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Linking local labour market conditions across the life course to retirement age: Pathways of health, employment status, occupational class and educational achievement, using 60 years of the 1946 British Birth Cohort

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ABSTRACT

Several studies have documented that older workers who live in areas with higher unemployment rates are more likely to leave work for health and non-health reasons. Due to tracking of area disadvantage over the life course, and because negative individual health and socioeconomic factors are more likely to develop in individuals from disadvantaged areas, we do not know at what specific ages, and through which specific pathways, area unemployment may be influencing retirement age.

Using data from the MRC National Survey of Health and Development, we use structural equation modelling to investigate pathways linking local authority unemployment at three ages (4y, 26y and 53y) to age of retirement (right-censored). We explored five hypothesized pathways: (1) residential tracking, (2) health, (3) employment status, (4) occupational class, and (5) education. Initially, pathways between life course area unemployment, each pathway and retirement age were assessed individually. Mediation pathways were tested in the full model.

Our results showed that area unemployment tracked across the life course. Higher area unemployment at ages 4 and 53 were independently associated with earlier retirement age [1% increase = mean −0.64 (95% CI: −1.12, −0.16) and −0.25 (95% CI: −0.43, −0.06) years]. Both were explained by adjustment for individual employment status at ages 26 and 53 years. Higher area unemployment at age 26 was associated with poorer health and lower likelihood of employment at aged 53; and these 2 individual pathways were identified as the key mediators between area unemployment and retirement age.

In conclusion, these results suggest that interventions designed to create local employment opportunities for young adults should lead to extended working through improved employment and health at mid-life.

1. Introduction

Aging populations in industrialized countries have prompted governments to encourage increased labour market participation of workers aged 50 and over. In the United Kingdom (UK), policies have been implemented to reduce government financial challenges of increasing life expectancy and demands on health and social care services, as well as provide positive health and financial outcomes for individuals (DWP, 2017). One of these policies is the raising of the State Pension Age (SPA) for women from age 60 to 65 by April 2018, and both genders to age 67 by 2028. However, most employees in the UK already stop working before the SPA (ONS, 2013). Early retirement can be a positive life change, reflecting a financial ability to stop paid work. For others, early retirement is a consequence of adverse factors, such as poor health or unemployment (Adams and Beehr, 2003), which can reduce accumulated wealth and exacerbate inequalities at older ages. Therefore, identification of adverse factors that lead to early exit from the labour market could be beneficial to both individuals and governments.

One factor that may contribute to inequalities in retirement timing

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is geographical variations in the labour market. Older workers who live in areas with higher levels of unemployment are more likely to be in receipt of a disability pension (Laaksonen and Gould, 2014; McVicar, 2007; Reime and Claussen, 2013; Thorlacius and Olafsson, 2012) and more likely to exit work for both health (Murray et al., 2016; Disney et al., 2006) and non-health reasons (Murray et al., 2016). The primary mechanism suggested to explain this relationship is local labour market demand: an individual living in an area of higher unemployment will have both a higher chance of losing employment and lower chance of regaining employment after redundancy (McCormick and Sheppard, 1992); especially older workers who find it harder than younger workers to regain employment after redundancy (Oldfield, 2014).

However, previous studies have only considered how local labour market conditions immediately preceding retirement age are associated with retirement outcomes. People residing in disadvantaged areas later in life are likely to have lived in areas with similar levels of disadvantage throughout life (Murray et al., 2012; Van Ham et al., 2012). Local labour market conditions earlier in the life course have been associated with individual factors that, in turn, influence retirement ages. For example, poor health is associated with increased likelihood of younger retirement age (van Rijn et al., 2014). Living in a disadvantaged area earlier in life, even in childhood, can influence later life health (Murray et al., 2013; Curtis et al., 2004; Dundas et al., 2014); most likely because health-harming (e.g. pollution) and health-promoting (e.g. walkability) features are unequally distributed across neighbourhoods (Diez Roux and Mair, 2010). Local area unemployment is frequently used as proxy for area disadvantage (Pickett and Pearl, 2001). It is therefore logical to hypothesize that residence in an area with higher unemployment earlier in life would be associated with earlier age of retirement through poorer mid-life health.

Second, early retirement is more likely if an individual was not in paid work in later adulthood (Visser et al., 2016), particularly for extended spells out of work (Radl, 2013; Visser et al., 2016). There is strong evidence that periods of unemployment in young adulthood can have a 'scarring' effect on the likelihood of employment later in life (Gregg, 2001; Nilsen and Reiso, 2011). For various reasons, including lower labour market demand, younger workers are particularly vulnerable to downturns in the local economy (Bell and Blanchflower, 2011; Freeman and Wise, 1982). Therefore, we hypothesize that residence in an area with higher unemployment in young adulthood is a particularly sensitive period in the life course, and in keeping with cumulative (dis)advantage theory, sets individuals on employment trajectories that lead to higher levels of retirement age inequality (Dannefer, 2003).

Third, individual occupational social class is also related to retirement age, with occupations in the middle of the class 'ladder' more likely to retire earlier than professional or unskilled manual workers (Radl, 2013). Lower class individuals are more likely to remain in work out of financial necessity, while higher class individuals retire later because they have better health, are better educated, enter the labour market later and are more likely to be sheltered from involuntary exit forces (such as unemployment) (Blossfeld and Buchholz, 2011). Mechanisms linking area unemployment earlier in life to class include unequal career development opportunities through unequal distribution of structural opportunities and resources in local areas (Dannefer, 2003). For example, an individual's ability to develop a higher social class career, such as in finance, is less likely in the 'North' than 'South' of England, where historical forces of de-industrialization of dominant mining and manufacturing industries have shaped persistently high unemployment local labour markets (McVicar, 2007).

Fourth, higher educational achievement has also been linked to older retirement ages through educated workers earning higher wages (Leinonen et al., 2012), having better employment opportunities (Leinonen et al., 2012) and health (Schuring et al., 2015). Educational achievement has also been shown to vary according to local area socioeconomic conditions, such as where individuals resided during school age (Nieuwenhuis and Hooimeijer, 2016). Five interrelated mechanisms have been proposed: shaping the type of role models young people are exposed to outside the home, monitoring and sanctioning of behaviour, helpful social networks, local perceptions of occupational opportunity and institutional characteristics (Ainsworth, 2002). Therefore, we hypothesize that lower educational achievement could be a pathway through which higher area unemployment during childhood could influence a lower retirement age.

In addition, individuals of pensionable age in the UK will have experienced fluctuations in area unemployment levels over their lifetimes (Murray et al., 2012), both through residential mobility and secular change (Lekkas et al., 2017). The selective migration literature has consistently shown that characteristics of people, including socioeconomic and health status, can influence what areas people move to (Van Ham et al., 2012). Therefore, it is important to account for selective migration of individuals to determine whether associations between local area unemployment and retirement are not due to selection bias.

Overall, we hypothesize that higher local area unemployment at ages before mid-life are associated with earlier retirement age, and that the association operates through health, employment status, occupational class and education. We analyse prospective longitudinal data using structural equation modelling (SEM) to investigate not just single pathways, but how each pathway operates within the larger complex system (Rutter et al., 2017) that leads to inequalities in retirement age. The age at which an individual retires is a result of not just one individual factor, but a push and pull of a myriad of factors (Adams and Beehr, 2003). Negative individual health and socioeconomic factors are highly correlated, and may all develop from early life disadvantage, but individual responses to early life disadvantage vary (O'Rand, 2009). Also, individuals who experience changes in local area unemployment may experience alteration of only one, or a few, of these individual factors later in life, depending on the structures and resources in their geographic location (Van Ham et al., 2012). We therefore believe that a systems life course approach is vital in planning interventions that will effectively target the specific pathways and ages that will be most effective in reducing disparities in retirement ages.

2. Methods

2.1. Study population

The Medical Research Council National Survey of Health and Development (NSHD) is a socially stratified sample of all births that occurred during one week in March 1946 across England, Scotland, and Wales (n = 5362). The cohort has been followed prospectively 24 times from birth onwards. At the most recent data collection in 2014 (age 68), a total of 2453 study members (84.2% of target) completed a postal questionnaire (Kuh et al., 2016). The current investigation uses data from sweeps in 1950 (study members aged 4), 1972 (26 years), 1999 (53 years), 2006–2010 (60–64 years) and 2014 (68 years); chosen to represent exposure in childhood, early adulthood and mid-life, and to be close to census years. An additional 145 cohort members were included in the sample that provided retirement age at the age 60–64 data collection, but did not complete a postal questionnaire at the age 68 data collection. The current analyses are based on those with data on retirement age, or who were in paid work at age 68 (n = 2526).

2.2. Retirement age

At ages 60–64 and 68 years, study members reported on postal questionnaires whether they had retired from their main occupation and, if so, at what age. If a cohort member reported at both ages that they were retired from their main occupation, and not in paid work, the age reported at age 60–64 was chosen. If a cohort member was retired at 60–64, but in paid work (full or part-time) at age 68, they were considered to not be retired.

2.3. Life-course area socioeconomic measures

Place of residence was recorded at every data collection, plus yearly updates past the age of 16 through postal reminders. Residential addresses at three different ages (4, 26 and 53 years) were previously linked to local government district socioeconomic measures (Murray et al., 2012). These ages were chosen to represent area socioeconomic exposure during major life stages: childhood (age 4), early adulthood (age 26) and midlife (age 53). If there was more than one data collection during a life stage, the data collection year closest to a census year was used to reduce misclassification of area conditions. Local government districts are subnational divisions of England and Wales used for the purpose of local governance (ONS, 17a), and reflect sizes of local labour markets in the UK (ONS, 17b). For this analysis, 'area unemployment' refers to the percentage of all economically active persons (men in 1951 census) in a local authority that were not employed.

2.4. Health

Health status was measured at ages 26 and 53 years based on self-reports from postal questionnaires. At age 26, cohort members were asked, "Would you say at the present time your state of health was … Excellent/good/fair/poor?" At age 53 health status was based on a derived number of doctor diagnosed health problems the cohort member was experiencing from a list of cardiovascular, respiratory, endocrine, and neurological disorders (Kuh et al., 2005). Both health indicators were collapsed into dichotomous variables: Aged 26: 0 = excellent/good, 1 = fair/poor, and aged 53: 0 = no health problems, 1 = 1 or more health problem(s).

2.5. Employment status over adulthood

At ages 26 and 53 years, study members reported whether they were in paid work and, if so, whether it was full-time (> 30 h per week) or part-time work (< =30 h per week).

2.6. Educational achievement

Highest qualification by age 26 was grouped into 'no qualifications', 'lower secondary' ('O-levels or equivalent', usually attained at 16 years), 'advanced secondary' ('A-levels or equivalent', usually attained at 18 years), and 'degree-level or equivalent'.

2.7. Occupational class

Occupational class at age 26 and 53 years was based on head of household's occupation and coded according to Registrar General's classifications: 'professional (I)', 'managerial/technical (II)', 'skilled non-manual (IIInm)', 'skilled manual (IIIm)', 'semi-skilled manual (IV)' and 'unskilled manual (V)'. For men, their own occupation was used to derive class at both ages. For women at age 26, the resident male of the house's occupation was substituted, if there was one present. At age 53, women's own social class was used if it was the more advantaged of their own and spouse's social class. Childhood social class was based on the occupational class of the father or mother's husband when the cohort member was aged 4 years.

2.8. Statistical analysis

All analyses included participants with either a non-missing age of retirement or those in paid work at age 68. Descriptive statistics, by gender, were calculated using non-imputed data using Analysis of Variance (ANOVA) for continuous variables and the chi-square statistic for categorical variables. Missing data for covariates were imputed using twenty data sets, obtained through the multiple imputation program in Mplus 7 (Muthen and Muthen, 2015). The imputation models included the outcome, all predictors, and gender; plus auxiliary variables predictive of missingness (childhood social class aged 4, home ownership age 60–64 and other measures of age 4 local area socioeconomic characteristics [percentage employed in partly- or un-skilled occupations, percentage overcrowded, percentage lacking household amenities and percentage lacking higher education]) (Murray et al., 2012).

To analyse potential pathways linking local area unemployment across the life course with retirement age (censored for those still in paid work at age 68), we used structural equation modelling (SEM) in Mplus 7 (Muthen and Muthen, 2015). This enabled us to fit multiple mediator models with a combination of binary and continuous variables. In all models, the final outcome was retirement age (continuous), which was treated as censored (tobit) without inflation at the censoring point (Tobin, 1958). This model supposes that there is a latent variable that linearly depends on x via a parameter β, which determines the relationship between the independent variable x and the latent variable y. Estimates were calculated using a percentile bootstrap applied to each imputed data set (Muthen, 2011; Preacher and Selig, 2012), with overall estimates calculated using Rubin's rule (Rubin and Schenker, 1991). Within models, estimates are mean differences when the dependent variable is continuous and odds ratios when the dependent variable is categorical. The analysis proceeded in five parts.

In the first part, we wanted to know whether area unemployment at ages other than mid-life were directly related to age of retirement. Initially, associations of area unemployment at each age (4, 26 and 53) with retirement age were fitted in separate models. Second, as tracking of area unemployment has been identified to occur over the life time, a saturated 'area tracking' model was fitted (see Supplementary Fig. 1a) with area unemployment at age 4 fitted as the most distal and paths specified for tracking of area unemployment across the life course, and direct paths between ages 4 and 26 and 53 area unemployment to retirement age that did not occur through area tracking. Third, to check for robustness of the hypothesized model, changes in model fit statistics were assessed when direct paths between area unemployment and retirement age, at ages 4 and 26, were individually removed from the saturated model. For all models, fit was assessed by the root mean square error of approximation (RMSEA), comparative fit indices (CFI), and the weighted root mean square residual (WRMR). Good overall model fit was indicated by RMSEA ≤0.06, CFI ≥0.96, and WRMR ≤1.0 (Hooper et al., 2008).

In the second part of the analysis, we wanted to verify that the four hypothesized mechanisms of health, employment status, occupational class, and educational achievement were mediators of the relationships between area unemployment and retirement age. Initially, we fitted each mechanism separately. Each model was constructed to include the following theory-driven pathways (See Supplementary Figs. 1b and 1c):

i. A direct 'area tracking' pathway (area unemployment at age 4 → area unemployment age 26 → area unemployment age 53 → retirement age).
ii. A direct path of the possible mechanism to retirement age (e.g. health at age 26 → health at age 53 → retirement age).
iii. Direct paths leading from local area unemployment to the mechanism in future (e.g. area unemployment age 4 → health at age 26; area unemployment at age 26 → health at age 53).
iv. A pathway indicating that area unemployment in childhood leads to retirement age through pathways other than the path specified in the model (e.g. area unemployment age 4 → retirement age)
v. A pathway indicating that individual mechanisms at age 26 could influence selection of individuals into local areas of certain unemployment levels later in life (i.e. residential selection) (Jokela, 2015).

Since educational achievement was measuring events that had occurred prior to age 26, an additional pathway was added between education → area unemployment at age 26 years (See Supplementary Fig. 1c).

In the third part, to assess whether individual pathways identified in the second part could be due to correlations between the hypothesized mechanisms, the separate pathways were combined into pairs. This included the addition of all potential pathways linking the mediators. The inclusion of potential pathways was based on prior literature. For example, when the health and occupational class pathways were combined, additional paths were added between aged 26 health and aged 53 occupational class (Radl, 2013), as well as aged 26 occupational class and aged 53 health (Bartley, 2016) (see Supplementary Fig. 2). In the paired model, if no association was apparent between area unemployment and the mediator, or the mediator and retirement age, then this mechanism was dropped from the final model.

In the fourth part, the final model only included combined pathways where statistically significant associations had previously been identified leading from area unemployment to retirement age through a mediator. To reduce the possibility that identified pathways between area unemployment and retirement age were not entirely due to confounding by gender and childhood social class, model fit was assessed before and after adding all potential pathways from the confounder to all variables in the analysis, separately for the two potential confounders. Effect modification between area unemployment and mediators by gender was also tested by inclusion of interaction terms in the final model, as well as re-running the model separately for men and women. Mediation was examined by creating and testing individual mechanism parameters that linked area unemployment to retirement age, using the model constraint function in Mplus.

In the fifth part of the analysis, a number of sensitivity analyses were conducted to check for robustness of findings. First, we assessed the influence of sample attrition by fitting the single path associations (i.e. Part 1) before and after exclusion for missing outcome data. Second, to justify the decision to right-censor retirement age, rather than adjusting for clustering within areas, we assessed associations of the area tracking model when (i) not censored and (ii) not censored with a cross-classified data structure. Third, robustness of the final model was assessed by comparing model fit when a dropped pathway or hypothesized mechanism was added to the final model. Fourth, to assess robustness of associations between area unemployment with potential mediators, we calculated “E-values”. These represent the minimum strength of association an unmeasured confounder would need to have with both area unemployment and each mediator to fully attenuate each association (Vanderweele, 2017).

3. Results

The distributions of sample characteristics, by gender, are summarized in Table 1. At the age of 68 years, 76.1% of men and 86.6% of women had retired from their main occupation; with a mean retirement age of 59.9 (SD = 5.7) and 58.7 (SD = 5.6), respectively. Mean local authority unemployment was 1.2% when cohort members were aged 4 (1950), 2.3% when aged 26 (1972) and 4.6% when aged 53 years (1999), with no differences by gender. Men were more likely than women to self-report their health as ‘excellent or good’ aged 26, but there were no gender differences in reporting at least one health condition aged 53 years. Men were also more likely than women to have achieved higher educational qualifications by age 26, be employed full-time, and more likely to work in professional occupations at both ages 26 and 53.

3.1. Part 1: single path models

Area tracking (Table 2). In unadjusted models, a 1% increase of area unemployment at age 4, 26 or 53 was associated with earlier retirement [regression coefficients 0.78 (95% CI: 1.25, 0.32), 0.54 (0.92, 0.15) and 0.29 (0.46, 0.13) years earlier, respectively] (Model 1). When the saturated residential tracking model was fitted (Supplementary Fig. 1a), area unemployment did track across the life course. For example, a 1% higher aged 4 area unemployment was associated with 0.47 (95% CI 0.43, 0.51) percentage point higher aged 26 area unemployment. In the saturated model all three area associations with retirement age were reduced, with only direct associations between area unemployment at ages 4 and 53 not attenuated (model 2). Model fit was improved by dropping the pathway between area unemployment at age 26 and retirement age (RMSEA 0.09 to 0.06). This path was dropped from further analysis, because there was also no significant association in any further model (data not shown). In sensitivity analyses, excluding individuals who were right-censored reduced all associations in this model, completely attenuating the relationship between age 53 area unemployment and retirement age (Supplementary Table 1, model 2). Adding a cross-classified data structure to the un-censored model did not change results substantially (Supplementary Table 1, model 3).

Health (Table 3a, model 2). Cohort members who reported a health problem aged 53, compared to those who did not, retired on average 1.27 (1.67, 0.86) years earlier. The odds of reporting a health problem aged 53 was 1.42 times higher (1.26, 1.59) for those who reported poorer health aged 26. Inclusion of the health pathway within the area tracking model reduced, but did not entirely explain, the association between mid-life area unemployment and retirement age [-0.20 (−0.38, −0.01)]. Higher area unemployment aged 26 was related to poorer health aged 53 [odds ratio = 1.09 (1.01, 1.18)], and poorer health aged 26 was associated with residence in an area with higher unemployment aged 53 [mean = 0.14 (0.01, 0.26)]. There was no association between area unemployment at age 4 and health status at age 26.

Employment status (Table 3a, model 3). Not being in work at age 53 was associated with earlier retirement (regression coefficient 4.65 (95% CI 4.34, 4.96) years) compared with cohort members who were in full-time work aged 53. There was no association of part-time work aged 53 with retirement age. Employment status aged 26 was related to employment status aged 53. Inclusion of the employment status pathways in the area tracking model explained the association between area unemployment at age 4 and aged 53 and retirement age [mean change per 1% increase area = −0.11 (−0.28, 0.06) and −0.48 (−0.97, 0.01) respectively]. Living in an area with higher unemployment aged 26 was associated with increased odds of not being in work aged 53 [1.11 (1.03, 1.20)], and decreased odds of being in part-time work aged 53 [0.90 (0.82, 0.99)], compared to those in full-time work. There was no association between area unemployment at age 4 and employment status at age 26, nor did employment status at age 26 predict area unemployment at age 53.

Occupational class (Table 3b, model 4). Cohort members who worked in semi- or un-skilled manual occupations aged 53 retired on average 0.69 (0.04, 1.34) years earlier than professional occupations, but there were no differences in retirement age for managerial/technical or skilled non-manual employees compared to professional occupations. Lower occupational class at age 26 was generally related to lower occupational class aged 53. Inclusion of the occupational class pathway in the area tracking model did not alter associations between aged 4 or aged 53 area unemployment and retirement age. Higher area unemployment at age 26 was associated with higher odds of being in the lowest class at age 53 [OR = 1.22 (1.01, 1.49)], and occupational class at age 26 was related to area unemployment at age 53 [Partly- and un-skilled vs professional = mean 0.11 (0.03, 0.19)]. Again, aged 4 area unemployment was not associated with aged 26 occupational class.

Educational achievement (Table 3b, model 5). Educational achievement by age 26 was not directly associated with retirement age. It was, however, indirectly related to retirement age through aged 26 and aged 53 area unemployment. For example, not obtaining any educational

Table 1
Characteristics of the analytical sample.

Variables	All		Men		Women		p-value gender difference
	N	%	N	%	N	%	
TOTAL	2526	100.0	1243	100.0	1283	100.00	–
Retirement status 68y							
Retired main occupation	2057	81.4	946	76.1	1111	86.6	
Paid work	469	18.6	297	23.9	172	13.4	< 0.001
Mean Retirement Age (SD)	2057	59.3 (5.7)	946	59.9 (5.7)	1283	58.7 (5.6)	< 0.001
Mean Area Unemployment (SD)							
Mid-life (aged 53)	2407	4.6 (1.9)	1189	4.7 (1.9)	1218	4.6 (1.9)	0.52
Early Adulthood (aged 26)	2337	2.3 (0.8)	1153	2.3 (0.8)	1184	2.3 (0.9)	0.77
Childhood (aged 4)	2470	1.2 (0.7)	1215	1.2 (0.6)	1255	1.2 (0.7)	0.59
Health status–mid-life							
1 + Health problems	553	21.9	265	21.3	288	22.4	
0 Health problems	1708	67.6	824	67.7	884	68.9	0.88
Missing	265	10.5	154	12.4	111	8.7	
Health status–early adulthood							
Fair/Poor	157	6.2	49	3.9	108	8.4	
Excellent/Good	2098	83.0	1052	84.6	1046	81.5	< 0.001
Missing	271	10.7	142	11.4	129	10.1	
Employment Status-mid-life							
Full time	1421	56.2	876	70.5	545	42.5	
Part-time	473	18.7	73	5.9	400	31.2	
Not in paid work	367	14.5	140	11.3	227	17.7	< 0.001
Missing	265	10.5	154	12.4	111	8.7	
Employment status–young adulthood							
Full time	1532	60.7	1089	87.6	442	34.5	
Part-time	148	5.9	5	0.4	143	11.2	
Not in paid work	635	25.1	40	3.2	593	46.3	< 0.001
Missing	211	8.4	109	8.8	102	8.0	
Occupational class–mid-life							
Professional	248	9.8	150	12.1	98	7.6	
Managerial/Technical & Skilled NM	1222	48.4	569	45.8	653	50.9	
Skilled Manual	509	20.2	257	20.7	252	19.6	
Partly skilled & Unskilled M	243	9.6	93	7.5	150	11.7	< 0.001
Missing	304	12.0	174	14.0	130	10.1	
Occupational class-early adulthood							
Prof & Managerial/Technical	893	35.4	447	36.0	446	34.8	
Skilled Non-manual & Manual	1070	42.4	519	41.8	551	42.9	
Partly skilled & Unskilled M	304	12.0	131	10.5	173	13.5	0.110
Missing	259	10.3	146	11.7	113	8.8	
Educational achievement 26y							
Degree/higher	289	11.4	204	16.4	85	6.6	
A level	657	26.0	344	27.7	313	24.4	
O level	502	19.9	169	13.6	333	26.0	
None/sub GCE	942	37.3	455	36.6	487	38.0	< 0.001
Missing	136	5.4	71	5.7	65	5.1	

qualifications by age 26 (compared to degree-level) was associated with 0.11 (0.07, 0.16) and 0.19 (0.11, 0.27) higher mean area unemployment at ages 26 and 53 years, respectively. There was no association between area unemployment at age 4 and educational achievement at age 26, and hence no direct path linking area unemployment to retirement age. Educational achievement was therefore dropped from further analysis.

Table 2
Direct effects using data obtained from multiple imputation (n = 2526), National Survey of Health and Development. The variables are retirement age (RetireA) and area unemployment (Area) at 3 ages − 4, 26 and 53.

	*Model 1. Crude**		*Model 2. Residential tracking + All*		*Model 3. Residential tracking*, age 4 & 53 only		*Model 4. Residential tracking*, age 26 & 53 only	
	B	CI	*B*	CI	*B*	CI	*B*	CI
Area53→RetireA	−0.29	−0.46,-0.13	−0.21	−0.42,0.00	−0.25	−0.43,-0.06	−0.15	−0.37,0.08
Area26→RetireA	−0.54	−0.92,-0.15	−0.11	−0.63,0.41	–	–	−0.41	−0.90,0.08
Area4→RetireA	−0.78	−1.25,-0.32	−0.61	−1.12,-0.10	−0.64	−1.12,-0.16	–	–
Area26→Area53	–	–	1.26	1.19,1.34	1.27	1.19,1.34	1.27	1.19,1.34
Area4 →Area26	–	–	0.47	0.43,0.51	0.47	0.43,0.51	0.47	−0.90,0.08
Model fit:								
df	-		1		2		2	
RMSEA	-		0.09		0.06		0.06	
CFI	-		0.99		0.99		0.99	
WRMR	–		0.88		0.90		1.10	

Table 3a
Direct effects using data obtained from multiple imputation (n = 2523), National Survey of Health and Development. The variables are retirement age (RetireA), area unemployment (Area), Health (Hlth), Not working (WKN), working part-time (WKP), occupational socio-economic position (SEP) and educational achievement (EA), at 3 pre-retirement ages – 4, 26 and 53.

	Model 1. Residential tracking		Model 2. Health		Model 3. Employment status	
	B	CI	*B*	CI	B	CI
Area unemployment:						
Area53→RetireA	−0.25	−0.43, −0.06	−0.20	−0.38, −0.01	−0.11	−0.28, 0.06
Area4→RetireA	−0.64	−1.12, −0.16	−0.67	−1.16, −0.19	−0.48	−0.97, 0.01
Area26→Area53	1.27	1.19, 1.34	1.28	1.20, 1.35	1.27	1.20, 1.35
Area4 →Area26	0.47	0.43, 0.51	0.47	0.44, 0.51	0.47	0.43, 0.51
Health retirement:						
Hlth53→RetireA	–	–	−1.27	−1.68, −0.87	–	–
Hlth26→Area53	–	–	0.14	0.01, 0.26	–	–
Area26→Hlth53	–	–	1.09[a]	1.01, 1.18	–	–
Hlth26→Hlth53			1.42[a]	1.26, 1.59		
Area4→Hlth26	–	–	0.90[a]	0.81, 1.01	–	–
Employment:						
WKP53→RetireA	–	–	–	–	−1.43	−0.28, 0.06
WKN53→RetireA	–	–	–	–	−4.65	−4.96, −4.34
WKP26→WKP53	–	–	–	–	1.95[a]	1.32, 2.88
WKP26→WKN53	–	–	–	–	0.74[a]	0.55, 0.99
WKN26→WKN53	–	–	–	–	1.09[a]	0.98, 1.22
WKN26→WKP53	–	–	–	–	0.74[a]	0.55, 0.99
Area4→WKP26	–	–	–	–	0.91[a]	0.81, 1.01
Area4→WKN26	–	–	–	–	1.04[a]	0.96, 1.13
Area26→WKP53	–	–	–	–	0.90[a]	0.82, 0.99
Area26→WKN53	–	–	–	–	1.11[a]	1.03, 1.20
WKP26→Area53	–	–	–	–	−0.05	−0.12, 0.03
WKN26→Area53	–	–	–	–	0.05	−0.05, 0.16
Model fit:						
df	2		6		12	
RMSEA	0.06		0.03		0.10	
CFI	0.99		0.99		0.89	
WRMR	0.90		0.87		2.57	

[a] *B* has been exponentiated, interpret as odds ratio.

3.2. Part 2: combined path models

Area unemployment, health and occupational class When health pathways were added to the area tracking and occupational class model, associations between occupational class and retirement age were fully attenuated. Occupational class pathways were therefore dropped from subsequent analyses (Supplementary Fig. 2).

Area unemployment, health and employment status When both mid-life health and employment status pathways were included in the model, both were associated with retirement age. Area unemployment at age 26 was related to age 53 area unemployment, health and employment status. Health at 26 was related to age 53 health and employment status, as well as age 26 employment status related to age 53 health and employment status. There was no association between area unemployment at age 4 and health or employment status age 26 (Supplementary Fig. 3).

Full model (Fig. 1). Therefore, the full model contained just the area tracking, health and employment status pathways (Model fit: RMSEA 0.06, CFI 0.92, WRMR 1.94). Regarding gender, we found women, compared to men, reported poorer health aged 26 and 53, and higher odds of being unemployed or working part-time (compared to full-time) at both age 26 and 53 [See Supplementary Figs. 4 and 5]. Model fit was improved when gender pathways were included [see Supplementary Table 2], but worsened considerably when childhood social class pathways were included [see Supplementary Table 3]; therefore only the significant gender pathways were included in the final model (see Fig. 1).

In the final model, both mid-life health and employment status still mediated the relationship between aged 26 area unemployment and retirement age (p-values for all 20 imputations = 0.001). Interaction tests showed that while area unemployment at age 26 was associated with health and working status at age 53 for both women and men, these associations were slightly stronger for women compared to men (p-values = 0.013 and 0.006). Sensitivity analyses showed that both adding back in the dropped pathway between age 26 area unemployment and retirement age (see Supplementary Table 4, model 3), as well as inclusion of dropped occupational status and educational achievement pathways (see Supplementary Table 4, models 4 to 5), worsened model fit for all indices. Therefore, the final model included both women and men with inclusion of the significant gender pathways, but not childhood social class, pathways (see Fig. 1). For the pathways between mid-life health and employment status with age 26 area unemployment, E-values for unmeasured confounders were 1.26 (95%CI: 1.08, 1.39) and 1.39 (1.24, 1.53), respectively.

4. Discussion

Using data from a prospectively-collected nationally-representative cohort of white British pensionable aged men and women, we have shown for the first time that early adulthood is a key life stage where local labour market conditions are related to retirement age. This relationship occurred through higher area unemployment at age 26 being related to worse health and more individual unemployment at age 53, which in turn were both related to earlier retirement ages. These findings imply that government strategies to extend the working lives of future generations would be most effective if they addressed youth unemployment, rather than focused on older workers in areas with high unemployment.

Our analysis highlights the importance of incorporating life course residential exposure histories when examining labour market influences on retirement age. In Sociology and Life Course Epidemiology there is a strong tradition of showing that factors earlier in life can effect later life

Table 3b
Direct effects using data obtained from multiple imputation (n = 2523), National Survey of Health and Development. The variables are retirement age (RetireA), area unemployment (Area), Health (Hlth), Not working (WKN), working part-time (WKP), occupational class (OC) and educational achievement (EA), at 3 pre-retirement ages – 4, 26 and 53.

	Model 1. Residential tracking		Model 4. Occupational SEP		Model 5. Educational achievement	
	B	CI	*B*	CI	*B*	CI
Area unemployment:						
Area53→RetireA	−0.25	−0.43, −0.06	−0.25	−0.46, −0.04	−0.26	−0.45, −0.07
Area4→RetireA	−0.64	−1.12, −0.16	−0.64	−1.13, −0.16	−0.65	−1.13, −0.17
Area26→Area53	1.27	1.19, 1.34	1.27	1.19, 1.35	1.23	1.15, 1.31
Area4→Area26	0.47	0.43, 0.51	0.47	0.43, 0.51	0.47	0.43, 0.51
Occupational social class:						
OC53_2→RetireA	–	–	−0.06	−2.63, 2.51	–	–
OC53_3→RetireA	–	–	−0.44	−1.05, 0.17	–	–
OC53_4→RetireA	–	–	−0.69	−1.34, −0.04	–	–
OC26_2→Area53	–	–	0.16	0.07, 0.25	–	–
OC26_3→Area53	–	–	0.11	0.03, 0.19	–	–
OC26_2→OC53_2	–	–	0.00[a]	0.00, > 10	–	–
OC26_2→OC53_3	–	–	0.00[a]	0.00, > 10	–	–
OC26_2→OC53_4	–	–	6.00[a]	3.62, 9.95	–	–
OC26_3→OC53_2	–	–	6.89[a]	4.25, 11.18		–
OC26_3→OC53_3	–	–	1.10[a]	0.99, 1.22	–	–
OC26_3→OC53_4	–	–	1.96[a]	1.67, 2.31	–	–
Area26→OC53_2	–	–	0.07[a]	0.00, > 10.0	–	–
Area26→OC53_3	–	–	1.16[a]	0.95, 1.41	–	–
Area26→OC53_4	–	–	1.22[a]	1.01, 1.49	–	–
Area4→OC26_2	–	–	1.00[a]	0.93, 1.08	–	–
Area4→OC26_3	–	–	1.02[a]	0.95, 1.10	–	–
Education:						
EA26_O→RetireA	–	–	–	–	−0.02	−0.44, 0.41
EA26_A→RetireA	–	–	–	–	−0.34	−0.79, 0.11
EA26_N→RetireA	–	–	–	–	−0.08	−0.56, 0.41
EA26_O→Area53	–	–	–	–	−0.05	−0.14, 0.04
EA26_A→Area53	–	–	–	–	−0.14	−0.25, −0.03
EA26_N→Area53	–	–	–	–	0.19	0.11, 0.27
EA26_O→Area26	–	–	–	–	−0.07	−0.11, −0.03
EA26_A→ Area26	–	–	–	–	−0.04	−0.09, 0.01
EA26_N→Area26	–	–	–	–	0.11	0.07, 0.16
Area4→EA26_O	–	–	–	–	0.99[a]	0.92, 1.08
Area4→EA26_A	–	–	–	–	0.98[a]	0.95, 1.10
Area4→EA26_N	–	–	–	–	1.02[a]	0.95, 1.10
Model fit:						
df	2		16		5	
RMSEA	0.06		0.26		0.71	
TLI	0.90		0.40		−3.53	
WRMR	2.00		6.85		13.41	

[a] Each path fitted as separate models.

outcomes (Ben Shlomo and Kuh, 2002; Dannefer, 2003; O'Rand, 2009), but area effects research has lagged behind. Previous research has found that work exit outcomes are associated with features of older workers' local labour markets, including employment rates (Laaksonen and Gould, 2014; McVicar, 2007; Reime and Claussen, 2013; Thorlacius and Olafsson, 2012). What we show here is that while there is a correlation between area unemployment at age 53 and retirement age, the dynamics - between local labour markets and retirement age - occur earlier in people's careers, and specifically through pathways of health and employment status. Previous literature, including on this same cohort, has shown that relationships exist between area socioeconomic factors and health (Lekkas et al., 2017; Diez Roux et al., 2010; Galster, 2012; Murray et al., 2013) and employment status (Bell and Blanchflower, 2011; Freeman and Wise, 1982); between mid-life health and employment status and retirement outcomes (van Rijn et al., 2014; Reeuwijk et al., 2017; Stafford et al., 2017); and between lower occupational class and poor health (Bartley, 2016). Our findings bring all of these relationships together into a cumulative advantage theory structure (Dannefer, 2003). We expand on earlier work showing that living under depressed national labour market conditions can predict negative career trajectories and socioeconomic achievement (Spilerman, 1977), by highlighting that even in times of high national employment (1971), geographic variations in local labour market conditions can have negative influences further along the career chain – for example, on the age at which people decide to end their working lives.

Moreover, by incorporating these relationships into a more comprehensive model, we were able to clarify that in mid-life it is health and employment status, rather than occupational class, which matters for retirement age. This is not to say that lower occupational class at age 26 is not associated with poorer health at mid-life; rather the relationship between mid-life occupational grade and retirement age was explained by health. Similarly, previous literature has been consistent in showing that early life neighbourhood conditions are related to educational achievement (Nieuwenhuis and Hooimeijer, 2016) and employment outcomes (Bell and Blanchflower, 2011; Freeman and Wise, 1982); with a growing body of literature showing associations with later life health (Murray et al., 2013; Curtis et al., 2004; Dundas et al., 2014). Our life course model showed that childhood area unemployment was related to retirement age, but only through tracking of area unemployment across the life course. A direct association was initially identified, but inclusion of the employment status pathway attenuated the relationship. We did not see any direct association between childhood area unemployment and any of the aged 26 individual factors that we examined in the study. Recent literature has also

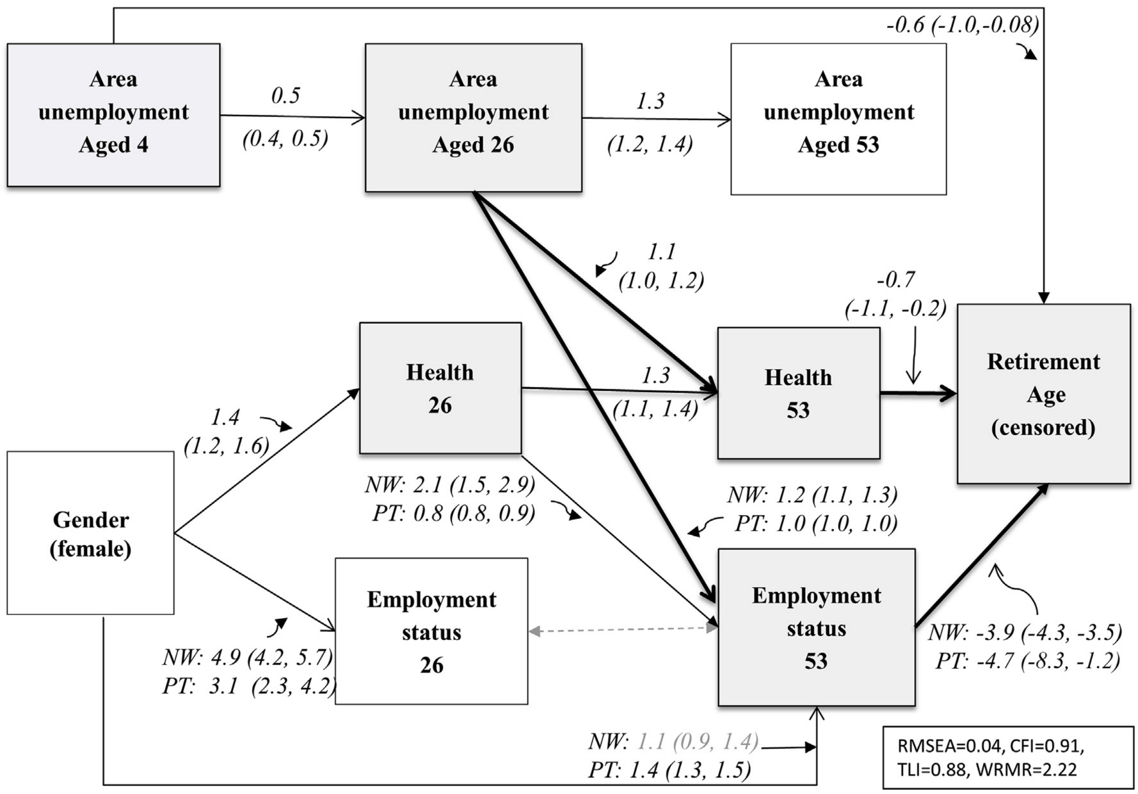

Fig. 1. Full structural equation model with health and employment status paths between area unemployment across the life course and retirement age, plus gender (n = 2526). Dotted line indicates non-significant path ($p > 0.05$). Bolded line indicates mediation test conducted.

documented that health inequalities emerge in early adulthood and widen until the early 60s (Norman and Boyle, 2014). In this cohort, 83.0% of the study members were in excellent or good health, and 87.6% of men were in full-time employment aged 26. This suggests that heterogeneity in health and employment status by childhood area unemployment may not have been wide enough in early adulthood to detect a difference with this population. Individuals of lower social class were also more likely to leave the study (Stafford et al., 2013), potentially further reducing our ability to detect area effects during this age period.

4.1. Strengths and limitations

NSHD is the only representative population-based data set that contains prospectively collected individual employment and health data from childhood to retirement age, linked to local area unemployment data. This allowed us to investigate when in the life course local area employment is important for retirement age; crucial for planning effective interventions. Another strength of this study was the use of structural equation models, which allowed us to explore multiple potential pathways linking area unemployment across the life course to retirement age and to model residential selection bias – a known issue in neighbourhood effects research. At time of writing, neither Mplus nor Stata could simultaneously estimate multiple imputed, censored, multilevel SEM models, which led us to dropping the multilevel structure from the full SEM models. Sensitivity analyses showed that adding a multi-level data structure hardly changed our results, whereas not including censored individuals in the analysis would have led to the conclusion that there was no association between area unemployment and retirement age.

One major challenge in this study was that due to data constraints, retirement ages were based on the cohort member's self-reported year of retirement from their main occupation. It would have been preferable if retirement age was more reliably determined, for example, through receipt of national insurance payments or using national or occupational employment registers. Our results could be biased if an individual's date of ‘retirement’ was different to their date of ‘work exit’ (e.g. homemakers or long-term unemployed), or if a high percentage of cohort members returned to work after age 68. To account for the latter possibility, we re-classified individuals from retired to not retired if they had returned to work by age 68 years (5.0% of sample). While individuals in our study may have returned to work after age 68, the proportion doing so is likely to be very low and occurring predominantly among the highly educated and healthy (Kanabar, 2015). If anything, our results are therefore likely to slightly underestimate the true relationships between the tested mechanisms and retirement age.

Second, another constraint of the data was that our definition of health was not congruent at the two ages studied; at age 26 a self-reported Likert scale measuring general health, and at age 53 a self-report of doctor diagnosed health problems. In our analysis, the two health measures were associated, with cohort members who reported fair or poor health, as opposed to excellent or good, having a 42% higher odds of reporting at least one doctor-diagnosed health problem at age 53. Earlier studies have identified that subjective, rather than objective, health measures are a better predictor of retirement (Dwyer and Mitchell, 1999), suggesting that we are underestimating the relationships between mid-life health and other factors. Contrarily, a Canadian study (Lindeboom and van Doorslaer, 2004) showed that younger respondents tended to rate their health lower than older respondents with a similar objective health assessment, suggesting any relationships with our aged 26 health measure might be conflated. Third, head of household occupation was used instead of the cohort member's own social class to minimize bias in coding men's versus women's occupations. Repeating these analyses with each individual's own social class did not change results (results not shown).

Fourth, as in any longitudinal observational study, study attrition of the sample occurred, despite high response rates. Prior studies on this cohort have shown that health, occupation, education and area unemployment, but not employment status, predict attrition at the age 60–64 (Stafford et al., 2013) and age 68 (Kuh et al., 2016) sweeps; all factors associated with younger retirement ages. While the age 60–64 sample of this cohort has been shown to be representative of the white-British population (Stafford et al., 2013), these studies suggest that strengths of effect in our study may be underestimated. The average retirement age of 59.0 in this study is lower than national estimates of 64.4 for men and 61.9 for women in 2008 (ONS, 2013). In addition, the low rate of employment at age 68 (e.g. 18.6% vs 31.6% nationally [ONS, 2013]) implies that this cohort left work at earlier ages than the national average; but censoring of the outcome was done to account for this bias in the data. Additionally, like all observational studies, relationships seen are based on observed data, with the potential for unmeasured confounders explaining relationships. Calculated E-values indicated that hypothetical unmeasured confounders would only need to be moderately related to area unemployment at age 26 and mid-life health and employment status to explain relationships. However, we believe that we have accounted for the major potential confounders in our analysis, with potential missing confounders, such as family wealth or income, likely partly or completely explained by correlations with included variables. To check for robustness of findings, we recommend that major mediating pathways be replicated in other data sets that contain additional potential confounders.

In conclusion, we provide evidence that policies to extend working life should focus not just on individuals, but also on the wider labour market context in which individuals reside. If these relationships are causal, providing assistance with maintaining employment and good health in mid-life are key to ensuring individuals are able to work longer. This is vital given that the SPA in the UK is rising and a significant number of older people still leave the labour market before the current SPA. Policies should recognise that individuals' health and employment in mid-life may reflect the employment opportunities and adversities that individuals have encountered earlier in life. Large scale interventions that create new jobs in areas with high youth unemployment may therefore have long-term positive consequences for future generations' extended working lives.

Contributions

E.T. Murray planned the study, conducted the data analyses and wrote the paper. P. Zaninotto and J. Head helped plan the study and revise the manuscript. M. Fleischmann, M. Stafford, E. Carr, N. Shelton, S. Stansfeld and D. Kuh revised the manuscript.

Conflicts of interest

The authors declare that they have no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2019.02.038.

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