov.uk. February 2017.

al., 2010, Kim and Feldman, 2000, Schils, 2008). Kubicek et al. (2010) find that job and family characteristics also influence early retirement decisions.

There are few studies of the relationship between retirement and informal care and we aim to contribute to the literature by being the first in analysing this relationship for the UK. The existing literature has tended to either analyse the impact of informal care on labour market participation or to calculate the opportunity cost associated with the provision of informal care, in terms of displaced of work activities (Carmichael and Charles, 1998, Carmichael and Charles, 2003, Ettner, 1995, Ettner, 1996, Heitmueller, 2007). This literature shows that carers are less likely to be in the labour market than non-carers and those who participate work fewer hours than non-carers, especially when the intensity of the care provision is high. Examining the retirement decision per se is of interest as, compared to other labour exits, is usually a permanent change in labour market status (Van Houtven et al., 2013).

3.1.1 Literature

The literature on the relationship between retirement and informal care uses different models, econometric methods, and retirement definitions and reports mixed results. The literature is for the US, Canada, and Germany and, there appear to be no published studies for the UK. Results from existing studies may therefore not be relevant for the UK given differences in pension arrangements and labour market characteristics. **Table 3.1** provides a summary of the existing literature.

Van Houtven et al. (2013) and Jacobs et al. (2017) use a Linear Probability Model (LPM) with individual fixed effects to study the effect of caregiving per se and caregiving intensity on retirement in the US. Van Houtven et al. (2013) examine the impact of providing informal care to a parent or parent in law over the previous two years on labour market outcomes including self-reported retirement. They use a longitudinal panel data set (Health and Retirement Study) and apply instrumental variables to allow for possible endogeneity between informal care and retirement coming from reverse causality: the effect of retirement on caregiving. Controlling for individual specific fixed effects will not remove time-varying endogeneity and so they use parental health and whether the parent or parent-in-law died or became widowed as time-varying instruments for informal care. However, they do not find evidence of endogeneity. Results from LPM with fixed effects show that females who provide informal care are more likely to be retired. They do not find significant effects of informal care on the probability of retirement for men.

Jacobs et al. (2017) study the effects of being an informal carer and the number of hours providing care on women's self-reported retirement using the American National Longitudinal Survey of Mature Women. They use the death of the parent over the last two years, and whether the parent is single or widowed as instruments to allow for the endogeneity of informal care. As in Van Houtven et al. (2013), they cannot reject the null hypothesis of exogeneity between informal care and retirement. After estimating a fixed effects LPM, they find that providing care for more than 20 hours a week has a positive impact on females' retirement.

Both these papers use the same estimation method and find significant results only for females. However, they do not focus on early retirements before the age at which individuals are entitled to Social Security, nor they allow for duration of employment to affect the timing of retirement.

Dentinger and Clarkberg (2002) and Meng (2012) use duration models to analyse the relationship between retirement decisions and informal care. Dentinger and Clarkberg (2002) use the US Retirement and Well-being study data from 1994-1995 and define retirement as departure from paid employment and assume that individuals are at risk of retirement one year before they observe that a respondent retires. The paper uses a number of measures of informal care including caring for more than one person, whether the care receiver is in the household or outside, and who the care receiver is (spouse, parent or parent in law). Men who provide informal care have a slower transition to retirement than male non-carers, and men who care for a partner have a smaller probability of retirement. For women, caring for more than one person or for a spouse increases the likelihood of retirement and the odds to retire when providing care are greater for women than for men. Although Dentinger and Clarkberg (2002) use current caregiving explanatory variables to analyse current retirement, they do not allow for potential endogeneity. They also have a short period of time (one year) during which an individual is considered at risk of retirement.

Meng (2012) uses the German Socio-Economic Panel (GSOEP) dataset to study the impact of having provided informal care and the hours of care provided in the previous year on the probability of retirement. Meng (2012) uses a complementary log-log model and defines the retirement as individuals aged 58 to 64 dropping out the labour market and receiving a public pension. Having provided care a year before retirement increases the rate of retirement only for women. For men, the intensity of care has an impact on retirement so that an extra hour of informal care last year increases their retirement rate.

Schils (2008) examines how state pension schemes in Germany, Netherlands, and the United Kingdom affect early retirement when having dependents (children or family members in need of care). She uses, respectively, GSOEP from 1990-2005, the Socio-Economics Panel (SEP) from 1990-2001, and the BHPS from 1991 to 2004. For the United Kingdom, Schils (2008) finds that having children or family members in need of care *decreases* the probability of early retirement perhaps due to fewer early retirement options in the UK state pension than in Germany and Netherlands. The paper does not study the direct effect of providing care on early retirement and is focussed on the effect on retirement of differences in pension schemes among the countries.

Jacobs et al. (2014) study the effect of the average amount of care provided in the past 12 months on the likelihood of being fully retired, retired and return to work, never retired and working, and not being in the labour market, for men and women aged 55 to 69 from the Canadian 2007 General Social Survey. They use a multinomial logit model and calculate relative risk ratios for the probability of being retired compared to being employed. Results show that men and women who provided care for up to 5 hours a week in the last 12 months and men who provided 15 or more hours of care have a greater probability to retire compared to being employed. A limitation of this study is the use of cross-sectional data and the use of correlations between the different labour market statuses without further econometric analysis.

Overall, results from the existing literature are heterogeneous, especially for men. For women, the majority of findings suggest that informal care increases the probability to retire. Results for men suggest either no effect of informal care on retirement, a decrease on the likelihood of retirement when providing care, or an increase when the intensity of care provision increases.

3.1.2 This study

In this paper, we are the first to investigate the impact of informal care on retirement decisions for the UK using 18 waves of data from the British Household Panel Survey. Use of this data constitutes an extension on existing research given the larger sample size and longer follow-up of individuals compared to previous studies. Second, we consider a broader age range in which an individual is considered at risk of retirement. Concretely, we select employed and self-employed individuals aged 50 to 64 in the case of men, and 50 to 59 in the case of women, i.e. up to the SPA (65 and 60 during our period).

We aim to determine whether having provided informal care in the previous year affects the transition from being in the labour market to retirement for individuals aged between 50 and the SPA. If employed individuals in the UK retire before the SPA, they will not get the State Pension until they reach SPA. Before the SPA, they can only rely on occupational or private pensions, along with any other household funds or incomes. The effect of caregiving on retirement decisions is a priori ambiguous. The additional calls on their time may lead carers to withdraw early from the labour market. But they may have greater expenses to cover and they might feel the need to remain in the labour market to cover these. Working may also enable them to psychologically recover from the burden of care (Kramer, 1997, Moen, 1992). The impact of informal care may differ for men and women. Women take the major bulk of caring activities, but a higher percentage of men retire early.

We analyse retirement using duration models as the chances of leaving employment and retiring in a given year may depend on the time already spent at the labour market, so that early retirement can be considered as a duration dependent state. Our approach is similar to Jones et al. (2012) who study the effect of health on retirement using duration models following the approach suggested by Jenkins (1995) and using the British Household Panel Survey. However, our research question is different, we use a different set of explanatory variables, a different sample definition and utilise more waves of the BHPS.

Section 3.2 presents the duration model and the estimation method used. Section 3.3 describes the sample at risk of retirement, and the formatting of the BHPS as a survival dataset. Section 3.4 describes the variables used in the model and provides the descriptive statistics. Section 3.5 presents the results and section 3.6 concludes.

3.2 Model and estimation

Our specific research question is: does providing informal care last year affect the current probability to retire of people aged between 50 and the State Pension Age (60 for women, and 65 for men)? In order to analyse the effect of informal care and other socio-economic variables on the transition to retirement we make use of a discrete-time duration models. This approach assumes that remaining time in the labour market is a discrete variable because follow-up of individuals occurs only once each year in the BHPS data, so that we have “grouped data” (Cameron and Trivedi, 2005).

We have annual data (observations) on individuals from the 18 waves of the BHPS. We measure age in years. Thus, an individual who was aged say 56 years and 11 months and employed when interviewed at wave t and was retired when interviewed in $t+1$ when aged 57 years and 11 months is defined as having retired at age 57.

Table 3.2 summarizes the notation. Let t denote the year and define t = 1 as the year of the first wave of the BHPS (1991). The sample of observations is determined by the age of the individuals, which we denote as a (measured from the individual's year of birth). Let α^o be the lowest age at which individuals can contribute observations (α^o = 50 throughout). We do not include observations on younger individuals since their probability of retirement is very low. We also exclude observations when individuals are over an upper age limit α^U. In most samples we set this equal to the State Pension Age (α^U = 60 for women, 65 for men). Let $a_i(t)$ be the age of individual i in year (or, equivalently, wave) t.

In order to apply duration models we construct a stock sample, or sample at risk of failure. In our case, this will be the sample at risk of retirement. **Table 3.3** provides a brief description of the requirements we use to construct the sample.

The first requirement is that individuals are interviewed at wave 1, so that we have information from wave 1 onwards, and they also have to provide a full interview.[26] Moreover, we select individuals that at the beginning of BHPS are of a particular age $a_i(1)$ and above. In our main model we select $a_i(1) \geq 47, \alpha^o = 50$ and $\alpha_f^U = 60$ for females and $\alpha_m^U = 65$ for males at $t = 1$. Individuals need also to be working at wave 1: employed or self-employed. At subsequent waves, transitions to other labour market states, including retirement, may be made (Jones et al. 2012). Furthermore, we only include individuals with complete sequences of responses, so that, if individuals drop out from the data at some point in time (and therefore, information in that wave will be

[26] We do not include individuals who join the BHPS at a later wave e.g. because they marry a BHPS member. More individuals are taken into account when we boost the samples later on.

missing) but return at a later wave we only consider information on the individuals until the first exit from the panel. For individuals who die we only use observations up the wave before they die. Therefore, an individual contributes an observation if she is in the sample (satisfying the stock sample conditions) at wave t and still in the BHPS (either retired or not) at wave $t+1$. Thus, the maximum number of observations an individual could contribute is 17. The minimum is 1.

After applying the above restrictions, we have a sample of 17,367 individual-wave observations of which 9,427 are for males and 7,940 for females.

We then follow those individuals for up to a year before the SPA, 64 in the case of men, and 59 for women. During their spell individuals can either remain in the labour market (survive) or retire (failure event). Therefore, we can observe whether an individual at the end of their spell is still at the labour market (either employed, self-employed, or in another labour market state different from retirement such as unemployed, on maternity leave, student, disabled, etc.) or whether they have retired.

Let t_i^o be the first year at which i could contribute an observation. If $a_i(1) \geq \alpha^o = 50$, then $t_i^o = 1$. If $a_i(1) < \alpha^o$ (so i is too young at wave 1, i.e. younger than 50), then $t_i^o = \alpha^o + 1 - a_i(1) = 50 + 1 - a_i(1)$ and i will be in the sample if BHPS wave t_i^o exists: i.e. if $t_i^o \in [1,17]$. Thus, for example, if i is 47 at $t = 1$, then she will contribute her first observation in wave 4 when she is 50. Thus, t_i^o is the first wave at which i is present in the BHPS and meeting the stock sample restrictions.

Define t_i^L as the last wave (year) in which i is present in the BHPS (having been at the labour market and meeting the age restrictions at $t_i^L - 1$). This last wave is either the first wave in which individuals are retired, have hit the upper age restriction and have not retired, or is the wave just before they drop out of the sample by death, or lost to follow up. The number of observations contributed by i is $t_i^L - t_i^o - 1$.

We draw the main sample from individuals in wave 1 who are working (or self-employed) at wave 1, and have $a_i(1) \in [\alpha^o - 3, \ \alpha^U - 1]$. Thus, for example, if $\alpha^U = 60$ we would include all individuals in wave 1 who are working and are aged at least 47 and at most 59.

The hazard rate captures the rate of retirement for individuals at a given point in time assuming that they are not already retired at the start of the year and still in the BHPS at the end of the year. Analysis time is defined as time at risk of retirement using the age instead of calendar time: $A = a_i(t) - \alpha^o$, i.e. the difference between their age at that particular moment $a_i(t)$, and the lowest age $\alpha^o = 50$ at which individuals start becoming at risk of retirement. In terms of analysis time the hazard rate is

$$h_{iA}\left(x_{iA}\right) = \Pr\left[T_i = A \mid T_i \geq A; \boldsymbol{X_{iA}}\right] \tag{17}$$

where $\boldsymbol{X_{iA}}$ is a vector of explanatories, and T_i is a discrete random variable representing the analysis time at which *i* retires (her spell ends) in terms of age rather than calendar years on BHPS waves.

The probability of *i* entering the labour market at age a_i^B and remaining in the labour market (surviving) to the end of the analysis time A is

$$S_{iA} = \Pr\left[T_i > A\right] = \prod\nolimits_{A^{'}=(a_i^B+1)-\alpha^o}^{A} \left(1 - h_{iA^{'}}\right) \tag{18}$$

This is the survival function for individual i and is the product of probabilities of remaining in the labour market in each year (where years are defined in terms of age) given that the individual was not retired at the previous year. a_i^B will vary among individuals and is not observed in the BHPS. Given that individuals must be employed when first included in the sample and at least aged α^o, $a_i^B + 1 - \alpha^o$ can be negative. As we will show this does not matter and the likelihood for our sample uses only non-negative analysis times.

We observe two types of history for individuals at the end of their last spell. Some individuals are still not retired at the end of their last observed spell t_i^L. This has probability

$$S_{iA} = \Pr\left[T_i > A^L = a_i(t^L) - \alpha^o\right] = \prod\nolimits_{A^{'}=(a_i^B+1)-\alpha^o}^{A^L} \left(1 - h_{iA^{'}}\right) \tag{19}$$

We do not know a_i^B but we do know that they were in the labour market at t_i^o when first observed in BHPS. Hence the probability of the observed history conditional on being in the labour market at $A^o = a_i(t_i^o) - \alpha^o$ is

$$\Pr\left[T_i > A^L \middle| T_i > A^o\right] = \frac{\Pr\left[T_i > A^L \text{ and } T_i > A^o\right]}{\Pr\left[T_i > A^o\right]} = \frac{\Pr\left[T_i > A^L\right]}{\Pr\left[T_i > A^o\right]}$$

$$= \frac{\prod_{A'=(a_i^B+1)-\alpha^o}^{A^L}\left(1-h_{iA'}\right)}{\prod_{A'=(a_i^B+1)-\alpha^o}^{A^o}\left(1-h_{iA'}\right)} = \prod_{A'=(a_i^o+1)-\alpha^o}^{A^L}\left(1-h_{iA'}\right) \qquad (20)$$

(Notice that, from the sample definition, $a_i(t_i^o) \geq 50$ so the analysis time at risk in (18) is non-negative).

In the other type of history, we observe individuals who retire at $A^L = a_i(t_i^L) - \alpha^o$ and the probability of this history conditional on being in the labour market at $A^o = a_i(t_i^o) - \alpha^o$ is

$$\Pr\left[T_i = A^L \middle| T_i > A^o\right] = \frac{\Pr\left[T_i = A^L \text{ and } T_i > A^o\right]}{\Pr\left[T_i > A^o\right]} = \frac{\Pr\left[T_i = A^L\right]}{\Pr\left[T_i > A^o\right]}$$

$$= \frac{h_{iA^L}\prod_{A'=(a_i^B+1)-\alpha^o}^{A^L-1}\left(1-h_{iA'}\right)}{\prod_{A'=(a_i^B+1)-\alpha^o}^{A^o}\left(1-h_{iA'}\right)} = h_{iA^L}\prod_{A'=(a_i^o+1)-\alpha^o}^{A^L-1}\left(1-h_{iA'}\right)$$

$$= \frac{h_{iA^L}}{\left(1-h_{iA^L}\right)}\prod_{A'=(a_i^o+1)-\alpha^o}^{A^L}\left(1-h_{iA'}\right) \qquad (21)$$

Hence the log of the likelihood of observing all the event histories is

$$\ln £ = \ln\left\{\prod_{i=1}^{n}\left[h_{iA^L}\left(1-h_{iA^L}\right)^{-1}\prod_{A'=(a_i^o+1)-\alpha^o}^{A^L}\left(1-h_{iA'}\right)\right]^{\delta_i}\left[\prod_{A'=(a_i^o+1)-\alpha^o}^{A^L}\left(1-h_{iA'}\right)\right]^{(1-\delta_i)}\right\}$$

$$= \sum_{i=1}^{n}\delta_i\left[\ln\left(h_{iA^L}\left(1-h_{iA^L}\right)^{-1}\right)+\sum_{A'=(a_i^o+1)-\alpha^o}^{A^L}\ln\left(1-h_{iA'}\right)\right]+\sum_{i=1}^{n}(1-\delta_i)\left[\sum_{A'=(a_i^o+1)-\alpha^o}^{A^L}\ln\left(1-h_{iA'}\right)\right]$$

$$= \sum_{i=1}^{n}\delta_i\ln\left[h_{iA^L}\left(1-h_{iA^L}\right)^{-1}\right]+\sum_{i=1}^{n}\left[\sum_{A'=(a_i^o+1)-\alpha^o}^{A^L}\ln\left(1-h_{iA'}\right)\right]$$

$$= \sum_{i=1}^{n}\sum_{A'=(a_i^o+1)-\alpha^o}^{A^L}D_{iA'}\ln\left[h_{iA'}\left(1-h_{iA'}\right)^{-1}\right]+\sum_{i=1}^{n}\sum_{A'=(a_i^o+1)-\alpha^o}^{A^L}\ln\left(1-h_{iA'}\right) \qquad (22)$$

where $D_{iA^L} = 1$ if i retires at analysis age A and is zero if not. Thus D_{iA} = 0 for all analysis ages for individuals who do not retire when last observed and for all analysis ages except A^L for individuals who retire i.e. for whom δ_i = 1. δ_i is a characteristic of observations for individuals but D_{iA} is a characteristic of each individual-year observations. Hence replacing δ_i with D_{iA} gives the logarithm of the likelihood of a set of individual-year observations of a binary event: the individual either retires or does not. Thus statistical software for binary models can be applied once we have specified the hazard function

3.2.1 Hazard function

To complete the above probabilities, we need to specify the distribution of the hazard function h_{iA}. In our model, the hazard is a function that depends on the variables of interest that might have an impact on retirement. The usual way to parametrise discrete-time duration models when handling interval-censored data, is by applying the complementary log-log specification to the hazard rate. The complementary log-log specification is the discrete-time counterpart of the proportional hazard model used for continuous time (Prentice and Gloeckler, 1978). In continuous time, the proportional hazard rate is defined as:

$$h_{iA} = \phi\left(\boldsymbol{X_{iA}}\beta\right)h_0 \tag{23}$$

where h_0 represents the baseline hazard or the model's duration dependence, and $\phi\left(\boldsymbol{X_{iA}}\beta\right)$ is a function of explanatory variables. We use the conventional assumption that $\phi\left(\boldsymbol{X_{iA}}\beta\right) = \exp\left(\boldsymbol{X_{iA}}\beta\right)$ and therefore,

$$h_{iA} = \exp\left(\boldsymbol{X_{iA}}\beta\right)h_0 \tag{24}$$

The β coefficients can be interpreted as the constant proportional effects of x_i on the conditional probability of completing a spell:

$$\frac{\partial \ln h_{iA}}{\partial x_{ik}} = \beta_k \tag{25}$$

Another way to report the results, which is the one we will use, is by using the hazard ratio:

$$\exp\left(\beta_k\right) \tag{26}$$

which is the ratio of the hazards when the explanatories change from $\left(x_{i1A},...,x_{ikA},...,x_{iKA}\right)$ to $\left(x_{i1A},...,x_{ikA}+1,...,x_{iKA}\right)$. If $\exp\left(\beta_k\right)>1$ then an increase in x_{ikA} increases the probability that individual *i* will retire during the period analysis *A*.

Using (24) and the corresponding survival function in continuous time, the discrete counterpart of the proportional hazard model is the complementary log-log model (Cameron and Trivedi, 2005, Prentice and Gloeckler, 1978):

$$\log(-\log(1-h_{iA}))=\boldsymbol{X_{iA}}\beta+\gamma_0 \tag{27}$$

or equivalently,

$$h_{iA}=1-\exp\left[-\exp(\boldsymbol{X_{iA}}\beta+\gamma_0)\right] \tag{28}$$

γ_0 is the baseline hazard for the discrete-time case which needs to be specified in order to define how the model depends on time. We can think about the baseline hazard as a common hazard or duration effect that all individuals from our sample face, i.e. the hazard that individual *i* faces is a function of that common hazard rate. There are several parametric and non-parametric forms to specify the baseline hazard. We follow Jones *et al.* (2012) and define baseline hazard using a semi-parametric approach and include dummy variables that correspond with each of the age ranges under observation ($a\in\left\{\alpha^o,\alpha^U\right\}$).

Therefore, our hazard function takes the following form:

$$h_{iA}=1-\exp\left[-\exp\left(\boldsymbol{X_{iA}}\beta+\boldsymbol{a}\theta\right)\right] \tag{29}$$

where, $\boldsymbol{a}$ is a vector of ages between α^o and α^U, and θ defines the respective age coefficients. Parameter estimates β and θ are obtained by Maximum Likelihood Estimation.

If we observed individuals entering into the stock sample at the same age, time dummies would be sufficient to pick up common duration effects. However, in our sample, individuals enter the stock at different ages. Thus, the effect of a one-year increase in time for a 55-year old will differ to that for a 60-year old. This is the reason why we use age dummies instead. In that case, a one-year spell implies the 55 year old ageing to 56 and a 60 year old to 61, so that, by including age dummies, we can control for the different impact on the hazard of retirement. Therefore, the baseline hazard would be the same for all individuals with the same age, and we expect the risk to be higher over the ages as individuals get closer to the state pension age.

3.2.2 Unobserved heterogeneity

When analysing the relationship between informal care and retirement, we test whether the model presented above suffers from unobserved heterogeneity or "frailty" (Cameron and Trivedi, 2005, Jenkins, 2008). Suppose the hazard rate with unobserved heterogeneity is:

$$h_{iA} = 1 - \exp\left(-\exp\left(\boldsymbol{X_{iA}}\beta + \boldsymbol{a}\theta + v_i\right)\right) \tag{30}$$

where v_i is not observed. In our model, frailty may be present because informal carers may have different characteristics than non-carers which may lead them to have different preferences and behaviours towards informal care. Carers may acquire unobserved individual traits, such as patience, empathy, and devotion through their caring responsibilities. Also, in duration models it is often recommended to check for potential frailty problems (Jenkins, 2008). Not allowing for frailty will over-estimate the negative duration dependence because observations with greater unobserved v will fail faster. Moreover, the presence of unobserved heterogeneity will also affect the estimated coefficients, under-estimating (over-estimating) the "true" effect of a positive (negative) impact of the regressors on the duration model (Jenkins, 2008).

To incorporate unobserved heterogeneity, we use a complementary log-log model within a panel data setting (*xtcloglog*), where the unobserved heterogeneity v_i is normally distributed. We also use the command *pgmhaz8* developed by (Jenkins, 2004) which estimates discrete-time duration models accounting for frailty by assuming a Gamma distribution for the unobserved heterogeneity.

3.3 Using BHPS for survival analysis

Stata does not have a direct command for discrete-time duration models with a stock sample. Jenkins (1995) shows that this can easily be remedied by re-arranging the dataset and estimating the model with a binary dependent variable, in our case whether retired or not.

Accordingly, our analysis time $A(t)$, is defined as the time elapsed since becoming at risk of retirement (at age 50) and all the analysis is performed in terms of that time. In our main analysis we select individuals from the age of 47. Our interest is in the impact of informal care on retirement for those individuals between 50 and the State Pension Age. We set the start age of becoming at risk of retirement to be 50 as very few retirements happen before that age. We set the minimum age at which individuals are selected in wave 1 to be 47 to boost the sample. For instance, when setting the minimum age at 47, an individual who is 47 at wave 1, i.e. $a_i(1)=47$, will become at risk of retirement when turning 50 years old in wave 4. If we had set the minimum age to be at 50 in wave 1, that individual would not have entered into the sample at risk of retirement.[27] By setting the lower age limit for inclusion in the sample at 47 we can include individuals who could contribute up to 14 observations before they reach the SPA age of 65. Extending the lower age limit below 47 will add fewer observations on individuals when they reach 50 and more of their observations will be at ages when they have a very low risk of retirement.

Thus, at wave 1 we have individuals with ages that vary between 47 years old and 64 if men and 59 if women. Those who are aged between 47 and 49 will become at risk of retirement once they reach the age of 50 at waves 4, 3, and 2, respectively, if they satisfy the conditions explained in Table 3.3.

Since the maximum age of interest is 64 ($(\alpha_m{}^U=65)-1$) for men and 59 $(\alpha_f{}^U=60)-1)$ for women, the maximum amount of time span since an individual is at risk of retirement is 14 periods for men and 9 periods for women.

Our data needs to be re-organized in a way that every individual appears for a maximum of 14 periods in the case of men, and 9 periods in the case of women. For each individual in the dataset, there are as many observations as time intervals at risk of retirement. This data re-organization resembles to a panel data set. However, analysis time is *time since becoming at risk of retirement* ($A=a_i(t)-50$). Calendar time (this is

[27] There are no retirements between the age 47 and 50.

wave 1 to wave 18 of BHPS) is no longer the unit of time in our survival analysis model as time to failure (retirement) does not depend on calendar time.

Notice that two individuals i and j with the same age at different calendar times have the same analysis time A. For instance, let individual i at wave 2 be 55 years old, and individual j at wave 7 be 55 years old as well, so that $a_i(2) = a_j(7) = 55$. Furthermore, let us assume that they enter into the survival model at different calendar points in time (for instance, individual i enters at $t = 1$ at age $a_i(1) = 54$ and individual j at age $a_j(1) = 49$). Even though entering into the survival model at different ages, their time at risk of retirement, or failure time, at the age of 55 is the same for both of them and equals $a_i - \alpha^o = a_j - \alpha^o = 55 - 50 = 5$. The risk they both face to retire at that particular age will only be the same if they also have the same characteristics at that age.

Once we have selected our stock sample and re-organized the data, we declare the dataset as survival data using the *stset* command in Stata. After setting the data as survival data we have 4,137 individual-year male observations, with 653 males of whom 222 retire throughout their spell. For the female subsample, there are 2,299 individual-year observations on 440 women, of whom 96 retire during their spell.

3.4 Variables and descriptive statistics

3.4.1 Variables

Retirement

We use self-reported job status. Concretely, when answering the job status question, individuals classify themselves as retired, self-employed, in paid employment, or other (unemployed, housework, full time student, long term sick/disable, on maternity leave, government training scheme, or something else).

Individuals might miss-report their retirement status (Radl, 2014) and the literature has noted that self-reported retirement may not be accurate (Bardasi et al., 2002, Hagan et al., 2008). Some individuals may only consider themselves as being retired if they hold a retirement pension instead of from the moment they leave permanently the labour market. Other individuals might report to be retired when reaching the pertinent age, but they could be unemployed for a short period of time and come back to work afterwards. To account for this, in the sensitivity analysis we use a wider definition of retirement as the individual reporting retirement, or unemployment.

Informal care

The BHPS has several questions pertaining to informal care including the type of care provided and its intensity. We use the care variables in our model lagged one period. This is to account for current retirement decisions being influenced by past caregiving activities rather than by current activities. Indeed, this is the effect we are looking for, as if caregiving activities have affected the transition from employment to retirement this happened before retirement. If an individual is employed at $t-1$ and retires at t we record them as retired at t. However, informal care is reported at the interview and thus informal care reported at t cannot have affected the retirement decision which occurred in the year up to t. Therefore, if we observe an individual in the labour market at $t-1$ we use the level of informal care reported at $t-1$ to explain whether they were retired or not at t. Using lagged care also reduces the possible endogeneity problem between care and retirement from reverse causality arising because retired individuals have lower opportunity cost in providing informal care.

Our main indicator of informal care is the number of hours per week the caregivers spends looking after or helping someone else. Informal care time is measured in the BHPS for those who provide care in 10 categories: 0-4 informal care hours per week, 5-9 hours per week, 10-19, 20-34, 35-49, 50-99, 100 or more hours per week, varies under 20 hours, varies 20 hours or more, and some other time.[28] Individuals who do not provide informal care are assigned to a zero hour's category, which is different from the category for individuals who say they provide informal care of 0 to 4 hours.

After experimentation combining categories we collapse the number of hours providing care into three categories: those who do not provide care, those whose responses for the number of hours providing care belong to a category below 20 hours per week (*below20hrs*), and those providing 20 or above the 20 hours per week (*more20hrs*).

In sensitivity analysis, we report models using other informal care specifications. We first include more lags. Second, we try to allow for persistence of care by creating a

[28] We drop 326 individual-wave observations in the "some other times" category which is too vague to be useful.

dummy variable that takes the value 1 if individuals have been providing more (less) than 20 hours of care per week for the past two years. Third, we use the distinction in the BHPS between informal care provided to someone living inside the same household, informal care provided to someone living outside the household, and both types of care provided at the same time. We construct three indicator variables: *careinonly* if the individual only cares for someone who lives in the same household as them, *careoutonly* if the only care provided by the caregiver is to someone outside the household and *careinout* if an individual provides care inside and outside the household.

Spouse characteristics

We also account for spouse characteristics, including whether the individual has one (*marcoup*), since the decision to retire is likely made jointly by couples (see for instance (An et al. (2004), O'Rand Angela (2002), Johnson and Favreault (2001)). We introduce a variable accounting for whether the spouse has any health limitations (*shlltyes*) and another for whether the spouse had a job in the previous year (*lspjb*). Following Jones et al. (2012), we lag *lspjb* by one period to avoid endogeneity problems given that an individual's retirement decision might be influenced by that of their spouse.

Income and wealth

We use household income for all waves of BHPS in which the individual appears and we distinguish between household labour and non-labour income. We use the Consumer Price Index and use the McClement's equivalence scale (McClements, 1977) to adjust income for the price year and for household size. We take logarithm for both income types. To allow for the effect of retirement on income we use the mean of incomes (*mlnhincl* and *mlnhincnl*) across all the waves in BHPS if the individual does not retire. If the individual retires, we take the mean income values up to retirement and use the mean of last year income for the retirement year.

We also account for household net wealth (*mhhnetwealth*). To construct the variable we add assets (total value of investments, house, and vehicles owned) and subtract liabilities (the sum of debts and mortgages). This variable is time-varying and lagged by one period.

We also include variables measuring pension entitlement and housing tenure to further allow for individual wealth. We use the indicator *everppenr* which takes value 1 if an individual has ever made contributions for a private pension, and 0 otherwise; and the indicator *everemppr* for whether the individual has ever belonged to an employer´s pension scheme. We account for whether individuals owned their own home (*lHseOwn*), had a mortgage (*lHseMort*), lived in a privately rented home (*lHseRent*), or in rented public housing (*lHseAuthass*). We lag the housing tenure information one period as it may change once the individual retires.

Other socioeconomic variables

We use a dummy for health limitations of the individual (*hlltyes*). We use the value at wave 1 (*hlltyes0*) to account for baseline or initial health, and its first lag (*lhlltyes*) as it is more likely that past health has an effect on retirement than current health. Any deviation of lagged health from the initial health value can be interpreted as a shock in health (Jones et al., 2012).

Other socioeconomic variables used are the highest education achieved by the individual: degree or higher degree (*deghdeg*), HND or A level (*hndalev*), CSE or O level (*ocse*); individual’s employment sector at wave 1:[29] employed within the private sector (*privcomp0*), within the civic or local government (*civlocgov0*), or in another sector (*jbsecto0*); and we include region dummies (*NorthE, NorthW, SouthE, SouthW, London, Midland, Scot, Wales*). As mentioned in section 3.2.2., we use age dummies to account for duration dependence to account for individuals entering the stock sample at different ages. For instance, a one-year time increase for a 50-year-old individual will have a different effect on retirement compared to a one-year time increase for a 60 year-old person, even if all other of the explanatories are identical.

Table A.1. in the Appendix provides a full description of the variables.

3.4.2 Descriptive statistics

Stock sample

Table 3.4 reports mean characteristics of the stock sample by gender and by retirement status. The differences in the pre- and post-retirement mean reflect the possible effects of retirement *and* of age. These differences could also be, in part, due to trends in the probability that individuals of a given age have certain characteristics. For example, the

[29] We set the employment sector dummies as time-invariant variables because they do not vary much over time by individual. It is also a way to control for other time invariant unobserved factors correlated with employment status.

probability of having a degree, conditional on age, has increased over the period covered by the BHPS.

On average, women are more likely to retire than men. Women participate more in caregiving activities, for instance, almost 22% of women provide informal care for less than 20 hours per week, against 16% of men. There is also a slightly higher proportion of women (5%) providing informal care for more than 20 hours per week than men (4%). Most care by both men and women is provided to individuals living in a different household: 19% of females and 13% of males. Around 6% of men and women provide care for someone living in the same household as them.

Comparing pre- and post-retirement caring activities, Table 3.4 shows that both male and females tend to care and devote more time to caring activities once they retire, with this difference tending to be greater for males than for females. For instance, about 15% of men provide care for less than 20 hours per week before retirement and 18% post retirement. The average number of women providing care for less than 20 hours per week remains around 20% pre and post retirement. Regarding the type of care provided, 4% of males care for someone inside the household before retirement and this percentage increases to about 9% after retirement. For women, the proportion of providing care inside the household increases by about 3% once they retire. 20% of women care for someone living outside the caregiver's household before retiring and this percentage drops to 17% after retirement.

Health limitations increase after retirement. Over 80% of individuals own their home and the proportion owning their home after retirement increases. Around 50% of men and women in our sample do not hold any educational qualification. The proportion of men who have ever made contributions to a private pension and who has received an occupational pension is bigger than for women. Moreover, about half of the sample works in the private sector.

Retirements

Male participants can be at risk of retirement up to 14 periods ($(\alpha_m^U - 1) - \alpha^o$) = 64 – 50), whilst female participants can be at risk of retirement up to 9 periods ($(\alpha_f^U - 1) - \alpha^o = 59 - 50$). **Table 3.5** and **Table 3.6** show the number of retirements in each of years since an individual became at risk. As expected, the number of individuals who retire increases the longer an individual has been at risk with an intermediate peak at the age of 60 ($A=10$) for men. The last column of Table 3.5 shows the probability of retirement at each age which tends to increase over time reaching the maximum value when men have been at risk of retirement for 13 periods. There is a similar profile for the female subsample in Table 3.6 with an intermediate peak at age 55.

Table 3.7 shows the retirement status for men and women by type of care lagged one period. It shows that the majority of observations were for males providing care for someone living in another household (535), while some provided care inside the household (171) and very few provided both types of care at the same time (25). Among those who provided care in the previous period for someone living in the same household, 10.53% retire. The proportion of male carers providing care outside their household who retire before the state pension age is around 6%. The majority of female carers provide care for someone outside the household, and among them almost 5% retired before the state pension age.

Table 3.8 shows the retirement status for men and women by intensity of care lagged one period. Among men who provided some care but for less than 20 hours per week last year, 6.31% decided to retire in the following year, and among males who were providing more than 20 hours of care in the previous period, almost 12% subsequently decided to retire. For women, Table 3.8 shows that most carers provided care for less than 20 hours per week. Among those, approximately 4% decided to retire in the following period. For those who provided 20 or more than 20 hours of care per week, the percentage of retired women increases to almost 11%.

Kaplan-Meier failure functions

Figure 3-1 and **Figure 3-2** present the Kaplan-Meier failure functions:[30] the probability of being retired at $A=a_i(t)-50$ by care intensity lagged one period for males and females. There is little difference for carers and non-carers when the time at risk of retirement is less than 4 years for males. However, for the sample at risk of retirement for 4 years or more, the probability of retirement is greater for individuals who have provided informal care compared to the non-carers, especially when provided care for 20 or more hours per week. For women, there is little difference in the failure curves for

[30] The Kaplan Meier failure function shows the cumulative probability of failure (retirement) conditional on not having retired before for each age, where age is $A=a_i(t)-50$.

non-carers and those providing under 20 hours of care per week. The probability of being retired for women that provided 20 or more weekly hours of care is higher from the age 55 than for those who did not provide any care or provided less than 20 hours a week.

We test for whether the survival function before retirement is homogeneous across the different types and intensity of care. We use two chi-squared tests. The first is the likelihood-ratio test of homogeneity among the categories where categories are either care types or care intensity. The second is the log-rank test for equality of the survivor functions.

Table 3.9 shows the results. When testing homogeneity across the care type variable and the care intensity variable using the likelihood ratio test we cannot reject homogeneity across intensity or across care types at 5% for both males and females. The log-rank test rejects the null hypothesis of homogeneity across the survival functions of the care types at 5% for men but not for women. Using the care intensity categories, we reject equality of the survival functions for both men and women subsample at the 5% significance level.

3.5 Regression results

Table 3.10 shows the results from complementary log-log models, for the male and female subsamples. The reported coefficients are hazard ratios, where, a coefficient greater (smaller) than one indicates that a one unit increase in the corresponding variable implies an increase (decrease) in the risk of retirement. The main variable of interest in each model is care intensity lagged one period, and defined as the number of weekly hours providing care last year being zero, below 20, and at least 20.

Table 3.10 shows that for the male and female subsamples, the hazard of early retirement is higher for individuals who provided any amount of informal care in the past than for those who did not provide any care. The hazard ratio for caring for 20 or more hours per week lagged one period is bigger than one and significant at 10% for males (1.95) and at 5% for females (2.34). Thus, the probability of retirement when providing at least 20 hours of informal care is around twice as high compared with those who do not provide informal care. The effect is higher for females than for males.

Effects of covariates

The effects of the covariates are generally intuitively plausible. Both men and women with heath limitations in the previous year are more likely to retire. Men and women whose spouse or partner has a job in the previous year have a lower hazard. The hazard associated with retirement increases as age increases for both men and women, and the effect and significance of the age dummies get higher as age gets closer to the State Pension Age.

Men who have made contributions to a private pension have a lower probability of early retirement. For men, both labour and non-labour income increases the hazard of retirement. Men working for the civil service or local government are more likely to retire early compared with the self-employed. Regarding the regional dummies, for the males subsample, people living in Wales seem to be more likely to retire before the State Pension Age than those living in the South East of UK or East Anglia (baseline category).

For women, belonging to an employer's pension scheme increases the hazard of retirement as does being married or living with their spouse. Having a house mortgage decreases the likelihood of retirement. Also, females living in North East, South West of England, Scotland and Wales are more likely to opt for early retirement compared with those living in the South East of East Anglia.

3.5.2 Unobserved heterogeneity

If unobserved heterogeneity is present, the coefficients in Table 3.10 will be biased. We would expect to observe larger hazard ratios of those variables with a positive (negative) effect on the hazard of retirement than those presented in Table 3.10.

Table 3.11 reports results from models allowing for unobserved heterogeneity. Column (a) shows the results for the male subsample when the model is estimated using a random effects complementary log-log model. Column (b) presents the results for the male subsample when using the *pgmhaz8* command. *Rho* in column (a) reports the proportion of the total unexplained variation due to unobserved heterogeneity. The Likelihood ratio test shows that we reject the null that unobserved heterogeneity is zero (*rho*=0). The results in column (b) using the *pgmhaz8* command reports the gamma variance and the Likelihood ratio test of the variance being zero. Both models show statistically significant frailty. We observe that the model accounting for frailty in Table

3.11 has a smaller AIC than the non-frailty model in Table 3.10, which indicates a better fit to the data (we cannot use the AIC to compare the frailty model in column (b) of Table 3.11 with the non-frailty model of Table 3.10 because they are based on different distributions). Thus, there is evidence of unobserved frailty for the male sample and the models in column (a) and (b) are preferred to that in Table 3.10 which does not allow for frailty.

Comparing the coefficients in the non-frailty model (in Table 3.10) for the male subsample and the frailty models in columns (a) and (b), we can see that the coefficients have changed in the expected direction: those coefficients corresponding with positive hazard ratios are greater in the frailty model, while the negative ones are smaller.

Accounting for unobserved heterogeneity, the estimated effect of providing 20 hours or more of care on the probability of retirement is now bigger and now statistically significant at 5% level compared to the non-frailty model (Table 3.10). Overall, it is important to account for unobserved heterogeneity in the retirement models for the males' subsample. Whether we assume a normal or gamma distribution for unobserved individual effects the likelihood ratio test for frailty is significant.

Column (c) in Table 3.11 shows the results for random effects complementary log-log model fitted in the female subsample with a normally distributed frailty. In this case, the total unexplained variation due to heterogeneity (*rho*) is very small and we cannot reject the null that unobserved heterogeneity is zero. Comparing the non-frailty model in Table 3.10 and the frailty model in Table 3.11 we see they have very similar estimated coefficients and the AIC favours the non-frailty model. However, the difference in the AIC scores between the two models is very small.

We could not fit the model for females in which the unobserved individual effects are assumed to be gamma distributed because the model estimation procedure did not converge. This usually happens when the model does not have any frailty, as it is looking for a very tiny frailty variance. Since the gamma variance is constrained by the program to be positive there are convergence problems. Jenkins (2008) reports that this is quite common when estimating frailty models in large data-sets.

In summary, it is important to account for unobserved heterogeneity in the male sample, as shown in Table 3.11. However, for the female sample, the non-frailty complementary log-log model in Table 3.10 is preferred as we have not found evidence of unobserved heterogeneity for females. So, it seems there are unobserved individual differences between men carers and non-carers in terms of traits but it does not seem this is the case for females. When comparing the estimated coefficients for the number of hours providing care for more than 20 hours per week for the males' frailty model and for either the females' frailty or non-frailty model, the effect of informal care on retirement is now slightly higher for men than for women.

3.5.3 Sensitivity checks

We carried out several robustness checks for the results presented in Table 3.10 and Table 3.11. Since we have found unobserved heterogeneity for the male subsample all the models for males presented in this section control for frailty using a random effects complementary log-log model with a normal distribution of the unobserved heterogeneity. First, we boost the sample of individuals in two ways: boosting from below, by extending the sample including those individuals who are 34 years old onwards at wave 1, and boosting from above the State Pension Age, by including those individuals who are older than the State Pension Age. Second, we vary the set of explanatory variables and how they enter the model. Third, we use a different definition of retirement to allow for possible ambiguities in the reporting of retirement status by respondents.

Boosting the sample

Table 3.12 compares the original and boosted samples. When boosting from below, we select individuals that at wave 1 are aged 34 and above. Individuals who are 34 years old at wave 1 will be 50 (the age at which individuals enter into risk of retirement) at wave 17 of BHPS and we will have one year of information for those individuals. Similarly, for individuals who are 35 years old at wave 1, we will have 2 years of information once they are 50 at wave 16, and so on. The age range when boosting the sample from below is 34 to 64 for males and 34 to 59 for females. When boosting the sample from above, we include men aged 47 to 70 and women 47 to 65 at wave 1 and so are investigating the effect of informal care on retirement decisions for those below and those above SPA

The number of retirements is greater than in the benchmark sample when boosting the sample from above and below. As expected, the proportion of retirements is lower when boosting the sample from below than in the benchmark case. When boosting the sample from above we have a higher proportion of retirements, as the extra individuals considered are around or above the retirement age. Compared to the benchmark case, there are about 23% more male retirements and 42% more for women when boosting the sample from above.

Table 3.13 shows the estimation results for men and women when boosting the sample. The first two columns have the estimation results when boosting the sample including individuals from the age of 34 and above. The last two columns are the estimation results when boosting from above. The estimations control for unobserved heterogeneity through a panel data complementary log-log model with the unobserved heterogeneity following a normal distribution. We only present the coefficients of interest regarding the care intensity (caring below or above 20 hours per week) and the age dummies.

The hazard ratio for caring for less than 20 hours per week remains insignificantly different from one. In the case of males and for both ways of boosting the sample, the effect of providing at least 20 hours is positive and significant at 5%. However, the hazard ratio is higher (3.35) when boosting from below and lower (1.83) when boosting from above than in the benchmark case in Table 3.11 (2.60).

In the female subsample, the coefficients for number of hours providing care are not significant once we extend our sample irrespective of the method for boosting the sample).

The age dummies have the expected sign. When boosting the sample from above the effect of age on the hazard of retirement is peaks at the male SPA and subsequently remains higher than before SPA.

As in the benchmark model, there is no evidence of unobserved heterogeneity for the females subsample but there is for males.

Different length of lags and cumulative care

We first investigate whether retirement is affected by care lagged over a longer time period. We first add to our main model the variables *l2below20hrs* and *l2more20hrs* to capture whether an individual was providing care for less or at least for 20 hours per week two years ago (extensions with more lags produce similar results). Since we are introducing another lag we drop the age dummy 52.

Results in **Table 3.14** show that the amount of caring two years ago, does not have a significant effect on the probability of retirement. However, caring for 20 or more hours per week last year remains significant. The age dummies have a similar pattern of significance and impact on the probability of retiring to our main model.

We also test whether the persistence of care affects retirement. We define two variables: *l1l2more20hrs* which is a dummy variable that takes the value one if an individual has been providing care for 20 or more hours per week for both of the previous two years.[31] The other variable is *carecumulhrs*, a dummy variable that takes value one if an individual has been caring for two consecutive years in any of the following combinations: caring for less than 20 hours last year and two years ago, caring for 20 or more than 20 hours last year and two years ago, caring for less than 20 hours the previous year and for 20 or more than 20 hours two years ago, and caring for 20 or more than 20 hours last year and for less than 20 two years ago.

Table 3.15 provides the results when introducing the variable *l1l2more20hrs*. For males, having cared for two consecutive years in the past for 20 or more than 20 hours per week decreases the likelihood of retirement, but this effect is not significant. For females, the coefficient and standard error for *l1l2more20hrs* are implausibly large, possibly because of the few female observations providing this type of care.

Table 3.16 shows the results when introducing the variable *carecumulhrs*. The hazard of retirement increases for males and females caring for two consecutive years in the past in any combination form (less and (or) more than 20 hours a week). However, none of those results are significant.

Different measures of informal care

We also experimented with other measures of informal care. First, we define a dummy variable that takes the value one if an individual reports to care for someone and zero otherwise and take the first and second lag of this variable. Second, we define more specific variables regarding the type of care, and construct three (1, 0) dummy variables for whether individuals report to be caring for someone that lives inside the same household, whether caring for someone that lives in another household different from the informal carer's household, and whether the individual provides care for both

[31] We create this variable only for caring for 20 or more hours as this variable is significant in the main model.

persons living in and out the informal carer's household. We take the first and second lag of each one. Similarly, as before, we also include variables accounting for the care persistence: *l1l2care* which takes the value one if the individual has been providing any form of informal care for two consecutive years and is zero otherwise.

Table 3.17 shows the results. Type of care seems not to have an effect on the probability of retirement for males or for females. We do not find significant of care persistence (*l1l2care*). It seems that the type of care and the mere fact of providing care for someone does not influence to the decision of an early retirement. As we have seen in our main model, it is the intensity of care that has an impact on the individual's retirement decisions.

Birthdays

We expect an individual's actual age to affect retirement. However, our age variable is measured in terms of interview wave. Consider a scenario where an individual decides to retire on his 55^{th} birthday, which falls between two interviewed dates. The retirement will be recorded at the second time of the interviews. The time elapsed between the retirement decision and the following interview can make a difference on the probability of retirement. We would expect that individuals that have birthdays later in the year between interviews to have a lower probability of retirement by the end of the year (the next time they are interviewed) than those who had their birthdays at the beginning of the year for whom the time elapsed until that day and the next interview is bigger. To allow for this, we create the variable *difbthday* accounting for the number of days between the last interview and the next birthday using the information in BHPS.

Table 3.18 shows the results when introducing the variable *difbthday* in our main model. As expected, the coefficient for number of days until next birthday reduces the hazard of retirement. However, the hazard ratio coefficient is not significant and is very close to one.

Calendar year dummies

We next introduce calendar year effects to allow for secular changes including macroeconomic factors which affect expectations about future income streams. We collapse the 18 years of BHPS into three time intervals and create three time dummy variables: one for waves occurring between 1991 and 1995 (wave 1 until wave 5 in

BHPS), another for 1996 to 2000, and another for waves occurring 2001 and 2008 (reference category).

Table 3.19 shows that the inclusion of these variables does not affect the estimated positive effects of informal care on the hazard of retirement. The coefficients for the time dummies show that during 1991-1995 and 1996-2000 the hazard of retirement was higher than in the period 2001-2008 for men given their age and other characteristics. For women the hazards were smaller in the two earlier periods. However, none of the effects are significant for men or women. This may be because real GDP growth for the period 1991 – 2008 was quite stable[32] as such, it may be reasonable to assume this explains the lack of variability in the retirement trends over time. There were also no major changes in the State Pension scheme during the period 1991 to 2008.

Other explanatory variables (wealth, work full / part time) and interactions

We also experimented with other explanatory variables. For instance, we wanted to account for household net wealth. Therefore, we constructed the variable *netwealth* which captures the difference between assets (the sum of investments, house value and vehicles) and liabilities (the sum of debts and mortgages). Unfortunately, the variables that are used to construct net wealth are missing in some of the BHPS waves. To circumvent this issue, we calculate the mean net wealth for each individual, so that it is time-invariant. We then introduce this variable to the model first without taking logarithms, and in a second try taking the logarithm of mean net wealth. We also try other specifications like taking the lag value of the mean for *netwealth* and the lag value of the logarithms. The coefficient for *netwealth* in all the above specifications is very close to one. The lack of an effect of *netwealth* in our model may be because we have other variables correlated with it such as education, housing tenure, and non-labour income.

We also investigate whether working full or pat-time affects individual's retirement decision and the inference of caring on retirement. We create a dummy variable that equals one if an individual works full time, and zero if works part time. However, when we introduce this variable to our main model, it is insignificant. We also interact the

[32] Office for National Statistics. Real GDP growth year-on-year, UK, 1980 to 2014: Second estimate GDP, Q1 2015, Table A1.

variable with the number of hours providing care and find no significant changes in the effect of caring.

We also investigated interactions between age and the number of hours providing care. The idea is to test whether older individuals that are providing informal care are more likely to retire because its greater burden. We define an age variable which takes the value 1 if their age is above the State Pension Age, and zero otherwise, and we interact that variable with the weekly number of hours providing care below and above 20. We estimate this model for the sample boosted from above the SPA but we do not find any significant effect.

Definition of retirement

As labour market status is self-reported in BHPS, it might be the case that individuals miss-report. For instance, an individual who became unemployed when close to the State Pension Age might keep reporting to be unemployed as his employment status even when reaching retirement age. To allow for this occurring, we construct a dependent variable *exit* and which include individuals that report to be retired or unemployed in a given period of time.

Table 3.20 presents the estimation results. As the table shows, when using a looser definition of retirement, the hazard of dropping from the labour market increases when caring for 20 or more hours per week. However, this effect is only significant for women and only at 10%.

We have also tried a model where exit from the labour market also includes whether the individual reports to be long term sick or disabled, and the results are very similar to the model provided here.

3.6 Conclusion

In this chapter, we studied the impact of providing informal care in the previous year on the current decision to retire before the State Pension Age for men and women in the UK. In the UK, individuals between the age of 50 and 64 constitute the bulk of carers and may include some people who carry out caring duties alongside participation in the labour market. Combining both activities can be hard and lead to retirement before the UK SPA if the burden of the informal care provision is high. Equally, individuals in this situation may decide to remain in the labour market to offset the extra expenses and possible emotional costs of providing informal care. We examined the impact of intensity of care provision in the previous year on retirement, as it is more likely that the decision to retire is influenced more by past caregiving activities than by the current individual's caregiving situation.

We used estimated complementary log-log discrete-time duration models controlling for the number of weekly hours providing care last year and other explanatories. Our results indicate that the rate of early retirement is higher for those caring in the previous year than for non-carers and economically and statistically significant for men and women who provided 20 or more hours of informal care: the rate of early retirement is doubled. The probability of retirement when caring for 20 or more hours per week is higher for men than for women. Our results are robust to a number of alternative specifications such as allowing for unobserved time invariant individual effects, considering retirement after the SPA, alternative measures of informal care, and allowing for effects to change with calendar time.

Our finding that caring affects retirement for females is in accordance with the literature. For males, results in the literature are mixed. Our results are in accordance with Meng (2012) who using German data, also finds a higher retirement rate when the intensity of care is above 20 hours per week.

Our results suggest that greater support for informal carers at work might affect their labour supply at the extensive margin of retirement decisions. In the UK, only 34% of employers have a formal written policy or informal verbal policy to support informal carers in their workplace, and only 20% are aware of how many of their workers have informal care duties after work[33].

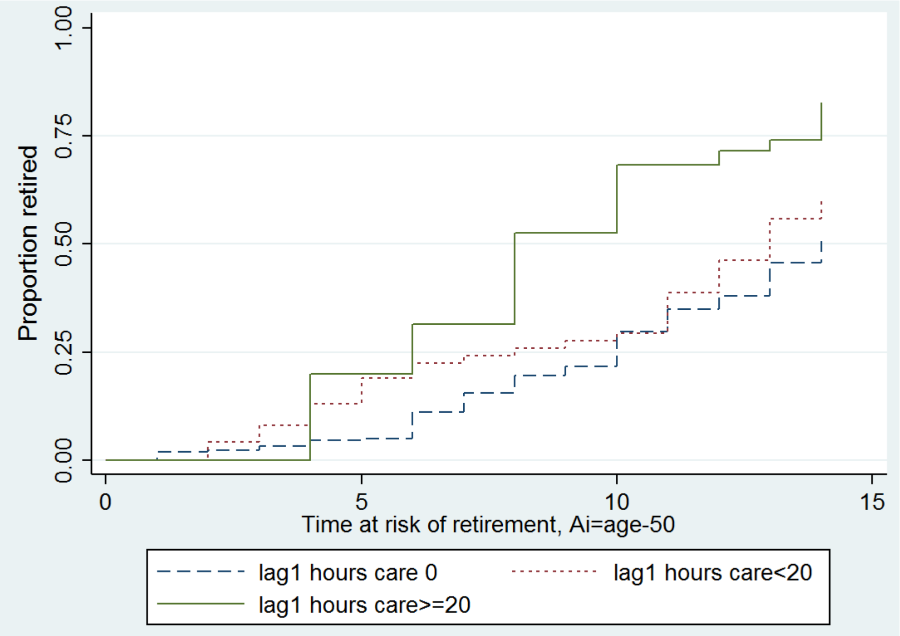
Most of the existing literature on retirement which uses longitudinal data only examines exits from employment to retirement (Dentinger and Clarkberg, 2002, Jones et al., 2010, Meng, 2012). An extension for future work would be to use a competing risk duration model (Jenkins, 2008) to allow for different types of exits from employment or self-employment, in addition to retirement. For instance, we could consider the time to exit from employment to unemployment and estimate additional hazard functions for time to exit by unemployment as well for exit by retirement. Schils (2008) for instance, uses a

[33] CIPD/Westfield Health (2016) Creating an Enabling Future for Carers in the Workplace. Available at: https://www.cipd.co.uk/knowledge/culture/well-being/enabling-carers

competing risk duration model where the alternatives are exiting to retirement and exiting to social security. However, most of the procedures to estimate competing risk models assume that the different types of exits are independent from each other. For discrete-time data, this assumption only holds when time is intrinsically discrete and the model is estimated by maximum likelihood using a multinomial logit model.

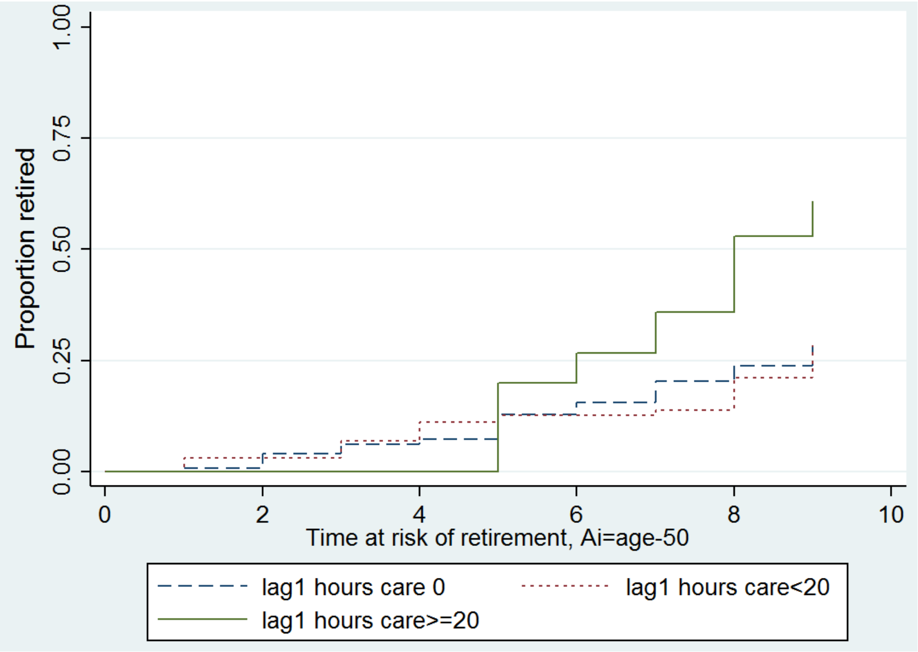
FIGURES

Figure 3-1 Kaplan Meier failure function over time by lagged care intensity. Males



Note: Kaplan Meier failure function is the cumulative probability of failure (retirement) at time $A_i = age - 50$ for the average individual not providing care, providing care for 20 or more than 20 hours per week, or for less than 20 hours a week who was not retired at $A_i - 1$.

Figure 3-2 Kaplan Meier failure function over time by lagged care intensity. Females



Note: Kaplan Meier failure function is the cumulative probability of failure (retirement) at time $A_i = age - 50$ for the average individual not providing care, providing care for 20 or more than 20 hours per week, or for less than 20 hours a week who was not retired at $A_i - 1$.

TABLES

Table 3.1 Existing literature on the impact of informal care on retirement

Existing literature	Van Houtven *et al*. (2013)	Jacobs *et al.* (2014)	Dentinger and Clarkberg (2002)	Meng (2012)	Schils (2008)	Jacobs, Laporte, Van Houtven, and Coyte (2014)
Data	Health and Retirement Study (American longitudinal). Men&Women aged 50-70.	American National Longitudinal Survey of Mature Women. Aged 30-44 and 50-64.	1994-1995 Cornell Retirement and Well-being Study (US). Men&Women aged 50-72.	German Socio-Economic Panel (GSOEP). Men&Women aged 58-64.	GSOEP (1990-2005), SEP for Netherlands (1990-2001), and BHPS (1991-2004). Men&Women aged 50-65.	Canadian 2007 General Social Survey. Men&Women aged 55-69
Retirement definition	Self-assessed retirement and hours worked.	Self-assessed retirement and working zero hours.	Any exit from paid work enabling to get any pension package.	If individual drops out the labour market and receive a public pension.	Duration in employment after age 50.	Self-assessed retirement, retired and return to work, never retired and working, not working.
Informal care (IC) variables	Whether caregiver and intensity of care over the last 2 previous years.	Caregiver and intensity of care at current time.	Caring for more than 1 receiver, whether receiver in or out household, and who the care receiver is. Current time variables.	Whether provided care last year and the hours of care provided.	Having children or family members in need of care.	Average weekly number of hours providing care over past 12 months: <5, 5-14.9, or ≥15.
Allow for endogeneity of IC	Yes, through IV approach. IVs: parental help with ADL and whether parent died or widowed.	Yes, through IV approach. IVs: whether parent died over the past 2 years and whether parent is single or widowed.	No.	No.	No.	No.

Estimation method	2 Stage Least Square of Linear Probability Model with fixed effects for men and women subsamples.	2 Stage Least Square of Linear Probability Model with fixed effects.	Duration model. Complementary log-log regressions for men and women.	Duration model. Complementary log-log model for men and women.	Discrete-time competing risks model. Log-likelihood estimation	Multinomial logit model. Maximum Likelihood estimation. Compute relative risk ratios.
Results	No endogeneity. IC increases the probability of being retired for women. No effects on the probability of retirement for males.	No endogeneity. Intensity of care only impacts females' retirement if care exceeds 20 hours per week.	All IC variables decrease retirement odd ratios for men carers compared to men non-carers. Caring for the spouse increases likelihood of retirement for women carers vs non-carers.	Providing care the year before retirement increases probability of current retirement for women. The intensity of the care provision increases the rate of retirement for men.	Having children or family members in need of care decreases the probability of retirement in the same time period.	Men and women caring for <5 hours per week and men who care for ≥15 hours have a higher probability of being retired.

Table 3.2 Notation

t	Year (BHPS wave) (1991 is the year of first BHPS wave)
$a_i(t)$	age of i at year t
a_i^B	age at which i first ever enter at the labour market.
α^o	lowest age to contribute observations
$\alpha^U - 1$	highest age to contribute observations: observations for i dropped at and after the wave t for which $a_i(t) = \alpha^U$
t_i^o	first year (wave) in which i included in sample
$a_i(t_i^o) \geq \alpha^o$	age at which first contribute observations.
t_i^L	last year (wave) in which i included in sample
$t_i^L - t_i^o -1$	number of observations contributed by i
δ_i	dummy = 1 if i retires (completed spell), 0 otherwise
T_i	year in which i retires
$h_{iA} = \Pr\left[T_i = A \middle\vert T_i \geq A; X_{iA}\right]$	hazard rate
X_{iA}	Explanatories
t_i^B	year in which i first at risk (enters labour market)
S_{iA}	probability that i survives (does not retire) before A

Table 3.3 Conditions to create the stock sample

1. To be interviewed and to provide a full interview in wave 1.
2. Be aged $a_i(1) \in [\alpha^o - 17,\ \alpha^U - 1]$ in wave 1.
3. Be employed or self-employed in wave 1.
4. To be in all waves in BHPS until wave in which report retirement or until lost to follow up.

Table 3.4 Summary statistics

	Male			Female		
Variable	**All**	**Pre-retirement**	**Post-retirement**	**All**	**Pre-retirement**	**Post-retirement**
Retired	0.362	0	1	0.414	0	1
Below20hrs	0.158	0.147	0.179	0.210	0.217	0.200
Above20hrs	0.036	0.027	0.051	0.053	0.046	0.062
Careinonly	0.056	0.040	0.085	0.064	0.054	0.078
Careoutonly	0.132	0.132	0.133	0.191	0.203	0.172
Careinoutd	0.009	0.006	0.015	0.013	0.011	0.015
Hlltyes	0.150	0.111	0.223	0.162	0.136	0.202
Shlltyes	0.169	0.153	0.198	0.149	0.140	0.162
Lspjb	0.431	0.590	0.189	0.380	0.555	0.169
Everppenr	0.461	0.536	0.349	0.296	0.350	0.230
Everemppr	0.597	0.594	0.601	0.430	0.446	0.406
HseOwn	0.539	0.407	0.773	0.564	0.436	0.745
HseMort	0.308	0.429	0.096	0.270	0.392	0.098
HseRent	0.054	0.071	0.025	0.034	0.046	0.016
HseAuthAss	0.098	0.093	0.106	0.132	0.125	0.141
Mlnhincl	9.447	9.465	9.414	9.197	9.266	9.100
Mlnhincnl	7.479	7.378	7.656	7.781	7.696	7.901
Mnetwealth	10.898	10.891	10.910	10.887	10.869	10.912
Privcomp0	0.526	0.515	0.544	0.479	0.490	0.464
Civlocgov0	0.125	0.111	0.151	0.231	0.225	0.239
Jbsecto0	0.099	0.092	0.110	0.194	0.191	0.198
Marcoup	0.867	0.890	0.828	0.755	0.797	0.696
Deghdeg	0.081	0.083	0.076	0.064	0.071	0.055
Hndalev	0.204	0.214	0.188	0.124	0.128	0.119
Ocse	0.222	0.223	0.219	0.271	0.276	0.265
NorthE	0.137	0.128	0.152	0.140	0.133	0.151
NorthW	0.087	0.092	0.079	0.104	0.097	0.112
SouthW	0.117	0.114	0.123	0.117	0.106	0.132
London	0.084	0.103	0.052	0.100	0.122	0.070
Midland	0.186	0.193	0.173	0.165	0.175	0.150
Scot	0.066	0.067	0.065	0.078	0.077	0.080
Wales	0.045	0.039	0.057	0.050	0.042	0.061

Table 3.5 Number of retirements between age 50 and 64. Males

A= a(t) - 50	Not retired	Retired	Total	Probability retirement
1	202	3	205	0.0146
2	227	2	229	0.0087
3	267	4	271	0.0148
4	298	8	306	0.0261
5	315	4	319	0.0125
6	315	21	336	0.0625
7	319	14	333	0.0420
8	320	18	338	0.0533
9	318	11	329	0.0334
10	304	32	336	0.0952
11	279	26	305	0.0852
12	269	17	286	0.0594
13	250	37	287	0.1289
14	232	25	257	0.0973
Total	3,915	222	4,137	0.0537

Note: Observations from the stock sample on individuals who are not retired at the beginning of the year.

Table 3.6 Number of retirements between age 50 and 59. Females

Analysis time A=a(t) – 50	Not retired	Retired	Total	Probability retirement
1	180	2	182	0.0110
2	207	5	212	0.0236
3	230	6	236	0.0254
4	245	5	250	0.0200
5	249	15	264	0.0568
6	271	7	278	0.0252
7	282	16	298	0.0537
8	279	19	298	0.0638
9	260	21	281	0.0747
Total	2,203	96	2,299	0.0418

Note: Observations from the stock sample on individuals who are not retired at the beginning of the year.

Table 3.7 Retirement by care type lagged 1 period

	Retirement status	No care	Care in	Care out	Care in&out	Total
Males	Not retired	3,175	153	501	24	3,853
	Retired (%)	167 (5.00%)	18 (10.53%)	34 (6.36%)	1 (4.00%)	220 (5.40%)
	Total	3,342	171	535	25	4,073
Females	Not retired	1,582	104	481	30	2,197
	Retired (%)	62 (3.77%)	8 (7.14%)	23 (4.56%)	2 (6.25%)	95 (4.14%)
	Total	1,644	112	504	32	2,292

Note: Number of observations in the stock sample by retirement status and care type.

Table 3.8 Retirement by care intensity lagged 1 period

	Retirement status	Zero hrs	Below 20hrs	Above 20hrs	Total
Males	Not retired	3,158	549	96	3,803
	Retired (%)	166 (5.00%)	37 (6.31%)	13 (11.93%)	216 (5.37%)
	Total	3,324	586	109	4,019
Females	Not retired	1,567	503	90	2,160
	Retired (%)	61 (3.75%)	20 (3.82%)	11 (10.89%)	92 (4.09%)
	Total	1,628	523	101	2,252

Note: Number of observations in the stock sample by retirement status and care intensity.

Table 3.9 Tests for homogeneity of groups and equality of survival functions.

Test chi2 (pvalue)	Group: Care type (no care, in, out, in&out)		Group: Care intensity (no care, <20hrs week, >20hrs week)	
	Males	Females	Males	Females
Likelihood-ratio	6.78 (0.08)	2.14 (0.545)	4.52 (0.104)	5.49 (0.064)
Log-rank	8.34 (0.04)	3.47 (0.324)	8.99 (0.011)	11.27 (0.004)

Note: Likelihood-ratio Ho: homogeneity between categories within each group (care type and care intensity). Log-rank test Ho: homogeneity of survival function between categories of group.

Table 3.10 Estimation results. Complementary log-log models for the probability of retirement.

Variables	Males		Females	
L1below20hrs	1.331	(0.262)	1.076	(0.288)
L1more20hrs	1.951*	(0.682)	2.335**	(0.886)
Lhlltyes	2.598***	(0.571)	2.944***	(0.857)
Hlltyes0	0.408***	(0.137)	0.423**	(0.189)
Shlltyes	0.774	(0.165)	0.618	(0.244)
Lspjb	0.699**	(0.126)	0.517**	(0.181)
Everppenr	0.523***	(0.0857)	0.666	(0.177)
Everemppr	1.259	(0.271)	1.706*	(0.504)
LhseMort	0.807	(0.130)	0.523**	(0.129)
LhseAuthAss	0.699	(0.215)	0.474*	(0.195)
LhseRent	0.397*	(0.190)	0.177*	(0.171)
Mlnhincl	1.611***	(0.273)	0.995	(0.268)
Mlnhincnl	1.167**	(0.101)	1.187	(0.140)
Privcomp0	1.307	(0.354)	0.462**	(0.186)
Civlocgov0	2.572***	(0.831)	0.499	(0.207)
Jbsecto0	1.282	(0.448)	0.593	(0.285)
Marcoup	0.98	(0.278)	2.363**	(1.006)
Deghdeg	0.95	(0.282)	0.642	(0.358)
Hndalev	0.947	(0.177)	0.97	(0.338)
Ocse	1.103	(0.218)	0.929	(0.253)
NorthE	1.282	(0.299)	3.165***	(1.391)
NorthW	0.911	(0.251)	2.167	(1.089)
SouthW	0.784	(0.211)	2.533**	(1.135)
London	0.509**	(0.157)	1.806	(0.901)
Midland	0.972	(0.227)	2.483**	(1.017)
Scot	0.828	(0.308)	4.599***	(2.412)
Wales	2.042**	(0.599)	5.627***	(2.832)
Age52	0.889	(0.726)	2.462	(2.067)
Age53	0.775	(0.635)	2.194	(1.853)
Age54	1.57	(1.092)	2.294	(1.893)
Age55	0.788	(0.604)	4.953**	(3.813)
Age56	4.236**	(2.636)	2.801	(2.244)
Age57	2.786	(1.790)	3.892*	(3.018)

Age58	3.151*	(1.986)	5.789**	(4.366)
Age59	1.725	(1.163)	5.621**	(4.279)
Age60	6.339***	(3.885)		
Age61	5.235***	(3.292)		
Age62	4.042**	(2.561)		
Age63	10.43***	(6.337)		
Age64	8.133***	(5.074)		
Constant	6.14e-05***	(0.0001)	0.00231**	(0.006)
Observations	3,688		2,095	
Log-likelihood	-666,392		-316,522	
AIC	1,414.785		705.0445	

Note: Reported results are hazard ratios (exp(β)). Robust Standard Errors of hazard ratios in parentheses. Number of observations is individual-year observations. *** p<0.01, ** p<0.05, * p<0.1 on Ho:exp(β)=1.

Table 3.11 Estimation results for the probability of retirement controlling for unobserved heterogeneity.

Variables	**Males**				**Females**	
	(a) Random Effects clog-log		(b) pgmhaz8		(c) Random Effects clog-log	
L1below20hrs	1.45	(0.331)	1.483*	(0.342)	1.076	(0.283)
L1more20hrs	2.605**	(1.134)	2.885**	(1.293)	2.335**	(0.826)
Lhlltyes	3.820***	(1.216)	4.063***	(1.225)	2.944***	(0.845)
Hlltyes0	0.341**	(0.166)	0.378**	(0.178)	0.423**	(0.191)
Shlltyes	0.781	(0.214)	0.791	(0.207)	0.618	(0.235)
Lspjb	0.652**	(0.137)	0.646**	(0.135)	0.517**	(0.179)
Everppenr	0.427***	(0.098)	0.412***	(0.0917)	0.666	(0.168)
Everemppr	1.517	(0.453)	1.606	(0.504)	1.706*	(0.500)
LhseMort	0.758	(0.162)	0.773	(0.162)	0.523**	(0.129)
LhseAuthAss	0.523	(0.209)	0.470*	(0.203)	0.474*	(0.191)
LhseRent	0.310**	(0.186)	0.318**	(0.181)	0.177*	(0.177)
Mlnhincl	1.686***	(0.369)	1.575**	(0.299)	0.995	(0.254)
Mlnhincnl	1.234**	(0.127)	1.233**	(0.118)	1.187	(0.144)
Privcomp0	1.41	(0.476)	1.401	(0.484)	0.462**	(0.179)
Civlocgov0	3.482***	(1.516)	3.536***	(1.596)	0.499	(0.202)
Jbsecto0	1.413	(0.649)	1.488	(0.698)	0.593	(0.275)
Marcoup	0.83	(0.310)	0.819	(0.286)	2.363**	(1.030)
Deghdeg	0.952	(0.363)	0.896	(0.371)	0.642	(0.351)

Hndalev	1.049	(0.284)	1.055	(0.291)	0.97	(0.347)
Ocse	1.261	(0.357)	1.326	(0.373)	0.929	(0.254)
NorthE	1.418	(0.462)	1.481	(0.497)	3.165***	(1.368)
NorthW	0.886	(0.333)	0.958	(0.357)	2.167	(1.100)
SouthW	0.755	(0.282)	0.789	(0.287)	2.533**	(1.127)
London	0.449*	(0.204)	0.476*	(0.203)	1.806	(0.883)
Midland	1.014	(0.321)	1.074	(0.342)	2.483**	(1.000)
Scot	0.747	(0.367)	0.712	(0.338)	4.599***	(2.464)
Wales	2.304**	(0.884)	2.194*	(0.976)	5.627***	(2.652)
age52	0.874	(0.707)	0.885	(0.732)	2.462	(2.065)
Age53	0.782	(0.676)	0.778	(0.642)	2.194	(1.861)
Age54	1.847	(1.365)	1.804	(1.271)	2.294	(1.883)
Age55	0.891	(0.719)	0.863	(0.673)	4.953**	(3.820)
Age56	5.655***	(3.805)	5.354***	(3.431)	2.801	(2.237)
Age57	3.930**	(2.752)	3.688**	(2.439)	3.892*	(2.019)
Age58	4.828**	(3.381)	4.484**	(2.957)	5.789**	(4.436)
Age59	2.676	(1.990)	2.506	(1.754)	5.621**	(4.303)
Age60	11.48***	(8.249)	10.73***	(7.108)		
Age61	10.05***	(7.386)	9.482***	(6.484)		
Age62	7.719***	(5.757)	7.308***	(5.094)		
Age63	22.13***	(16.360)	21.09***	(14.578)		
Age64	19.86***	(15.42)	19.67***	(14.404)		
Constant	1.12e-05***	(0.00003)			0.00231**	(0.006)
Log-likelihood	-661.454		-660.762		-316.522	
Observations	3,688		3,688		2,095	
Rho/Gamma Var	0.4907	(0.126)	1.531	(0.595)	0.00231	(0.00564)
Likelihood-ratio test (pvalue)	9.88	(0.001)	11.26	(0.00396)	5.40E-05	(0.497)
AIC	1406.907		1405.523		707.0446	

Note: Reported results are hazard ratios (exp(β)). Robust Standard Errors of hazard ratios in parentheses. Number of observations is individual-year observations. Ho for Likelihood-ratio test is no unobserved heterogeneity i.e. rho=0 or gamma variance=0. *** p<0.01, ** p<0.05, * p<0.1 on Ho:exp(β)=1.

Table 3.12 Comparison across samples

	Benchmark case		Boosting from below		Boosting from above	
	Men	**Women**	**Men**	**Women**	**Men**	**Women**
Age range	47-64	47-59	34-64	34-59	47-70	47-65
Observations that meet criteria	4,137	2,299	7,402	5,409	4,725	3,387
Number of individuals	652	440	1193	995	703	548
Number of retirements (single failure per subject)	222	96	303	191	404	348
Proportion of retired individuals	0.34	0.218	0.254	0.192	0.575	0.635

Table 3.13 Random effects complementary log-log model with unobserved heterogeneity. Probability of retirement. Different samples.

	Boosting sample from below (34+))				Boosting sample from above (SPA +)			
Variables	**Males**		**Females**		**Males**		**Females**	
l1below20hrs	1.134	(0.237)	0.888	(0.179)	1.159	(0.198)	1.029	(0.163)
l1more20hrs	3.347***	(1.236)	1.369	(0.475)	1.833**	(0.533)	1.211	(0.322)
age52	1.524	(0.749)	1.540	(0.681)	0.902	(0.738)	2.452	(2.054)
age53	1.381	(0.704)	2.019*	(0.859)	0.765	(0.626)	2.133	(1.787)
age54	1.280	(0.710)	2.233*	(0.953)	1.657	(1.149)	2.314	(1.893)
age55	2.377*	(1.181)	3.495***	(1.432)	0.810	(0.622)	5.024**	(3.808)
age56	6.632***	(3.176)	2.020	(0.924)	4.502**	(2.805)	2.661	(2.109)
age57	5.776***	(2.910)	3.175***	(1.377)	3.035*	(1.951)	3.824*	(2.930)
age58	8.318***	(4.345)	4.389***	(1.940)	3.485**	(2.213)	5.619**	(4.210)
age59	4.625***	(2.587)	5.243***	(2.441)	1.917	(1.296)	6.783**	(5.064)
age60	18.35***	(10.27)			7.204***	(4.484)	30.67***	(22.45)
age61	14.73***	(8.749)			6.135***	(3.926)	17.39***	(13.12)
age62	11.81***	(7.231)			4.874**	(3.163)	17.67***	(13.43)
age63	35.36***	(22.25)			12.18***	(7.623)	15.03***	(11.63)
age64	35.34***	(24.31)			10.23***	(6.585)	21.13***	(16.50)
age65					68.85***	(44.93)	49.86***	(39.76)
age66					36.28***	(25.16)		
age67					25.58***	(18.88)		
age68					19.94***	(15.69)		
age69					17.40***	(13.91)		
age70					41.14***	(32.66)		
L-R test pvalue	0.00		0.204		0.020		0.258	

Note: Reported results are hazard ratios (exp(β)). Robust Standard Errors of hazard ratios in parentheses. Number of observations is individual-year observations. Models also contain covariates. Ho for Likelihood-ratio (L-R) test is no unobserved heterogeneity i.e. rho=0 *** p<0.01, ** p<0.05, * p<0.1 on Ho:exp(β)=1.

Table 3.14 Random effects complementary log-log models. Probability of retirement. Different lag lengths

	Lag 2 informal care hours			
Variables	**Males**		**Females**	
l2below20hrs	0.910	(0.271)	1.163	(0.372)
l1below20hrs	1.488	(0.431)	1.084	(0.360)
l2more20hrs	1.030	(0.646)	0.757	(0.417)
l1more20hrs	3.236**	(1.873)	2.631**	(1.146)
age53	0.794	(0.981)	1.927	(1.225)
age54	4.785*	(4.091)	1.799	(1.095)
age55	2.886	(2.649)	3.719**	(1.967)
age56	16.74***	(13.95)	1.867	(1.105)
age57	11.92***	(10.39)	2.389	(1.330)
age58	14.60***	(12.94)	4.056***	(2.099
age59	6.566**	(6.214)	4.213***	(2.191)
age60	41.31***	(38.49)		
age61	36.12***	(35.28)		
age62	26.43***	(26.04)		
age63	78.01***	(78.23)		
age64	77.60***	(82.01)		
L-R test pvalue	0.001		0.498	
Observations	3,173		1,795	

Note: Reported results are hazard ratios (exp(β)). Robust Standard Errors of hazard ratios in parentheses. Number of observations is individual-year observations. Models also contain covariates. Ho for Likelihood-ratio (L-R) test is no unobserved heterogeneity i.e. rho=0 *** p<0.01, ** p<0.05, * p<0.1 on Ho:exp(β)=1.

Table 3.15 Random effects complementary log-log models. Probability of retirement. Care persistence >20 hours.

	Care persistence for caring > 20hrs			
Variables	**Males**		**Females**	
l2below20hrs	0.894	(0.268)	1.211	(0.418)
l1below20hrs	1.485	(0.429)	1.111	(0.398)
l2more20hrs	1.454	(1.244)	3.41e-07***	(1.20e-07)
l1more20hrs	3.787**	(2.409)	1.765	(0.956)
l1l2more20hrs	0.542	(0.614)	5.445e+06***	(3.824e+06)
age53	0.798	(0.987)	1.937	(1.259)
age54	4.892*	(4.191)	1.801	(1.114)
age55	2.915	(2.679)	3.710**	(2.047)
age56	16.94***	(14.13)	1.826	(1.117)
age57	12.12***	(10.59)	2.317	(1.319)
age58	14.73***	(13.07)	3.950***	(2.084)
age59	6.652**	(6.299)	4.385***	(2.384)
age60	41.75***	(38.89)		
age61	36.53***	(35.66)		
age62	26.55***	(26.14)		
age63	78.73***	(78.88)		
age64	78.80***	(83.20)		
L-R test pvalue	0.001		No frailty assumption	
Observations	3,173		1,795	

Note: Reported results are hazard ratios (exp(β)). Robust Standard Errors of hazard ratios in parentheses. Number of observations is individual-year observations. Models also contain covariates. Ho for Likelihood-ratio (L-R) test is no unobserved heterogeneity i.e. rho=0. Regression for females is estimated without unobserved heterogeneity as otherwise, convergence is not achieved *** p<0.01, ** p<0.05, * p<0.1 on Ho:exp(β)=1.

Table 3.16 Random effects complementary log-log models for the probability of retirement. Care persistence <20 and >20 hours.

	Care persistence for caring<20 and caring>20			
Variables	**Males**		**Females**	
l2below20hrs	0.773	(0.336)	1.316	(0.556)
l1below20hrs	1.335	(0.477)	1.21	(0.499)
l2more20hrs	0.861	(0.618)	0.866	(0.544)
l1more20hrs	2.794	(1.791)	2.952**	(1.491)
carecumulhrs	1.393	(0.858)	0.775	(0.463)
age53	0.798	(0.986)	1.909	(1.214)
age54	4.685*	(4.004)	1.803	(1.098)
age55	2.867	(2.629)	3.721**	(1.967)
age56	16.62***	(13.82)	1.856	(1.099)
age57	11.72***	(10.20)	2.368	(1.318)
age58	14.35***	(12.69)	4.057***	(2.099)
age59	6.422**	(6.063)	4.204***	(2.187)
age60	40.55***	(37.64)		
age61	35.18***	(34.26)		
age62	25.90***	(25.44)		
age63	75.87***	(75.82)		
age64	75.96***	(79.91)		
L-R test pvalue	0.001		No frailty assumption	
Observations	3,173		1,795	

Note: Reported results are hazard ratios (exp(β)). Robust Standard Errors of hazard ratios in parentheses. Number of observations is individual-year observations. Models also contain covariates. Ho for Likelihood-ratio (L-R) test is no unobserved heterogeneity i.e. rho=0. Regression for females is estimated without unobserved heterogeneity as otherwise, convergence is not achieved *** p<0.01, ** p<0.05, * p<0.1 on Ho:exp(β)=1.

Table 3.17 Random effects complementary log-log model. Probability of retirement. Different measures of informal care.

	Lags and persistence for care/no care				Lags and persistence for care type			
Variables	**Males**		**Females**		**Males**		**Females**	
l1care	1.345	(0.438)	1.367	(0.572)				
l2care	0.709	(0.294)	1.157	(0.525)				
l2careinonly					1.250	(0.721)	1.135	(0.804)
l1careinonly					1.377	(0.702)	1.516	(0.917)
l2careoutonly					0.588	(0.263)	1.174	(0.554)
l1careoutonly					1.385	(0.489)	1.329	(0.612)
l2careinout					3.098	(2.416)	1.119	(1.212)
l1careinout					0.922	(1.064)	0.988	(1.031)
l1l2care	1.899	(1.070)	0.900	(0.587)	1.612	(0.919)	0.924	(0.609)
L-R test pvalue	0.009		0.373				0.372	
Observations	3,261		1,852		3,261		1,852	

Note: Reported results are hazard ratios (exp(β)). Robust Standard Errors of hazard ratios in parentheses. Number of observations is individual-year observations. Models also contain age and covariates. Ho for Likelihood-ratio (L-R) test is no unobserved heterogeneity i.e. rho=0 *** p<0.01, ** p<0.05, * p<0.1 on Ho:exp(β)=1.

Table 3.18 Random effects complementary log-log model. Probability of retirement. Introducing birth days

	Accounting for birthdates			
Variables	**Males**		**Females**	
l1below20hrs	1.442	(0.345)	1.246	(0.341)
l1more20hrs	2.828**	(1.295)	2.753***	(1048)
Difbthday	0.999	(0.000897)	0.999	(0.000912)
L-Ratio test pvalue	0.000		0.497	
Observations	3,550		2,042	

Note: Reported results are hazard ratios (exp(β)). Robust Standard Errors of hazard ratios in parentheses. Number of observations is individual-year observations. Models also contain age and covariates. Ho for Likelihood-ratio (L-R) test is no unobserved heterogeneity i.e. rho=0. *** p<0.01, ** p<0.05, * p<0.1 on Ho:exp(β)=1.

Table 3.19 Random effects complementary log-log model. Probability of retirement. Introducing calendar year dummies.

	Using calendar year dummies			
Variables	**Males**		**Females**	
l1below20hrs	1.456	(0.336)	1.062	(0.287)
l1more20hrs	2.643**	(1.132)	2.267**	(0.855)
year91-95	1.189	(0.377)	0.839	(0.317)
year96-00	1.344	(0.337)	0.797	(0.292)
L-R test pvalue	0.007		0.497	
Observations	3,688		2,095	

Note: Reported results are hazard ratios (exp(β)). Robust Standard Errors of hazard ratios in parentheses. Number of observations is individual-year observations. Models also contain age and covariates. Ho for Likelihood-ratio (L-R) test is no unobserved heterogeneity i.e. rho=0. *** $p<0.01$, ** $p<0.05$, * $p<0.1$ on Ho:exp(β)=1.

Table 3.20 Radom effects complementary log-log model with unobserved heterogeneity. Dependent variable is exit from the labour market.

Variables	Males		Females	
l1below20hrs	1.033	(0.212)	0.976	(0.231)
l1more20hrs	1.171	(0.506)	1.900*	(0.686)
age52	0.968	(0.432)	1.214	(0.816)
age53	1.013	(0.445)	2.218	(1.316)
age54	1.394	(0.580)	2.073	(1232)
age55	0.545	(0.278)	3.071**	(1.727)
age56	1.921	(0.779)	1.624	(0.981)
age57	1.645	(0.692)	2.481	(1.417)
age58	1.223	(0.542)	3.671**	(2.020)
age59	1.243	(0.552)	3.756**	(2.077)
age60	2.766**	(1.170)		
age61	2.953**	(1.295)		
age62	1.816	(0.851)		
age63	4.469***	(1.964)		
age64	3.779***	(1.794)		
L-R test pvalue	0.004		0.496	
Observations	3,272		1,974	

Note: Reported results are hazard ratios (exp(β)). Robust Standard Errors of hazard ratios in parentheses. Number of observations is individual-year observations. Models also contain covariates. Ho for Likelihood-ratio test is no unobserved heterogeneity i.e. rho=0 *** p<0.01, ** p<0.05, * p<0.1 on Ho:exp(β)=1.

Appendix

Table A.1 Variable definitions

Dependent variables	
Retired	Binary variable: 1 if respondents state they are retired, 0 otherwise.
Exit labour market	Binary variable: 1 if respondents state they are retired, unemployed or disable, 0 otherwise.
Indicators of informal care	
Hourscare	Weekly number of hours providing informal care
Below20hrs	1 if providing care for less than 20 hours, 0 otherwise.
More20hrs	1 if providing care for 20 hours or more, 0 otherwise.
Zerohrs	1 if not providing any care, 0 otherwise.
Caredum	Type of care provision
Careinonly	1 if only caring for someone inside household, 0 otherwise.
Careoutonly	1 if only caring for someone outside household, 0 otherwise.
Careinout	1 if caring for someone in and outside household, 0 otherwise.
Controls	
Hlltyes	Self-assessed health limitations: 1 if health limits daily activities, 0 otherwise.
shlltyes	1 if spouse has a health limitation, 0 otherwise.
Spjb	1 if spouse/ partner has a job, 0 otherwise.
Everppenr	1 if individual has made contributions to a private pension plan during observational period, 0 otherwise.
Everemppr	1 if individual has been a member of an occupational pension plan during observational period, 0 otherwise.
HseOwn	1 if respondent owns a house, 0 otherwise (baseline category)
HseMort	1 if respondent owns a house with mortgage, 0 otherwise.
HseAuthAss	1 if house is own by a local authority, 0 otherwise.
HseRent	1 if house is rented, 0 otherwise.
Mlnhincl	Individual mean income of log equivalized real household labour income.
Mlnhincnl	Individual mean income of log equivalized real household non-labour income.
Mhhnetwealth	Individuals mean net wealth of the difference between household assets and liabilities.
Privcomp	1 if respondent's sector of employment is within the private sector, 0 otherwise.
Civlocgov	1 if respondent's sector of employment is within civic or local government, 0 otherwise.
Jbsecto	1 if respondent's sector of employment is another one, 0 otherwise.
Marcoup	1 if married or living as a couple, 0 otherwise.
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 qualification, 0 otherwise (baseline category).

NorthE	1 if respondent resides in North, South Yorkshire, West Yorkshire, North Yorkshire, Humberside or Tyne & Wear, 0 otherwise.
NorthW	1 if respondent resides in North West, Merseyside or Greater Manchester, 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.
London	1 if respondent resides in Inner or Outer London, 0 otherwise.
Midland	1 if respondent resides in East or West Midlands or West Mid, 0 otherwise.
Scot	1 if respondent resides in Scotland, 0 otherwise.
Wales	1 if respondent resides in Wales, 0 otherwise.
Age50-Age64	Age dummies (1 if individual is aged x=50,…,64, 0 otherwise)

Chapter 4. Impact of caregiving on caregiver's health

4.1 Introduction

The objective of this chapter is to study the impact of providing informal care on caregiver's health by analysing several mental and physical health outcomes for the UK population. We use British Household Panel Dataset (BHPS) from 1991 until 2008 to investigate whether changes in informal care provision are associated with changes in the self-reported physical and/or mental health of carers.

Caregiving might be rewarding but might also be psychologically stressful and physically intense, such that it could lead to mental health problems and the appearance or increase of health conditions for informal carers. In 2015, 54% of UK carers reported suffering from depression, 77% reported being more anxious, and 83% being more stressed due to their caring responsibilities[34]. The GP Patient Survey in 2015 showed that the prevalence of long-standing health conditions was higher for carers (63%) than non-carers (51%), and was much higher for those providing care for 50 or more hours per week (70%). In a 2011 study for Scotland, almost half of the surveyed carers reported having health conditions that started after they began providing care[35].

From 2001 to 2015, the number of people aged 85 and over increased by more than 38% and the number of people in need of care increased by more than 16%[36]. During the same period, the number of people providing informal care has grown by 16.5%. There has also been a 43% increase in the number of individuals providing care between 20 to 49 hours per week, and a 33% rise in individuals providing care for more than 50 hours a week.

Given the magnitude of informal caregiving, we believe it is important from a policy perspective to examine the effects of informal care on health in a sample of UK carers. We use a variety of health measures which capture different aspects of health. We use the General Health Questionnaire (GHQ) as a mental health measure, Self-Assessed-Health (SAH) as a general health measure, the number of physical problems as a

[34] Carers UK (2015) State of Caring 2015.

[35] Carers Scotland, 2011. Sick tired, and caring: the impact of unpaid caring on health and long term conditions.

[36] Valuing Carers 2015. The rising value of carers' support. Buckner, L. Yeandle, S. Carers UK, University of Leeds, and University of Sheffield 2015.

measure of physical health, and the SF-6D index measure for both physical and mental health.

We construct a dynamic model for health following the Grossman health production function model (Grossman, 1972). We assume there exists persistence in health such that current stock of health depends on past health status. Our dynamic longitudinal model for health faces two potential endogeneity problems. First, when taking either first-differences or mean deviations of the model in order to control for the individual's specific effect following standard panel data estimation methods to control for time invariant endogeneity, the first difference or the mean difference of the error term is correlated with the first differences or mean differences of past health. To solve for this, we use two different approaches and we either parameterize the individual specific effect following Mundlak (1978) and include initial values for health to solve for the initial conditions problem (Wooldridge, 2005); or we take first differences of the model and use past values of health as instruments for health lagged one period.

Second, there may be time varying endogeneity in caregiving due to changing health or labour market opportunities (Coe and Van Houtven, 2009, Di Novi et al., 2015, Do et al., 2015, Heger, 2016, Schmitz and Westphal, 2015). To control for the time varying potential endogeneity of informal care we use instrumental variables. Depending on the method of estimation used, we use two set of instruments: lagged values of informal care and the number of health limitations and the number of health conditions of other household members as direct instruments for informal care.

To estimate our dynamic health model, we use different econometric techniques according to the nature of the health measure (continuous or ordered categorical). Concretely, we use Generalized Methods of Moments (GMM) for those health outcomes that can be treated as continuous measures (GHQ, number of health conditions, and SF-6D), and correlated random effects models for the ordered and categorical health outcome SAH.

4.1.1 Literature

The literature is summarized in **Table 4.1**. Some papers ignore the potential endogeneity of informal care, others use matching methods, and some use a variety of instrumental variables. Only one allows for health dynamics. However, despite the different specifications, in general the existing literature finds a negative impact of providing informal care on the health of the caregiver.

For the US, Schulz et al. (2001) compares the health changes of carers and non-carers before and after the death of the spouse. Although the sample size is very small and the paper only uses covariance analysis, it finds adverse mental and physical health effects for caregivers.

Coe and Van Houtven (2009) use a seven years US longitudinal dataset to study the effect of providing informal care to an elderly mother on the physical and mental health of her adult children. To control for selection in to and out of caregiving, they use the number of siblings, whether the eldest child is female, and the number of boys and girls in the family to control for selection into caregiving, and death of the mother to control for selection out of caregiving. Their preferred dynamic health model estimated by system GMM finds an increase in the number of depressive symptoms for continuing caregivers compared to those who stop caregiving due to the death of their mother for married women and men. Informal care also decreases the self-assessed health of married and single women who are caregivers but no effects are found for men.

Do et al. (2015) study the impact of providing informal care to parents and parents in law on the health of the daughters and daughters in law in Korea. They use as instruments the health limitations of the father in law for the sample of daughters in law caregivers, and health limitations of parents for the sample of daughters' caregivers. For the daughter-in-law sample, caregiving increases the probability of pain and the probability of reporting a health status of fair and poor. For daughters, caregiving adversely affects all their health outcomes.

Schmitz and Westphal (2015) study the effect of informal care on health for female carers in Germany. They find a short-term negative effect of informal care provision on mental health where the effect attenuates over time. There are no short or medium term effects of informal care on physical health.

Heger (2016) analyses the effect of providing informal care to a disable parent on the mental health of adult children pooling the information of 13 European countries and using four waves of the Survey of Health, Ageing and Retirement (SHARE) dataset.

The author instruments for informal care using an indicator of whether only one parent is alive. Results of fixed effects instrumental variables estimation pooled across all countries show a negative and small effect of caregiving on the mental health of sons and daughters who care for their parents.

Di Novi et al. (2015) also use SHARE data. Using matching they find that the provision of informal care to a parent or a parent-in-law has a positive effect on self-assessed health for the North European countries and there are no significant differences for carers and non-caregivers in the South European countries.

De Zwart et al. (2016) also use SHARE data and matching techniques to analyze the impact of providing informal care on several health outcomes when the caregiver is the spouse of the care-receiver. They find short term negative effects of the provision of informal care on the health of spouses' caregivers, increasing depression symptoms and worsening self-reported health. Mixed results among these three SHARE based papers might be due to the different individuals studied estimation methods, and the waves used.

In a cross-section analyses, Wolf et al. (2015) study the impact of informal caregiving on depression in Bulgaria, France, Georgia, Romania, and Russia and find female caregivers have higher depression scores. Hansen and Slagsvold (2013) also find a negative psychological effect of providing informal care to a partner for Norwegian women.

4.1.2 Contribution to the literature

This paper is the first analyzing the impact of informal care on the health of caregivers in the UK. We analyse several health outcomes. We use a much larger panel than previous studies with more years of data for every individual. Moreover, except from Coe and Van Houtven (2009), none of the previous literature allows for the dynamics of health. Although the research question is not the effect of previous health on current health but the effect of informal care on current health, not allowing for health dynamics could lead to bias estimates because the model would be miss-specified as past health is an important predictor for current health (Contoyannis et al., 2004).

Section 4.2 presents the BHPS variables. Section 4.3 discusses the model, endogeneity, and the econometric methods we use. Section 0 presents the results and section 4.5 concludes.

4.2 British Household Panel Dataset

4.2.1 Health outcomes

We use four different health outcomes to measure mental and physical health.

General Health Questionnaire

First, we use responses to GHQ as our main outcome of interest. The GHQ (Goldberg and Williams, 1988) attempts to quantify the risk of developing minor psychiatric disorders such as depression and anxiety. The GHQ version available in BHPS is the GHQ-12. The 12 questions of the GHQ-12 short form ask individuals about their concentration, loss of sleep, their believe about playing a useful role, capability of making decisions, constantly under strain, problem overcoming difficulties, enjoy day-to-day activities, ability to face problems, unhappy or depressed, losing confidence, believe in self-worth, and general happiness. Each of these questions has four possible answers ranging from being “better/healthier than usual”, through “same as usual”, “less so”, to “much less/ worse than usual”. The exact gradient and wording varies for each particular question.

We use the BHPS variable HLGHQ1 constructed from GHQ as it can be treated as a continuous variable. HLGHQ1 is derived by first changing the scale range from 0-3 instead of 1-4 and then summing the answers in all questions so that the overall measure ranges in a scale from 0 (the least distressed) to 36 (the most distressed). Higher GHQ scores indicate worse levels of mental health. Therefore, we will expect an increase in the number of hours providing care to increase GHQ scores.

SF-6D

Second, we use a preference-based health measure, the Short Form 6D (SF-6D) from the Short Form 36 (SF-36) health survey available in BHPS. The SF-36 is a standardized health questionnaire with 8 dimensions covering physical and mental health: physical functioning, role of physical limitations, role of emotional limitations, energy and vitality, mental health, social functioning, body pain, and general health.

Brazier et al. (2002) constructed a preference-based index measure, the SF-6D, using selected questions from 6 out of the 8 dimensions of SF-36: physical functioning, role of physical limitations, social functioning, body pain, mental health, and energy and vitality[37]. To create a preference-based measure, answers to the SF-6D questions are combined with preference weights which are obtained from a sample of the general UK population using the standard gamble valuation technique. The SF-6D is then defined on a continuous scale from 0 (health state is death) to 1 (perfect health). We apply these weights to the items of SF-36 version 2 available in BHPS. We create the SF-6D domains using the selected questions from SF-36 that every domain in SF-6D uses. Then, for every possible answer in each of the SF-6D domain, we assign the weights recommended and given in Brazier et al. (2002).

Information on SF-36 in BHPS is only available for waves 9 and 14. In order to generate the SF-6D values for all the waves, we follow the approach suggested in Jones et al. (2014). We estimate a pooled Ordinary Least Square (OLS) of wave 9 and 14 SF-6D on a health problems dummy variables (arms, sight, hearing, skin, heart, stomach, diabetes, chest, depression, alcohol, epilepsy, migraine, and other problems), dummy variables derived from the self-assessed health measure (very poor or poor, fair, good or very good, and excellent health as baseline). We also include age and gender as regressors. These variables are available in all waves. We then predict SF-6D values for all waves from this regression. In this way, we obtain a continuous cardinal measure ranging from 0 to 1 for individuals in all waves where values closer to 1 will indicate better health.

The fact that SF-6D is only available for two waves and we use predicted values for the remainder could harm the quality of our estimation results as they will already come from a prediction and not from the true SF-6D value. This will lead to measurement error in the dependent variable which may reduce the precision of the estimated effects. However, SF-6D is very widely used as a measure of health in economic evaluation studies.

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[37] As explained in Brazier et al. (2002), the number of dimensions to construct SF-6D was reduced from 8 to 6 by excluding the general health item as it argues it is redundant if the purpose is to generate a general health index. Second, role of physical and emotional limitations was combined into a single role limitation dimension.

Health conditions

Our third measure of health is the number of health conditions of an individual in every wave. This variable is constructed by summing, for every wave, 14 dummy variables accounting for different health problems: arm, sight, hearing, skin, chest, heart, stomach, diabetes, alcohol, epilepsy, migraine, cancer, stroke, and other health problems.[38] This is a physical health measure as non-mental health issues are taken into account. We treat it as continuous and cardinal.

Self-Assessed health

We also use the BHPS variable asking about self-assessed health (SAH) over the past 12 months compared to people of own age. This is an ordered categorical measure of an overall health with four categories ranging from 1 (very poor) to 4 (excellent). Originally, SAH has 5 categories: very poor, poor, fair, good and excellent. However, in wave 9, there is a different wording and only 4 categories: very poor or poor, fair, good or very good, and excellent. Drawing on Hernandez-Quevedo et al. (2004) we collapse the SAH measure into four categories as in wave 9.

4.2.2 Measures of informal care

We construct two measures of informal care: a continuous and an ordered categorical measure. The first is *hourscare* which measures the weekly number of hours caregivers spend looking after or helping someone else. Informal care time is originally measured in the BHPS as an index variable of 10 categories: 0-4 informal care hours per week, 5-9 hours per week, 10-19, 20-34, 35-49, 50-99, 100 or more hours per week, varies under 20 hours, varies 20 hours or more, and some other time. We drop individuals in the last category as they are very few (326 individual-wave observations) [39]. We take the mid-point value of each category and treat the variable as continuous. We assign a value of 100 for the category “100 or more than 100”, and 10 and 20 hours for the categories “varies under 20”, and “varies 20 hours or more, respectively.

[38] The listed conditions have data in all waves of BHPS except for cancer and stroke where data is available from wave 11 to 18. In the models reported we assume that time dummies control for these missing years. We have also constructed the number of health conditions dropping cancer and stroke and there is very little difference in the estimation results compared to those in our main model.

[39] Individuals in the 0-4 hour’s category classify themselves as carers as they report to provide informal care. Then, when they are asked how many hours per week they provide care they report to do so between 0 and 4 hours without specifying the exact number of hours.

The second measure is ordered categorical. We collapse the hours' categories to create 3 dummy variables: individuals who do not provide care, report less than 20 hours (*below20hrs*), and those reporting 20 or more hours per week (*more20hrs*).

4.2.3 Socioeconomic and demographic variables

We use the indicator variable *male* which takes value 1 if male and 0 if the individual is a female. For marital status we construct indicators for whether the individual is married (baseline category), widowed, divorced, or single. To account for individuals' race we use an indicator variable that takes value 1 if the individual comes from a white ethnicity and 0 otherwise. We also account for education attainment (*deghdeg* if highest education is degree or higher degree, *hndalev* if highest education is HAD or A level, *ocse* if it is O level or CSE, and *noqual* if no qualification), household size (*hhsize*), and number of children within a household from 0-4, 5-11, and 12-18 years old (*nch04*, *nch511*, and *nch1218*, respectively). To control for income, we use the logarithm of annual real household income equivalized by the McClement's scale to adjust for household size. We also control for labour market status and occupation: *prof* if professional occupation; *mantech* if managerial and technical occupation; *skillmn* if work classifies into a skilled and non-manual occupation; *ptskill* if work classifies in partly skilled; and *unskill* if it classifies in non-skilled occupation; *armed* if the individual works in the armed forces, and *nowork* if the individual does not work. We also include a dummy variable *wave* to control for time trends. Definitions of variables are summarized in **Table A.13**.

4.3 Empirical model

Following Grossman (1972), we assume there is persistence in health so the current stock of health depends on previous health[40]. Health status in the previous period is an important predictor for contemporaneous health (Contoyanis et al., 2004) and not including it can lead to omitted variable bias. Therefore, we use a dynamic panel structure to model health:

$$H_{it} = \beta_1 H_{it-1} + \beta_2 care_{it} + \boldsymbol{X_{it}}\beta_3 + \alpha_i + \omega_t + u_{it} \tag{31}$$

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[40] The Grossman model for health looks at decisions to invest in health and shows that investment depends on current health, so that health in one period depends on previous health levels. We are focussing on how one factor (informal care hours) affects health but we do need to allow for the persistence in health suggested by Grossman.

for $i = 1,...,N$ and $t = 1,...,T$. H_{it} represents the health status of individual i in period t , $care_{it}$ is informal care, $\boldsymbol{X_{it}}$ is a vector of covariates, α_i is the time-invariant individual specific fixed effect which captures unobserved heterogeneity, ω_t are wave dummies to control for time trends common to all individuals, and u_{it} is a time-varying and individual specific error term.

4.3.1 Endogeneity of informal care

Regarding the relationship between health and care we assume that there may be omitted factors in u_{it} correlated with informal care, *care*$_{it}$, creating potential endogeneity of the informal care variable.. For example, an individual may have personality characteristics which make them more willing to provide care and which make them better able to withstand the stresses of caring. Then, the detrimental effect of care on health will be underestimated ($0 > \beta_2 > \hat{\beta}_2$). Or, an individual who is working in a more stressful occupation may do less caring and have worse health so that $0 > \hat{\beta}_2 > \beta_2$ doing more paid work.

To account for the possible endogeneity of the number of hours providing care we use instrumental variables. We either lag our measure of informal care, or we use direct instruments which are the physical health of other members in the household. We measure the physical health of other household members using two variables, the number of health conditions and the number of health limitations of other household members. We count how many of the following health conditions each other member of the household reports: arm, sight, hearing, skin, chest, heart, stomach, diabetes, depression, alcohol, epilepsy, migraine, cancer, stroke and other problems. We also count the number of health limitations of all other members of a household: housework, climbing stairs, getting dressed, walking, and other limitations. We then take the first lag of these variables as there might be some time difference between when a household member develops a health condition or limitation and when individuals consider themselves as carers and start reporting that they provide care.

We use the total number of health conditions of other household members rather than the average number of conditions per other household member as it is more likely that care will be provided if the household has two other members each with a number of problems rather than one other member with the same number of problems.

Regarding the exclusion restriction, we assume that the lag of number of health conditions and limitations of other household members will not have a direct impact on the current health of the individual. Literature around the impact of other's health in own health mainly focusses on individuals and their partners and on the impact of the partners mental health on own mental health (Lee et al., 2011, Lu et al., 2016, Siegel et al., 2004, Umberson and Montez, 2010), where some of the literature only finds correlation but not a causal relationship (Idstad et al., 2010). Our instrumental variables are physical conditions of other household members, and there is little evidence of the impact of physical health of the spouse on both mental and physical health outcomes of the partner (Siegel et al., 2004). Moreover, we do not only focus on the spouse caregiver-receiver relationship but on all possible caregiver-receiver family relationships, where the direct impact of other household members' health on own health is likely to be damped. Using lags of health conditions and limitations of other household members will also make it more plausible that the exclusion restriction is valid.

4.3.2 Estimation

In addition to instrumenting informal care, we also need to deal with the endogeneity problem of H_{it-1} in our dynamic model in (31). In the presence of a lagged dependant variable as a regressor, the OLS estimator for H_{it-1}, $\hat{\beta}_1$, will be biased because H_{it-1} would be correlated with the fixed effects in the error term (Nickell, 1981). Standard fixed effects estimation in dynamic panel data models will generate downward bias for the parameter H_{it-1} because the strict exogeneity[41] assumption is violated and this is a necessary assumption for the use of fixed effects. Instead, in dynamic panel data models we are allowing for weak exogeneity where only past values of H_{it} are assumed to be exogenous to the error term u_{it}, but future values can be correlated.

Therefore, other methods need to be applied. We use two different approaches to deal with weak exogeneity and unobserved heterogeneity depending on the nature of the dependent variable (continuous or ordered categorical). When the health outcome is continuous, we use GMM which controls for unobserved heterogeneity by taking first

[41] The strict exogeneity assumption states that the error term is uncorrelated with all the regressors and the individual fixed effects.

differences and, using the weak- exogeneity assumption, past values of H_{it-1} can be used as its own instruments. When the health outcome is ordered categorical, since we cannot take either first differences or mean deviations to control for the unobserved individual-specific effect due to the incidental parameters problem, we use correlated random effects. Following Mundlak (1978) we parameterize α_i allowing for the possibility that the observed regressors are correlated with the individual specific effect. We follow (Wooldridge, 2005) and allow the individual specific effect to depend on the initial values of health there by controlling for the initial conditions problem.

Generalized method of moments

When the measures of health are continuous (GHQ, SF-6D or number of health conditions) we use GMM (Arellano and Bond, 1991) to model (31). We first-difference the model in (31) such that we control for the individual specific time-invariant effect (i.e. the unobserved heterogeneity) dealing with the correlation between H_{it-1} and α_i :

$$\Delta H_{it} = \Delta H_{it-1}\beta_1 + \Delta care_{it}\beta_2 + \Delta \boldsymbol{X_{it}}\beta_3 + \Delta u_{it} \tag{32}$$

Differencing equation (31) eliminates the fixed effects but in equation (32) the first difference of the error term $\Delta u_{it} = u_{it} - u_{it-1}$ is correlated with the first difference of the regressor $\Delta H_{it-1} = H_{it-1} - H_{it-2}$ as shown in (33):

$$\begin{aligned} E(\Delta H_{it-1}\Delta u_{it}) &= E\left[\left(H_{it-1} - H_{it-2}\right)\left(u_{it} - u_{it-1}\right)\right] \\ &= E(H_{it-1}u_{it}) + E(H_{it-2}u_{t-1}) - E(H_{it-2}u_{it}) - E(H_{t-1}u_{t-1}) \\ &= -E(H_{t-1}u_{t-1}) \neq 0 \end{aligned} \tag{33}$$

To allow for the correlation between ΔH_{it} and Δu_{it} , we construct instruments for ΔH_{it-1} using lagged values of H_{it-1}. The number of available lagged values that can be used as valid instruments is determined by the serial correlation of the first differenced error term. Δu_{it} is correlated with H_{it-1} but it is not correlated with further lags of H, so that H_{it-2}, H_{it-3} etc. are valid instruments. Arellano and Bond (1991) suggest exploiting all the moment conditions available in each period, so that the set of moment conditions increases with t. For instance, at $t = 3$, the first year for which the model can be estimated, we would have one available instrument, H_{i1} with $E\left[H_{i1}\Delta u_{i3}\right]=0$. At wave 4, we would have two available instruments, H_{i1} and H_{i2}, with $E\left[H_{i1}\Delta u_{i4}\right]=E\left[H_{i2}\Delta u_{i4}\right]=0$, and so on.

In our model, we assume all the variables in $\boldsymbol{X_{it}}$ are strictly exogenous, so that $E\left[\boldsymbol{X_{it}}u_{is}\right]=0$. Then, the first difference of all the $\boldsymbol{X_{it}}$ are valid instruments and they are used to instrument for themselves in the first differenced equation in (32), so that the moment equation for the exogenous variables are of the type $E\left[\Delta \boldsymbol{X_{it}}\Delta u_{it}\right]=0$.

To allow for the endogeneity of informal care ($E\left[care_{it}u_{it}\right]\neq 0$), we use lag 2 and onwards of informal care in levels as instruments for $\Delta care_{it}$ with the corresponding moment equations. To further control for the endogeneity of informal care, we also run GMM models where we use additional instruments for informal care: the number of health problems and limitations of other household members lagged one period.

First difference GMM model can perform poorly when the number of periods is small and the autoregressive parameter is moderately large. Blundell and Bond (1998) augment the Arellano and Bond first difference GMM estimator into a system of equations. For that, the equation in levels is also estimated using lagged differences of the dependent variable as instruments. This estimator also assumes that the first differences instruments are not correlated with the individual specific fixed effects such that $E(\Delta H_{it-1}\alpha_i)=0$. In this way, additional instruments are used and our matrix of instruments is augmented with extra moment conditions, $E\left[\Delta H_{it-1}u_{it}\right]=0$ for $t\geq 3$.

Blundell and Bond (1998) show that by estimating that system of equations, in our case equations (31) and (32), the augmented GMM estimator has improved asymptotic properties with efficiency gains and reduced possible sample bias. Moreover, estimation of the equation in levels also allows estimating time invariant regressors.

We use both first differences GMM and system GMM estimations. However, first differences GMM did not perform as well as system GMM estimations in terms of the validity of the instruments used and the performance of the coefficients as using system GMM increased the significance of the coefficients. Therefore, to estimate our models we prefer Blundell and Bond System GMM estimation. We start by first estimating our model proposed in (31) with the first lag of H_{it} as a regressor and using the set of instruments described above. For our panel of 18 waves we have a large set of instruments and too many moment conditions can bias the results as the additional contribution of every additional instruments is weaker the further we go back in time. Roodman (2009) suggests taking a subset of moment conditions to reduce the bias. Therefore, we first estimate our model using all the available instruments, and then we restrict the set of instruments used. We use efficient two-step system GMM[42] estimation applying the Windmeijer finite-sample correction to the reported standard errors (Windmeijer, 2005). To evaluate the performance of the System GMM estimation, we report the test for serial correlation and the Hansen test of the joint validity of the moment conditions (an over-identification test of whether the instruments are jointly exogenous).

The consistency of the GMM estimator relies upon the assumption that there is no serial correlation on the errors of the equation in levels. When estimating our system of equations we cannot reject the null of the presence of second-order serial correlation in the residuals. If the errors are serially correlated, one empirical solution is to add more lags of the dependent variable as regressors and check whether this eliminates the serial correlation in the error term (Cameron and Trivedi (2010); Roodman (2009)). We follow this procedure and include H_{it-2} and H_{it-3} as additional regressors in our model when the outcome of interest is GHQ or SF-6D and for the outcome "number of health conditions" we also need to introduce H_{it-4} as additional regressor to solve for autocorrelation.

To estimate our model by system GMM we use the command *xtabond2* available in Stata (Roodman, 2009). GMM models can also be estimated using other Stata commands such as *xtabond*, *xtdpd*, and *xtdpdml*. The command *xtdpd* is more flexible in case of the presence of serial correlation in the residuals if adding further lags of the dependant variable as regressors does not remove the problem, as it allows the error term to follow a moving-average process of low order. Although we estimated some models using *xtdpd* to see how it performs, since we managed to eliminate the serial correlation problem by introducing more lags of the dependent variable as regressors,

[42] 2-step GMM estimates in the first step the model using a consistent but not efficient estimator in order to get a prediction of the residuals. It then uses these predicted residuals to obtain the GMM estimator.

we report results from *xtabond2*. The command *xtdpdml* (Williams et al., 2016) uses maximum likelihood and was very slow to run with 18 time periods and with a large range of variables as in our case.

Correlated Random effects and 2-Stage Residual Inclusion

When our health outcome is the ordered categorical measure self-assessed health (SAH), our model is represented by the following equation:

$$SAH_{it}^{*} = SAH_{it-1}\gamma_1 + care_{it}\gamma_2 + \boldsymbol{X_{it}}\gamma_3 + \alpha_i + v_{it} \qquad (34)$$

where, SAH_{it}^{*} is not observed as it is a latent health variable. Instead, we observe an indicator variable SAH_{it} of the category in which our latent variable falls. The observed SAH_{it} and the latent variable SAH_{it}^{*} are related by the following observation rule:

$$SAH_{it} = j \;\; ; \; \mu_{j-1} < SAH_{it}^{*} \le \mu_j \text{ for } j = 1, 2, 3, 4. \qquad (35)$$

where, $\mu_0 = -\infty$, $\mu_{j-1} \le \mu_j$.

SAH_{it-1} in equation (34) is a vector of dummy variables for the reported different health in the previous wave: very poor or poor, fair, good (baseline category), and excellent. As before, $care_{it}$ is the weekly number of hours providing care; $\boldsymbol{X_{it}}$ is a vector of exogenous variables; α_i is the unobserved time-invariant individual specific random effect; and v_{it} is a time-varying error which we assume to be normally distributed and uncorrelated across individuals and waves, and not correlated with the exogenous regressors. However, we also assume that v_{it} is formed by omitted factors that can be correlated with the number of hours providing care, creating therefore, a potential endogeneity problem.

To control for α_i and be able to identify the model and solve the incidental parameter problem (Neyman, and Scott (1948), Lancaster (2000)) we use correlated random effects and allow for the possibility that observed regressors might be correlated with the time-invariant individual specific effect. Following Mundlak (1978) we specify α_i as a function of the average of the exogenous regressors over time.

The endogeneity of the lagged dependent variable leads to the problem of initial conditions. Heckman (1981) describes two necessary assumptions that discrete-time stochastic processes with a non-linear outcome as our model in (34) need to satisfy. The first assumption is that the initial observation of the dependant variable is exogeneous. However, this is not true in our case as the first observation is not the true initial outcome of the process. The second assumption is that the process is in equilibrium. This is however, not possible in our model as non-stationary variables such as age and time dummies are included.

Wooldridge (2005) presents a convenient approach to deal with the initial conditions problem in non-linear dynamic random effects models. Concretely, it models the distribution of the unobserved effect conditional on the initial values of SAH and the exogenous explanatory variables. The model is then estimated by maximum likelihood based on the joint distribution of the observations conditional on the initial observations. Therefore, α_i is parameterized as

$$\alpha_i = \alpha_0 + \alpha_1 SAH_{i0} + \alpha_2 \overline{\boldsymbol{X}_{\boldsymbol{i}}} + a_i \tag{36}$$

So, our model in (34) is augmented to

$$SAH_{it}^{*} = \gamma_1 SAH_{it-1} + \gamma_2 care_{it} + \boldsymbol{X}_{\boldsymbol{it}}\gamma_3 + \alpha_0 + \alpha_1 SAH_{i0} + \alpha_2 \overline{\boldsymbol{X}_{\boldsymbol{i}}} + a_i + v_{it} \tag{37}$$

where it can be assumed that a_i is independent of the exogenous variables, the initial conditions, and v_{it}, and it is assumed it follows a standard normal distribution.

In order to deal with the potential endogeneity of informal care in a non-linear dynamic panel data setting, we follow Papke and Wooldridge (2008) and apply 2-Stage Residual Inclusion (2SRI). When the outcome is non-linear, the nature of the endogenous explanatory variable (continuous, discrete, etc.) is important and needs to be taken into account (Wooldridge, 2011). 2SRI corrects for endogeneity by including the predicted residual of a first stage model of the endogenous variable as a regressor in the second stage, instead of using the prediction of the endogenous variable. It is usually applied in cross-sectional studies (see for instance, (Terza et al. (2008); and Zimmer (2010)). Papke and Wooldridge (2008) apply 2SRI in a static panel data setting when the outcome of interest is non-linear and the endogenous explanatory variable is continuous. We use this method in our dynamic panel data model in (37).

The first stage of 2SRI is to estimate a linear reduced form for $care_{it}$ as a function of the exogenous explanatory variables, $\boldsymbol{X_{it}}$, the exogenous instruments for informal care, and the average over time of the exogenous regressors as in Mundlak (1978). We use the number of health problems and the number of health limitations of other household members lagged one period as instruments for the number of hours providing care. Therefore, we estimate a random effects model for $care_{it}$

$$care_{it} = \boldsymbol{Z_{it}}\psi_1 + \boldsymbol{X_{it}}\psi_2 + \overline{\boldsymbol{X_i}}\psi_3 + \vartheta_{it} \tag{38}$$

where, $\boldsymbol{Z_{it}}$ is a vector containing the two exogenous instruments, and ϑ_{it} is assumed to follow a normal distribution and it is not correlated with the instruments in $\boldsymbol{Z_{it}}$.

Then, the endogeneity of the number of hours providing care comes through correlation between ϑ_{it} and $a_i + v_{it}$, so we allow $care_{it}$ to be correlated with both the unobserved heterogeneity and the time-varying omitted factors. From equation (38) we are interested in the predicted value of ϑ_{it}, ϑ_{it}, which will be added as a regressor in the second stage to control for the endogeneity of informal care. Therefore, following Papke and Wooldridge (2008), we assume that v_{it} given ϑ_{it} is conditionally normal, so one can write the following relationship:

$$u_{it} = \eta_1\vartheta_{it} + e_{it} \quad ; \quad e_{it} \mid (\boldsymbol{Z_{it}}, \boldsymbol{X_{it}}, \vartheta_{it}) \sim Normal(0, \sigma^2) \tag{39}$$

Where $u_{it} = v_{it} + a_i$. Then, the residual ϑ_{it} is, by construction, uncorrelated with $care_{it}$ and e_{it} is independent of $\boldsymbol{Z_{it}}$ and ϑ_{it} then, it is also independent of $care_{it}$.

In the second stage, given that we have parameterized the individual specific effect following in order to control for it, as well as to solve the initial condition problem caused by the fact that SAH is a dynamic model, we estimate a random effects ordered probit model including the predicted residual of the first stage, ϑ_{it} :

$$SAH^*_{it} = SAH_{it-1}\gamma_1 + care_{it}\gamma_2 + \boldsymbol{X_{it}}\gamma_3 + \alpha_0 + \alpha_1 SAH_{i0} + \alpha_2\overline{\boldsymbol{X_i}} + \eta_1\vartheta_{it} + e_{it} \tag{40}$$

The coefficient η_1 in (40) is capturing the endogeneity of the number of hours providing care. Then, rejecting the null hypothesis of $\eta_1 = 0$ will indicate that informal care is an endogenous variable.

Estimates from equation (40) are from the latent SAH scale so, as Papke and Wooldridge (2008) pointed out, only the direction of the effect of the coefficient can be identified. To give a more meaningful result, in the results section, we calculate predicted probabilities for the SAH categories varying the number of hours providing care that an average individual provide.

4.4 Results

4.4.1 Summary statistics

Table 4.2 shows the summary statistics for the full sample. The mean score for GHQ is 11.19. The GHQ manual suggests that the threshold for depression or anxiety is 11 to 12 (Golderberg and Williams, 1988), suggesting that individuals in the sample, on average, may be at the edge of presenting symptoms of depression or anxiety. . Individuals seem to have a fair health reporting an average SAH value of 2.84 assigning 1 to the lowest category and 4 to the highest, and have one health condition. With respect to SF-6D, individuals on average report a score of 0.803, close to full health. Overall, all the measures show individuals in the sample have good mental and physical health, without any major problems.

The caregivers in the sample provide informal care for 18 hours a week and 16% of the observations are for individuals providing care.

Other members of the household have about 1 health condition on average and 0.44 health limitations in total.

Average age is 45 years, 46% of the sample is male, more than half (64%) are married or living as a couple, and 33% do not hold any education qualifications, while approximately 31% hold a certificate of secondary education. Almost half of the sample (45%) either has a manual occupation, a non-manual skilled or managerial and technical occupation; 40% of the sample does not work, and the remaining have a partly skilled, non-skilled occupation, or work for the armed forces. Household are composed of 3 members, and have approximately 1 child. Annual average household income is

£18,261, although as the standard deviation and the maximum value for income show, the dispersion is quite high.

Next, we describe informal carers. **Table 4.3** shows the number of individuals providing care per wave, the percentage they represent out of the total number of individuals for each year, and how many hours per week they devote to caring: less than 20 hours, or 20 hours or more. On average, 16% of individuals provide informal care each year. There seems to be an increasing trend over time, especially between waves 8 and 9 where there was a boost of individuals in the BHPS. From that wave onwards, a higher proportion provides care, perhaps because potential recipients are aging an requiring more care. Most carers provide care for less than 20 hours per week. Averaging across years, 76% of carers provide care for less than 20 hours per week and 24% for at least 20 hours a week.

Table 4.4 shows the mean health for non-carers and carers. The higher the number of hours providing care per week the worse is health. For instance, for GHQ individuals who provide 20 hours or more of care per week report on average a GHQ score 2 points higher than those who do not provide care.

We also describe the distribution of two of our main health outcomes, GHQ and SAH, by the number of weekly hours of care provided to see whether they are associated with the intensity of care. **Figure 4-1** an increasing trend in the GHQ scores as the number of hours providing care rises, indicating that individuals report feeling more distressed when providing more hours of informal care per week. We observe a similar pattern when looking at SAH in **Figure 4-2**. As the number of hours providing care increases, there is an increase in the number of individuals reporting feeling in very poor or poor health, and in fair health, while the number of individuals reporting feeling very good, good, or excellent decreases.

4.4.2 Estimation results

Next, we provide the results for each health outcome of interest, GHQ, SF-6D, number of health conditions and SAH using the appropriate estimation method for each measure, system GMM or correlated random effects. For each health measure we present the estimated coefficient results for lagged health and for our main variable of interest informal care either treating it as an index variable (care below 20 hours per week, care for 20 or more hours, no care) or as a continuous variable. Full estimation results are shown in the appendices.

We estimate OLS, FE and system GMM models for our continuous measures of health. For the GHQ and SF-6D system GMM estimations, we manage to get rid of serial correlation after including lag two and three of GHQ, and SF-6D. For the number of health conditions system GMM estimations, we need to include up to lag four to achieve that. For each of these models, we also include those extra lags in the OLS and FE estimations to make the results comparable across methods.

In order to deal with the problem of too many lagged instruments and the fact that they might be weaker the further we go back in time, we performed the system GMM estimations varying the set of lag values used as instruments for both the lagged regressors and care. We present the results when we restrict the number of instruments from lag 2 to 5 in each of our continuous health measures. We believe this is the best model based on the performance of the Hansen test, and the overall performance of the model. Estimation results using the full set of instruments (from lag 2 to 17) and other restrictions are provided in the appendices.

Estimation results for GHQ

Table 4.5 summarizes our estimation results for the health outcome GHQ when treating informal care as a discrete variable. Column one and two show the results from the OLS and the FE estimation for our model in (31). The OLS estimates for the lagged regressors of the dependant variables in dynamic panel data models are upward biased and the FE estimates downward biased. The FE estimates for the lagged GHQ variables are smaller than the OLS estimates. Both estimations show a decreasing gradient for those regressors showing weaker impacts of GHQ answers on current GHQ score at longer lags.

Column three presents the system GMM estimates for our system of equations in (31) and (32) where we instrument informal care using past values of care from period $t-2$ onwards. Column four adds to this estimation our two direct instruments for informal care, health conditions and health limitations of other household members.[43]

[43] In the appendix A.16 presents results from a model of informal care which shows that the direct IV's are very strong.

First, comparing the estimated coefficient results for lagged values of GHQ of the system GMM estimations with those form the OLS and FE estimations, they lie, as expected, between the OLS and the FE estimated coefficients. The GMM coefficients for informal care in columns three and four are about three times bigger than the OLS and FE coefficient.

Second, the coefficient results in both system GMM estimations are fairly similar for both the lagged regressors of GHQ and informal care. The estimates for informal care show that providing care increases the GHQ score so that an increase in the weekly number of hours providing care has a negative impact on the mental health outcome GHQ as it increases the level of distress reported by carers with respect to individuals who does not provide any care. The effect is only significant when the intensity of care is high (caring for 20 hours or more per week). The coefficient for care is slightly smaller once we include its direct instruments in the model.

The main difference between the system GMM estimations in columns three and four in Table 4.5 is in the Hansen test of over-identification. It shows that both models are over-identified so that the set of instruments we use for the system of equations are valid. Not including the direct instruments for informal care produces a higher p-value (0.314) for the test than when including them (0.143). This, in principle, would favour the estimation without the direct instruments for informal care, as models with extra instruments weaken the power of the Hansen test (Roodman (2009)). On a note on the use of too many instruments in System GMM, Roodman (2009) suggests that Hansen tests slightly higher than the standard significance levels of 0.05 and 0.1 should be treated with caution as those levels are not adequate when trying to choose between model specifications in System GMM. It suggests that to reduce the danger of not rejecting the null hypothesis of over-identification when we actually should, Roodman (2009) recommends to report always several specifications using a different number of instruments. In table A.15 of the appendix we show that when increasing the number of lagged instruments used for lagged GHQ and including the direct instruments for informal care, the Hansen tests specification gets higher than 0.143, showing that our direct instruments for informal care may be valid. However, taking into account this discussion in the literature, Roodman (2009) suggests that we should only trust Hansen tests values above 0.25, and therefore, we believe the system GMM estimation in column three where not using the direct instruments for informal care is the most appropriate model for the health outcome GHQ.

Table 4.6 has results when we treat informal care as a continuous variable. The interpretation of the coefficients is very similar as before. Columns one and two have the OLS and the FE estimates, and columns three and four show the system GMM estimates.

The system GMM estimates for lagged GHQ lie between the OLS and the FE estimated coefficients. The coefficient for informal care is positive and significant in all the four models. The OLS and the FE estimations provide smaller coefficients for informal care, suggesting downward bias when not taking into account the potential endogeneity of informal care. For the continuous measure of informal care the system GMM estimations provide very similar results both in terms of coefficient estimates and in terms of the Hansen test. Both models show that an increase in the number of hours providing care increases the levels of individuals' distress such that the reported GHQ increases by 0.034 points in the model with no direct instruments for informal care, and by 0.0289 points when using direct instruments for informal care.

Estimation results for SF-6D

Table 4.7 presents the results for the health outcome SF-6D when treating informal care as a categorical variable. The SF-6D measures physical and mental health.

The system GMM coefficients for lagged SF-6D in columns three and four lie between the OLS and the FE estimates. The coefficients for informal care in both system GMM estimations show that the SF-6D is decreased by 0.025 and 0.03 points for individuals caring for at least 20 hours per week compared to those who do not provide any care. Both coefficients show very similar results in terms of the effect of informal care on the SF-6D score and, as for GHQ, when introducing the direct instruments of informal care, the coefficient for informal care gets bigger in absolute value. Moreover, and similar as for the GHQ models, the OLS and FE coefficients for informal care seem to be downward biased when not taking into account the potential endogeneity of informal care compared with the system GMM ones.

Table 4.8 provides the results when treating informal care as continuous. The coefficient estimates for hours providing care in columns three and four are of a similar magnitude and show that the impact of an additional hour of informal care on SF-6D is even small. An individual supplying the mean number of hours for carers (18 hours) would have SF-6D reduced by 0.0058 compared to the SF-6D mean of 0.803.

However, system GMM estimations for SF-6D when either treating informal care as an indicator or as a continuous variable performs poorly in terms of the Hansen test. In both Table 4.7 and Table 4.8 the p-values for the Hansen tests are zero, rejecting the null hypothesis of over-identification, invalidating at least some of our instrumental variables. This might be due to the fact that SF-6D is only asked directly in two out of 18 waves of BHPS and the values for the remaining waves have been estimated. Although a favourable Hansen test would be desirable to reinforce our SF-6D results, Roodman (2009) notes that the test is sometimes prone to weakness and might not always be fully reliable.

Estimation results for number of health conditions

Table 4.9 presents the estimation results for the number of physical health conditions.

As per with the other health measures, the system GMM estimated coefficients for lagged health conditions are between the OLS and the FE results. The coefficients for informal care in all models are positive and significant, showing an increase in the number of health conditions for an extra hour of care provided. Once more, the OLS and FE coefficients for informal care seem downward biased.

For the model in column three the informal care coefficient is significant when an individual is caring for less than 20 hours a week. For the model in column four informal care is significant only for the individuals that provide 20 or more hours of care per week. In both cases the increase in the number of health conditions is of 0.11 or 0.23, suggesting a small impact of informal care on this health outcome.

Table 4.10 shows the results for the continuous version of the informal care variable. Results for that variable are significant only for the OLS and the system GMM estimation when using both the lag values of care and its direct instruments. However, the impact of weekly hours of care is small, even compared to the mean of 1.15 conditions.

The system GMM models in Table 4.9 and Table 4.10 do not pass the Hansen tests of over-identification showing that at least some of the instruments used are invalid. Since the number of health conditions is a measure of physical health, we would expect less contamination in the instruments and to be less worried about the exclusion restriction as the number of health conditions of other members of the household does not seem correlated with the number of health conditions of an individual could have. However, the overall performance of those models seems quite poor. This might be due to the way we have created the number of health conditions by summing the number of reported health problems of each individual over time. We could have treated this variable as a count variable and use count data models, instead of treating it as a continuous variable. We treated it as a continuous measure as the health conditions are very heterogeneous, so it is not obvious the use of count data is approachable.

Comparing the results across the three continuous measures of informal care, GHQ models perform better when using system GMM estimation. This might be due to the fact that GHQ is asked directly in BHPS and in all waves, contrary to SF-6D and some of the health conditions (cancer and stroke). However, the results in all models are broadly consistent showing the pattern that providing informal care has a small and detrimental effect on individuals' health. Also, it seems that the major impact of informal care is on mental health and there is a smaller impact on physical health.

Estimation results for SAH

Table 4.11 shows the results for our model in equation (40) for the ordered categorical variable self-assessed health. Column one presents the results of a RE ordered probit estimation for the discrete measure on informal care and when assuming it is an exogenous variable. Estimates for these regressors are only significant for the category caring for 20 or more hours per week and show that those individuals who care for that number of hours report lower answers in the SAH scale (and therefore towards poorer health) than non-carers. Column two shows the RE ordered probit results when using the continuous informal care measure and when treating it as an exogenous variable. In this case, an extra hour of informal care per week has a negative effect on the self-assessed health scale. Columns three and four show estimation results when lagging informal care in order to reduce its potential endogeneity. The results are very similar as the ones in columns one and two showing a negative but somewhat larger impact of informal care on SAH.

Column five in Table 4.11 shows the second stage random effects ordered probit estimation when treating informal care as a continuous variable. The coefficient for the predicted first stage residual (0.00195) is significant, indicating the presence of significant endogeneity of informal care damping its negative effect on the SAH scale. The coefficient for informal care shows there is a larger negative and significant effect of providing an extra hour of informal care on the SAH scale when we instrument for informal care.

In column five we also show the coefficient results of the first stage instruments for informal care. The coefficients show there is a positive and highly significant effect of previous health problems and limitations of other household members on the number of hours providing care. The F-statistic is much greater than the conventional level (10) used to test for non-weak instruments (Stock and Yogo, 2005).

Given the significant endogeneity of informal care, our preferred estimation for the SAH health measure is the correlated random effects estimation using 2SRI. Given the ordered categorical nature of the SAH measure we compute the predicted probabilities of every outcome of the SAH scale (poor or very poor, fair, good or very good, and excellent) for different values of the variable care and setting the rest of the variables at their mean values. We compute the SAH probabilities when the average individual provides zero hours of care, twenty hours, forty-two hours, or a hundred hours. **Table 4.12** provides those results. In the first column of that table we show the predicted probability of feeling in poor or very poor health when providing care for 0, 20, 42, and 100 hours per week. We can see that the probability of feeling in poor or very poor health when not providing care is 3.4% while this probability increases when providing care for twenty hours a week, forty-two, and a hundred hours where this probability is 5.1%. For instance, last column of the table shows the predicted probability of feeling in excellent health which decreases as hours of care increase. Overall, individuals who provide 20 or more weekly hours of informal care tend to report worst health status than those who does not provide care.

4.5 Conclusion

In this chapter, we study the impact of providing informal care on several health outcomes. We analyse whether informal care has negative consequences for the health of informal caregivers, measuring health using both physical and mental outcomes. We use GHQ as a pure mental health measure, the number of health conditions as a pure physical outcome, and both SAH and SF-6D as measures of overall health.

For all the health outcomes analysed, we find a negative effect of informal care on health, where the negative impact is higher when caring for 20 hours or more per week compared to individuals who do not provide informal care. This effect seems small, especially for physical health, but it is consistent across all health measures. Comparing our results across our four health measures, we find that the major impact of informal care provision on health and the greatest difference between carers and non-carers is for outcomes that either measures only mental health, in our case GHQ, or that involves some mental health individuals' aspects, such as the SF-6D health measure.

Among our continuous health measures, informal care seems to have the greatest impact on the pure measure of mental health GHQ, such that carers feel more distressed than non-carers and every extra hour of informal care provided increases the levels of depressive symptoms by 2.42 points compared to the overall GHQ mean of 11.19. As we have discussed in the results section, this could be due to either a better construction of this measure as it is directly provided in BHPS for all waves, or also because informal care provision has higher repercussion on carers' mental health than on physical health. From an econometric point of view, GHQ is the measure which performs better. Regarding our ordered categorical outcome SAH, providing care for at least 20 hours per week reduces the probability of at least good health by 0.002. So, overall our results meet our preliminary hypothesis of a negative effect of informal care and the intensity of the care provision on health.

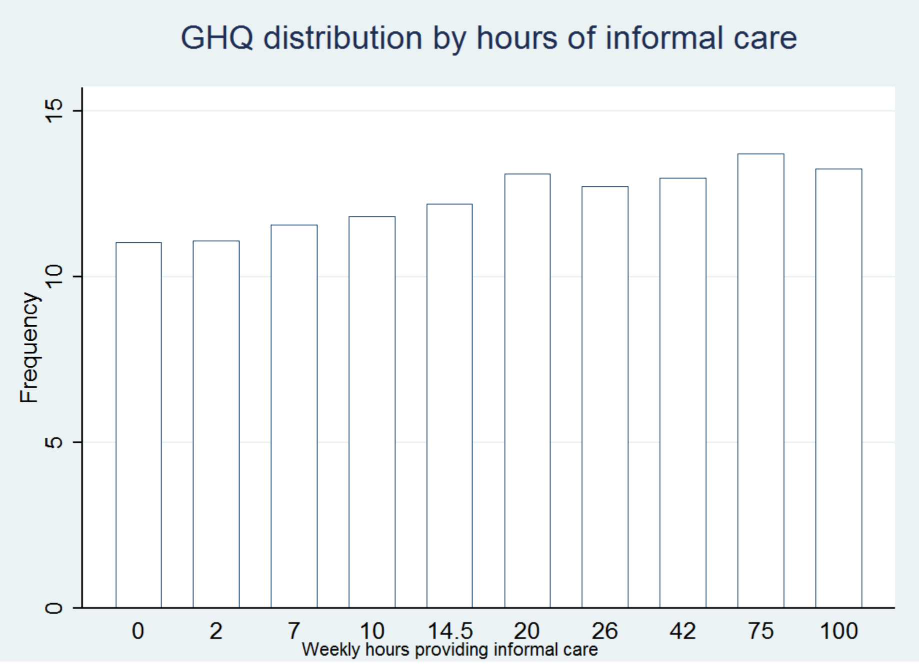
Our findings are in accordance with those of the existing literature around this topic. For instance, even though using a different dataset and samples, we find similar results to Coe and Van Houtven (2009) which, in terms of methodology, is the closest study compared to ours. In general, the existing literature also finds negative and small impacts of informal care on health, especially for mental health outcomes.

We believe our study is of policy relevance for the UK as we have shown that the health of caregivers tends to deteriorate with the intensity of care. This has general policy implications but also implications for cost effectiveness analysis of health care interventions. Increasing the health of individuals will reduce their need for informal care and this in turn will lead to health improvements for their carers which should be taken into account.

Further research into the topic could be made by first analysing more specific and direct physical health conditions such as smoking, alcohol consumption, or heart problems of informal carers. Moreover, the analysis could also be extended by looking at separate effects for men and women subsamples, or by age cohorts.

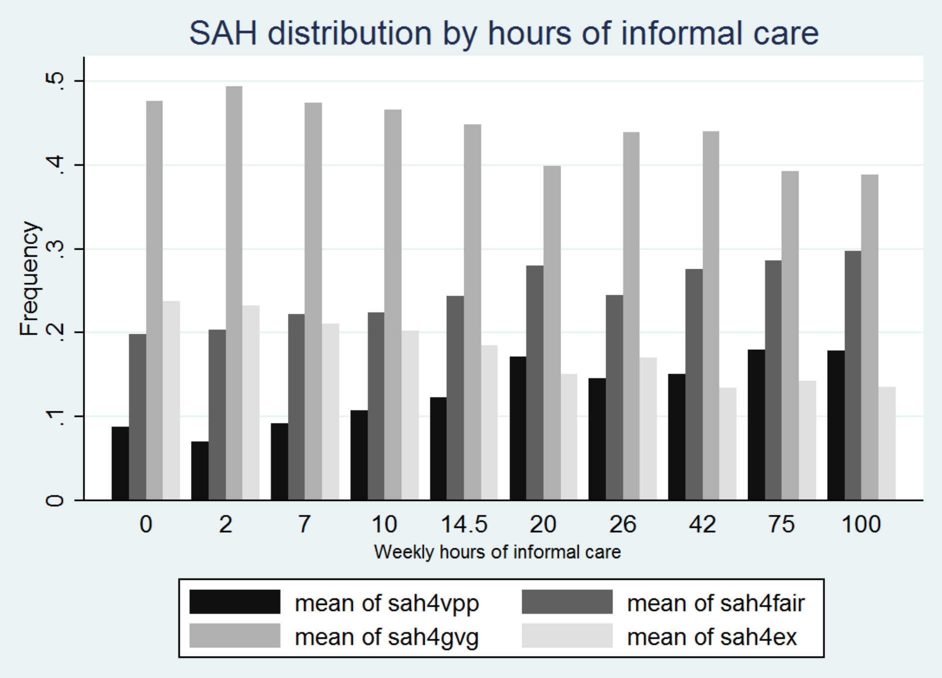
FIGURES

Figure 4-1 Distribution of the General Health Questionnaire by weekly number of hours providing care



Note: Average GHQ individual-year observations.

Figure 4-2 Distribution of Self-Assessed Health by weekly number of hours providing care



Note: Average SAH responses individual-year observations.

TABLES

Table 4.1 Existing literature impact of providing informal care on carer's health

Existing literature	Data / Caregiver-receiver	Health Measure	Informal care	Allows for endogeneity of care	Econometric model	Results
Schulz, et al. (2001)	Population-based cohort study for US communities, 1993-1998. Partner (aged 66-96) - partner	Changes in depression symptoms, antidepressant medication use, 6 health risk behaviours, weight before and after spouse dies.	Whether caregiver (with strain or not) or not	No	Covariance analysis	Decrease on health risk behaviours for carers with strain after the partner dies. Depression symptoms do not change.
Coe, Van Houtven, (2009)	US longitudinal 1992-2004. Adult children (aged 50-64) - ill mothers.	CES-D8 Mental health, heart condition, high blood pressure, good health at t+2.	Spent ≥100 hours helping parents in previous 2 years	Instrumental variables: Number of siblings, eldest child female, number of boys and girls in family, death of mother.	GMM (dynamic model)	Continue caregiving increases depressive symptoms and decreases self-assessed health.
Do,, et al. (2015)	Korean Longitudinal Study of Aging (2006, 2008, 2010). Daughters/daughters-in-law (45+) - parents/ parents-in-law.	Daily activities, SAH, drug prescription.	Providing care (binary)	Instrumental variables: health limitations of fathers and fathers in law.	2SLS	Caring increases probability of pain, drug prescription, decreases SAH for daughters.
Schmitz, et al. (2015)	German Socio-Economic Panel (7 years). Female carers.	Mental & physical health score	Provide informal care ≥2hrs week	Matching techniques	OLS	Short term effect on mental health.
Heger, (2016)	SHARE (4 waves). Adult children (50+) - disable parent.	Mental health	Provide weekly or daily informal care	Instrumental variable: only one parent alive.	FE	Negative and small caregiving effects.

Di Novi, et al. (2013)	SHARE (2 waves). Females aged 50-65 - parents/ parents-in-law.	Self-assessed-health & QoL	Provide weekly or daily informal care	Matching techniques	Probit	Positive effect on SAH for North European, no effect for South European.
De Zwart, et al (2016)	SHARE (waves 1-2 and 4-5). Spouse(50+) - partner	Depression, prescription drugs, doctor visits, self-perceived health	Provide informal care at t-2	Statistical matching	Probit	Short term negative effect of informal care provision on depression.
Wolf, et al. (2015)	Generations and Gender Programme data: Bulgaria, France, Georgia, Romania, and Russia. Adult children - parent(s).	Depression score	Providing regular care over the past 12 months.	No	Zero-inflated negative binomial regression.	Depression score increases for female carers in all countries and only in Bulgaria for men.
Hansen, Slagsvold, (2013)	Norwegian Life Course, Ageing and Generation study (2 waves). Partner-Partner.	Psychological functioning	Whether providing informal care	No	ANOVA	Negative impact of caregiving on psychological functioning.

Table 4.2 Summary statistics full sample

	Mean	Std. Dev	Min	Max
Health measures				
GHQ	11.19	5.43	0	36
SAH	2.84	0.88	1	4
SF-6D	0.803	0.098	0	1
Sum health conditions	1.15	1.35	0	11
Informal care				
Hourscare (sample carers)	18.67	28.99	2	100
No care	0.841	0.366	0	1
Care<20	0.121	0.327	0	1
Care≥20	0.038	0.073	0	1
Sociodemographic				
Male	0.462	0.498	0	1
Age	45.26	18.68	15	101
Married	0.641	0.479	0	1
Widowed	0.076	0.266	0	1
Divorced	0.069	0.254	0	1
Single	0.213	0.409	0	1
White	0.973	0.161	0	1
Deghdeg	0.118	0.322	0	1
Hndalev	0.246	0.431	0	1
Ocse	0.306	0.461	0	1
No qualification	0.329	0.469	0	1
Hhsize	2.871	1.394	1	16
Nch04	1.19	0.42	1	4
Nch511	1.4	0.6	1	6
Nch1218	1.33	0.55	1	5
Household income	18,261	14,354	0	962,493
Prof	0.032	0.176	0	1
Mantech	0.189	0.391	0	1
Skillmn	0.26	0.438	0	1
Ptskill	0.091	0.288	0	1
Unskill	0.025	0.156	0	1
Armed	0.001	0.0326	0	1
No work	0.400	0.490	0	1
Direct instruments				
H cond others	1.165	1.618	0	21

H limit others	0.44	1.175	0	21

Note: See Table A.13 for variable definition.

Table 4.3 Number of observations providing care in each year

Wave	No care	Providing care	% Caring	Care <20hrs	Care≥20hrs
1	8,400	1,348	13.83%	1,085	263
2	8,094	1,234	13.23%	1,003	231
3	7,584	1,345	15.06%	1,104	241
4	7,667	1,311	14.60%	1,033	278
5	7,460	1,090	12.75%	825	265
6	7,786	1,203	13.38%	934	269
7	9,111	1,548	14.52%	1,154	394
8	8,964	1,433	13.78%	1,068	365
9	12,453	2,348	15.86%	1,752	596
10	12,250	2,487	16.88%	1,869	618
11	14,650	3,060	17.28%	2,232	828
12	12,726	2,661	17.29%	2,017	644
13	12,532	2,512	16.70%	1,919	593
14	11,992	2,495	17.22%	1,922	573
15	12,047	2,375	16.47%	1,781	594
16	11,820	2,389	16.81%	1,791	598
17	11,155	2,540	18.55%	1,960	580
18	11,018	2,215	16.74%	1,657	558
Total	187,709	35,594			

Note: Individual-year observations.

Table 4.4 Average responses in health outcomes by hours providing care

Health outcome	No care	Care <20hrs	Care≥20hrs
GHQ	11.049	11.432	13.088
SAH	2.863	2.828	2.539
SF6D	0.806	0.796	0.758
Num. health conditions	1.034	1.225	1.573

Note: SAH mean computed assigning values of 1 to 4 to categories very poor/poor, fair, good/very good, excellent.

Table 4.5 Estimation results for GHQ. Hours care is discrete

	OLS	FE	System GMM	System GMM
			No direct IVs for care	Direct IVs for care
Coefficient results	(1)	(2)	(3)	(4)
GHQ t-1	0.336*** (0.0041)	0.056*** (0.0051)	0.200*** (0.007)	0.194*** (0.0076)
GHQ t-2	0.199*** (0.0040)	-0.013*** (0.0043)	0.074*** (0.006)	0.0658*** (0.0068)
GHQ t-3	0.165*** (0.0039)	-0.039*** (0.0042)	0.0337*** (0.0050)	0.0306*** (0.0058)
Care < 20hrs	0.069* (0.037)	-0.010 (0.0507)	0.352 (0.260)	0.114 (0.2790)
Care ≥ 20hrs	**0.749*** (0.0712)**	**0.859*** (0.1070)**	**2.878*** (0.535)**	**2.423*** (0.5677)**
Instruments				
Past values			Y	Y
Lags GHQ			(2 5)	(2 5)
Lags care			(2 5)	(2 5)
Direct IVs				
Lag h cond others			**N**	**Y**
Lag h limit others			**N**	**Y**
Hansen test (P-value)			0.314	0.143
Serial Correlation (P-value)				
Order (1)			-53.46 (0.000)	-51.70 (0.000)
Order (2)			-0.24 (0.809)	0.77 (0.439)
Order (3)			-0.46 (0.645)	-0.24 (0.809)
Order (4)			0.71 (0.478)	0.64 (0.519)
Observations	124,746	124,746	124,746	124,746

Note: Models include full set of covariates and wave dummies. Robust standard errors for estimated coefficients in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.6 Estimation results for GHQ. Hours care is continuous

	OLS	FE	System GMM	System GMM
			No direct IVs for care	Direct IVs for care
Coefficient results	(1)	(2)	(3)	(4)
GHQ t-1	0.336*** (0.0041)	0.056*** (0.0051)	0.198*** (0.0072)	0.192*** (0.0078)
GHQ t-2	0.199*** (0.0040)	-0.013*** (0.0043)	0.072*** (0.0064)	0.064*** (0.0069)
GHQ t-3	0.165*** (0.0039)	-0.039*** (0.0042)	0.032*** (0.0056)	0.0295*** (0.0057)
Hours care	**0.0095*** (0.001)**	**0.012*** (0.0015)**	**0.034*** (0.0079)**	**0.0289*** (0.0085)**
Instruments				
Past values			Y	Y
Lags GHQ			(2 5)	(2 5)
Lags care			(2 5)	(2 5)
Direct IVs				
Lag h cond others			**N**	**Y**
Lag h limit others			**N**	**Y**
Hansen test (P-value)			0.262	0.246
Serial Correlation (P-value)				
Order (1)			-53.86 (0.000)	-51.78 (0.000)
Order (2)			-0.16 (0.872)	0.80 (0.423)
Order (3)			-0.38 (0.706)	-0.12 (0.905)
Order (4)			-0.38 (0.513)	0.57 (0.567)
Observations	124,746	124,746	124,746	124,746

Note: Models include full set of covariates and wave dummies. Robust standard errors for estimated coefficients in parenthesis *** p<0.01, ** p<0.05, * p<0.1.

Table 4.7 Estimation results for SF-6D. Hours care is discrete

	OLS	FE	System GMM	System GMM
			No direct IVs for care	**Direct IVs for care**
Coefficient results	(1)	(2)	(3)	(4)
SF-6D t-1	0.420*** (0.0037)	0.124*** (0.0047)	0.254*** (0.0109)	0.247*** (0.0132)
SF-6D t-2	0.229*** (0.0038)	0.020*** (0.0040)	0.092*** (0.0077)	0.083*** (0.0094)
SF-6D t-3	0.180*** (0.0035)	-0.021*** (0.0039)	0.035*** (0.0062)	0.034*** (0.0071)
Care < 20hrs	-0.00018 (0.0005)	0.0008 (0.0007)	-0.0008 (0.0037)	0.0046 (0.0043)
Care ≥ 20hrs	**-0.0046*** (0.0009)**	**-0.0045*** (0.0014)**	**-0.025*** (0.0074)**	**-0.030*** (0.0080)**
Instruments				
Past values				
Lags GHQ			(2 5)	(2 5)
Lags care			(2 5)	(2 5)
Direct IVs				
Lag h cond others			**N**	**Y**
Lag h limit others			**N**	**Y**
Hansen test (P-value)			0.000	0.000
Serial Correlation (P-value)				
Order (1)			-52.73 (0.000)	-46.25 (0.000)
Order (2)			-0.78 (0.435)	0.25 (0.804)
Order (3)			-0.18 (0.858)	-0.98 (0.329)
Order (4)			1.05 (0.293)	0.67 (0.503)
Observations	136,751	136,751	136,751	136,751

Note: Models include full set of covariates and wave dummies. Robust standard errors for estimated coefficients in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.8 Estimation results for SF-6D. Hours care is continuous

	OLS	FE	System GMM	System GMM
			No direct IVs for care	**Direct IVs for care**
Coefficient results	(1)	(2)	(3)	(4)
SF-6D t-1	0.420*** (0.0037)	0.124*** (0.0047)	0.236*** (0.0114)	0.224*** (0.0141)
SF-6D t-2	0.229*** (0.0038)	0.020*** (0.0040)	0.082*** (0.0078)	0.070*** (0.0096)
SF-6D t-3	0.180*** (0.0035)	-0.021*** (0.0039)	0.029*** (0.0062)	0.026*** (0.0072)
Hours care	**-0.00006*** (0.00001)**	**-0.00006** (0.00002)**	**-0.0002** (0.0001)**	**-0.00032*** (0.0001)**
Xit	Y	Y	Y	Y
Wave dummies	Y	Y	Y	Y
Instruments				
Past values				
Lags GHQ			(2 5)	(2 5)
Lags care			(2 5)	(2 5)
Direct IVs				
Lag h cond others			**N**	**Y**
Lag h limit others			**N**	**Y**
Hansen test (P-value)			0.000	0.000
Serial Correlation (P-value)				
Order (1)			-51.08 (0.000)	-44.23 (0.000)
Order (2)			-0.75 (0.454)	0.36 (0.720)
Order (3)			0.26 (0.796)	-0.59 (0.557)
Order (4)			0.73 (0.466)	0.31 (0.759)
Observations	136,751	136,751	136,751	136,751

Note: Models include full set of covariates and wave dummies. Robust standard errors for estimated coefficients in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.9 Estimation results for number of health conditions. Hours care is discrete

	OLS	FE	System GMM	System GMM
			No direct IVs for care	**Direct IVs for care**
Coefficient results	(1)	(2)	(4)	(3)
Hcond t-1	0.388*** (0.0041)	0.122*** (0.0052)	0.312*** (0.0126)	0.349*** (0.0075)
Hcond t-2	0.230*** (0.0042)	0.051*** (0.0047)	0.166*** (0.0095)	0.196*** (0.00743)
Hcond t-3	0.149*** (0.0042)	0.007 (0.0046)	0.081*** (0.0074)	0.101*** (0.0066)
Hcond t-4	0.139*** (0.0039)	0.006 (0.0043)	0.053*** (0.0066)	0.0625*** (0.0063)
Care < 20hrs	**0.032*** (0.0068)**	**0.026** (0.0094)**	**0.111** (0.0498)**	0.0527 (0.0489)
Care ≥ 20hrs	**0.036** (0.0136)**	0.008 (0.0194)	0.0027 (0.0927)	**0.232*** (0.0749)**
Instruments				
Past values				
Lags GHQ			(2 5)	(2 5)
Lags care			(2 5)	(2 5)
Direct IVs				
Lag h cond oth			**N**	**Y**
Lag h limit oth			**N**	**Y**
Hansen test (P-value)			0.000	0.000
Serial Correlation (P-value)				
Order (1)			-49.01 (0.000)	-57.28 (0.000)
Order (2)			-0.54 (0.592)	-1.41 (0.159)
Order (3)			0.44 (0.658)	-0.38 (0.703)
Order (4)			-1.36 (0.174)	-1.50 (0.134)
Observations	117,388	117,388	117,388	113,902

Note: Models include full set of covariates and wave dummies. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.10 Estimation results for number of health conditions. Hours care is continuous

	OLS	FE	System GMM	System GMM
			No direct IVs for care	**Direct IVs for care**
Coefficient results	(1)	(2)	(4)	(3)
Hcond t-1	0.388*** (0.0041)	0.122*** (0.0052)	0.278*** (0.0168)	0.347*** (0.0074)
Hcond t-2	0.230*** (0.0042)	0.051*** (0.0047)	0.146*** (0.0116)	0.192*** (0.00745)
Hcond t-3	0.149*** (0.0042)	0.007 (0.0046)	0.069*** (0.0084)	0.099*** (0.0067)
Hcond t-4	0.139*** (0.0039)	0.006 (0.0043)	0.049*** (0.0067)	0.0627*** (0.0063)
Hours care	**0.0006*** (0.0002)**	0.0003 (0.0003)	-0.0002 (0.0012)	**0.0036*** (0.001)**
Instruments				
Past values				
Lags GHQ			(2 5)	(2 5)
Lags care			(2 5)	(2 5)
Direct IVs				
Lag h cond others			**N**	**Y**
Lag h limit others			**N**	**Y**
Hansen test (P-value)			0.000	0.000
Serial Correlation (P-value)				
Order (1)			-41.25 (0.000)	-57.44 (0.000)
Order (2)			-0.43 (0.664)	-1.06 (0.290)
Order (3)			0.81 (0.418)	-0.30 (0.761)
Order (4)			-1.46 (0.143)	-1.59 (0.112)
Observations	117,388	117,388	117,388	113,902

Note: Models include full set of covariates and wave dummies. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4.11 Random effects ordered probit models for SAH

	RE ordered probits				RE ordered probit using 2-SRI
Coefficient results	(1)	(2)	(3)	(4)	(5)
SAHvpp t-1	-0.923*** (0.0169)				-0.962*** (0.0194)
SAHfair t-1	-0.406*** (0.0094)				-0.405*** (0.0105)
SAHex t-1	0.392*** (0.0108)				0.406*** (0.0116)
Care < 20 hrs	0.0179* (0.0104)				
Care ≥ 20 hrs	-0.041** (0.0184)				
Hours care (continuous)		-0.00066** (0.00026)			-0.00239*** (0.00063)
Lagged Care < 20 hrs			-0.0157 (0.0104)		
Lagged care ≥ 20 hrs			-0.0721*** (0.0186)		
Lagged hours care (continuous)				-0.00105*** (0.00026)	
1st stage predicted residual					0.00195** (0.000725)
1st stage instruments for care					
Lagged h conditions others (IV1)					0.373*** (0.0437)
Lagged h limitations others (IV2)					1.507*** (0.0745)
F-stat IV1&IV2 chi2 (p-value)					521.82 (0.000)
Log Likelihood	-175,007.09	-175,008.86	-174,138.24	-174,138.56	-144,145.71
Number of observations	185,330	185,330	184,399	184,399	153,155

Note: Models include full set of covariates and wave dummies. Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Linear RE estimation in first stage of 2SRI.

Table 4.12 Predicted probabilities of SAH at different number of hours providing care

	Predicted probabilities			
Number of hours providing care	**SAH= poor/v.poor**	**SAH=fair**	**SAH= good/v.good**	**SAH=Excellent**
0	0.034*** (0.0006)	0.194*** (0.0017)	0.588*** (0.0022)	0.184*** (0.0018)
20	0.035*** (0.0010)	0.203*** (0.0026)	0.586*** (0.0023)	0.174*** (0.0028)
42	0.040*** (0.0019)	0.213*** (0.0050)	0.583*** (0.0027)	0.163*** (0.0053)
100	0.051*** (0.0054)	0.240*** (0.0122)	0.572*** (0.0066)	0.136*** (0.0112)

Note: Standard errors using the Delta method in parenthesis. ***p<0.01.

Appendices

A1. Complete system GMM estimation results for GHQ

Table A.14 shows the complete System GMM estimation results for the health outcome GHQ when treating informal care as a categorical variable (column 1) and as a continuous measure (column 2). We report the estimated coefficient results for lagged GHQ, informal care, as well as the control variables used to estimate our system of equations (31) and (32).

The performance of the exogenous regressors seems plausible in both models. Widowed individuals tend to score about 3 points higher than married individuals (reference category) on the GHQ scale, so they tend to feel slightly more distressed. Divorced individuals also feel more distressed than those who are married. An increase in the number of children in the household decreases GHQ scores. The effect of age on the GHQ score seems to vary over the years. At the beginning, getting older seems to increase the levels of distress, but at a later stage, an extra year seems to decrease the levels of distress. Individuals who have a job report lower GHQ scores than those who are unemployed. For the estimated results in column one, the wave dummies are not significant but they show a moderate increasing gradient towards higher GHQ scores i.e. more distress levels over time. For the model with continuous hours of care in column two the results show a similar pattern where coefficients for waves prior to wave 18 (reference category in this case) are negative, meaning that over time, GHQ scores were lower compared to the GHQ in wave 18, and therefore, there is again an increasing gradient.

A2. System GMM estimations for GHQ restricting the set of instruments

Table A.15 shows the results for system GMM estimation for the coefficients of lagged GHQ and hours providing care using different sets of lags as instruments other than lag 2 to 5 used in our main results.

In column one we use the full set of available lags that can be used as instruments taking into account the number of years in our data (18 waves). Columns two, three, and four present respectively, the same model restricting the set of lags from 2 to 10, from lag 2 to 7, and from lag 2 to 6. We observe that the more we restrict the instrument set, the higher the p-value for the Hansen test, confirming the fact that greater lags are less informative (and therefore, weaker). However, the key coefficients for informal care are not very sensitive to the lags used.

We obtain similar results when treating the coefficient for informal care as a continuous variable, and therefore, we only show the system GMM estimation when using the full set of instruments (column five) where results are very similar to our main results.

A3. Strength of instruments

Xtabond2 does not produce tests of the strength of the direct instruments. In **Table A.16** we report results from the random effects ordered probit model for informal care regressed on all the explanatories in the system GMM model of GHQ. The coefficients on the two direct instruments are highly significant.

A4. Complete system GMM estimation results for SF-6D

In **Table A.17** we present the complete system GMM estimation results for SF-6D. Estimation in column one shows the results for the model when using informal care as a categorical variable, and estimation in column two shows the results when treating informal care as a continuous variable.

The performance of the exogenous explanatory variables in terms of significance is similar to the GHQ models for both estimations in columns one and two. Moreover, the significance of the coefficients and the sign is the same for both models, except for some wave dummies. Both models show that males report SF-6D scores that are higher than females and, therefore, reporting to be on a better physical and mental health condition. For example, for the model in column one, men report an SF-6D scores that is 0.109 points higher than women. Widowed and divorced individuals report slightly lower SF-6D scores towards poorer health than married individuals, but those effects are very small in both models in column one (-0.0075 and -0.0074) and two (-0.0079 and -0.0068). White individuals report better SF-6D scores than individuals from other ethnicities. An increase in the number of children decreases the SF-6D scores towards a poorer physical and mental health for individuals having a children from 0 to 4 years old, although the effect is very small. Individuals in the job market report on average better SF-6D scores than unemployed individuals in both models. The coefficient results for the time trends in column one are positive and quite stable over time, showing a very minor increasing trend towards better SF-6D scores on average. The same interpretation can be done for those coefficients in column 2, as the results show that SF-6D scores in waves prior to wave 18 are lower compared with this category and that magnitude decreases over time.

A5. System GMM estimations for SF-6D restricting the set of instruments

Symmetrically as for GHQ, **Table A.18** presents system GMM estimations varying the number of lags used as instruments for the SF-6D system GMM estimation when using both lags and direct instruments for informal care. As for GHQ, the magnitude of the informal care coefficients is similar across models. However, in this case, the performance of the Hansen test does not improve and, as in our main result for SF-6D in Table 4.7, it indicates that the set of instrumental variables is not valid of the restrictions we make.

A6. Estimation results for SAH

Table A.19 presents the full random effects ordered probit estimation results for SAH. Results are generally plausible. For example, white individuals are more likely to report better self-assessed health than individuals from other ethnicities. Education at any degree has a positive impact on SAH. Working in the labour market also has a positive impact. Household size has a negative impact on self-assessed health, while an increase in the number of children has a positive impact. Both the initial conditions and some of the mean variables of the coefficients are significant.

A7. Estimation results excluding the subsample of carers providing care outside the household

BHPS does not have data on family members who do not live in the household. Therefore, we have only information on the health of individuals living in the same household as the interviewee. Consequently, the direct instruments for the number of hours providing care informal care, number of health problems and number of health limitations of other household members, will be more powerful for those individuals who provide care inside the household and less powerful for those only providing care outside their household.

We re-estimate our main models restricting the sample of carers to those who only provide care inside the household together with non-carers and compare the results with the ones obtained along the results section. By excluding individuals who only provide care for someone outside their household we aim to test the performance of our direct instruments as well as the overall performance of the models.

Results for GHQ in **Table A.20** show that the coefficient results for the models are very similar in magnitude and significance to the results in our main models in Table 4.5 and Table 4.6. Individuals who provide 20 or more hours of care per week report GHQ scores that are on average 2.65 points higher than those individuals who do not provide informal care. That impact is 0.22 points higher than when using the full sample of carers. Similarly, for the continuous measure of weekly number of hours providing care, an increase in the number of hours providing care increases the GHQ score towards poorer mental health by 0.026 points, which is slightly smaller than the effect when not restricting the sample of carers (0.028 points).

However, changing the sample does affect the Hansen test results. The Hansen tests in Table A.20 show that, when excluding individuals who care for someone outside their household, we reject the null hypothesis of exogeneity of the instrument set at 5% significance level.

For SF-6D, the coefficients for number of hours providing care in columns 3 and 4 of Table A.20 are smaller than the results in the main models in columns 4 of Table 4.7 and Table 4.8. Coefficients on informal care are only statistically significant at 10% while when using the full sample of carers, the coefficients are significant at 1%. As in the main models, where the Hansen test shows that the models are not over-identified.

When using the number of health conditions as the health outcome of interest, the coefficient results for informal care in columns 5 and 6 in Table A.20 are very similar in magnitude and have the same level of significance as in our main models in column 4 of Table 4.9 and Table 4.10.

Results are very similar as in our main models. This might indicate that the direct instruments, even though they do not capture the health problems and health limitations of care-receivers and relatives outside the household, they may also be adequate to identify the potential increase in the number of hours providing care for those individuals who care for someone outside their household. It is also worth noticing that restricting the sample introduces sample selection bias.

Table A.21 shows the results for the continuous number of hours providing care when using the SAH health outcome, after estimating a random effect ordered probit model using 2SRI. Results are very similar to those with the full sample of carers.

A8. Estimation results for the sample of informal carers

Table A.22 and **Table A.23** show the results from models estimated only on the sample of carers. This may create selection bias but we think it is still interesting to explore how the models perform on this sample. Results are similar to those on the full sample. There is a small detrimental effect of informal care on health.

A9. Static models

Since our main interest is the effect of informal care on health and we are not directly interested in the dynamics of health, we investigate if similar results are obtained in static health models. The model is

$$H_{it} = \gamma_t + \delta_1 care_{it} + \delta_2 \boldsymbol{X_{it}} + \alpha_i + e_{it} \tag{41}$$

where we assume that current health does not depend on past health. Even though this model might be miss-specified, we think it is interesting to investigate whether a similar conclusion regarding the impact of informal care on health can be obtained. From an econometric point of view, the advantage of estimating equation (41) is that it is simple than the dynamic specification and we do not need to deal with the problems regarding weak exogeneity or the initial conditions. The main econometric problem is the endogeneity of informal care.

We start by estimating random and fixed effects versions of the model in equation (41) assuming informal care is exogenous. The results for GHQ are in **Table A.24**. Columns one and two have random and fixed effects estimates with informal care as a current categorical variable. Results show that an extra hour of care for those providing 20 or more hours increases the GHQ score. In columns three and four we lag informal care to reduce potential endogeneity. Both the coefficients for caring below and for at least 20 hours per week are significant. Similar results are shown in columns five to eight where we follow the same procedure when treating informal care as a continuous variable. In these estimations, as in the dynamic models, the effects of informal care on GHQ are positive and significant but small.

Table A.25 shows the 2SLS estimation results when instrumenting for informal care. Columns one and two have results for GHQ. The effect is significant and larger than in the uninstrumented models in Table A.24. F-stat of jointly significance shows that they are strong valid instruments.

With respect the results for SF-6D, column three in Table A.25 shows the random effects 2SLS. Results indicate a negative and small impact of informal care on SF-6D which is in accordance with our main dynamic model. In column four, the fixed effects 2SLS coefficient is positive and significant at 5% though very small given the scale (0, 1) of SF-6D.

For the health outcome number of health conditions, columns five and six show the RE 2SLS and the FE 2SLS. As with the dynamic model, those static models also show a moderate increase on the number of health conditions when an extra hour of informal care per week is provided.

Appendices tables

Table A.13 Variable definition

Dependant variables	
GHQ	General Health Questionnaire (0-36 point scale). Mental health: quantifies minor psychiatric disorders such as depression and anxiety. GHQ-12 unified answers & re-scaled to a continuous measure from 0 (least distressed) to 36 (most distressed).
SF-6D	Health index of physical and mental health ranging from 0 (poorest score) to 1 (highest score). Constructed by selecting appropriate questions of SF-36 and assigning weights for each question (Brazier *et al.*, 2002). SF-36 available in 2 waves of BHPS. Need to predict SF-6D for the remaining waves.
Health conditions	Number of physical health problems an individual has (up to 14 health problems). Arm, sight, hearing, skin, chest, heart, stomach, diabetes, alcohol, epilepsy, migraine, cancer, stroke, others.
SAH	Self-Assessed Health (1 if very poor/poor, 2 if fair, 3 if good/very good, 4 if excellent).
Hourscare	Weekly number of hours providing informal care (mid points of 0-4; 5-9; 10-19; 20-34; 35-49; 50-99, ≥100, varies <20, varies ≥20).
Below20hrs	1 if providing care for less than 20 hours, 0 otherwise.
More20hrs	1 if providing care for 20 hours or more, 0 otherwise.
Zerohrs	1 if not providing any care, 0 otherwise.
Controls	
Male	1 if male, 0 if female.
Married	1 if married, 0 otherwise.
Widowed	1 if widow, 0 otherwise.
Divorced	1 if divorced, 0 otherwise.
Single	1 if never married, 0 otherwise.
White	1 if ethnic group is white, 0 otherwise.
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 qualification, 0 otherwise (baseline category).
Hhsize	Number of individuals living in the household.

Nch04	Number of children in household between 0-4 years old.
Nch511	Number of children in household between 5-11 years old.
Nch1218	Number of children in household between 12-18 years old.
Age	Age in years at current wave.
lnincome	Equivalized annual real household income in pounds (logarithm).
Prof	1 if professional occupation, 0 otherwise.
Mantech	1 if managerial and technical occupation, 0 otherwise.
Skillmn	1 if skilled occupation and manual, 0 otherwise.
Ptskill	1 if partly skilled occupation, 0 otherwise.
Unskill	1 if unskilled occupation, 0 otherwise.
Armed	1 if armed forces, 0 otherwise.
Nowork	1 if not working, 0 otherwise (baseline category).
Wave	Wave dummies.
Informal care instruments	
H cond others	Count of number of health conditions of all other household members: arm, sight, hearing, skin, chest, heart, stomach, diabetes, depression, alcohol, epilepsy, migraine, cancer, stroke, and other problems.
H limit others	Count of number of health limitations of all other household members: housework, climbing stairs, getting dressed, walking, other limitations.

Table A.14 System GMM estimation Results for GHQ. Complete results

	Care below/above20	Hours care continuous
	(1)	(2)
GHQ t-1	0.194*** (0.00767)	0.192*** (0.00785)
GHQ t-2	0.0658*** (0.00685)	0.0641*** (0.00692)
GHQ t-3	0.0307*** (0.00580)	0.0295*** (0.00578)
care < 20hrs	0.114 (0.279)	
care ≥ 20hrs	2.423*** (0.568)	
hours care		0.0289*** (0.00847)
male	1.314 (1.547)	-0.910 (1.716)
widowed	3.016*** (0.304)	2.908*** (0.311)
divorced	1.544*** (0.238)	1.519*** (0.240)
single	0.192 (0.178)	0.228 (0.178)
white	0.932 (4.340)	-3.197 (4.253)
deghdeg	-0.165 (0.625)	0.00754 (0.636)
hndalev	-0.303 (0.591)	-0.191 (0.605)
ocse	0.245 (0.577)	0.442 (0.589)
hhsize	0.0425 (0.0479)	0.0450 (0.0478)
nch04	-0.0243 (0.0826)	-0.0309 (0.0825)
nchild511	-0.156** (0.0784)	-0.172** (0.0785)
nch1218	-0.137* (0.0774)	-0.145* (0.0773)
age	0.351*** (0.101)	0.339*** (0.107)
age2	-0.741*** (0.191)	-0.708*** (0.192)
age3	0.461*** (0.120)	0.438*** (0.121)
lninc	-0.0157 (0.0468)	-0.00980 (0.0467)
prof	-0.989*** (0.175)	-1.010*** (0.175)
mantech	-0.865*** (0.125)	-0.882*** (0.124)
skillmn	-0.989*** (0.109)	-1.001*** (0.110)
ptskill	-1.003*** (0.129)	-1.014*** (0.129)
unskill	-0.730*** (0.188)	-0.761*** (0.187)
armed	-1.591** (0.642)	-1.624** (0.635)
4.wave	1.669 (5.082)	-0.734 (0.630)
5.wave	1.779 (5.095)	-0.596 (0.585)
6.wave	1.803 (5.104)	-0.594 (0.541)
7.wave	1.745 (5.118)	-0.626 (0.495)
8.wave	1.698 (5.126)	-0.700 (0.453)
9.wave	1.563 (5.136)	-0.807** (0.410)
10.wave	2.014 (5.147)	-0.357 (0.365)

11.wave	1.956 (5.157)	-0.429 (0.323)
12.wave	1.957 (5.171)	-0.436 (0.278)
13.wave	1.908 (5.183)	-0.497** (0.234)
14.wave	1.990 (5.197)	-0.414** (0.188)
15.wave	2.163 (5.207)	-0.228 (0.148)
16.wave	2.141 (5.221)	-0.266** (0.106)
17.wave	2.083 (5.232)	-0.319*** (0.0708)
18.wave	2.404 (5.242)	(reference wave)
Constant	(reference)	7.465* (4.518)
Observations	124,746	124,746
Number of pid	18,297	18,297

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A.15 System GMM estimation results for GHQ. Restricting number of lags used as instruments

	(1)	(2)	(3)	(4)	(5)
GHQ t-1	0.191 (0.0078)***	0.192 (0.0077)***	0.191 (0.0077)***	0.192 (0.007)***	0.1912 (0.0078)***
GHQ t-2	0.065 (0.0069)***	0.065 (.0069)***	0 .0656 (0.0069)***	0.065 (.0069)***	0.063 (0.0069)***
GHQ t-3	0.031 (0.0058)***	0.033 (0.0058)***	0.031 (0.0058)***	0.031 (0.0057)***	0.03 (0.0057)***
Care < 20hrs	0.375 (0.266)	0.403 (0.269)	0.248 (0.273)	0.131 (0.275)	
Care ≥ 20hrs	2.0015 (0.551)***	1.805 (0.562)***	2.14 (0.566)***	2.248 (0.570)***	
Hours care					0.0196 (0.008)**
Instruments					
Lags GHQ	**(2 17)**	**(2 10)**	**(2 7)**	**(2 6)**	**(2 17)**
Lags care	**(2 17)**	**(2 10)**	**(2 7)**	**(2 6)**	**(2 17)**
Lag h cond other	Y	Y	Y	Y	Y
Lag h limit other	Y	Y	Y	Y	Y
Hansen test (P-value)	0.033	0.053	0.104	0.159	0.179
Serial Correlation (P-value)					
Order (1)	-50.69 (0.000)	-51.08 (0.000)	-51.34 (0.000)	-51.48 (0.000)	-51.22 (0.000)
Order (2)	0.63 (0.531)	0.91 (0.365)	0.62 (0.533)	0.72 (0.469)	0.82 (0.411)
Order (3)	-0.28 (0.782)	-0.59 (0.553)	-0.32 (0.753)	-0.29 (0.775)	-0.24 (0.807)
Order (4)	0.66 (0.511)	0.76 (0.445)	0.68 (0.499)	0.65 (0.514)	0.61 (0.541)
Observations	124,746	124,746	124,746	124,746	124,746

Note: Models include full set of covariates and wave dummies. Robust standard errors for estimated coefficients in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A.16 First-stage Random Effects ordered probit model for informal care

	RE ordered probit
hlconditionshh_others t-1 (IV1)	0.0618*** (0.0060)
hllimitshh_others t-1 (IV2)	0.1912*** (0.00723)
Observations	123,775
Number of pid	18,568
F-stat (chi-square) IV1&IV2	1117.39
P-value	0.000

Note: Model includes all the explanatories on the system GMM model of GHQ. Robust standard errors for estimated coefficients in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A.17 System GMM estimation results for SF-6D.

	Care below/above20	**Hours care continuous**
	(1)	(2)
SF-6D t-1	0.247*** (0.0132)	0.225*** (0.0141)
SF-6D t-2	0.0835*** (0.00935)	0.0702*** (0.00964)
SF-6D t-3	0.0344*** (0.00713)	0.0264*** (0.00717)
Care < 20hrs	0.00461 (0.00425)	
Care ≥ 20hrs	-0.0303*** (0.00804)	
Hours care		-0.000317*** (0.000113)
male	0.109*** (0.0303)	0.137*** (0.0415)
widowed	-0.00750** (0.00379)	-0.00793** (0.00384)
divorced	-0.00736*** (0.00285)	-0.00678** (0.00283)
single	-0.00196 (0.00224)	-0.00163 (0.00220)
white	0.142** (0.0657)	0.248*** (0.0886)
deghdeg	0.0125 (0.00835)	0.0126 (0.00851)
hndalev	0.00888 (0.00793)	0.00984 (0.00812)
ocse	0.00599 (0.00796)	0.00753 (0.00820)
hhsize	0.000259 (0.000606)	0.000219 (0.000596)
nch04	-0.00367*** (0.00112)	-0.00365*** (0.00110)
nchild511	0.00104 (0.00103)	0.000958 (0.00101)
nch1218	-0.000517 (0.00101)	-0.000492 (0.000986)
age	-0.000782 (0.00136)	-0.00118 (0.00136)
age2	0.00180 (0.00271)	0.00105 (0.00269)
age3	-0.00322* (0.00176)	-0.00286 (0.00175)
lninc	0.000628 (0.000642)	0.000617 (0.000632)
prof	0.00395* (0.00221)	0.00381* (0.00218)
mantech	0.00228 (0.00154)	0.00236 (0.00151)
skillmn	0.00507*** (0.00141)	0.00510*** (0.00139)

ptskill	0.00449*** (0.00170)	0.00463*** (0.00167)
unskill	0.00499* (0.00258)	0.00537** (0.00254)
armed	0.0130 (0.0100)	0.0151 (0.00955)
4.wave	0.348*** (0.0719)	-0.0128** (0.00535)
5.wave	0.348*** (0.0720)	-0.0127** (0.0050)
6.wave	0.344*** (0.0721)	-0.0155*** (0.00465)
7.wave	0.345*** (0.0722)	-0.0139*** (0.00433)
8.wave	0.345*** (0.0723)	-0.0135*** (0.00401)
9.wave	0.352*** (0.0724)	-0.00539 (0.00364)
10.wave	0.341*** (0.0726)	-0.0158*** (0.00328)
11.wave	0.344*** (0.0727)	-0.0121*** (0.00296)
12.wave	0.342*** (0.0728)	-0.0137*** (0.00263)
13.wave	0.345*** (0.0729)	-0.00981*** (0.00232)
14.wave	0.346*** (0.0730)	-0.00795*** (0.00204)
15.wave	0.351*** (0.0731)	-0.00241 (0.00179)
16.wave	0.351*** (0.0733)	-0.00129 (0.00105)
17.wave	0.350*** (0.0734)	-0.00178** (0.000803)
18.wave	0.351*** (0.0735)	
Constant		0.309*** (0.0865)
Observations	136,751	136,751
Number of pid	19,371	19,371

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A.18 System GMM estimation results for SF-6D. Restricting the number of lags used as instruments

	(1)	(2)	(3)	(4)	(5)
SF-6D t-1	0.243 (0.013)***	0.242 (0.013)***	0.244 (0.0131)***	0.245 (0.0131)***	0.221 (0.0142)***
SF-6D t-2	0.080 (0.0094)***	0.081 (0.009)***	0.082 (0.009)***	0.082 (0.009)***	0.0689 (0.00962)***
SF-6D t-3	0.032 (0.0071)***	0.032 (0.007)***	0.033 (0.007)***	0.033 (0.007)***	0.024 (0.00716)***
Care < 20hrs	0.0027 (0.004)	0.003 (0.004)	0.0034 (0.004)	0.004 (0.004)	
Care ≥ 20hrs	-0.0263 (0.00769)***	-0.0269 (0.008)***	-0.0269 (0.007)***	-0.0285 (0.008)***	
Hours care					-0.000264 (0.000117)***
Instruments					
Lags SF-6D	**(2 17)**	**(2 10)**	**(2 7)**	**(2 6)**	**(2 17)**
Lags care	**(2 17)**	**(2 10)**	**(2 7)**	**(2 6)**	**(2 17)**
Lag h cond othr	Y	Y	Y	Y	Y
Lag h limit othr	Y	Y	Y	Y	Y
Hansen test (P-value)	0	0	0	0	0
Serial Correlation (P-value)					
Order (1)	-45.45 (0.000)	-45.74 (0.000)	-46.17 (0.000)	-46.19 (0.000)	-43.53 (0.000)
Order (2)	0.21 (0.835)	0.09 (0.928)	0.18 (0.859)	0.24 (0.807)	0.15 (0.881)
Order (3)	-0.69 (0.492)	-0.68 (0.499)	-0.80 (0.425)	-0.88 (0.381)	-0.28 (0.779)
Order (4)	0.54 (0.590)	0.54 (0.591)	0.60 (0.548)	0.62 (0.535)	0.18 (0.854)
Observations	136,751	136,751	136,751	136,751	136,751

Note: Models include full set of covariates and wave dummies. Robust standard errors for estimated coefficients in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A.19 Random effects ordered probit model (2nd stage of 2SRI) for SAH. Complete estimation

	RE ordered probit
hrscare	-0.0024*** (0.0006)
resid	0.002** (0.0007)
l1sah4vpp	-0.9616*** (0.0194)
l1sah4fair	-0.4055*** (0.0105)
l1sah4ex	0.4060*** (0.0116)
male	0.0042 (0.0121)
widowed	-0.0851 (0.0551)
divorced	-0.0273 (0.0313)
single	0.0098 (0.0248)
white	0.1608*** (0.0357)
deghdeg	0.1895*** (0.0237)
hndalev	0.1224*** (0.0178)
ocse	0.0877*** (0.0165)
hhsize	-0.0177** (0.0068)
nch04	0.0047 (0.0118)
nchild511	0.0502*** (0.0084)
nch1218	0.0254** (0.0091)
age	-0.0089 (0.0094)
age2	0.0039 (0.0197)
age3	-0.0272** (0.0131)
lninc	0.0023 (0.0084)
prof	0.0662** (0.0314)
mantech	0.0711*** (0.0172)
skillmn	0.0853*** (0.0150)
ptskill	0.1020*** (0.0181)
unskill	0.1267*** (0.0284)
armed	0.0658 (0.1493)
sah4vpp0	-1.0516*** (0.0303)
sah4fair0	-0.5189*** (0.0167)
sah4ex0	0.5971*** (0.0158)
mlninc	0.1191*** (0.0162)
mwidowed	0.0653 (0.0621)
mdivorced	-0.0279 (0.0455)
msingle	0.0637* (0.0351)
mhhsize	0.0142 (0.0100)
mnch04	0.0674** (0.0293)

mnch1218	0.0535** (0.0217)
mage	-0.0425*** (0.0124)
mage2	0.0907 (0.0257)
mage3	-0.0244 (0.0170)
mprof	0.5456*** (0.0594)
mmantech	0.4431*** (0.0332)
mskillmn	0.3531*** (0.0286)
mptskill	0.3305*** (0.0368)
munskill	0.2421*** (0.0584)
marmed	1.2554*** (0.2792)
dwave2	-0.0294 (0.0325)
dwave3	-0.0499 (0.0312)
dwave4	-0.0843** (0.0300)
dwave5	-0.0902** (0.0288)
dwave6	-0.1169*** (0.0276)
dwave7	-0.0564** (0.0267)
dwave8	-0.1133*** (0.0245)
dwave9	0.0265 (0.0218)
dwave10	-0.1283*** (0.0226)
dwave11	-0.0224 (0.0207)
dwave12	-0.0704*** (0.0197)
dwave13	-0.0397** (0.0184)
dwave14	-0.0192 (0.0176)
dwave15	0.0386** (0.0175)
dwave16	0.0708*** (0.0162)
dwave17	0.0274 (0.0167)
cut1	-1.2917*** (0.1858)
cut2	0.0085 (0.1858)
cut3	1.9849*** (0.1858)
Observations	153,155

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Variables “mxxx” are the mean of variables “xxx”.

Table A.20 GMM estimation results excluding subsample of carers who provide care outside household

	GHQ		SF-6D		Health conditions	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Care < 20hrs	0.274 (0.194)		0.006** (0.003)		0.006 (0.031)	
Care ≥ 20hrs	2.650*** (0.716)		-0.017* (0.009)		0.261*** (0.081)	
Hours care (continuous)		0.026** (0.009)		-0.0002* (0.0001)		0.003*** (0.001)
Instruments						
Past values						
Lags Dependant Var	(2 5)	(2 5)	(2 5)	(2 5)	(2 5)	(2 5)
Lags care	(2 5)	(2 5)	(2 5)	(2 5)	(2 5)	(2 5)
Direct IVs						
Lag h cond others	Y	Y	Y	Y	Y	Y
Lag h limit others	Y	Y	Y	Y	Y	Y
Hansen test (P-value)	0.021	0.038	0.000	0.000	0.000	0.000
Serial Correlation (P-value)						
Order (1)	-47.98 (0.000)	-47.37 (0.000)	-45.13 (0.000)	-41.18 (0.000)	-53.04 (0.000)	-53.25 (0.000)
Order (2)	0.84 (0.401)	0.82 (0.412)	0.29 (0.770)	0.23 (0.817)	-1.09 (0.275)	-0.71 (0.478)
Order (3)	-0.54 (0.587)	-0.46 (0.645)	-1.05 (0.295)	-0.63 (0.528)	-0.78 (0.437)	-0.82 (0.414)
Order (4)	0.42 (0.675)	0.34 (0.731)	0.62 (0.534)	0.27 (0.790)	-1.32 (0.187)	-1.46 (0.144)
Observations	111,016	111,016	121,995	121,995	101,374	101,374

Note: Models include full set of covariates and wave dummies. Robust standard errors for estimated coefficients in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A.21 2-SRI RE ordered probit. Excluding subsample of carers who provide care outside household

Estimation results	SAH
Hours care (continuous)	-0.0045*** (0.0008)
1st stage predicted residual	0 .004*** (0.0009)
1st stage instruments for care	
Lagged h conditions othr (IV1)	0.413*** (0.046)
Lagged h limitations othr (IV2)	1.602*** (0.079)
F-stat IV1&IV2 chi2 (p-value)	536.86 (0.000)
Log Likelihood	-132,722.88
Number of observations	137,280

Note: Models include full set of covariates and wave dummies. Robust standard errors for estimated coefficients in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A.22 GMM estimation results only for the sample of informal carers.

Estimation results	GHQ		SF-6D		Health conditions	
	(1)	(2)	(3)	(4)	(5)	(6)
Care < 20hrs	-0.116 (0.133)		0.0016 (0.0019)		0.086** (0.034)	
Care ≥ 20hrs	1.362** (0.527)		-0.023** (0.008)		0.234** (0.075)	
Hours care (continuous)		0.003 (0.009)		-0.0004** (0.0001)		0.002* (0.001)
Instruments						
Past values						
Lags Dependant Var	(2 5)	(2 5)	(2 5)	(2 5)	(2 5)	(2 5)
Lags care	(2 5)	(2 5)	(2 5)	(2 5)	(2 5)	(2 5)
Direct IVs						
Lag h cond others	Y	Y	Y	Y	Y	Y
Lag h limit others	Y	Y	Y	Y	Y	Y
Hansen test (P-value)	0.290	0.183	0.001	0.000	0.154	0.226
Serial Correlation (P-value)						
Order (1)	-17.65 (0.000)	-17.54 (0.000)	-19.57 (0.000)	-18.83 (0.000)	-20.44 (0.000)	-20.64 (0.000)
Order (2)	-0.13 (0.894)	-0.03 (0.974)	0.43 (0.669)	0.49 (0.621)	0.13 (0.899)	0.05 (0.958)
Order (3)	1.15 (0.251)	1.31 (0.189)	0.17 (0.867)	0.22 (0.827)	-0.07 (0.946)	0.10 (0.920)
Order (4)	-0.41 (0.685)	-0.36 (0.716)	0.22 (0.829)	0.03 (0.976)	-0.79 (0.429)	-1.14 (0.252)
Observations	21,039	21,039	22,966	22,966	18,441	18,441

Note: Models include full set of covariates and wave dummies. Robust standard errors for estimated coefficients in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A.23 2-SRI RE ordered probit estimation only for the sample of informal carers

Estimation results	SAH
Hours care (continuous)	-0.005*** (0.001)
1st stage predicted residual	0.004*** (0.001)
1st stage instruments for care	
Lagged h conditions othr (IV1)	0.701*** (0.136)
Lagged h limitations othr (IV2)	2.504*** (0.157)
F-stat IV1&IV2 chi2 (p-value)	389.74 (0.000)
Log Likelihood	-25,757.319
Number of observations	25,408

Note: Models include full set of covariates and wave dummies. Robust standard errors for estimated coefficients in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A.24 Static models. RE and FE estimations for GHQ treating informal care as an exogenous variable

	RE (1)	FE (2)	RE (3)	FE (4)	RE (5)	FE (6)	RE (7)	FE (8)
Care < 20 hours	0.052 (0.037)	0.008 (0.039)						
Care ≥ 20 hours	0.922 (0.078)***	0.790 (0.083)***						
Lag Care < 20 hours			0.159 (0.039)***	0.112 (0.042)***				
Lag Care ≥ 20 hours			0.829 (0.084)***	0.665 (0.090)***				
Hours care					0.013 (0.001)***	0.0114 (0.001)***		
Lag Hours care							0.0114 (0.0012)***	0.00949 (0.00131)***
Observations	211,558	211,558	178,889	178,889	211,558	211,558	178,889	178,889

Note: Models include full set of covariates and wave dummies. Robust standard errors for estimated coefficients in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table A.25 Static models. RE and FE 2-SLS estimations. Informal care endogenous

	GHQ		SF-6D		Health conditions	
	2SLS RE (1)	**2SLS FE (2)**	**2SLS RE (3)**	**2SLS FE (4)**	**2SLS RE (5)**	**2SLS FE (6)**
Hours care	0.0987 (0.0077)***	0.0993 (0.0124)***	-0.0012*** (0.00013)	0.0005** (0.00016)	0.014*** (0.002)	0.0055** (0.002)
Lag h cond othr (IV1)	0.430 (0.037)***	0.314 (0.045)***	0.355*** (0.037)	0.282*** (0.046)	0.383*** (0.036)	0.314*** (0.045)
Lag h limit othr (IV2)	1.698 (0.066)***	1.168 (0.08)***	1.555*** (0.064)	1.243*** (0.079)	1.412*** (0.879)	1.142*** (0.077)
F-stat IV1&IV2 chi2 (p-value)	630.89 (0.000)	140.05 (0.000)	658.25 (0.000)	147.44 (0.000)	630.89 (0.000)	140.05 (0.000)
Observations	175,100	175,100	173,634	173,634	180,687	180,687

Note: Models include full set of covariates and wave dummies. Robust standard errors for estimated coefficients in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Chapter 5. Conclusions

In this thesis, we have studied three main topics around informal care: its impact on carer's well-being, early retirement decisions and physical and mental health. We had three core research questions:

- What effects does informal care have on carer's well-being and what is the monetary value of these effects?
- Are informal carers in their middle ages more likely to retire before the UK State Pension Age than non-carers due to their caring responsibilities?
- Is there a negative impact of informal care provision on the physical and mental health of carers?

To answer the first question, in the first core chapter, we calculate monetary values for informal care using the well-being valuation method to determine what change in income is required to compensate for an increase in provision of informal care. We examine whether valuations are sensitive to the measure of well-being used (self-reported happiness and life satisfaction), the estimation method, and the way in which hours care enters into the well-being function. We use panel data from the British Household Panel Data Survey and estimate both linear and ordered logistic models with fixed effects to allow for individual heterogeneity. Our results show that monetary values are sensitive to the well-being measure used, the estimation method, and the specification of the number of hours providing care. Monetary values using the happiness scale are higher for both linear (£21.22) and ordered logit (£24.30) models than using the life satisfaction scale (£18.69 and £18.23 respectively). Men and women require about the same compensation for providing informal care. Money values are sensitive to the specification of hours care and are higher when well-being is assumed to be a non-linear (logarithmic, polynomial, or categorical) function of hours.

To answer question 2 above, we study the impact of providing informal care on early retirement decisions and whether its effect differs between men and women. We estimated a discrete-time duration model in which the sample at risk of retirement is composed of individuals that are aged 50 or over, and employed or self-employed when first observed. We followed them up until retirement or up to a year before the State Pension Age (65 for men and 60 for women). We estimated random effects complementary log-log models in which the retirement probability depends on past weekly number of hours providing care and covariates. Results showed that the probability of early retirement for both males and females providing care for at least 20 hours per week last period is higher than for non-carers. The hazard ratio for caring for 20 or more hours per week lagged one period versus not caring is 2.61 for men and 2.34 for women, implying that their probability of retirement is around twice as high compared with those who do not provide informal care. Thus the intensity of care plays an important role into the transition to retirement for both men and women.

To study the impact of providing informal care on caregiver's health, we have analysed a variety of mental and physical health outcomes for the UK population: GHQ, SF-6D, the number of health conditions and self-assessed health (SAH). We used data from the British Household Panel Dataset and estimate a dynamic panel models for health allowing for the potential endogeneity of informal care. We used Generalized Methods of Moments (GMM) estimation for those health outcomes that can be treated as continuous measures (GHQ, SF6D, and the number of health conditions), and correlated random effects models for the ordered categorical health outcome SAH. We allowed for the endogeneity of informal care by using instrumental variables (lagged health of other individuals in the household or lag values of informal care). For all the health outcomes, we found a negative, though quite small, effect of informal care on health. Carers on average provide 18 hours of care per week and, compared to an individual who supplies no informal care, will have their GHQ mental distress score higher by 0.52 compared to an overall mean GHQ score of 11.19. Their SF-6D score is reduced by 0.0058 compared to an overall mean of 0.803, and their number of health conditions is increased by 0.065 compared to an overall mean of 1.15. A carer providing 20 hours of informal has their probability of excellent health reduced by 0.010 from 0.184 to 0.174.

Our contributions in the studies reported in this thesis are to provide new UK evidence on the effects of informal care on carers from a panel with many (18) waves which enables us to allow for unobserved individual factors and using appropriate analytical methods to account of the nature of the research questions and the way in which key variables are measured in the BHPS.

Future work addressing the question of the effects of informal care on carers could utilise newer data sets. The last wave of the BHPS was 2008 and was replaced by the UK Household Longitudinal Study (UKHLS)panel which has a larger sample but includes BHPS participants. Using this longer panel would enable the longer term effects of informal care to be examined. Another possible data set is the English Longitudinal Study of Ageing (ELSA) dataset which currently has seven waves covering fourteen years and collects very rich health related data. Given that the bulk of informal care is provided by those aged 50 and over the restriction of the ELSA sample to those in this age range is not a problem. Both ELSA and US have permission to access detailed administrative data on participants, so that it would be possible to examine the effects of informal care on, for example, healthcare use.

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