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Carmichael, Fiona; Ercolani, Marco

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Unpaid caregiving and paid work over life-courses: different pathways, diverging outcomes[*]

Fiona Carmichael[a] and Marco G. Ercolani[b]

[a] Corresponding author: Department of Business and Labour Economics, Birmingham Business School, University of Birmingham, UK. email: f.carmichael@bham.ac.uk; Tel: 01214156699
[b] Department of Economics, Birmingham Business School, University of Birmingham, UK

Abstract
We investigate the extent to which people's earlier circumstances and experiences shape subsequent life-courses. We do this using UK longitudinal data to provide a dynamic analysis of employment and caregiving histories for 4339 people over 15-20 years between 1991 and 2010. We analyse these histories as sequences using optimal matching and cluster analysis to identify five distinct employment-caregiving pathways. Regression analysis shows that prior to embarking on these pathways, people are already differentiated by life-stage, gender and attitudes towards family and gender roles. Difference-in-differences estimation shows that some initial differences in income, subjective health and wellbeing widen over time, while others narrow. In particular, those following the most caregiving-intensive pathways not only end up poorer but also experience a relative decline in subjective health and wellbeing. These results confirm that earlier circumstances exert a strong influence on later life-courses consistent with pre-determination, persistence and path dependence.

Key words: caregiving, unpaid work, labour force participation, social attitudes, life-course

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1. Introduction

This paper investigates how employment and unpaid caregiving histories evolve over time as people age and considers the influence of gender and social attitudes. The policy context is population ageing which has created an imperative to extend working lives and is projected to lead to extra demands on health and caring services (HSCIC, 2014). At the same time there has been increased political emphasis on patient choice and the provision of care in the home. This combination is likely to increase the demand for both formal and informal care at home (Pickard *et al.*, 2007; Wittenberg *et al.*, 2011). Whether projected rises in demand for informal care will be met is difficult to know. The calculations in this paper suggest that unpaid caregiving already draws in 38.74 percent of the UK adult population at some point during their lives. As working lives extend, the time available to provide care is being constrained and pressures to combine caregiving and work are likely to increase. In this context, understanding how unpaid caregiving and paid work are interlinked is crucial.

However, much of the evidence on the conflicts and trade-offs between caregiving and paid work considers individual circumstances at a moment in time or over the very short-term (see Lilly *et al.*, 2007 for a review). This is an omission since individual decisions about caregiving are unlikely to be made in an historical vacuum and may be made far in advance of a need arising. More generally, there is a need to explore the dynamic nature of relationships between employment and family context over life-courses (Moen and Sweet, 2004). The study by Moen *et al*. (1994) which draws on retrospective data for 293 women is one of the few to have examined how caregiving is embedded within individual life histories. Larger-scale empirical studies that have incorporated caregiving histories have mainly used lags or leads of caregiving, employment or family circumstances to explain an association at a point in time (Michaud *et al.*, 2010; Carmichael *et al.*, 2010; Heitmueller, 2007; Stern, 1995). This does not fully capture the ways in which caregiving and employment histories evolve together and are intertwined over life-courses. Overall the caregiving literature lacks rigorous, longitudinal studies that would enable us to understand how caregiving trajectories and trade-offs evolve over time.

This paper addresses these gaps using longitudinal data from 20 waves, *i.e.* years, of the combined British Household Panel Survey and follow-on Understanding Society (BHPS-US). The methodology involves four integrated stages. In the first stage we use sequence analysis to map out respondents' observed histories over a period of 15 to 20 years. We then use optimal matching with cluster analysis to group individuals with similar histories. This allows us to create a typology of employment and caregiving histories without reducing them to single events (Brzinsky-Fay *et al.*, 2006). The advantage of using sequence analysis over other methods, such as event history analysis, is that the method allows us to capture the sequential and multifaceted nature of life histories as entities. To our knowledge this is the first time that caregiving and employment histories have been analysed together in this way. In the third stage we use regression analysis to explore how gender, life-stage and social attitudes shape the pathways that people follow. In the final stage we use difference-in-differences estimation to examine whether any initial differences in income, health and wellbeing widen as people's caregiving and employment histories evolve. The results support pre-determination and persistence in caregiving and show that those who follow the most caregiving intensive pathways not only end up poorer but also with relatively lower subjective health and wellbeing.

The next section provides the framework for the analysis by summarising previous research on the role of social attitudes in the provision of care and the potential costs and possible longer term, cumulative effects of caregiving. The subsequent sections describe the data, the empirical methodology and the results. The final section summarises the main results and the limitations of the analysis.

2. Research context

At different stages of their lives people may take on a caregiving role because they feel obliged to provide care for a family member who becomes ill (Badgett and Folbre, 1999). This sense of responsibility or duty is tied to social attitudes, norms and expectations (Folbre, 1995) or binding systems of reciprocity (Daatland and Lowenstein, 2005). From this perspective, subjective norms, such as perceived social pressure to provide care, are predictors of behaviour (Ajzen, 2011). Research linking social norms and attitudes to female employment and the division of work within the home is consistent with these arguments (Farré and Vella, 2013; Michaud *et al.*, 2010; Crompton *et al.*, 2005).

A different view, consistent with orthodox neo-classical economics, is that caregiving decisions are determined by individual and household level cost-benefit calculations and efficiency considerations. These take into account any satisfaction (process utility) derived from caregiving (Brouwer *et al.*, 2005) and the expected costs due to loss of income, ill-health and increased stress (Adelman et al, 2014). Efficiency at the household level additionally exploits comparative advantages in market work and unpaid household labour, including caregiving, to achieve gains from specialisation (Mincer and Polachek, 1974).

Income losses associated with the demands of caregiving are in the main due to conflicts at the work-family interface (Erickson *et al.*, 2010) leading to substitution between care provision and labour supply, predominantly for more intensive carers. There is considerable evidence for such trade-offs particularly in Europe, the US and Canada and at the extensive margin of work including retirement (see Jacobs *et al.* 2014 for a recent summary). Such trade-offs will have dynamic effects in household decision-making due to obsolescence and deterioration of human capital. Caregivers could experience a reduction in their comparative advantage for market work reflected by the ratio of the market wage to marginal household productivity. A lower wage would also reduce the caregiver's threat point, lowering bargaining power within the household (Doss, 2011). This is important when, as discussed in Stern (1995), individual family members make decisions relative to long-term care strategically. Carers as a group have also been found to suffer disproportionately from ill-health (Vitlic *et al.*, 2015; ONS, 2013) and lower levels of wellbeing (Hirst, 2005; Marks *et al.*, 2002). Lower wellbeing may stem from the loss of autonomy (Dolan *et al.*, 2008; Brouwer *et al.* 1999) leading to greater emotional stress, physical strain and negative health effects (Schulz *et al.*, 2012).

From a life-course perspective, these effects suggest predetermination and possible persistence in caregiving roles, perhaps underlying a "*de facto* incompatibility between family life and full-time careers" (Crompton and Birkelund, 2000:350). Comparative (dis)advantage for market work is also likely to be a missing variable in estimates of the relationship between employment and caregiving leading to selection bias. In the literature this endogeneity has been addressed using instrumental variables (He and McHenry, 2015; Heitmueller, 2007), simultaneous equations methods and panel data, either to model time invariant individual heterogeneity (Van Houtven *et al.*, 2013), or the sequence of time

(Michaud *et al.* 2010; Carmichael et al., 2010; Spiess and Schneider, 2003). Here we extend the latter approach using sequence data for 4339 individuals to explicitly model employment and caregiving pathways as interdependent entities and use difference-in-differences to explore outcomes.

3. Data and sample

Eighteen annual 'waves' of the BHPS were carried out from 1991 to 2008 and thereafter BHPS respondents became part of Wave 2 in the larger US survey. Both the BHPS and US are administered by the Institute for Social and Economic Research at the University of Essex, England and are designed as nationally representative surveys of the British population. Though smaller than other representative longitudinal surveys, such as the Census or the Labour Force Survey, they differ insofar as they are annual and are repeated for the same individuals to form a panel. In 1991, 10264 respondents in 5511 households were surveyed. By 2008 the BHPS had expanded to reach 14418 individuals in 8144 households. Each year steps were taken to minimise respondent attrition and the 18 year balanced panel contains 4098 individuals. In 2009 the BHPS was absorbed into the US surveys. After three years the balanced panel for the US surveys included 31184 individuals.

In the BHPS-US unpaid, informal caregivers are identified as people who are looking after, helping, or providing a regular service for someone who is sick, disabled or elderly either in or outside their household. The surveys also ask questions on hours of care provided. Data on labour force status and hours of work identify people who are in full-time or part-time employment. Because decisions about childcare may have implications for future decisions about caregiving and employment we also identify individuals with young children living in the same household.

These data were analysed for a sub-sample of 4339 BHPS-US respondents for whom data were available for a minimum of 15 consecutive years between 1991 and 2010 (1,909 males and 2,430 females). This restriction reduces the sample size but ensures that the data were available for a sufficiently long period, one that constitutes a significant proportion of an individual's adult life. In addition, the restriction implies that initial observations for each individual were all made within a comparable relatively short time-frame (between 1991 and 1996, *i.e.* the first five waves of the BHPS). A wide age range, reflecting different age-cohorts within the sub-sample also allowed us to model life-stages. When first observed the youngest respondent was 16, the oldest was 85 and the mean age was 39.13.

4. Empirical Analysis

The data were first compiled as sequences in order to create an 'interpretable typology' (Anyadike-Danes and McVicar, 2010, p. 486) of clustered employment-caregiving pathways. The clusters were then used in multiple regressions to explore how individual characteristics shape the pathways people follow and how income, wellbeing and health diverge over time along different pathways. Ethics approval was granted by the University of Birmingham (ERN_15-1073).

4.1. Sequence analysis: Employment and unpaid caregiving pathways

Method:

In order to assemble the sequences the data were first coded as follows. Employed respondents were categorised as either in full-time or part-time employment (less than 35 hours a week). We classified the intensity of informal caregiving commitment using a 20 hours-per-week threshold. This is consistent with the literature in which it is well established that the trade-off between employment and caregiving is more evident for time-intensive caregivers, although a lower threshold has been identified in some studies. We also identified individuals living in households with young children (under eight years old) and utilised these data as a proxy for the individual having responsibilities for young children. The under eight threshold was selected to capture a sufficiently large proportion of the sample (15.1 percent). Other indicators that might have better captured responsibilities for young children such as the BHPS variable recording "who cares for ill children" or the US variable recording "who is responsible for childcare" were either not available for all years and/or varied across the BHPS and US. This lead to three main indicators recording nine non-mutually exclusive states:

(1) Employment status: (a) Employed full-time (FT work); (b) Employed part-time (PT work); (c) Not Employed; (d) Student.

(2) Informal caregiving status: (e) Not caregiving (IC=0hrs); (f) Caregiving for less than 20 hours a week (IC<20hrs); (g) Caregiving at least 20 hours a week (IC>=20hrs).

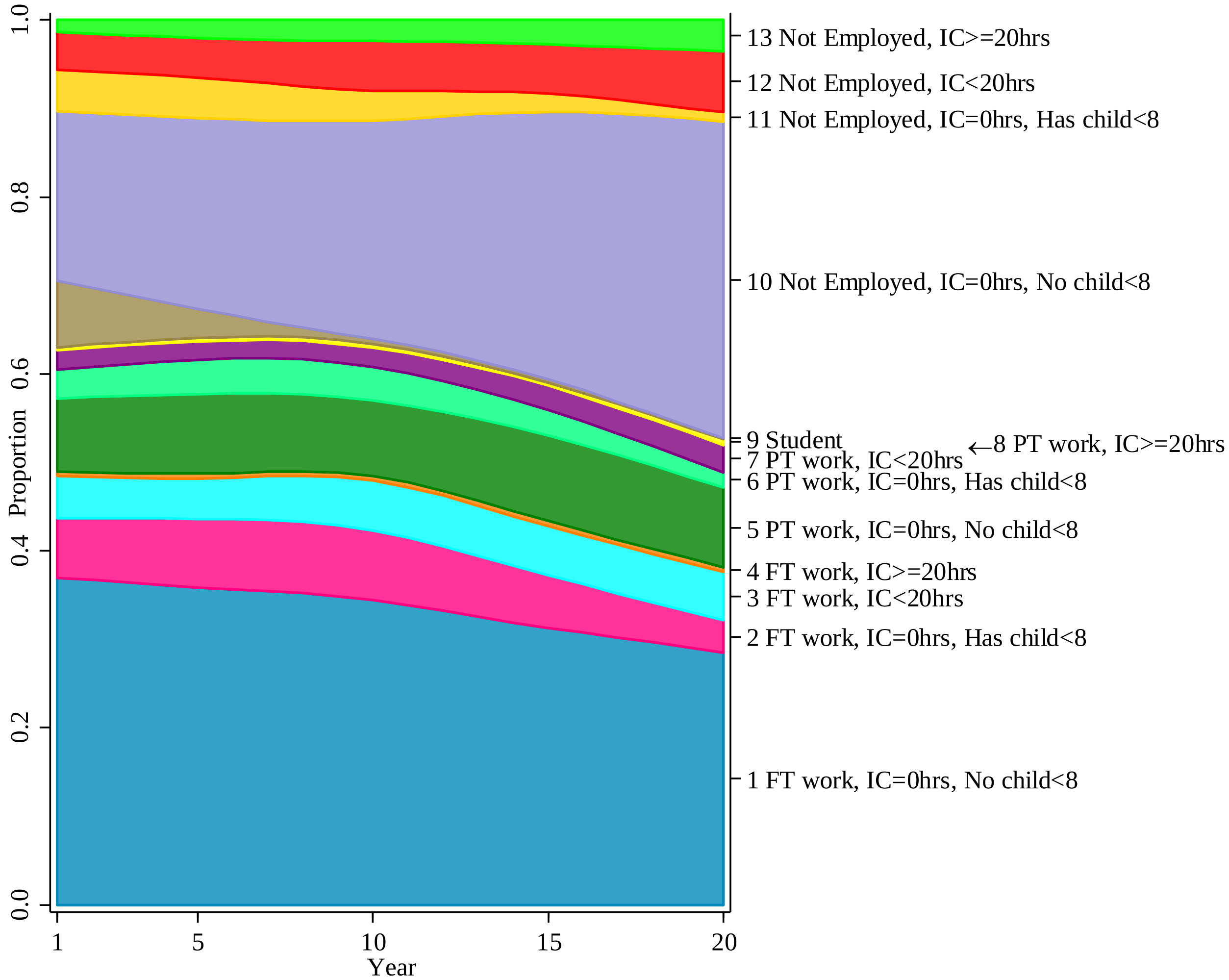
(3) Responsibility for young children: (h) Child aged seven or younger in household (Has child<8); (i) No child aged seven or younger in household (No child<8).

These nine states were interacted to construct a new variable recording the joint status of every individual in each year. Potentially there were 23 interacted states. However, states in which caregivers, particularly intensive carers, shared their household with young children and states in which students were also informal carers and/or shared their households with young children were very infrequent. These states were merged within broader student and caregiver categories to avoid groups with very few observations (Mojena, 1977). This resulted in 13 coded categories. The 81,564 coded activity states were then analysed as 4339 employment-caregiving sequences using the SQ-Ados scripts by Brzinsky-Fay *et al.* (2006).

Results:

Figure 1 shows the state-time distribution representing aggregated views of successive slices of time for the whole sample. Moving up through Figure 1, states can be interpreted as reflecting increasing detachment from the paid labour market and within the three main employment categories increasing commitment to unpaid caregiving. 16.19 percent of the observed states record caregiving (16.35 percent including student carers) of which 20.54 percent is time-intensive care (≥20 hours per week). 52.21 percent of caregiving states are also combined with time in paid employment (see Supplementary Table A1. On an individual level the incidence of caregiving is higher still: 38.74 percent of the sample had provided care in at least one recorded year (28.13 percent of males and 47.08 percent of females); 16.29 percent had provided time-intensive care (16.08 percent of males and 16.46 percent of females). This picture of caregiving incidence is comparable with that for the full BHPS-US sample which includes respondents observed for fewer than 15 years, suggesting that caregivers, intensive or otherwise, were no more likely to drop out of the sample than other respondents.

Fig. 1: Proportion of respondents in each category by year



FT: full-time employment. PT: part-time employment.
IC: informal caregiving (0 hours, 1-19 hours, or 20 hours or more).
No child<8: no child aged 7 or less in household. Has child<8: child aged 7 or less in household.

In Figure 1 the incidence of the different states remain relatively constant over time except for an unsurprising decline in the incidence of students and the incidence of employment. Nevertheless, the life cycle representation in Figure 1 is limited since the sample includes different age-cohorts. Figure 2 illustrates these effects more clearly by stratifying the state-time distribution by age-cohort. The five age-cohorts are: (i) post-baby boomer generations X and Y, born after 1964 (n=1,132); (ii) trailing edge baby-boomers born between 1955 and 1964 (n=1,025); (iii) leading edge baby-boomers born between 1946 and 1954 (n=743); (iv) pre-baby boomers born after the Great Depression (n=739) and; (v) pre-baby boomers born before/during the Great Depression (n=700).

Figure 2 shows how the distribution of the employment-caregiving states evolves over life-stages and by cohort. Employment participation is initially increasing for post and trailing edge baby boomers then very clearly decreasing for older cohorts. Post baby-boomer cohorts are increasingly likely, and baby boomers increasingly less likely, to have responsibility for young children. Instead, baby boomers are increasingly likely to be involved in caregiving. Trailing edge boomers combine this with employment but older cohorts are much less likely to combine caregiving with employment. While the pathways in Figure 2 are mapping the life-courses of different cohorts rather than individuals, the synthetic construction of the passage of age is in line with a life-cycle model of labour supply (Mincer and Polachek,

1974) as well as a life-course for the "work–family interface" (Moen and Sweet, 2004; Erickson *et al.*, 2010). Nevertheless, some caution regarding this interpretation is needed as age and cohort effects are difficult to untangle.

Fig. 2: Proportion of respondents in each category by year and age-cohort

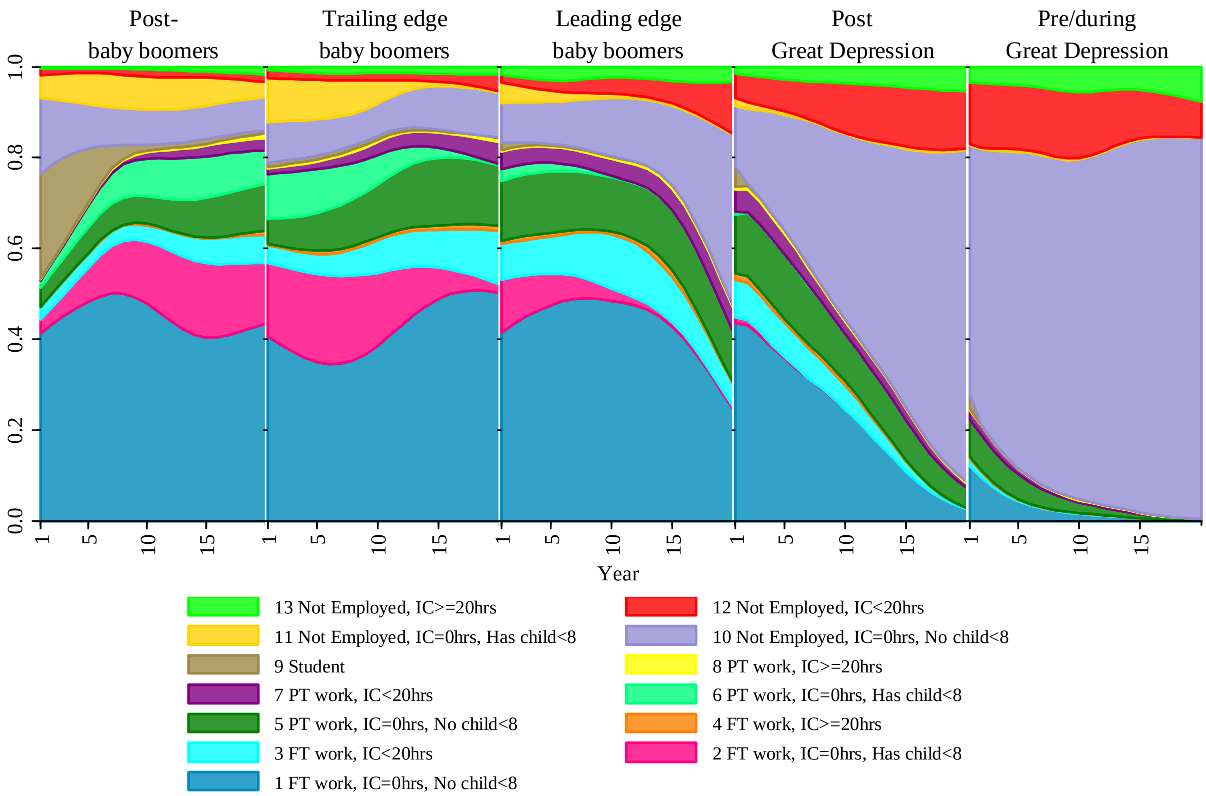
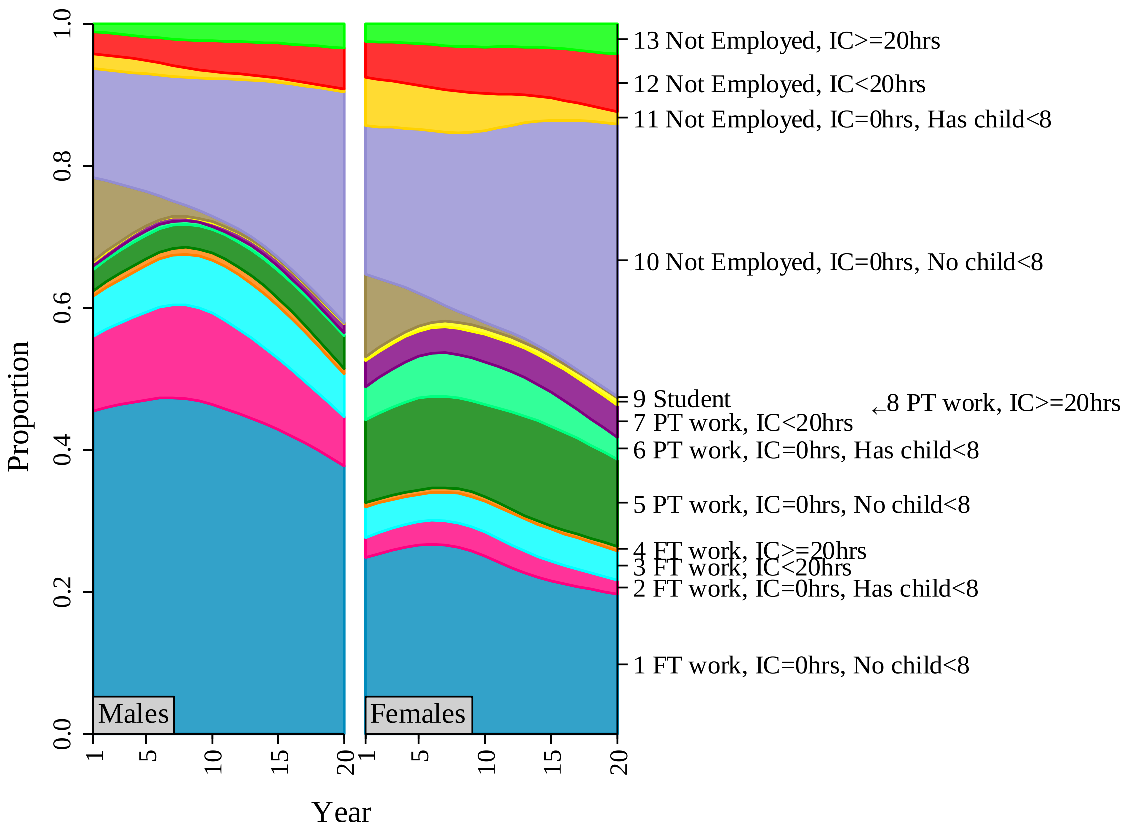


Figure 3 shows the distributions for males and females separately. The plots suggest that decisions about employment, childcare and caregiving are highly gendered. Males are more likely to be employed full-time whether or not their household has responsibility for a young child and women are more likely to work part-time. The majority of caregiving is undertaken by females (60.71% and 62.44% of less intensive and time-intensive care respectively) and females are less likely than males to combine caregiving with full-time paid work. This pattern is consistent with the established evidence that, at least among the working age population, females are more likely to be caregivers.

Fig. 3: Proportion of respondents in each category by year and gender



4.2. Cluster analysis

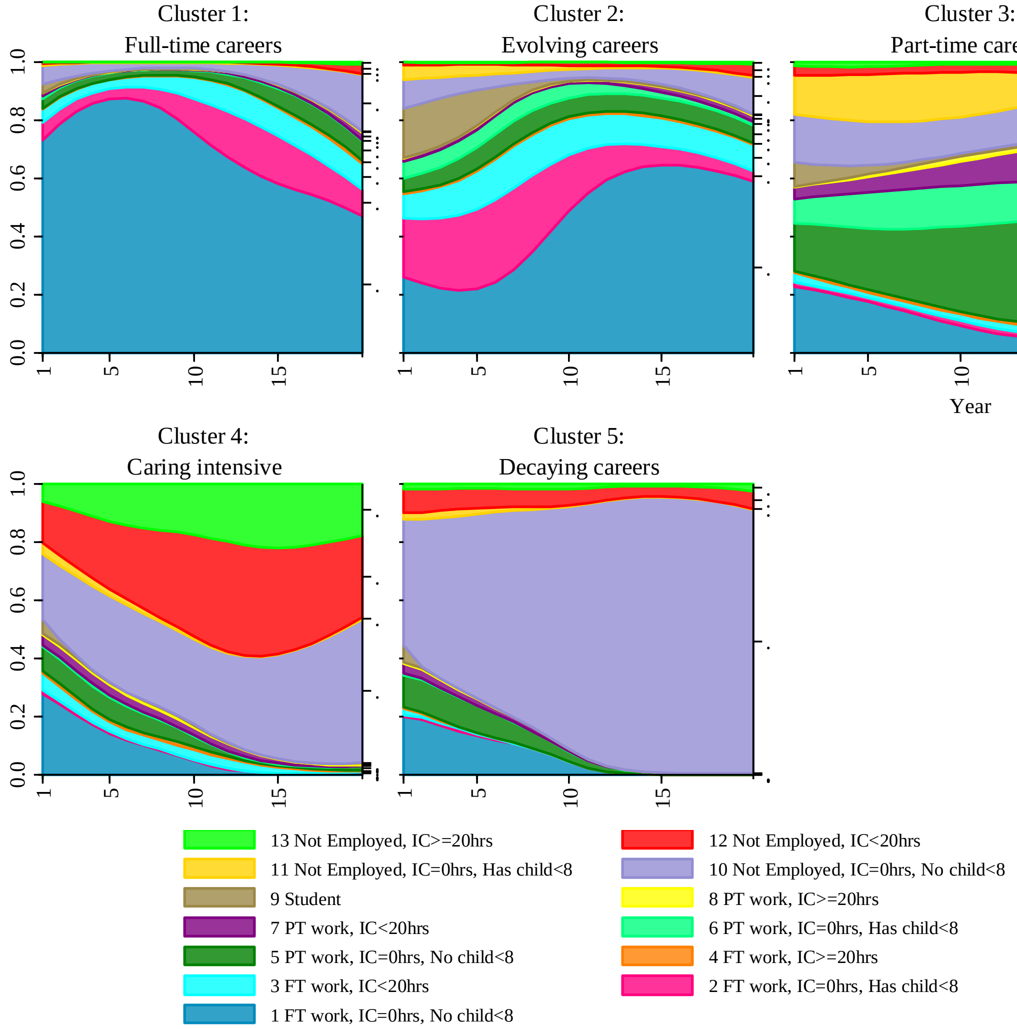
Method:

The length and variety of the sequences makes it difficult to say more without conducting further analyses. To optimally reduce the variation between sequences while maintaining the focus on multiple life-events we used ‘optimal matching’ to compare all sequence pairs. This non-parametric method has become increasingly popular in careers and family formation research (Anyadike-Danes and McVicar, 2010; (Davia and Legazpe, 2014; Potârcă *et al.*, 2013). The procedure uses the Needleman-Wunsch (1970) algorithm to compute the minimum distance, in terms of elementary but costly operations, to turn one sequence into another (Brzinsky-Fay *et al.*, 2006; Potârcă *et al.*, 2013). Substitution costs were generated using a symmetric transition frequency-based substitution cost matrix which attributes higher costs to less frequent transitions. Insertion/deletion (indel) costs were fixed at half the maximum substitution cost and standardised (by the length of the longest sequence in the respective alignment) as recommended by Brzinsky-Fay *et al.* (2006).The resulting distance matrix was used with the widely used Ward linkage algorithm to cluster the sample. The Duda/Hart Je(2)/Je(1) stopping rule index suggested that the five cluster solution was optimal and although the Calinski/Harabasz index was inconclusive, the strength of the five cluster solution was supported by low dissimilarity measures for the fusion values of additional clusters (see Supplementary Figure A1.

Results:

With 5 clusters, 26.41 percent of sequences are in cluster 1, the largest cluster and 10.21 percent of sequences are in cluster 4, the smallest cluster. Figure 4 shows how the composition of the clusters differs by the pattern of their flows into and out of full-time and part-time employment and the ways people do, or do not, combine employment with childcare and informal caring responsibilities (Supplementary Table A1 provides frequency data). Figure 4 shows very clearly how the clusters are differentiated not simply by higher incidences of particular states but also by different transition patterns. Cluster 1, labelled 'full-time careers', is characterised by a high (71.25%) but declining incidence of full-time employment mainly without caregiving or childcare responsibilities. In cluster 2, labelled 'evolving careers', there is lower but increasing incidence of full-time employment which is more likely to be combined with caregiving and childcare responsibilities. There is also a higher incidence of both part-time employment and time out of paid work including earlier periods with childcare responsibilities or as a student. Cluster 3, labelled 'part-time careers', is characterised by a high incidence of part-time employment often combined with childcare responsibilities and caregiving, particularly time-intensive caregiving. Cluster 4, labelled 'caring intensive', is notable for the high incidence of caregiving, particularly time intensive caring undertaken mainly while out of employment (over 50% of states involve caregiving, 33.34% of all caregiving states and 54.99% of all time-intensive caregiving). Cluster 5, labelled 'decaying careers', is characterised by a high and increasing frequency of time out of work. Clusters 3 to 5 illustrate increasing detachment from the labour market while clusters 2 and 4 in particular capture alternative ways in which caring responsibilities are interwoven with time in and out of paid work.

Fig. 4. Proportion of respondents in each category by year and cluster



4.3. Regression analysis: Characteristics of cluster members

This part of the analysis explores how individual characteristics and circumstances shape the pathways people follow.

Method:

Multinomial logit (MNL) regression was used to explore cluster membership in the baseline year (t=0) prior to the realisation of any subsequent, pathway specific effects. Setting the first outcome as the reference category $(\beta^{(1)} = 0)$ the MNL specification was:

$$
\begin{aligned}
\Pr(\text{CLUSTER}=1) &= \frac{1}{1+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}+e^{X\beta^{(4)}}+e^{X\beta^{(5)}}} \\
\Pr(\text{CLUSTER}=2) &= \frac{e^{X\beta^{(2)}}}{1+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}+e^{X\beta^{(4)}}+e^{X\beta^{(5)}}} \\
\Pr(\text{CLUSTER}=3) &= \frac{e^{X\beta^{(3)}}}{1+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}+e^{X\beta^{(4)}}+e^{X\beta^{(5)}}} \\
\Pr(\text{CLUSTER}=4) &= \frac{e^{X\beta^{(4)}}}{1+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}+e^{X\beta^{(4)}}+e^{X\beta^{(5)}}} \\
\Pr(\text{CLUSTER}=5) &= \frac{e^{X\beta^{(5)}}}{1+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}+e^{X\beta^{(4)}}+e^{X\beta^{(5)}}}
\end{aligned}
\qquad (1)
$$

where the dependent variable, CLUSTER, is cluster membership coded 1 to 5 for individuals 1 to 4339 and cluster 1 ‘full-time careers’, the largest cluster, is the base category. The *n* baseline independent variables, *X*, included four life-stage variables interacting age with age-cohort; Age×Trailing-edge_BB, Age×Leading-edge_BB, Age×Post-depression_preBB, Age×Pre-depression_preBB. The post-baby boomer cohort (the largest) is the reference cohort. *X* also included a dummy variable recording gender (Female), dummy variables recording highest level of educational attainment (HighQ_Degree, HighQ_OtherH, HighQ_ALevel and HighQ_OLevel) and a variable indicating marital status (ms_MarCohCiv).

Three attitudinal indices were included as independent variables. These were constructed using factor analysis and were included to explore whether traditional attitudes, particularly towards gender-roles, influence the pathways taken. The attitudinal indices were constructed from 14 questions about gender roles in the family and work, marriage and religion (see Supplementary Table A2 for details). These questions were prepared by the Social & Community Planning Research group (now the National Centre for Social Research) and first asked in the British Social Attitudes Survey 1989 and then again in 1994. They were included in the BHPS in 1991 and every two years thereafter. They continue to be asked in the Understanding Society surveys and by the National Centre for Social Research in the International Social Survey Programme 2013-2015. The first attitudinal index factor, measures support for ‘Traditional Gender Roles’, the second reflects agreement with ‘Traditional Family’ values and the third factor captures positive perceptions of ‘Working Women’.

Indicators of financial and emotional wellbeing and health were also included. Financial wellbeing was measured by total income at 2011 prices divided by 100 (IncomeTot). Subjective wellbeing was measured using the 12 item General Health Questionnaire 36 point Likert scale (Goldberg, 1978) recoded so that 36 corresponds to the highest level of wellbeing (GHQ_Wellbeing). Health was captured by a subjective measure of health coded from 1 (poor/very poor) to 5 (excellent). Other measures of wellbeing and health were either unavailable for all years or inconsistent across the BHPS and US. Supplementary Table A3 provides full definitions of all variables.

Results:

Table 1 shows the results of the MNL estimation with the dependent variable CLUSTER (Supplementary Figure A2 provides a visual interpretation as an odds-ratio plot). We have reported relative risk odds ratios rather than marginal effects as the interpretation of the former does not depend on the values of the other included variables (Long and Freese, 2014). Confidence intervals rather than standard errors are reported since the odds ratio is a nonlinear transformation. Hausman and Small-Hsiao tests indicated that assumption of the independence of irrelevant alternatives was not violated.

In interpreting the results in Table 1 the odds ratios for the binary explanatory variables (e.g. Female) can seem large since they capture the effect of switching from one state to another. In contrast, the odds ratios for the continuous variables can seem small since they represent the response to a per unit change (e.g. one pound sterling in the case of IncomeTot). The results for life-stage and gender show that relative to cluster 1 'fulltime careers', older individuals are more strongly represented in clusters 4 'caring intensive' and 5 'decaying careers' and females are more strongly represented in all other clusters but particularly cluster 3 'part-time careers'. When first interviewed, individuals in clusters 2 to 4 were more likely to be married, cohabiting or in a civil relationship than individuals in clusters 1 and 5 (ms_MarCohCiv). The pattern of significance of the attitudinal indices suggest that members of clusters 3 to 5 have more traditional attitudes towards female roles (Traditional Gender Roles) and family values (Traditional Family) than clusters 1 and 2 'evolving careers'. Conversely, they are less likely to share positive attitudes towards working women (Working Women).

The patterns of significance for the indicator of economic wellbeing (IncomeTot) imply that when first observed, cluster 1 'full time careers' (the reference category) were already wealthier. Cluster 2 'evolving careers' were marginally the least well off. This is consistent with working fewer hours and a part-time pay penalty (Connolly and Gregory, 2010). At the start of the sequences, the clusters were not strongly distinguished by subjective wellbeing (GHQ_Wellbeing). Only the lower wellbeing of cluster 4 'caring intensive' is weakly significant. However, the reported health status of clusters 4 and 5 'decaying careers' is significantly lower compared with cluster 1. This is particularly true for those in cluster 5 who are also older.

Most of the indicators of educational attainment are insignificant due mainly to the inclusion of the income measure. Supplementary Table A3 shows the results of estimating the MNL equation excluding the measures of income, wellbeing and health. In this estimation most of the education variables are highly significant and the results indicate that the memberships of clusters 2 to 5 have lower levels of educational attainment relative to cluster 1 'full time careers'.

Together these results suggest that gender, life-stage and social attitudes have an important role in shaping people's future lives. In particular, women, older individuals and those with more traditional attitudes to gender and family roles are more likely to follow pathways characterised by higher incidences of caregiving (clusters 3 and 4). The significance of traditional attitudes may mean that evolution of social norms will be associated with reduced willingness to supply unpaid care.

Table 1: Multinomial Logit regression results on cluster membership in first year of sequence (reference group is Cluster 1 'full-time careers')

Variables:	Cluster 2 Evolving careers	Cluster 3 Part-time careers	Cluster 4 Caring intensive	Cluster 5 Decaying careers
Age×Trailing-edge_BB	1.01**	1.00	1.02**	1.07***
	(1.00-1.02)	(0.99 - 1.01)	(1.00-1.04)	(1.05-1.09)
Age×Leading-edge_BB	0.98***	0.98***	1.03***	1.06***
	(0.98-0.99)	(0.97 - 0.99)	(1.02-1.05)	(1.04-1.08)
Age×Post-depression_preBB	0.98***	0.99	1.06***	1.11***
	(0.97-0.99)	(0.99-1.00)	(1.05-1.08)	(1.09-1.12)
Age×Pre-depression_preBB	0.98*	1.01*	1.10***	1.13***
	(0.96-1.00)	(1.00-1.03)	(1.08-1.11)	(1.12-1.15)
Female	1.27**	15.9***	3.77***	3.60***
	(1.03-1.56)	(11.7-21.6)	(2.72-5.23)	(2.6 -4.92)
Traditional Gender Roles	1.06	1.22***	1.23***	1.17**
	(0.95-1.17)	(1.09-1.38)	(1.06-1.44)	(1.01-1.35)
Traditional Family	1.05	1.20***	1.33***	1.28***
	(0.95-1.17)	(1.07-1.35)	(1.14-1.55)	(1.11-1.48)
WorkingWomen	0.95	0.83***	0.84**	0.81***
	(0.87-1.04)	(0.74-0.92)	(0.74-0.96)	(0.71-0.91)
IncomeTot	0.98***	0.94***	0.96***	0.95***
	(0.97-0.99)	(0.93-0.96)	(0.95-0.98)	(0.9 -0.96)
GHQ_Wellbeing	0.99	0.98	0.97*	0.99
	(0.97-1.01)	(0.96-1.01)	(0.94-1.00)	(0.96-1.02)
Health	1.08	0.91	0.74***	0.60***
	(0.96-1.22)	(0.79-1.04)	(0.62-0.88)	(0.5 -0.70)
ms_MarCohCiv	1.92***	2.13***	1.67***	0.82
	(1.54-2.38)	(1.64-2.76)	(1.17-2.39)	(0.60-1.14)
HighQ_Degree	0.97	1.16	0.78	0.76
	(0.68-1.39)	(0.75-1.82)	(0.42-1.44)	(0.43-1.35)
HighQ_OtherH	0.88	0.80	0.78	0.51***
	(0.66-1.18)	(0.57-1.12)	(0.53-1.16)	(0.35-0.74)
HighQ_ALevel	0.96	0.77	0.81	0.73
	(0.71-1.30)	(0.54-1.11)	(0.51-1.27)	(0.48 -1.12)
HighQ_OLevel	1.36**	0.83	0.81	0.76
	(1.05-1.75)	(0.63-1.11)	(0.55-1.18)	(0.54-1.09)
Constant	0.85	0.42**	0.23***	0.18***
	(0.45-1.62)	(0.20-0.88)	(0.089-0.59)	(0.069-0.49)
Observations	4105			
Log-likelihood	-4459.59			
LR-χ^2	3942.28***			
Pseudo-R^2	0.3065			

Reported figures are odds-ratios
Confidence intervals in (parentheses)
*** p<0.01, ** p<0.05, * p<0.1

4.4. Difference-in-differences analysis: Convergence and divergence

The results in Table 1 show that there were already differences in income, health and (to a lesser degree) emotional wellbeing between the clusters prior to embarking along different pathways. Some of these initial differences may have constrained or shaped future choices relating to employment and unpaid caregiving. Some differences may have widened, or narrowed as a consequence of the pathways followed. Both possibilities would be consistent with comparative (dis)advantages in terms of income, health and wellbeing accumulating over time. This idea of cumulative (dis)advantage in careers as originally defined by Merton (1973, p. 606) refers to the ways in which initial comparative advantage makes for "successive increments of advantage such that the gaps between the haves and the have not's widen".

Method:

To consider this possibility we estimated difference-in-differences models that pool data for the first and last year of each sequence and included three dummy variables, LAST_yr, CLUSTER*j* and CLUSTER*j*×LAST_yr,. LAST_yr records whether the observation is for the last, the follow-up, year of the sequence (LAST_yr = 1) or the first, baseline, year (LAST_yr = 0). CLUSTER*j* records cluster membership with cluster 1 the 'control' group and clusters *j*, from 2 to 5, the 'treated' groups. The third set of dummy variables, CLUSTER*j*×LAST_yr, interacts cluster membership and the last, follow-up, year of the sequence. This third set of dummy variables captures the difference-in-differences effects. The difference-in-differences estimations were specified as:

$$\begin{aligned}\text{IncomeTot} = \beta_{10} + \beta_{1L}\text{LAST\_yr} + \textstyle\sum_{j=2}^{5}\beta_{1j}\text{CLUSTER}j \\ + \textstyle\sum_{k=2}^{5}\beta_{1k}\text{CLUSTER}k \times \text{LAST\_yr} + \textstyle\sum_{n=1}^{N}\beta_{1n}X_n + \varepsilon_1\end{aligned} \tag{2}$$

$$\begin{aligned}\text{GHQ\_Wellbeing} = \beta_{20} + \beta_{2L}\text{LAST\_yr} + \textstyle\sum_{j=2}^{5}\beta_{2j}\text{CLUSTER}j \\ + \textstyle\sum_{k=2}^{5}\beta_{2k}\text{CLUSTER}k \times \text{LAST\_yr} + \textstyle\sum_{n=1}^{N}\beta_{2n}X_n + \varepsilon_2\end{aligned} \tag{3}$$

$$\begin{aligned}\text{Health} = \beta_{30} + \beta_{3L}\text{LAST\_yr} + \textstyle\sum_{j=2}^{5}\beta_{3j}\text{CLUSTER}j \\ + \textstyle\sum_{k=2}^{5}\beta_{3k}\text{CLUSTER}k \times \text{LAST\_yr} + \textstyle\sum_{n=1}^{N}\beta_{3n}X_n + \varepsilon_3\end{aligned} \tag{4}$$

where the interpretation of the coefficients is outlined below.

The $\beta_{\#0}$ and $\beta_{\#0} + \beta_{\#L}$ are the mean outcomes for cluster 1, the control group, in the first (baseline) year and the follow-up year. The $\beta_{\#0} + \beta_{\#j}$ and $\beta_{\#0} + \beta_{\#L} + \beta_{\#j} + \beta_{\#k}$ are the mean outcomes for each of clusters 2 to 5, the 'treated' clusters in the baseline and follow-up years. The $\beta_{\#j}$ reflect the differences between cluster 1 and each of clusters 2 to 5 at the baseline. The $\beta_{\#k}$ measure the difference-in-differences, or impact, of being in clusters 2 to 5 for the 15-20 years from the baseline to the follow-up. In these estimations, the set of individual characteristics X_n additionally included sequence duration (SEQ_length). To control for interrelationships between financial wellbeing and both physical and mental health, equation (2) included GHQ_Wellbeing and Health and equations (3) and (4) included IncomeTot.

Results:

Table 2 shows the results of the difference-in-differences estimations. For brevity, we only report and discuss the results for the dummy variables LAST_yr, CLUSTER*j* and CLUSTER*j*×LAST_yr (Supplementary Table A5 shows full results). Estimates (1) to (3) in Table 2 used OLS and estimated coefficients are reported. Since Health is an ordinal variable coded 1 to 5 (poor/very poor to excellent) we also estimated equation (3) using ordered logit, estimate (4), and odds ratios are reported.

In estimate (1) the dependent variable is IncomeTot and the positive significance of LAST_yr shows that real income rose over time. In line with the results from the MNL regression, the negative signs for clusters 2 to 5 in estimate (1) confirm that cluster 1 (the control group) is the richest overall. However the difference-in-differences interactions between each cluster and LAST_yr show that while cluster 2 'evolving careers' gained economically in relation to cluster 1, clusters 3 to 5 fell behind with the difference widening most for cluster 4. This is unsurprising given that the incidence of full-time employment is lower in clusters 3 to 5. It is nevertheless interesting that the relative fall in income is greatest for those in cluster 4 'caring intensive' where the incidence of informal caring is highest.

The dependent variable in estimate (2) is the index of emotional wellbeing (GHQ_Wellbeing). The negative significance of LAST_yr suggests that the sample recorded lower wellbeing over time. The results show that overall the membership of clusters 3 to 5 have lower subjective wellbeing compared with cluster 1. However, only the interaction terms for clusters 4 and 5 are negatively significant with the latter only weakly significant. This suggests that the gap in subjective wellbeing between clusters 1 and 4 widened most over time. This is line with evidence that informal caring commitments are associated with lower levels of wellbeing (Hirst, 2005; Marks *et al*., 2002) and could be indicative of lack of choice in relation to the supply of informal care (Schulz *et al.*, 2012; Brouwer *et al.*, 2005). That caring decisions are constrained by social norms and expectations is also consistent with the MNL results (Table 1) which show a positive association between the odds of following a caring intensive pathway and traditional attitudes towards gender roles, the family roles and working women.

Table 2: Difference-in-differences estimates for income, wellbeing and health

	(1) OLS	(2) OLS	(3) OLS	(4) Ordered Logit
Main variables:	Income Tot	GHQ_ Wellbeing	Health	Health
LAST_yr	4.01***	-0.69***	-0.26***	0.48***
	[0.54]	[0.22]	[0.034]	(0.41-0.57)
CLUSTER2	-3.25***	-0.14	0.0052	1.00
	[0.55]	[0.22]	[0.035]	(0.85-1.19)
CLUSTER3	-5.93***	-0.45*	-0.14***	0.70***
	[0.61]	[0.25]	[0.039]	(0.58-0.85)
CLUSTER4	-4.23***	-1.17***	-0.17***	0.68***
	[0.76]	[0.31]	[0.047]	(0.53-0.85)
CLUSTER5	-5.15***	-0.93***	-0.26***	0.51***
	[0.65]	[0.26]	[0.040]	(0.42-0.62)
CLUSTER2*LAST_yr	2.05***	-0.22	-0.0059	1.00
	[0.78]	[0.31]	[0.049]	(0.79-1.26)
CLUSTER3*LAST_yr	-2.39***	-0.16	0.094*	1.32**
	[0.83]	[0.33]	[0.052]	(1.03-1.69)
CLUSTER4*LAST_yr	-4.99***	-0.98**	-0.24***	0.60***
	[1.02]	[0.41]	[0.063]	(0.45-0.82)
CLUSTER5*LAST_yr	-2.87***	-0.71**	-0.25***	0.67***
	[0.82]	[0.32]	[0.050]	(0.53-0.84)
Observations	8,124	8,371	8,525	
R-squared(adjusted)	0.292	0.041	0.130	
F-statistic	151.82***	17.00***	60.57***	
Log-likelihood				-9539.60
LR-χ^2				1138.96***
Pseudo-R^2				0.0563

Reported figures are coefficients in estimates 1 to 3 [standard errors in brackets]; odds ratios in estimate 4 (confidence interval in parentheses)
*** p<0.01, ** p<0.05, * p<0.1

The negative effect of LAST_yr in estimate (3) indicates that health deteriorated as the sample aged. In line with the results in the MNL regression, overall health status is lower in clusters 3 to 5. The coefficient for the difference-in-difference interaction term with cluster 3 (CLUSTER3_LAST_yr) is positive and weakly significant indicating that after 15-20 years the gap between the health status of individuals in cluster 3 ‘part-time careers’ and cluster 1 narrowed. This suggests that part-time career pathways are associated with better health maintenance over the long-term. In contrast, the negative coefficients for the interaction terms for clusters 4 and 5 indicate a relative deterioration in health status. The ordered logit results in estimation 4 are largely consistent with those in estimation 3 although the significance of the interaction term with cluster 3 (CLUSTER3_LAST_yr) is higher (p<0.05). This pattern of narrowing and widening health gaps cannot be attributed entirely to career and caregiving histories since at various points in time along the pathways health may have impacted on employment participation. However, the difference-in-differences results suggest that some pathways are associated with worsening health outcomes. In particular, the health gap widened most for cluster 4 ‘caring intensive’ in line with evidence of negative health effects of caring particularly when choices are constrained (Schulz *et al.*, 2012; ONS, 2013).

These results suggest that some differences in income, wellbeing and health that existed at the start of the observed sequences widened over time while others narrowed. In particular the income gap between those in the largest group, cluster 1 'full-time careers', and clusters 3 to 5 widened while the income gap between clusters 1 and 2 'evolving careers' narrowed. There were no strong statistical differences in subjective wellbeing at the start of the sequences but over time the relative wellbeing of people in cluster 4 'caring intensive' and to a lesser extent cluster 5 'decaying careers' deteriorated. Relative to cluster 1 the health status of people in cluster 3 'part-time careers' marginally improved while that of cluster 4 and cluster 5 deteriorated. The deterioration in health status was most significant for cluster 4. The narrowing health gap between clusters 1 and 3 combined with only weakly significant differences in reported wellbeing may reflect evidence of the value attached to part-time work by the predominately female members of cluster 3 (Connolly and Gregory, 2010). Nevertheless the price of a better work-life balance is a widening income gap and cumulative financial disadvantage.

4.5. Sensitivity Analysis

We conducted a sensitivity test of the difference-in-differences analysis by estimating first difference models. In this analysis the dependent variable was the difference between the outcome variable measured in the first and last year of the observed sequence. The included independent variables were measured in the baseline year or differenced in the case of income, wellbeing and health. Supplementary Table A6 shows that the results of these estimates are largely consistent with those in Table 2.

We additionally modelled the quasi-panel features of the first and last sequence years by estimating individual random effects and fixed effects models (not reported). The pattern of the results was unchanged in the random effects models. In the fixed effects models the *F*-tests of the individual fixed effects were insignificant while the results for the interaction terms were largely unaffected. However, the cluster dummy variables are time invariant and could not be included making comparisons difficult.

5. Summary and conclusions

The analysis presented in this paper contributes a dynamic extension to previous research on employment and caregiving thus addressing the lack of longitudinal empirical evidence on caregiving trajectories and trade-offs and how they evolve over time. The use of sequenced longitudinal data in this context is original and enabled the 'sequential character' of the employment and caregiving histories of 4339 respondents to be modelled without reducing them to individual events. Optimal matching combined with cluster analysis identified five distinct groups of sequences spanning 15-20 years. These were further analysed using multinomial logit and difference-in-differences regression techniques.

The clustering of histories into full-time careers, evolving careers, part-time careers, caring intensive and decaying careers provides evidence of pre-determination and year-to-year persistence in employment and caregiving status. Age, gender and social attitudes all appear to be instrumental in shaping the pathways that people follow. Persistence of different states suggests significant path dependence in line with Connolly and Gregory (2010). However, the age profiles of the five clusters and the synthetic construction of life-cycles illustrated in Figure 2 suggest that pathways can merge into one another in predictable ways as people age.

For example, evolving careers progress into full-time careers, full-time careers will at some point decay and some part-time career pathways may become caring intensive.

Our regression analysis of initial cluster characteristics revealed that people who subsequently followed full-time career pathways started out richer than people who embarked on alternative paths. While this is perhaps unsurprising, given that when first interviewed they were already more likely to be in full-time employment, they were also healthier than people whose subsequent careers were characterised as decaying (even after controlling for age). Furthermore, and in line with evidence of caregiver burden (Adelman *et al*., 2014), those on full-time career pathways were not only richer but also healthier and happier than people embarking on caring intensive trajectories. The difference-in-differences analysis suggests that some of these differences widened while others narrowed over time. On the one hand, people on evolving career pathways start to catch up in terms of their financial wellbeing and the relative health of those following part-time career paths (mainly women) appears to improve. On the other hand, income, wellbeing and health gaps between full-timers and intensive caregivers all widen. This, coupled with predetermination and persistence, is indicative of a pattern of cumulative disadvantage (Merton, 1973) accrued by intensive caregivers over time. Part of the explanation may be that time out of paid work reduces the earning power of caregivers giving them a comparative disadvantage in paid work. Re-entering the labour market can also be problematic. In these circumstances an efficient division of work within the family (Mincer and Polachek, 1974) would have path dependent repercussions leading to persistence or lock-in into caregiving roles (Liebowitz and Margolis, 1995). As such, lack of choice could be a factor contributing to lower wellbeing for those on caring intensive pathways (Schulz *et al*., 2012; Brouwer *et al*., 2005).

The results of this analysis are limited by the available data. While 15-20 years is a large proportion of most people's adult lives the data can only capture initial work histories for younger post-baby boomers who were in their teens or early 20s when first interviewed. We do not know where the pathways of these younger cohorts will lead and we do not know the prior histories of older cohorts. As noted above, we can make some predictions based on a synthetic life-cycle approach but until more years of data are available these are only hypotheses. However an issue for future analysis is that over time original samples are subject to attrition. There is also a lack of consistency and availability of some measures between the BHPS and US datasets. Retrospective life history datasets, such as the Work-life History files in the BHPS, the Life History Interviews in wave three of the English Longitudinal Study of Ageing (ELSA) and the Survey of Health, Ageing and Retirement in Europe Retrospective Survey (SHARELIFE), can also be used to explore occupational histories. However, none of these sources lend themselves well to an analysis of employment and caregiving trajectories since none contain detailed records of caregiving. Furthermore, in those datasets, paid employment and unpaid family caregiving are also treated as mutually exclusive which, as our analysis shows, is not always appropriate (within our sample over 50 percent of caregiving events are combined with employment).

The usefulness of sequence analysis has also been challenged because of the discretion over substitution penalties used to calculate the distance matrix in the optimal matching procedure and the number of clusters (Potârcă *et al.*, 2013; Halpin, 2010). We experimented with different ways of setting substitution penalties in the optimal matching as well as differentiating caregivers with responsibilities for young children and student carers. The broad patterns characterising the five cluster solution remained robust. This is in line with the goals of optimal matching which are "about fishing for patterns" (Potârcă *et al.*, 2013, p. 81, paraphrasing Abbott, 2000). Alternative techniques, such as survival or time series analysis, do not allow researchers to capture the sequential character of each life history as an entity, focusing rather on events, hazards or associations at different points in time (Brzinsky-Fay *et al.*, 2006).

To summarise, the analysis presented here indicates that the employment-caregiving trajectories that people follow over their life-courses are to some extent predictable and persistent. These results confirm the often held view that early decisions about employment and caregiving can shape lives for many years to come. The implications of such decisions can be far reaching for persistent caregivers who can end up poorer, unhappier and less healthy. However, the results also suggest that the burden of caregiving is potentially reduced when a balance can be struck between paid work and unpaid caregiving. Further research is needed to establish how policies such as flexible work practices can be better designed to support caregivers to maintain such a balance.

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Appendix/Supplementary Material

Table A1: Distribution of sequence states across the whole sample and the five clusters

	Whole	Cluster				
	sample	1	2	3	4	5
		Full-	Evolv-	Part-	Caring	Decay-
Sequence states:		time	ing	time	inten-	ing
1 FT work, IC=0hrs, No child<8[a]	27,491	15,464	8,325	1,760	692	1,250
	(33.7)	(71.25)	(44.33)	(11.92)	(8.21)	(6.99)
2 FT work, IC=0hrs, Has child<8	5,573	2,143	3,153	205	32	40
	(6.83)	(9.87)	(16.79)	(1.39)	(0.38)	(0.22)
3 FT work, IC<20hrs[b]	4,239	1,443	2,088	396	248	64
	(5.2)	(6.65)	(11.12)	(2.68)	(2.94)	(0.36)
4 FT work, IC>=20hrs	436	95	140	124	62	15
	0.53	(0.44)	(0.75)	0.84	0.74	0.08
5 PT work, IC=0hrs, No child<8	7,327	832	1,206	4,089	345	855
	(8.98)	(3.83)	(6.42)	(27.7)	(4.09)	(4.78)
6 PT work, IC=0hrs, Has child<8	2,708	73	792	1,780	41	22
	(3.32)	(0.34)	(4.22)	(12.06)	(0.49)	(0.12)
7 PT work, IC<20hrs	1,959	136	241	1,176	199	207
	(2.4)	(0.63)	(1.28)	(7.97)	(2.36)	(1.16)
8 PT work, IC>=20hrs	333	14	42	201	51	25
	(0.41)	(0.06)	(0.22)	(1.36)	(0.61)	(0.14)
9 Student[c]	1,567	106	1,028	328	43	62
	(1.92)	(0.49)	(5.47)	(2.22)	(0.51)	(0.35)
10 Not Employed, IC=0hrs, No child<8	21,042	1,174	1,086	2,158	2,729	13,895
	(25.8)	(5.41)	(5.78)	(14.62)	(32.38)	(77.66)
11 Not Employed, IC=0hrs, Has child<8	2,650	77	391	1,890	115	177
	(3.25)	(0.35)	(2.08)	(12.8)	(1.36)	(0.99)
12 Not Employed, IC<20hrs	4,296	116	230	447	2,490	1,013
	(5.27)	(0.53)	(1.22)	(3.03)	(29.55)	(5.66)
13 Not Employed, IC>=20hrs	1,943	31	57	209	1,380	266
	(2.38)	(0.14)	(0.3)	(1.42)	(16.38)	(1.49)
Number of states with IC>0hrs	13,339	1,840	2,854	2,601	4,447	1,597
(% of all states with IC>0hrs)	(100)	(13.79)	(21.40)	(19.50)	(33.34)	(11.97)
(% of states with IC>=20hrs)	(100)	(5.14)	(8.85)	(19.75)	(54.99)	(11.27)
Total number of states	81,564	21,704	18,779	14,763	8,427	17,891
(% of all states)	(100)	(26.61)	(23.02)	(18.10)	(10.33)	(21.94)
Number of sequences	4339	1146	1005	790	443	955
(% of all sequences)	(100)	(26.41)	(23.16)	(18.21)	(10.21)	(22.01)

Notes: Percentages in (parentheses).

FT: full-time employment. PT: part-time employment. IC: informal caregiving (0 hours, 1-19 hours, or 20 hours or more). No child<8: no child aged 7 or less in household. Has child<8: child aged 7 or less in household.

[a]The < 8 years age threshold captures a sufficiently large minority of the sample (15.1 percent).

[b]Only 9.8 per cent of states recording caregiving also recorded a household with young children.

[c]Only 8.9 percent of states recording student status also recorded a household with young children and only 8.4 percent also recorded caregiving.

Table A2: Attitudinal variables used to construct the three attitudinal indices: Factor loadings, uniqueness values and sample means

Attitudinal variables	Mean	Factor loadings > 0.4: Factor 1 Traditional Gender Roles	Factor 2 Traditional Family	Factor 3 Working Women	Uniqueness
1. Pre-school child suffers if mother works	3.26	0.7990			0.3385
2. Family suffers if mother works full time	2.99	0.8074			0.2927
3. Woman and family happier if she works	2.89	-0.4296		0.5308	0.5247
4. Husband and wife should contribute to income	3.56			0.7032	0.4747
5. Full time job makes women independent	3.27			0.6854	0.5157
6. Husband should earn, wife should stay at home	2.46	0.6170	0.4442		0.4187
7. Children need fathers as much as mother	4.19	0.4632			0.6263
8. Employers should help mothers combine jobs and childcare	3.98			0.5034	0.6581
9. Single partners are as good as couples	3.07	-0.4827			0.7245
10. Cohabiting is always wrong	2.39		0.7089		0.4343
11. Adult kids should care for parent	3.02		0.4101		0.7923
12. Divorce better than unhappy marriage	3.98		-0.4158		0.6973
13. Man should be head of household	2.61		0.6204		0.4926
14. Bible is god's word and true	2.61		0.7151		0.4688
Eigenvalue		3.48	1.84	1.22	
Cronbach's alpha scale reliability			0.72 (acceptable)		
Kiaser-Meyer-Olkin (KMO) sampling adequacy			0.80 (meritorious)		
Sub-sample means (first year observed)					
Males		0.190	-0.002	-0.036	
(Females)		(0.158)***	(-0.114)***	(0.118)**	
Post-baby boomers		-0.343***	-0.337***	0.184***	
Trailing edge baby boomers		-0.194***	-0.322***	0.009**	
Leading edge baby boomers		0.031	-0.060	-0.050***	
Post great depression pre-baby boomers		0.231***	0.176***	0.055	
Pre/during great depression pre-baby boomers		0.535***	0.498***	0.192**	

In *t* tests of difference of sample means by gender and cohort: *** p<0.01, ** p<0.05
Blanks represent (absolute) loading <0.4.

Notes:

i. Variables record strength of agreement with the statements on a Likert scale of 1 to 5 (strong disagreement to strong agreement).

ii. The three attitudinal indices were constructed using principal components factor analysis with varimax rotation. The three factors account for 46.72% of the total variance. Only two statements have cross factor loading greater than 0.4 and none are greater than 0.5.

iii. Factor 1, ‘Traditional Gender Roles’ loads positively on 4 statements supporting women taking a more traditional role in the home and loads negatively on 2 statements supporting working women and non-traditional families.
iv. Factor 2, ‘Traditional Family’ loads positively on 5 statements consistent with more traditional attitudes towards marriage, family and religion including. ‘Adult kids should care for parent’. It loads negatively on ‘Divorce better than unhappy marriage’ which reflects lack of support for more modern attitudes towards marriage and family.
v. Factor 3, ‘Working Women’, loads highly on statements supportive of working and independent women and of less traditional roles in the family.
vi. The sample means indicate that traditional attitudes towards gender and family roles and working women are more strongly represented among males. Traditional attitudes towards gender and family roles are more strongly represented among older cohorts. Attitudes towards working women appear most traditional among leading edge baby boomers.

Table A3: Definitions of variables used in the analysis

Variable	Definition
$CLUSTER_j$	Cluster grouping, j= 1,5
Female	Female gender = 1; male gender = 0
ms_MarCohCiv	Marital status: Ever married/civil partnership. Control = always single/never married or divorced/separated/widowed.
HighQ_Degree	Highest educational qualification = Degree. Constructed from BPHS variable qfedhi and US variable hiqual
HighQ_OtherH	Highest educational qualification = Other higher. Constructed as above.
HighQ_ALevel	Highest educational qualification = A-level or equivalent. Constructed as above.
HighQ_OLevel	Highest educational qualification = GCSE/O-level or equivalent. Constructed as above.
HighQ_None_Other	No educational qualifications or highest educational qualification = other (Control)
Traditional Gender Roles	Attitudinal index/factor 1. Constructed using principal component factor analysis from 14 attitudinal variables.
Traditional Family	Attitudinal index/factor 2. Constructed as above.
WorkingWomen	Attitudinal index/factor 3. Constructed as above.
GHQ_Welbeing	36 point index of emotional/subjective wellbeing from 12 item General Health Questionnaire (GHQ 12) screening instrument for psychological distress (Cox *et al.*, 1987). Recoded (higher numbers record higher wellbeing)
ΔGHQ_Wellbeing	Change in GHQ_Welbeing between first and last year of sequence
Health	Index of self-reported health status in last 12 months (change in index). Constructed from BHPS variable hlstat & Understanding Society variable sf1. Coded 1-4 (1= poor/very poor; 2 = Fair; 3 =Very good/good; 4 = excellent
ΔHealth	Change in Health between first and last year of sequence
IncomeTot	Total individual income in 2011 prices (change in total income)
ΔIncomeTot	Change in IncomeTot between first ad last year of sequence
SEQ_length	Number of years in sequence (min = 15, max = 20)
Post-baby_boomer	Post-baby boomers born after 1964 (control)
Age×Trailing-edge_BB	Age of trailing edge baby-boomers born 1955-1964 (0 otherwise)
Age×Leading-edge_BB	Age of leading edge baby-boomers born 1946-1954 (0 otherwise)
Age×Post-depression_preBB	Age of pre-baby boomers born after the Great Depression (0 otherwise)
Age×Pre-depression_preBB	Age of pre-baby boomers born before/during the Great Depression (0 otherwise)

Table A4: Multinomial Logit regression results on cluster membership in first year of sequence excluding IncomeTot, GHQ_Welbeing and Health
(reference group is Cluster 1 ‘full-time careers’)

Variables	Cluster 2 Evolving careers	Cluster 3 Part-time careers	Cluster 4 Caring intensive	Cluster 5 Decaying careers
Age×Trailing-edge_BB	1.00	0.99**	1.02	1.06***
	(1.00-1.01)	(0.98-1.00)	(1.00-1.03)	(1.04-1.08)
Age×Leading-edge_BB	0.98***	0.97***	1.03***	1.05***
	(0.97-0.99)	(0.96-0.98)	(1.01-1.04)	(1.04 - 1.07)
Age×Post-depression_preBB	0.98***	0.99***	1.06***	1.10***
	(0.97-0.98)	(0.98-0.99)	(1.04-1.07)	(1.08-1.11)
Age×Pre-depression_preBB	0.98*	1.01	1.09***	1.13***
	(0.96-1.00)	(1.00-1.02)	(1.08-1.11)	(1.11-1.14)
Female	1.43***	24.1***	5.20***	5.56***
	(1.18-1.74)	(17.9-32.5)	(3.86 -7.01)	(4.19-7.39)
Traditional Gender Roles	1.05	1.29***	1.29***	1.25***
	(0.95-1.16)	(1.15-1.45)	(1.11-1.49)	(1.09-1.43)
Traditional Family	1.07	1.27***	1.37***	1.34***
	(0.97-1.18)	(1.13-1.42)	(1.18-1.59)	(1.17-1.55)
Working Women	0.95	0.81***	0.86**	0.82***
	(0.87-1.04)	(0.73-0.90)	(0.75-0.97)	(0.73-0.93)
ms_MarCohCiv	1.82***	1.96***	1.58**	0.75*
	(1.46-2.25)	(1.52-2.53)	(1.11-2.24)	(0.55-1.03)
HighQ_Degree	0.75*	0.55***	0.39***	0.34***
	(0.54-1.04)	(0.36-0.82)	(0.22 - 0.70)	(0.20-0.58)
HighQ_OtherH	0.74**	0.51***	0.51***	0.31***
	(0.56-0.98)	(0.37-0.69)	(0.35-0.74)	(0.22-0.44)
HighQ_ALevel	0.88	0.61***	0.60**	0.52***
	(0.65-1.18)	(0.43-0.86)	(0.39-0.93)	(0.34-0.79)
HighQ_OLevel	1.32**	0.74**	0.69*	0.62***
	(1.02-1.69)	(0.56-0.98)	(0.48-1.00)	(0.44-0.87)
Constant	0.67***	0.12***	0.032***	0.022***
	(0.52-0.87)	(0.084-0.17)	(0.018-0.056)	(0.011-0.042)
Observations	4,170			
Log-likelihood	-4615.83			
LR-χ^2	3836.33***			
Pseudo-R^2	0.2936			

Reported figures are odds-ratios
Confidence intervals in (parentheses)
*** p<0.01, ** p<0.05, * p<0.1

Table A5: Difference-in-differences estimates (full results) for income, wellbeing and health

Variables:	(1) OLS Income Tot	(2) OLS GHQ_ Wellbeing	(3) OLS Health	(4) Ordered Logit Health
LAST_yr	4.01***	-0.69***	-0.26***	0.48***
	[0.54]	[0.22]	[0.034]	(0.41-0.57)
CLUSTER2	-3.25***	-0.14	0.0052	1.00
	[0.55]	[0.22]	[0.035]	(0.85-1.19)
CLUSTER3	-5.93***	-0.45*	-0.14***	0.70***
	[0.61]	[0.25]	[0.039]	(0.58-0.85)
CLUSTER4	-4.23***	-1.17***	-0.17***	0.68***
	[0.76]	[0.31]	[0.047]	(0.53-0.85)
CLUSTER5	-5.15***	-0.93***	-0.26***	0.51***
	[0.65]	[0.26]	[0.040]	(0.42-0.62)
CLUSTER2*LAST_yr	2.05***	-0.22	-0.0059	1.00
	[0.78]	[0.31]	[0.049]	(0.79-1.26)
CLUSTER3*LAST_yr	-2.39***	-0.16	0.094*	1.32**
	[0.83]	[0.33]	[0.052]	(1.03-1.69)
CLUSTER4*LAST_yr	-4.99***	-0.98**	-0.24***	0.60***
	[1.02]	[0.41]	[0.063]	(0.45-0.82)
CLUSTER5*LAST_yr	-2.87***	-0.71**	-0.25***	0.67***
	[0.82]	[0.32]	[0.050]	(0.53-0.84)
Age×Trailing-edge_BB	0.054***	-0.014***	-0.0025***	0.99***
	[0.0094]	[0.0038]	[0.00058]	(0.99-1.00)
Age×Leading-edge_BB	0.0082	0.0031	-0.0020***	1.00***
	[0.0086]	[0.0034]	[0.00053]	(0.99-1.00)
Age×Post-depression_preBB	0.014	0.012***	-0.00088*	1.00
	[0.0087]	[0.0034]	[0.00053]	(1.00-1.00)
Age×Pre-depression_preBB	0.010	0.012***	-0.00035	1.00
	[0.0085]	[0.0033]	[0.00051]	(1.00-1.00)
Female	-5.78***	-0.92***	0.032	1.08*
	[0.31]	[0.13]	[0.019]	(0.9 -1.19)
GHQ_Wellbeing	0.021			
	[0.029]			
Health	1.15***			
	[0.19]			
IncomeTot		0.013***	0.0048***	1.01***
		[0.0044]	[0.00068]	(1.01-1.01)
ms_MarCohCiv	1.15***	0.50***	0.087***	1.22***
	[0.32]	[0.13]	[0.020]	(1.11-1.34)
HighQ_Degree	13.7***	0.41*	0.30***	2.06***
	[0.51]	[0.21]	[0.033]	(1.76-2.42)
HighQ_OtherH	4.89***	0.21	0.19***	1.61***
	[0.40]	[0.16]	[0.025]	(1.43-1.81)
HighQ_ALevel	3.09***	0.28	0.12***	1.37***
	[0.49]	[0.20]	[0.030]	(1.19-1.59)
HighQ_OLevel	0.44	0.53***	0.19***	1.57***

	[0.41]	[0.17]	[0.026]	(1.39-1.78)
SEQ_length	0.23**	0.090**	0.019***	1.04***
	[0.090]	[0.036]	[0.0055]	(1.02-1.07)
Constant(cut 1)	7.78***	23.8***	2.55***	0.14***
	[1.87]	[0.69]	[0.11]	(0.081-0.23)
Constant(cut2)				0.64*
				(0.39-1.08)
Constant(cut3)				8.07***
				(4.82-13.5)
Observations	8,124	8,371	8,525	
R-squared(adjusted)	0.292	0.041	0.130	
F-statistic	151.82***	17.00***	60.57***	
Log-likelihood				-9539.60
LR-χ^2				1138.96***
Pseudo-R^2				0.0563

Reported figures are coefficients in estimates 1 to 3 [standard errors in brackets]; odds ratios in estimate 4 (confidence interval in parentheses)
*** p<0.01, ** p<0.05, * p<0.1

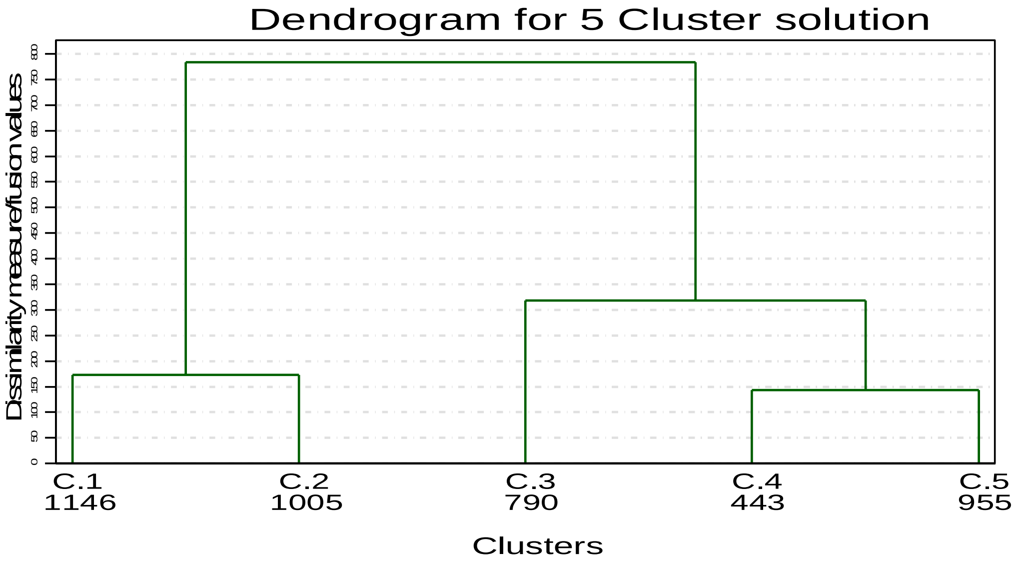
Note:
We also estimated the model in column (2) on the logarithm of GHQ_Wellbeing but this did not affect the significance pattern of the results.

Table A6: OLS first difference estimates for Total income at 2011 prices (ΔIncomeTot); Subjective wellbeing (ΔGHQ_Wellbeing); and Health (ΔHealth)

Variables	ΔIncomeTot	ΔGHQ_Wellbeing	ΔHealth
CLUSTER2	2.43***	-0.041	-0.018
	(0.69)	(0.28)	(0.042)
CLUSTER3	-4.04***	0.14	0.019
	(0.79)	(0.32)	(0.048)
CLUSTER4	-3.72***	-1.06***	-0.13**
	(1.02)	(0.41)	(0.061)
CLUSTER5	-1.87**	-0.70*	-0.089
	(0.96)	(0.38)	(0.057)
AgeTrailing-edge_BB	-0.22***	-0.21	0.092***
	(0.023)	(0.21)	(0.032)
AgeLeading-edge_BB	-0.30***	0.011	-0.0079***
	(0.020)	(0.0092)	(0.0014)
AgePost-depression_preBB	-0.26***	0.042***	-0.0093***
	(0.019)	(0.0080)	(0.0012)
AgePre-depression_preBB	-0.12***	0.034***	-0.0062***
	(0.53)	(0.0076)	(0.0011)
Female	1.28**	-0.0017	-0.0089***
	(0.017)	(0.0067)	(0.00100)
ms_MarCohCiv	-0.89	-0.36	0.015
	(0.57)	(0.23)	(0.034)
HighQ_Degree	3.16***	-0.092	0.039
	(0.94)	(0.37)	(0.056)
HighQ_OtherH	-1.69**	-0.41	0.038
	(0.71)	(0.28)	(0.042)
HighQ_ALevel	-0.80	-0.53*	0.025
	(0.80)	(0.32)	(0.048)
HighQ_OLevel	-0.59	-0.20	0.019
	(0.65)	(0.26)	(0.039)
SEQ_length	-0.14	0.13**	0.0062
	(0.16)	(0.062)	(0.0093)
ΔGHQ_Wellbeing	0.075*		
	(0.040)		
ΔHealth	0.43		
	(0.26)		
ΔIncomeTot		0.014**	0.0020**
		(0.0062)	(0.00093)
Constant	16.02***	-3.41***	-0.19
	(2.98)	(1.19)	(0.18)
Observations	4088	4089	4239
R^2	0.142	0.022	0.063
F-statistic	39.58***	5.77***	17.88***

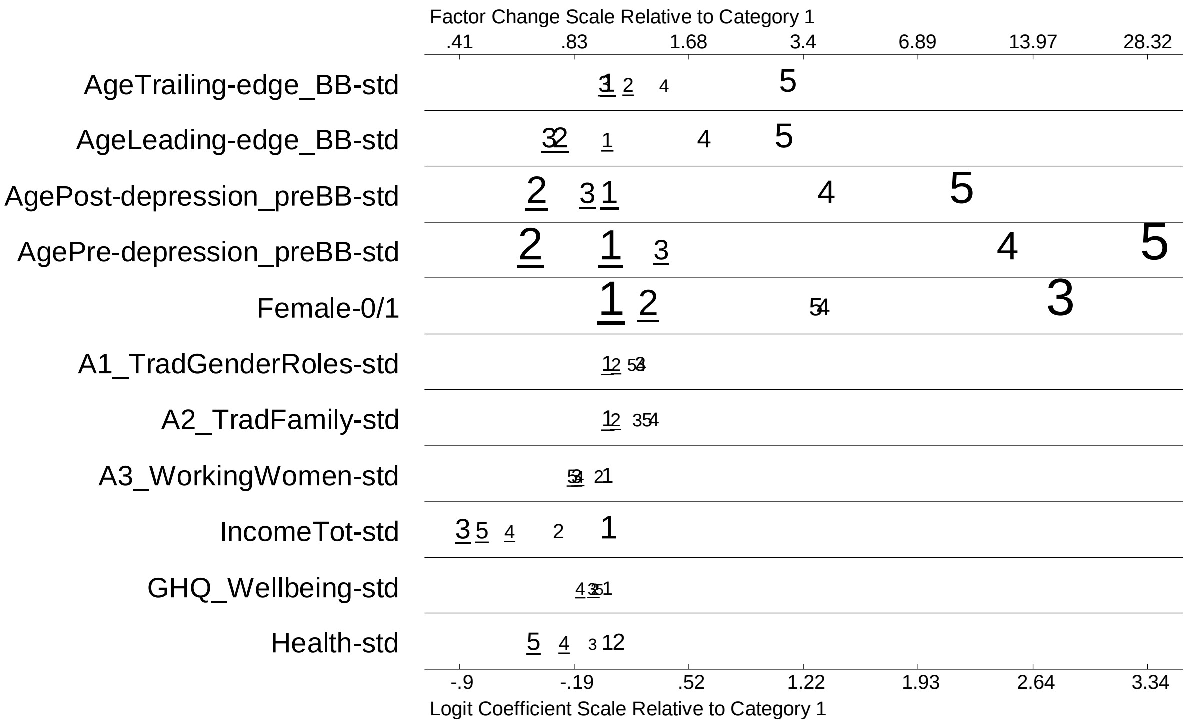
Notes:
Reported figures are coefficients; Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.
Results in line with difference-in-differences estimation: In estimate 1, clusters 3 to 5 are negative and significant and cluster 2 is positive and significant. In estimate 2, clusters 4 and 5 are negatively significant (the latter only weakly). In estimate 3 cluster 4 is negatively significant and cluster 3 is positive but insignificant.

Figure A1: Dendogram tree-diagram for the five cluster solution



Notes: Large fusion values (the dissimilarity measure at which clusters are fused or split in the hierarchical structure) indicate more distinct clusters. The four cluster solution merges clusters 4 and 5 (fusion value=150) while the six cluster solution splits cluster 1 (fusion value=135).

Figure A2: Odds Ratio plots for MNL with dependent variable CLUSTER



Notes: Plot constructed using SPost13 command mlogplot (Long and Freese, 2014). All variables except the gender dummy are standardised. The category numbers correspond to Clusters 1-5. Cluster numbers to the right (left) of another (e.g. Cluster 1) indicate that increases in the independent variable make the Cluster outcome to the right more (less) likely, the distance between numbers indicates the magnitude of the effect. The size of the numbers is proportional to the discrete change in the odds.