Investigating health and work participation in later working life: multi-state modelling of Healthy Working Life Expectancy using national population datasets

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Abstract

Introduction

Retirement ages are rising in many countries due to population ageing and increasing life expectancy. It is unclear whether people in later working life (age $\geq$50) are able to work for longer due to health conditions and a lack of job opportunities. The work described in this thesis aimed to determine the average number of years that adults in England are expected to be healthy and in work from age 50, and investigate inequalities, projections until the year 2035, and association with health, lifestyle and workplace factors including osteoarthritis (OA) as an exemplar of a common long-term health condition.

Methods

Healthy Working Life Expectancy (HWLE) was identified through a systematic review as a potential indicator of population ableness to work for longer and operationalised as years spent healthy (no limiting long-standing illness) and in paid work ((self-)employment) from age 50. HWLE was estimated with discrete-time and continuous-time multistate models using IMaCh/R software, and longitudinal data from the English Longitudinal Study of Ageing and the North Staffordshire Osteoarthritis Project. HWLE projections were estimated using Health Survey for England data and official mortality rate statistics.

Results

HWLE at age 50 was 9.42 years (men: 10.94 years, women: 8.25 years). Subgroup analyses highlighted inequalities by socioeconomic status, and to an extent by occupation type and region. Having OA was associated with reduced HWLE, as was obesity, physical inactivity, pain interference, mental health problems, unsupportive work environments, and having no control at work. Projected from 2020 to 2035, life expectancy gains (men:

3.37 years; women: 2.46 years) exceeded HWLE gains (men: 0.38 years; women: 1.08 years).

Conclusion

HWLE in England is less than the years to the State Pension age. HWLE has potential to be used as a population indicator for work and support a joined-up approach between policymakers, employers and healthcare providers to extend working lives.

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"The LORD remembers and blesses us." Psalm 115:12a

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Papers in preparation

Healthy working life expectancy projections for England until the year 2035 *(thesis chapter 3)*

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Postgraduate symposium (Keele University 16/05/18): 3 Minute Thesis

Postgraduate symposium (Keele University 16/05/19): 3 Minute Thesis ***Won the prize for the best 3 Minute Thesis and first runner up for the PPIE (Patient and Public Involvement and Engagement) prize**

The Department for Work and Pensions (London 10/12/18): An overview of the PhD project, methods, and findings to date

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Contents

Abstract iii

Acknowledgements iii

Publications and thesis dissemination vii

Table of Contents xv

List of Figures xx

List of Tables xxv

List of Abbreviations xxvii

1 Introduction 1

1.1 Life expectancy improvements around the world 1

1.2 Hypotheses of the relationship between mortality and morbidity 2

1.2.1 Compression of morbidity hypothesis 3

1.2.2 Expansion of morbidity hypothesis 3

1.2.3 Dynamic equilibrium hypothesis 4

1.3 Population health indicators 5

1.3.1 Health expectancy 5

1.3.2 Health gap 7

1.4 Demographic changes in the United Kingdom 8

1.4.1 Trends in life expectancy 8

1.4.2 Population ageing 11

1.5 Extending working lives 12

1.5.1 Increasing numbers of older workers 12

1.5.2 The UK State Pension age 13
Affordability 13
Fairness 14
Fuller Working Lives 14
Government response 15
1.6 Health and paid work 16
1.6.1 Biopsychosocial models of health and work 19
1.7 Systematic review of estimated length of healthy working life 26
1.7.1 Methods 27
Search strategy and identification of studies (stage 1) 27
Study selection (stage 2) 31
Data extraction and quality assessment (stage 3) 33
Analysis (stage 4) 36
1.7.2 Results 37
Inter-rater agreement 40
Overview of eligible records 41
Quality assessment 45
Data extraction 49
1.7.3 Evidence synthesis: narrative review 53
1.7.4 Discussion 54
Clinically examined and self-assessed measures of health 56
Healthy Working Life Expectancy 59
Study strengths and limitations 59
Implications for policy 60
Implications for research 61
Conclusion 63
1.8 Thesis aims 63

2 Estimates of Healthy Working Life Expectancy at age 50 in England 67
2.1 Data source: The English Longitudinal Study of Ageing (ELSA) 69
2.1.1 Survey design 71
2.2 Statistical methods 74

2.2.1 Introduction to multi-state models 75
2.2.2 Markov chains 79
2.2.3 Method for estimating HWLE 81
2.2.4 IMaCh software for estimating HWLE 88
Missing data handling in IMaCh 89
2.3 Operationalisation of variables for analysis 90
2.3.1 Definitions of health and work for HWLE in ELSA 90
Operationalisation of health 90
Operationalisation of work 94
2.3.2 Identifiers of population subgroups 94
2.4 Analysis plan 96
2.4.1 Subgroup analyses 97
2.4.2 Specifications for model estimation 97
2.4.3 Sensitivity analyses 98
Interpolation step size 98
Individuals with missing data in subpopulation identifiers 99
Alternative operationalisations of health 99
Approach to estimating prevalence of health and work state occupation in the population 100
2.5 Data management 100
2.5.1 Variable management 100
2.5.2 Data cleaning and sample size 102
2.6 Descriptive summaries of the data 106
2.6.1 Missing health and work data 107
2.6.2 Number of observed transitions for analysis 111
2.7 Results 113
2.7.1 HWLE by sex in England 113
2.7.2 HWLE by deprivation level, occupation type, education level and region in England 114
2.7.3 Healthy Life Expectancy, Working Life Expectancy and Total Life Expectancy 121
2.7.4 Sensitivity analyses 122

Sensitivity analysis of HWLE to population based or observed state occupation prevalence 125

Sensitivity analysis of HWLE to exclusion of missing region and education data 125

Sensitivity analysis of HWLE results to IMaCh interpolation step size 125

Life expectancy sensitivity analyses using the life table method . . 127

2.8 Discussion 134

2.8.1 Comparison of results with offical published estimates 136

2.8.2 Study strengths and limitations 137

2.9 Conclusion 139

3 Projections of Healthy Working Life Expectancy in England to 2035 141

3.1 Introduction 141

3.2 Statistical methods 142

3.3 Data sources: Health Survey for England (HSE) and age specific mortality rates from national life tables 151

3.4 Operationalisation of health and work for HWLE 152

3.5 Components of the HWLE projections 154

3.5.1 Age specific prevalence of being healthy and in work (state 1) (HSE data) 154

3.5.2 Prevalence of being healthy and in work (state 1) at age 50 for HWLE projected years 2015-2035 (HSE data) 156

3.5.3 Calculation of the projected transition rate from healthy and working to unhealthy and/or not working 158

3.6 Sensitivity analyses 161

3.7 Missing data 161

3.8 Results 162

3.8.1 Life expectancy projections 162

3.8.2 HWLE projections 163

3.8.3 Sensitivity analyses results 169

3.9 Discussion 173

3.9.1 Comparison of life expectancy estimates and projections to official statistics . . . 174
3.9.2 Strengths and limitations . . . 176
3.9.3 Implications for future research . . . 178
3.10 Conclusion . . . 180

4 Examining HWLE in people with a long term health condition using osteoarthritis as an exemplar 181

4.1 Introduction . . . 181
4.2 Data source: The English Longitudinal Study of Ageing (ELSA) . . . 184
4.2.1 Measurement of variables and identification of OA status . . . 184
4.3 Data source: The North Staffordshire Osteoarthritis Project (NorStOP) . . . 185
4.3.1 Survey design . . . 186
4.3.2 Definitions of health and work for HWLE in NorStOP . . . 188
4.3.3 Measurement of variables and identification of OA and non-OA groups . . . 189
4.3.4 Data management . . . 189
4.4 Methods . . . 190
4.4.1 Analysis plan . . . 191
Part 1: ELSA . . . 191
Part 2: NorStOP . . . 191
4.4.2 Sensitivity analyses . . . 192
ELSA . . . 192
NorStOP . . . 192
4.5 Results . . . 193
4.5.1 Sample size and missing data . . . 193
ELSA . . . 193
NorStOP . . . 195
4.5.2 Number of observed transitions for analysis . . . 200
ELSA . . . 200
NorStOP . . . 200
4.5.3 Estimates of HWLE at age 50 in England (ELSA data) . . . 202

HWLE for males and females over ages 50-75 202
HWLE for people with non-manual, manual and self-employed occupations over ages 50-75 203
HWLE for people with and without osteoarthritis over ages 50-75 . 203
HWLE for males and females with and without osteoarthritis over ages 50-75 204
HWLE for people with manual, non-manual and self-employed occupations with and without osteoarthritis over ages 50-75 205
HWLE for males and females with manual, non-manual and self-employed occupations, with and without osteoarthritis over ages 50-75 207
4.5.4 Estimates of HWLE at age 50 in the NorStOP population (NorStOP data) 213
HWLE for people with and without OA in the NorStOP population 215
4.5.5 Sensitivity analyses 216
ELSA 216
Examining the HWLE estimates from two ELSA samples (described in this chapter and chapter 2) 218
NorStOP 219
4.6 Discussion 223
4.6.1 Strengths and limitations 225
4.6.2 Implications for policy and research 229
4.6.3 Conclusion 230

5 Investigating factors associated with reduced Healthy Working Life Expectancy 231
5.1 Aims and objectives 233
5.2 Methods 233
5.2.1 Data source: The English Longitudinal Study of Ageing (ELSA) . . 237
5.2.2 Health, socio-demographic and workplace factors 237
5.2.3 Operationalisation of variables for analysis 238
5.2.4 Analysis plan 240

Transition hazard rate ratios associated with osteoarthritis and health, socio-demographic and workplace factors 241
Estimating the effect on HWLE of hazard rate ratios associated with osteoarthritis and health, socio-demographic and workplace factors 243
5.2.5 Sensitivity analyses 244
Sensitivity of results to use of the simplified 3-state HWLE model . 244
Sensitivity of results to the operationalisation of health using limiting long-standing illness 244
5.2.6 Missing data 244
5.2.7 Implementation in R 249
5.2.8 Data management 252
5.3 Results 253
5.3.1 Sample size 253
5.3.2 Associations between OA and health, socio-demographic and lifestyle factors and transitioning out of health and work 257
5.3.3 Healthy Working Life Expectancy estimates 264
5.3.4 Sensitivity analyses 272
Sensitivity of results to use of simplified 3-state HWLE model . . . 272
Sensitivity of results to operationalisation of health using limiting long-standing illness 273
5.4 Discussion 278
5.4.1 Study strengths and limitations 281
5.4.2 Implications for policy and practice 284
5.5 Conclusion 286

6 Summary and discussion 287
6.1 Key findings 287
6.1.1 HWLE can be operationalised and used as a population indicator for work 288
6.1.2 HWLE in England is 9.42 years, which is over six years less than the number of years to State Pension age 289

6.1.3 There are inequalities in HWLE between population subgroups according to sex, region, occupation type, education level, and deprivation . . . 290
6.1.4 HWLE is unlikely to rise with the State Pension age without interventions to reduce inequalities and improve population health and wellbeing . . . 292
6.1.5 Having osteoarthritis reduces remaining length of healthy working life by over one third . . . 293
6.1.6 Health, lifestyle and workplace factors are associated with reduced length of healthy working life . . . 295
6.2 Discussion . . . 296
6.2.1 Recently published studies of population ableness to work for longer 298
6.2.2 The changing nature of work . . . 301
6.2.3 Implications for policy and practice . . . 303
6.2.4 Challenges and further research . . . 306
Identification of data source(s) for long-term HWLE surveillance . 306
Methodological challenges for long-term HWLE surveillance . . . 307
Developing new methods . . . 307
6.3 Final conclusions . . . 308

Bibliography **311**

A Systematic Review Medline Search Strategy (OVID) **341**

B QUIPS Template **345**

C IMaCh parameter file for estimating HWLE in England **351**

D Stata '.do' file for preparing ELSA data for IMaCh analysis (shortened) **357**

E R code to impute death dates written by Stata '.do' file **373**

F HSE sample size: number of respondents at each year of age 50-75 for years 1996-2017 **377**

G Raw and smoothed prevalence of being healthy and work among women and men aged 50-75 (for HWLE projections) 389

G.1 Females 389

G.2 Males 393

List of Figures

1.1 The survivorship function for a hypothetical population 6

1.2 Life expectancy for females, males and the total population from 1960 to 2018 in the UK 8

1.3 UK population size estimates (1976-2016) and projections (2026-2046) by age group 11

1.4 The Karasek job-demand-control model 21

1.5 The Karasek job-demand-control-support model of the psychosocial work environment 22

1.6 The expanded ICF-scheme incorporating work related external factors, other relevant external factors and personal factors that influence functioning (including work related activities and participation in work) 24

1.7 The Sherbrooke model: the arena in work disability prevention 26

1.8 Confounding definition diagram 34

1.9 Systematic review study flow diagram 39

2.1 ELSA achieved samples for waves 1 to 6 compared to cohort baseline response 73

2.2 States and permitted transitions in the HWLE model 75

2.3 Simple survival multi-state model 76

2.4 Competing risks multi-state model 77

2.5 Illness-death multistate models 78

2.6 Conceptual and practical criteria for a Global Activity Limitation Indicator (GALI) (Robine et al., 2003a, p. 11) (box). 93

2.7 ELSA sample size for analysis 103

2.8 Barchart of health expectancy and total life expectancy results for England population subgroups by education, occupation and region with life table sensitivity analyses 119
2.9 Map of HWLE in years by region in England 120
2.10 Barchart of health expectancy and total life expectancy results for England with sensitivity analyses 128
2.11 Barchart of health expectancy and total life expectancy results for males and females in England with life table sensitivity analysis 132
2.12 Barchart of health expectancy and total life expectancy results for England population subgroups by education, occupation and region with life table sensitivity analyses 133

3.1 3-state multistate model for HWLE projections 144
3.2 HSE data time series forecast of prevalence of being healthy and in work among males at age 50 (observed 1996-2014, projected 2015-2035) with 95% confidence interval 157
3.3 HSE data time series forecast of prevalence of being healthy and in work among females at age 50 (observed 1996-2014, projected 2015-2035) with 95% confidence interval 157
3.4 Main fit estimate of transition rate from healthy and working to unhealthy and/or not working for males in 2035 using HSE data 159
3.5 Lower bound estimate of transition rate from healthy and working to unhealthy and/or not working for males in 2035 using HSE data 159
3.6 Upper bound estimate of transition rate from healthy and working to unhealthy and/or not working for males in 2035 using HSE data 160
3.7 Upper bound estimate of transition rate from healthy and working to unhealthy and/or not working for males in 2035 using HSE data shown on restricted y-axis 160
3.8 HWLE observed (1996-2014) and projected (2015-2035 with 95% CI) for males shown with Sullivan method estimates with 95%CI 168
3.9 HWLE observed (1996-2014) and projected (2015-2035 with 95% CI) for females shown with Sullivan method estimates with 95%CI 168

3.10 Observed life expectancy (1996-2018) and projected life expectancy (2019-2035) for males with ONS published past life expectancy estimates (1996-2018) and projected life expecancy estimates (2019-2035) with low and high variants 175
3.11 Observed life expectancy (1996-2018) and projected life expectancy (2019-2035) for females with ONS published past life expectancy estimates (1996-2018) and projected life expecancy estimates (2019-2035) with low and high variants 176

4.1 Biopsychosocial model of osteoarthritis pain 182
4.2 NorStOP study participant flow chart 187
4.3 Plot of remaining years expected to be spent healthy and in work (HWLE) by sex at ages 50-75 with 95% confidence intervals 202
4.4 Plot of remaining years expected to be spent healthy and in work (HWLE) by occupation at ages 50-75 with 95% confidence intervals 203
4.5 Plot of remaining years expected to be spent healthy and in work (HWLE) by osteoarthritis status at ages 50-75 with 95% confidence intervals 204
4.6 Plot of remaining years expected to be spent healthy and in work (HWLE) by sex and osteoarthritis status at ages 50-75 with 95% confidence intervals 205
4.7 Plot of remaining years expected to be spent healthy and in work (HWLE) by occupation and osteoarthritis status at ages 50-75 with 95% confidence intervals 207
4.8 Plot of remaining years expected to be spent healthy and in work (HWLE) by sex, occupation and osteoarthritis status at ages 50-75 with 95% confidence intervals 208
4.9 HWLE for adults in the NorStOP population overall and for the OA and non-OA subpopulations 215
4.10 Barchart of health expectancy and total life expectancy results for the NorStOP population (overall and stratified by osteoarthritis status) with total life expectancy estimates using the life table method 222

5.1 The convergence of ageing, obesity and lifestyle choices in the development of age-related cartilage dysfunction in OA 232

5.2 Risk factors for OA and OA-related disability 232
5.3 States and permitted transitions (shown with arrow heads) in the 3-state HWLE model 234
5.4 ELSA sample size for analysis in R 'msm' and 'elect' packages 254

List of Tables

1.1 Official UK life expecancy projections for 2020 from 2012, 2014, 2016 and 2018 . . . 9
1.2 Changes in life expectancy at birth in England by region from 2012-14 to 2016-18 . . . 10
1.3 Official estimates of life expectancy at birth in England by region 2016-18 . 10
1.4 The six types of bias assessed by the QUIPS tool (box) . . . 35
1.5 2x2 table of inter-rater title screening agreement . . . 40
1.6 Quality assessment of included studies using the QUIPS tool . . . 46
1.7 Overview of research identified through systematic review . . . 50
1.8 Estimates of work capacity duration from age 50 . . . 52

2.1 ELSA fieldwork dates for waves 1-6 . . . 70
2.2 ELSA sample member birth date range and samping frame HSE year(s) by cohort . . . 70
2.3 Steps in methodology for estimating HWLE . . . 82
2.4 Number of successful interviews per study participant in ELSA waves 1-6 106
2.5 Descriptive statistics of study sample size . . . 108
2.6 Descriptive statistics of responses at wave 1 and responses at all waves combined given by the 15,284 participants in the study sample . . . 109
2.7 ELSA non-response according to health and work status at previous wave 110
2.8 ELSA sample size for IMaCh analyses by HWLE status . . . 110
2.9 ELSA missing health and work data for HWLE status at waves 1-6 . . . 111
2.10 Contingency table of HWLE status transitions observed in ELSA sample . 112
2.11 HWLE status transition information loss in ELSA sample . . . 112

2.12 Population based average health expectancy results with standard errors at ages 50 and 65 from ELSA sample 113
2.13 IMaCh health expectancy results (in years) at age 50 by starting state from ELSA sample 114
2.14 Health expectancies with 95% confidence intervals for males and females in England from ELSA data 114
2.15 Health expectancy results for England 116
2.16 Percentage agreement of health as defined for main analyses and self-assessed health (all observations in waves 1-6) 123
2.17 Percentage agreement of health as defined for main analyses and ADL-based health (all observations in waves 1-6) 123
2.18 Sensitivity analyses of HWLE and other health expectancy results at age 50 using alternative health definitions, using the stable prevalence approach (instead of observed prevalence) to estimating population levels of state occupation, including data for people with missing subpopulation identifiers, and using the life table approach to estimating LE 124
2.19 Sensitivity analyses of health expectancies to interpolation step size using ELSA data 126
2.20 Sensitivity analyses of health expectancy results for England 129
2.21 HWLE and Healthy, Working and Total Life Expectancy results with published ONS statistics 137

3.1 Steps in methodology for estimating HWLE projections. 145
3.2 Number of missing health and/or work responses among respondents aged 50-75 in HSE surveys 1996-2014 162
3.3 HWLE observed (1996-2014) and projected (2015-2035) for men; life expectancy observed (1996-2018) and projected (2019-2035) for men; Sullivan method HWLE estimates (1996-2017) for men; official published life expectancy estimates (1996-2019) and projections (2020-2035) for men . . . 164

3.4 HWLE observed (1996-2014) and projected (2015-2035) for women; life expectancy observed (1996-2018) and projected (2019-2035) for women; Sullivan method HWLE estimates (1996-2017) for women; official published life expectancy estimates (1996-2019) and projections (2020-2035) for women 166
3.5 Sensitivity analyses of male HWLE observed and projected estimates to ratio of mortality rate from being healthy and working compared to mortality rate from being unhealthy and/or not working 171
3.6 Sensitivity analyses of female HWLE observed and projected estimates to ratio of mortality rate from being healthy and working compared to mortality rate from being unhealthy and/or not working 172

4.1 NorStOP number of respondents and response dates at baseline, three year follow-up and six year follow-up by cohort 187
4.2 ELSA sample size for IMaCh analyses with covariates by HWLE status . . 194
4.3 ELSA descriptive statistics for time invariant variables sex and occupation 194
4.4 ELSA descriptive statistics of osteoarthritis status per wave 1-6 195
4.5 NorStOP population with linked medical records compared to the total group of NorStOP participants (with or without linked medical records) by HWLE status 196
4.6 NorStOP sample size (and sample size with OA) for IMaCh analyses by HWLE status 197
4.7 NorStOP missing health and work data for HWLE status at each time point 198
4.8 NorStOP responses to 3 year and 6 year follow-up according to OA status and sex 199
4.9 Number of achieved surveys among NorStOP participants 199
4.10 Contingency table of HWLE status transitions observed in NorStOP study sample 200
4.11 Contingency table of HWLE status transitions observed in NorStOP population with OA 201
4.12 Contingency table of HWLE status transitions observed in NorStOP population without OA 201

4.13 Remaining years expected to be spent healthy and in work (HWLE) at ages 50, 55, 60, 65, 70 and 75 with covariate combinations sex, osteoarthritis and occupation 209
4.14 Health expectancies and life expectancy from age 50 with covariate combinations sex, osteoarthritis and occupation 211
4.15 Health expectancies for adults in the NorStOP population overall and by osteoarthritis status 214
4.16 Sensitivity of health expectancy results for England overall population to status reassignment from -1 (alive but unknown status) to -2 (unknown vital status / ignore transition) due to missing osteoarthritis status 217
4.17 Contingency table of HWLE status transitions observed in whole NorStOP sample (including people without linked medical record data) 219
4.18 Health expectancies from NorStOP sample at age 50 with results of sensitivity analyses 220

5.1 Variable definitions 238
5.2 Covariate combinations to be modelled 243
5.3 Patterns of missingness in modelling variables (ELSA) 246
5.4 Number and percentage of missing observations in ELSA variables for modelling across waves 2-6 248
5.5 Variables in the imputation model for ELSA data waves 2-6 251
5.6 Contingency table of HWLE status transitions observed in one imputed dataset for R multi-state analysis of HRRs according to covariate values at the start of the transition 255
5.7 Hazard rate ratios for each year of age and binary covariates from models estimated with combinations of covariates for transitions 261
5.8 Remaining years expected to be spent healthy and in work (HWLE) at age 50 and life expectancy (LE) at age 50 from models estimated with combinations of covariates 264
5.9 Remaining years expected to be spent healthy and in work (HWLE) at age 50 based on starting state occupied at age 50 with combinations of covariates 267

5.10 Sensitivity analyses of hazard rate ratios to health definition and number of model states (3 or 5-state model) 274
5.11 Sensitivity analyses of starting-state health expectancies to health definition and number of model states 275
5.12 Sensitivity analyses of HWLE and life expectancy to health definition and number of model states 277

6.1 Key findings from this thesis 288

A.1 Systematic review Medline search strategy (using OVID) 341

List of Abbreviations

ADL	**A**ctivities of **D**aily **L**iving
AMED	**A**llied and Complementary **Me**dicine **D**atabase
ARIMA	**A**uto**R**egressive **I**ntegrated **M**oving **A**verage
DALY	**D**isability **A**djusted **L**ife **Y**ears
DFLE	**D**isability-**F**ree **L**ife **E**xpectancy
DoH	**D**epartment **o**f **H**ealth
DWP	**D**epartment for **W**ork and **P**ensions
ECHP	**E**uropean **C**ommunity **H**ousehold **P**anel
ELSA	**E**nglish **L**ongitudinal **S**tudy of **A**geing
EU	**E**uropean **U**nion
GALI	**G**lobal **A**ctivity **L**imitation **I**ndicator
GP	**G**eneral **P**ractitioner (practice)
HE	**H**ealth **E**xpectancy
HG	**H**ealth **G**ap
HLE	**H**ealthy **L**ife **E**xpectancy
HMIC	The **H**ealthcare **M**anagement **I**nformation **C**onsortium
HSE	**H**ealth **S**urvey for **E**ngland
HWLE	**H**ealthy **W**orking **L**ife **E**xpectancy
ICIDH	**I**nternational **C**lassification of **I**mpairments, **D**isabilities, and **H**andicaps
IMaCh	**I**nterpolated **Ma**rkov **Ch**ain
LE	**L**ife **E**xpectancy
MLE	**M**aximum **L**ikelihood **E**stimation (estimate, estimator)
NorStOP	**Nor**th **St**affordshire **O**steoarthritis **P**roject
OA	**O**steo**a**rthritis
OALE	**O**ccupationally **A**ctive **L**ife **E**xpectancy

OHFLE	**O**ccupational **H**andicap-**F**ree **L**ife **E**xpectancy
ONS	**O**ffice for **N**ational **S**tatistics
PHE	**P**ublic **H**ealth **E**ngland
PRISMA	**P**referred **R**eporting **I**tems for **S**ystematic **R**eviews and **M**eta-**A**nalyses
QALY	**Q**uality **A**djusted **L**ife **Y**ears
QUIPS	**QU**ality **I**n **P**rognosis **S**tudies
SPa	**S**tate **P**ension **a**ge
SVD	**S**ingular **V**alue **D**ecomposition
UK	**U**nited **K**ingdom
WHO	**W**orld **H**ealth **O**rganization
WHO-ICF	**W**orld **H**ealth **O**rganization **I**nternational **C**lassification of **F**unctioning, Disability and Health
YLD	**Y**ears **L**ived with **D**isability
YLL	**Y**ears of **L**ife **L**ost

Chapter 1

Introduction

1.1 Life expectancy improvements around the world

Life expectancy is defined as the average number of years (from birth unless stated otherwise) that a person in a population is expected to live based on population mortality rates at each year of age (ONS, 2019j). Equivalently, life expectancy gives the average age of death. Life expectancy is a leading indicator of population health; gains in expectation of life reflect improvements in public health through sanitation, nutrition, medical advances, improved access to medicine, education, income and behaviour change (Oeppen and Vaupel, 2002). 'Period life expectancy' is estimated using average age-specific mortality rates in a calendar year or years with the assumption that the same mortality conditions apply throughout the lifecourse. 'Cohort life expectancy' is estimated using age-specific mortality rates observed (and/or projected) in incremental calendar years corresponding to the age of the cohort. The two types of life expectancy are key population indicators to understand demographic changes and population health trends, as well as to guide policy making for the future with period life expectancy valued for its objectivity while cohort life expectancy (often reflecting expert opinion on future mortality conditions to affect current cohorts) holds particular interest from policy-makers (ONS, 2019j).

Every country in the world has experienced life expectancy gains in the last two centuries (Roser et al., 2020). In 1800, there was no country in which life expectancy exceeded 40 years and the global average (period) life expectancy was 29 years from birth; the global average life expectancy has since risen from 46 years in 1950 (Europe average 62 years) to 72.6 years in 2019 (Europe average 78.6 years) (Roser et al., 2020). Record life expectancy (the highest life expectancy estimate from around the world at any given time) has increased linearly for both men and women since 1840 while individual countries have experienced periods of rapid or slower improvement as they ‘catch up’ or ‘fall behind’ (Oeppen and Vaupel, 2002).

Recent decades have seen debate over the existence of a longevity ceiling - a natural limit to human lifespan that causes life expectancy increases to slow down and eventually cease. In 1928, statistician Louis Dublin proposed a natural limit to human life expectancy of 64.75 years (Dublin 1928, p.361 as cited in Oeppen and Vaupel, 2002, p.1029). This limit had, however, already been overtaken by the women of New Zealand’s non-Maori population - data for whom Dublin did not have access to (Oeppen and Vaupel, 2002). Various estimates of a maximum life expectancy have been published and subsequently exceeded since Dublin’s (Jagger and Robine, 2011; Oeppen and Vaupel, 2002).

Mortality improvements may only affect some age groups to lead to life expectancy gains; declining child and infant mortality rates drove improvements to expectation of life prior to 1950 (Roser et al., 2020; Oeppen and Vaupel, 2002). Since then, life expectancy gains in high income countries have been largely attributed to longevity in later life with increases to life expectancy at age 65 (for example due to medical advances in the treatment and prevention of acute, fatal disease) (Eggleston and Fuchs, 2012; Jagger and Robine, 2011). Major chronic diseases and non-fatal diseases now present the dominant health challenges, weakening the longstanding correlation between life expectancy and health-related quality of life (Jagger and Robine, 2011).

1.2 Hypotheses of the relationship between mortality and morbidity

Three main hypotheses have been proposed with regards to the relationship between mortality and morbidity as life expectancy has and continues to extend (Robine et al., 2003b).

1.2.1 Compression of morbidity hypothesis

The compression of morbidity hypothesis (Robine et al., 2003b; Fries, 1980) sees population health improve as life expectancy increases. Fries (1980) conceptualised morbidity by measurable functional limitation (Beltrán-Sánchez et al., 2014). Fries (1980) hypothesized that life expectancy will approach a natural limit of maximum life potential, leading to the duration of time spent in disability and chronic disease (with associated functional limitation) being reduced ('compression of morbidity'). Human maximum life potential was theorised to be biologically constrained, and it would be primarily through the improvement of lifestyles (eating a balanced diet, taking regular exercise, and avoiding habits associated with negative health outcomes) and medical progress in preventative medicine that chronic diseases are deferred or avoided (Manton, 1982; Fries, 1980). A "pattern of natural death" (Fries, 1980, p. 249) sees death occur primarily and consistently within a narrow interval of old age years - with or without disease.

1.2.2 Expansion of morbidity hypothesis

An alternative view of the association between mortality and morbidity as life expectancy increases is the expansion of morbidity hypothesis, where morbidity may be defined as any deviation from a state of good health (Robine et al., 2003b; Olshansky et al., 1991). Mortality is deferred but the duration of morbidity is drawn out ('expansion of morbidity') by one (or both) of two mechanisms. The first mechanism of expanded morbidity is that life expectancy increases but healthy life expectancy (the number of years a person is expected to live without morbidity) does not. This could be an effect of reducing incidence of premature death and fatalities from chronic conditions but not preventing or deferring the onset of chronic conditions (Robine et al., 2003b). The second mechanism sees the new oldest-old population (80 years of age and older (UN DESA, 2015)) expand morbidity due to being at very high risk of disease and disability (quantity of life has been increased through improved survival, but the oldest-old population is frail as quality of life is not enhanced). The expansion of morbidity hypothesis represents an absolute expansion of morbidity that leads to a reduction in the proportion of life expected to be spent in good health.

1.2.3 Dynamic equilibrium hypothesis

Following the hypotheses of compression of morbidity and expansion of morbidity, Manton (1982) proposed an alternative hypothesis wherein morbidity undergoes an absolute but relative expansion. 'Dynamic equilibrium' sees a maintenance of the proportion of healthy life expectancy relative to total life expectancy (Robine et al., 2003b; Manton, 1982), where durations of diseases might extend due to improved survival but medical progress allows persons in early stages of illnesses to enjoy good health through disease management. In this hypothesis, the term morbidity refers to severe morbidity (Robine et al., 2003b, p. 38).

In the latter decades of the 20th century, it was unknown whether increased life expectancy would be accompanied by an increased demand for healthcare and concerns about expanded morbidity were prevalent (Robine et al., 2003b). With growing numbers of older adults and without evidence of a longevity ceiling (Jagger and Robine, 2011), there is apprehension over the strain of more prevalent disability and dependency. A degree of international reprioritization has occurred from seeking to prolong life to improving older adults' health and quality of life (Jagger et al., 2007).

Although some research suggests that age-specific disability prevalence has improved overall with life expectancy gains (Spijker and MacInnes, 2013), trends differ across countries (Jagger, 2015). Some of the apparent differences in findings may be attributable to the various population indicators (and associated definitions of terms such as 'disability' and 'dependency') that have been employed to quantify population health (Jagger and Robine, 2011). Policy makers and healthcare providers require population health evidence to inform pension policy, project healthcare burdens and address social needs (Oeppen and Vaupel, 2002) - but life expectancy may not (or may no longer) fulfil this evidence requirement (Robine et al., 2003b).

There is no consistent correlation between mortality rates and populations' burdens of poor health (Jagger et al., 2007). In the UK, evidence is suggestive of limited improvement to older adults' health despite gains in Healthy Life Expectancy and Disability Free Life Expectancy from birth and gains in life expectancy at birth, age 65 and age 85 (Jagger, 2015). Similar expansions of morbidity have been observed in several European countries, while compressions of morbidity have been observed in others (Jagger, 2015).

1.3 Population health indicators

Whereas life expectancy is a measure of average lifespan in a given population, summary measures of population health combine mortality and morbidity into a single value to convey population health information used for monitoring or comparing population health and inequalities as well as to inform research, policy and health service priorities and planning (Murray and Lopez, 2000). Various summary measures of population health have been proposed and employed in research, often with different operationalisations of concepts such as dependency, disability, successful ageing, quality of life, activity limitation, and health. Population health summary indicators are measures of health expectancy (average lifespan in a defined health state) or measures of health gaps (quantifying years lost to poor health and premature death compared to a reference population).

1.3.1 Health expectancy

Measures of health expectancy are derived from the formula (Murray and Lopez, 2000):

$$HE = A + f(B) \tag{1.1}$$

Where:

HE = health expectancy

A = the number of years lived in full health

B = the number of years lived in less than full health

And $f(.)$ = a function weighting the years B determined in accordance with the health state represented.

Life expectancy from birth (or 'total life expectancy' (TLE)) is found by summing A and B (that is, $TLE = A + B$) (figure 1.1). Disability-Free Life Expectancy (DFLE, sometimes also referred to as Healthy Life Years (HLY)) uses weighting function $f(B) = 0$ to give the total number of years lived free from disability. Operationalisation of disability for DFLE varies but for HLY it is taken as any limitation in usual activities lasting at least six months (Jagger et al., 2008).

Healthy Life Expectancy (HLE) estimates are produced by the Office for National Statistics (ONS) in the UK measuring the average number of years spent in a perceived state of good (or very good) health (ONS, 2019d). Others have estimated HLE by assigning weights to health conditions according to severity within the range $f(B) = 0$ (perfect health) to $f(B) = 1$ (equivalent to death) (Salomon et al., 2012).

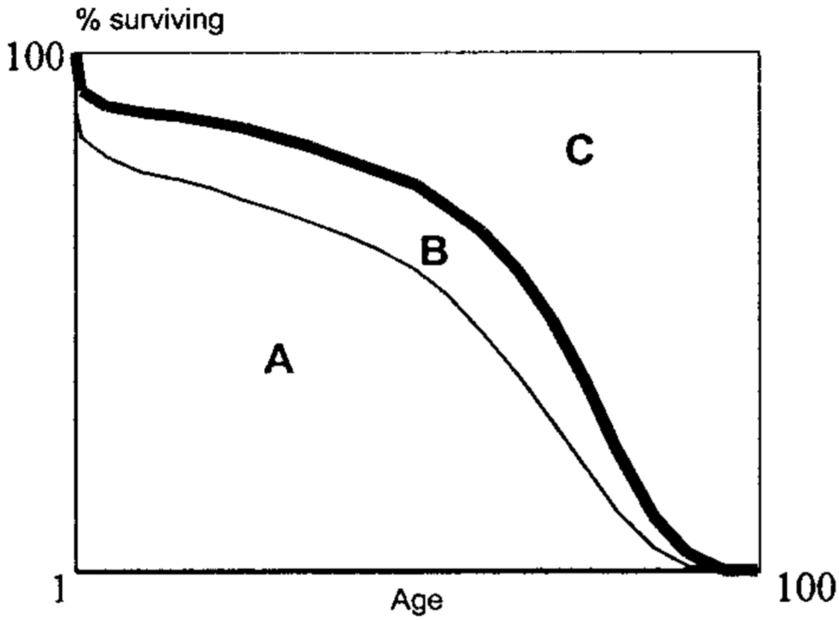


FIGURE 1.1: The survivorship function for a hypothetical population (Murray and Lopez, 2000). Image reproduced with permission of the rights holder, John Wiley and Sons.

1.3.2 Health gap

Health gap measures sum the number of years of life lost (YLL) to premature mortality (compared to a reference population) and the number of years lived in less than full health (years lived with disability (YLD)), where YLDs are weighted according to the nature of the health state.

$$HG = C + g(B) \tag{1.2}$$

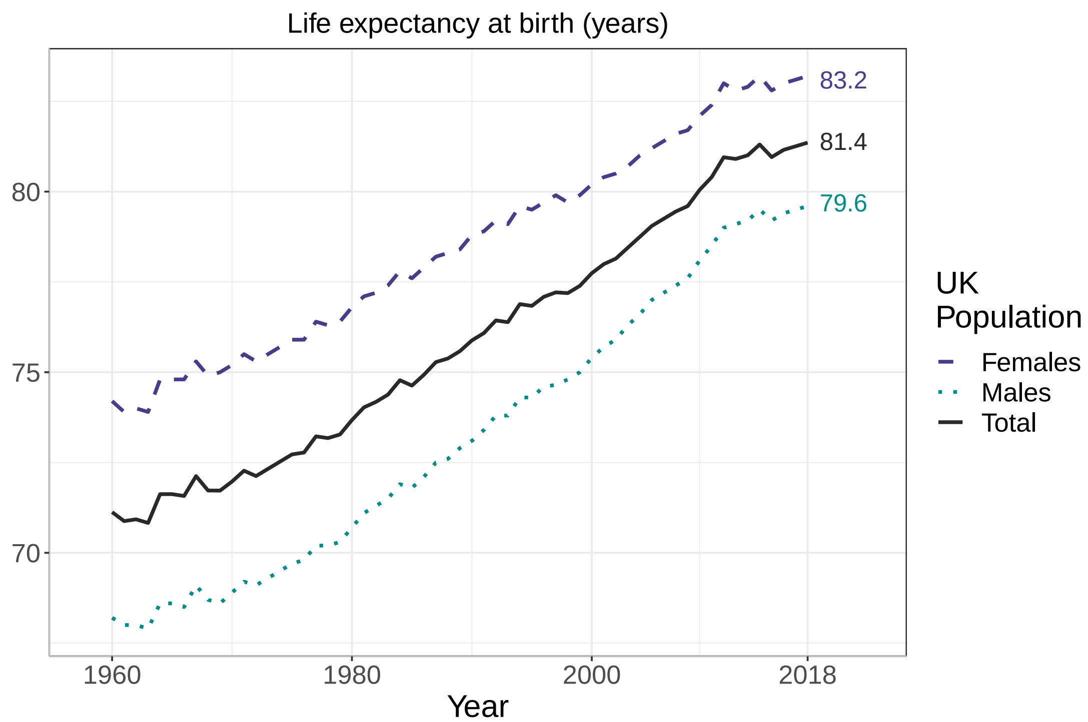
Where:
HG = health gap
C = YLL to premature mortality compared to a reference survival curve
B = the number of years lived in less than full health
And $g(.)$ = a function weighting the years B determined in accordance with the health state represented.

The extent of premature morbidity and mortality is dependent on the ‘goal’ for health and survival, which a reference survival curve should be selected to represent (Murray et al., 2012; Robine et al., 2003b). The goal might be based on the health and survival characteristics of a different real population or it might be more arbitrarily defined - for example, the goal might be that all years of life expectancy are lived healthily (Murray et al., 2012; Robine et al., 2003b). Equalising interventions are those designed to minimise a health gap between two existing populations (Murray and Lopez, 2000). Disability Adjusted Life Years (DALY) is a health gap indicator where YLL and YLD are both compared to the standard life expectancy from birth, with disability weights according to severity of the health condition. DALY calculation can optionally incorporate age-weighting to favour young adulthood and discounting of healthy years lived in the future after disability onset compared to healthy years enjoyed before disability. Without age-weighting or discounting, DALYs are inversely related to Quality Adjusted Life Years (QALY), in which years are weighted according to absence of disability (Sassi, 2006). A new medical treatment may result in QALYs being ‘gained’ while DALYs are reduced/‘saved’ (Sassi, 2006).

1.4 Demographic changes in the United Kingdom

1.4.1 Trends in life expectancy

In the United Kingdom (UK) in 1960, the average number of years that a person could be expected to live from birth was 71.1 (figure 1.2). This figure was higher for women (74.2 years) and lower for men (68.2 years). By 2018, the combined estimate of total life expectancy from birth had increased by over ten years to 81.4, with estimates for women and men being 83.2 years and 79.6 years respectively. The faster rate of improvement in life expectancy for men than women over this time narrowed the gender gap from six years to 3.6.



Source: The World Bank, 2020

FIGURE 1.2: Life expectancy for females (dashed line), males (dotted line) and the total population (solid line) from 1960 to 2018 in the UK (The World Bank, 2020).

Life expectancy improvements in the UK have slowed since 2011 (ONS, 2019d). Slowing life expectancy improvements have also been observed across other high income countries in the last decade including temporary declines in 2014-15, however gains in the UK have been among the weakest and - unlike most other high income countries - trends in life expectancy increases have not recovered in the period following 2014-15 (Leon et al., 2019; Ho and Hendi, 2018). Life expectancy projections by UK's Office for National Statistics (ONS) have been down-revised with each new release since 2012 (ONS, 2019c). In 2012, official life expectancy projections for 2020 were 81.1 years from birth for men and 84.6 years from birth for women; these have since been lowered by 1.3 years for both men and women (table 1.1) (ONS, 2019c).

TABLE 1.1: Official UK life expecancy projections for 2020 from 2012, 2014, 2016 and 2018 (ONS, 2019c).

Period life expectancy projections for 2020		
	Males	Females
2012-based	81.1	84.6
2014-based	80.9	84.2
2016-based	80.3	83.6
2018-based	79.8	83.3

Source: 2012-based, 2014-based, 2016-based and 2018-based principal projections of period expectation of life for the UK (ONS, 2019c)

The plateauing of life expectancy for the UK overall is the average of the changes observed in the constituent countries; small gains or losses have been observed in recent years for men and women in England, Wales, Scotland and women in Northern Ireland. Larger gains have been achieved by men in Northern Ireland (4.3 months from 2013-15 to 2016-18) (ONS, 2019d). From 2013-15 to 2016-18, small gains in life expectancy for both men and women in England outperformed changes in Wales and Scotland (ONS, 2019d). However, inequalities are widening in England - particularly among women - and recent life expectancy increases in England have been driven by gains in areas of London and the South East (tables 1.2 and 1.3) (ONS, 2019f). Life expectancy for women in the East Midlands, West Midlands and South West of England is lower (in 2016-18) than it was in 2012-14 (table 1.2) (ONS, 2019f).

TABLE 1.2: Changes in life expectancy at birth in England by region from 2012-14 to 2016-18 (three year rolling estimates) (ONS, 2019f).

Change in life expectancy from 2012-14 to 2016-18		
Region	Males	Females
England	*0.2*	*0.1*
North East	0.0	0.1
North West	0.2	0.1
Yorkshire And The Humber	0.1	0.1
East Midlands	0.1	-0.1
West Midlands	0.1	-0.1
East	0.0	0.0
London	0.6	0.5
South East	0.2	0.2
South West	0.1	-0.1

Source: Three year average period life expectancy estimates for men and women in England by region (ONS, 2019f)

TABLE 1.3: Official estimates of life expectancy at birth in England by region 2016-18 (three year rolling estimate) (ONS, 2019f).

	Life expectancy in 2016-18	
Region	Males	Females
England	*79.6*	*83.2*
North East	77.9	81.7
North West	78.3	81.9
Yorkshire And The Humber	78.7	82.4
East Midlands	79.4	82.9
West Midlands	78.9	82.7
East	80.3	83.7
London	80.7	84.5
South East	80.7	84.1
South West	80.2	83.8

Source: Three year average period life expectancy estimates for men and women in England by region (ONS, 2019f)

1.4.2 Population ageing

The proportion of the UK population aged 65 and over is increasing (ONS, 2017; ONS, 2019k). The total population size is projected to increase from 56 million in 1976 to 73 million in 2046 (figure 1.3). The number of adults aged 65 and older is expected to increase from the 1976 estimate of 8 million (14.2% of the 1976 total UK population) to 18 million in 2046 (24.3% of the 2046 total UK population).

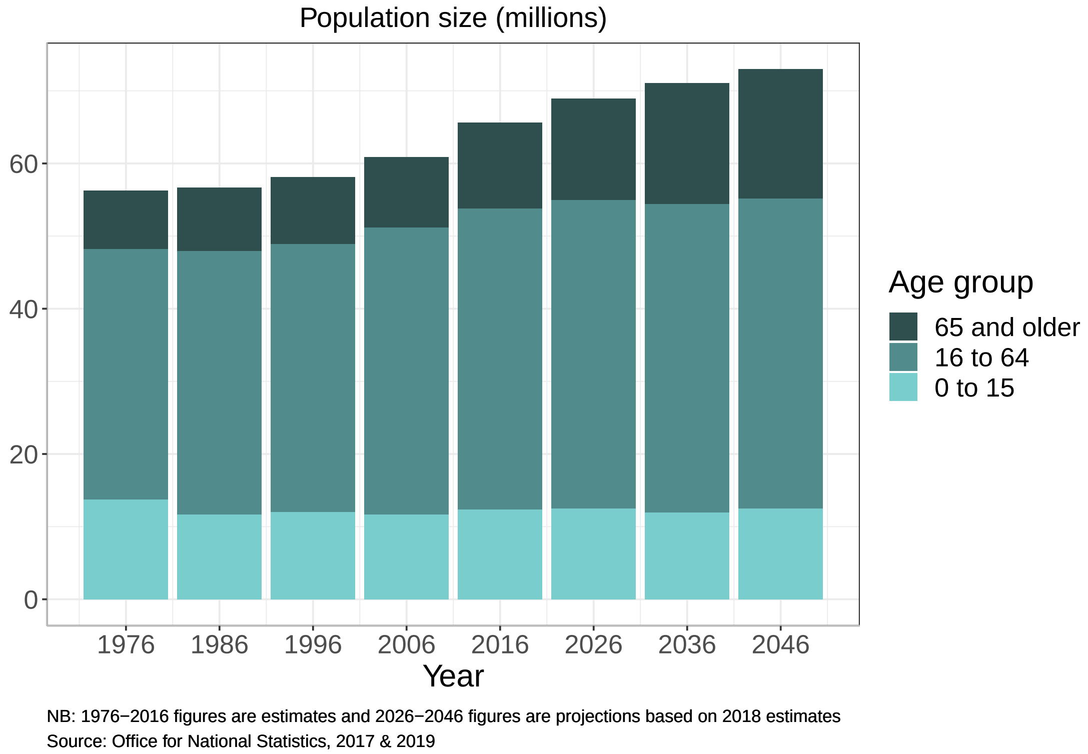


FIGURE 1.3: UK population size estimates (1976-2016) and projections (2026-2046) by age groups : 0 to 15 years (lowest portion of bars); 16 to 64 years (middle); and aged 65 and older (upper) (ONS, 2017; ONS, 2019k).

Trends in the United Kingdom indicate that further increases in the number and proportion of people age at least 65 are to be expected over the next decades, with a decrease in the population proportion constituted by working aged adults. The Old Age Dependency Ratio (OADR) compares the size of the working age population (persons aged 15-64) to the size of the old age population (defined as adults aged 65 years and older) to quantify the number of 'dependent' adults that each working age adult 'financially supports' through taxation and National Insurance contributions (or equivalent) (Muszyńska and Rau, 2012, p. 158). The OADR carries implications additional to supporting older people through healthcare and pension provision; changes in old-age dependency (as defined for the OADR) can indicate that the structure and needs of a society are changing (Walker, 2000). For example, with increased longevity, there is likely to be an observed increase in the number of multigenerational families - even where the age of adults at first childbirth increases. Working adults in the UK today often have caring responsibilities for older dependents whilst nearing their own retirement age, perhaps caring for their own children or grandchildren at the same time (Cridland, 2017; Loretto and Vickerstaff, 2015). Where people in a population increasingly take on (sometimes multiple) caring responsibilities, changes can be expected in their own requirements for provision such as flexible working arrangements, childcare, financial support from the government and care support for older dependents. Many countries are seeking to defer retirement and thereby shift the age threshold for old-age dependency; this is likely to affect levels of unpaid socially productive activity (such as volunteering, caring for older dependents and providing childcare for younger family members) and is likely to be affected by the health and work capacity of adults in this age group. There is a need (and opportunity) for policy and individual behaviour adjustments to shape the future landscape of ageing populations' actual health and economic dependency needs (Bussolo et al., 2015).

1.5 Extending working lives

1.5.1 Increasing numbers of older workers

One third of people in the UK workforce are now aged 50 or over (ONS, 2020a). In addition to population ageing contributing to an increasing proportion of older workers, employment rates among those aged 50 and over has increased over time. In 1992, fewer than half of women in the UK aged 50-64 were in employment compared to around two thirds of men (ONS, 2020c). The employment rate in men aged 65 and over was two and half times higher for men than women (male employment rate 8.5% and female employment rate 3.5%). Employment rates in ages 50-64 increased to 68.4% for women and 76.8% for men in 2019, narrowing the gender gap from 19.1% in 1992 to 8.4% (ONS, 2020c). Over the same time period, employment rates for women aged 65 and over have more than doubled to 8.4% and the employment rate for men aged 65 and over increased to 13.9%.

1.5.2 The UK State Pension age

In the United Kingdom, the State Pension is a taxable payment made regularly to individuals who have reached the statutory age. Eligibility is based on a history of National Insurance contributions, and the State Pension age (SPa) is determined primarily based on life expectancy (Cridland, 2016). With increasing life expectancy, retired people are receiving the State Pension for increasingly longer durations (DWP, 2010). Further, the changing ratio of working-age adults to pension-age adults has increased the burden of pension related spending on the working proportion of the population (DWP, 2010).

Prior to 2010, SPa was 65 for men and 60 for women. Increases to SPa for women legislated in 1995 and implemented from 2010 are likely to have contributed to increasing employment rates among women aged 50 and over in recent years and the faster pace of this increase in the last decade. Legislation to increase SPa for women was later expedited to achieve equalisation of male and female SPa in 2019. SPa for men and women reached 66 in September 2020 and will increase to 67 by the end of 2028. Legislated increases to 68 are expected to be brought forward to 2037-2039 (DWP, 2017b).

In 2017, an independent review of the UK's State Pension age was carried out by John Cridland CBE (2016; 2017), which highlighted three key areas to be considered in legislating State Pension age increases: affordability; fairness; and fuller working lives.

Affordability

The UK State Pension operates on a 'pay as you go' system, where current workers' National Insurance contributions are funding (amongst other things) todays' State Pension payments. OADR changes therefore have important consequences on national budgets. The national spending on State Pensions in the UK is projected to increase by 1% of GDP between 2016/17 (5.2% of GDP) and 2036/37 (6.2% of GDP), corresponding to a 20% increase in State Pension expenditure (Cridland, 2017; OBR, 2017). Enough individuals in the population must be in paid work and making National Insurance contributions for systems such as the State Pension to be sustainable. National Insurance contributions also contribute towards the funding of the NHS; a further consideration of affordability recognises that health care (especially social care) expenditure is heavily influenced by the number of people aged 85 years and older (Cridland, 2017).

Fairness

The issue of intergenerational fairness arises not only in the amount of State Pension income a person receives, but also the length of time (number of years) they receive it for as well how accessible the qualifying criteria are for receiving the full (maximum) State Pension payments. In addition, the financial burdens placed on each generation (in terms of taxation and National Insurance contributions due) should be considered for fairness across generations and with respect to the maximum payment each generation received or will receive.

Issues of intragenerational fairness relate to the different State Pension experiences that individuals in the same generation might have. Within each generation, inequalities in social and political factors could mean that pension policies that are fair 'on average' disadvantage those that need the State Pension the most. For example, the State Pension age is determined largely in accordance with life expectancy, but there are large discrepancies in life expectancy across residential areas (Cridland, 2016). Some people may be able to work until they are older and receive the State Pension for the intended number of years or longer, while others may receive the State Pension for only a few years and struggle financially with reduced work capacity in the years leading up to SPa.

Fuller Working Lives

The Fuller Working Lives strategy seeks to facilitate healthy and rewarding working lives into older age. It involves preparation for an inflated population of older workers and tackling barriers that prevent people (especially those in their later working lives) from entering or re-entering the workforce. As life expectancy increases and the State Pension age rises, the Fuller Working Lives strategy recommends that people in the population should benefit from an extended healthy and working life.

Cridland (2017) also recommended that the pace of SPa increases be limited such that SPa increases by no more than one year in every ten-year period and that all changes are legislated at least ten years in advance to allow individuals time to plan.

Government response

The UK government has committed to legislating SPa changes ten years in advance, maintaining a 'managed pace' of change, and considering intergenerational fairness on average by limiting the average duration of State Pension receipt to no more than 32% of adult life on average (DWP, 2017b).

Public Health England (PHE, 2017a) report that both healthy life expectancy from birth and total life expectancy from birth have increased over the last decade in England, but with gained healthy years being lived earlier in life. While life expectancy at age 65 increased from 2000-02 to 2012-14, healthy life expectancy at age 65 stayed the same; gains in life expectancy from age 65 were unhealthy years leading to an increasing proportion of years in later life spent in poor health (PHE, 2017a). Life expectancy and healthy life expectancy at age 65 has remained largely unchanged for men and women in England since 2012-14 (PHE, 2019a; PHE, 2017a).

If increasing life expectancy results in a larger share of older adults' lives being spent in poor health, this challenges the assumption that adults are axiomatically able to lengthen their working lives in line with increases to total life expectancy. Studies of different populations find differences in how population morbidity and disability are changing with life expectancy gains (Jagger, 2015; Muszyńska and Rau, 2012). It is unclear whether increasing retirement age in line with life expectancy could be achievable as an isolated policy change. Evidence is needed in order to assess whether old-age dependency can be functionally redefined, and whether interventions can improve dependency rates through increased workforce participation.

1.6 Health and paid work

There are key links between work and health that drive important effects of one on the other (Burgard and Lin, 2013). A systematic review concluded that work has a positive effect on health through well-being, social inclusion, and sense of role and identity (Black, 2008; Waddell and Kim Burton, 2006). A fundamental link between work and health is through earning income to enable payment for food, housing, medication and basic health necessities (Burgard and Lin, 2013). Unemployment and loss of work is a driver of poor physical and mental health (Waddell and Kim Burton, 2006); financial strain is an important mediator of this link, associated with stress, depression, and role and emotional functioning, which in turn are associated with physical health problems, further reduced role and emotional functioning, and reduced access to re-employment (Burgard and Lin, 2013; Price et al., 2002). The effect of worklessness through financial strain can extend beyond the individual through negatively affecting social support networks and relationships with partners, as well as affecting the health of children throughout the lifecourse where parents may not have the resources to provide items and activities that promote improved health (Burgard and Lin, 2013). Children from workless families are themselves more likely to experience poorer health as well as worklessness in adulthood (Black, 2008). As well as financial strain, a decrease in sense of personal control resulting from job loss or worklessness is associated with reduced role and emotional funtioning and physical and mental health problems (Price et al., 2002).

Despite a generally positive association between health and work, and although health and safety at work has improved in the UK (Black, 2008), work can still cause risks to health. Exposures and physical hazards including dust, noise, temperature, vibration, dangerous chemicals and biohazards can impact health in a directly observable way in the short or long term (for example accidents involving machinery or flammability or toxicity, or asbestos-related diseases from exposure in the workplace) (Sen, 2015; Burgard and Lin, 2013; Makin and Winder, 2009). The nature of work role can also affect health; heavy manual work and poor sitting posture in sedentary work are risk factors for musculoskeletal disorders, and repetitive work can lead to repetitive strain injuries (Costa and Vieira, 2010). Through circadian and social disruption, non-standard working hours (such as shift work or using email or social media outside of working hours) have been linked with sleep problems, depression, and chronic physical health problems including cancer and coronary heart disease as well as less favourable health-related behaviour in dietary intake, smoking, alcohol use, screen time, physical activity and maintaining healthy bodyweight (Wong et al., 2019; Winkler et al., 2018; Lee et al., 2017; Burgard and Lin, 2013; Vyas et al., 2012).

Creativity at work (problem solving, learning new skills, tackling challenges in different ways and having the opportunity to be original and imaginative in accomplishing tasks) as well as well-matched support and control at work can positively impact health and well-being (Mirowsky and Ross, 2007); however, these job opportunities may be unattainable to those without high education levels thereby fuelling socioeconomic inequalities in healthy work (Burgard and Lin, 2013). While job strain (for example resulting from inadequate support at work while working under time pressure or with limited resources or with high levels of risk and responsibility) is more prevalent among those working in lower status occupations, job strain is increasingly reported among workers in higher status roles (Bonsaksen et al., 2019; Burgard and Lin, 2013). Job strain can drive musculoskeletal symptoms and is associated with increased risk of diabetes as well as cardiovascular disease through health-relevant higher risk behaviour change including physical inactivity (Nyberg et al., 2013; Fransson et al., 2012; Bongers et al., 2006). Job strain has also been linked with depression through susceptibility to burnout (Ahola and Hakanen, 2007). Experience of job strain has been found to be exacerbated among employed people with common musculoskeletal disorders who may need to manage pain, fatigue and functional limitation at work (Gignac et al., 2007). There is a higher burden of job strain among females and non-white workers ; gender and racial differences in experience of job strain could reflect differences in occupational conditions for people with the same skill level, self-identifying differently with work and home lives, and extent of prioritization needed to meet non-work responsibilities (Hurtado et al., 2012; Padkapayeva et al., 2018), which highlights the role of social mechanisms in linking health and work (Brooker and Eakin, 2001).

Another important psychological stresser that can arise from work is role conflict and negative spillover from work to other domains including family, social life, caring responsibilities and management of existing health conditions (Wilkie et al., 2020; Burgard and Lin, 2013; Gignac et al., 2012). Work to family conflict exists where work circumstances lead to being stressed and irritable at home, distracted by work problems, or being too tired or busy to fully engage in home activities and tasks (Grzywacz and Bass, 2003). Work to family conflict increases the odds of problem drinking, depression and anxiety (Grzywacz and Bass, 2003). Disabling rheumatic and musculoskeletal diseases are common in working age adults over 50 but work demands and schedules can interfere with time needed to care for muscles and joints leading to compromised health management and role loss where other activities and relationships are then avoided to prioritize facilitating work participation (Wilkie et al., 2020). Role conflict in workers with rheumatic and musculoskeletal diseases is associated with lower mental health, reduced job satisfaction, and increased absenteeism and presenteeism (Wilkie et al., 2020; Dür et al., 2016) which could contribute to the higher rates of premature work loss observed in this group or job-lock where individuals are unhealthy and experience increasing limitation at work but are unable to retire for financial reasons (Wilkie et al., 2014b; Wilkie et al., 2011). There is scope for biopsychosocial interventions to shape and improve work-family fit and work-life balance (Wilkie et al., 2020; Grzywacz and Bass, 2003). For example, support at home can mitigate against health consequences of negative spillover from work to family (Grzywacz and Bass, 2003). Policy and communication with employers can influence role conflict through flexibility to prioritize important aspects of each role as well as providing support and information networks (Wilkie et al., 2020; Grzywacz and Bass, 2003).

Job uncertainty is a work stressor with negative implications for physical and mental health, well-being, job satisfaction and work-related behaviour (Burgard et al., 2012; Sverke et al., 2002). A perceived threat to employment position often also represents a threat to income and ability to provide for basic needs as well as to one's schedule and social contacts (Sverke et al., 2002). Job uncertainty can cause prolonged stress and feelings of powerlessness, and is associated with depression, anxiety including anxiety attacks, poor self-assessed health and physical health problems (Burgard et al., 2012; Sverke et al., 2002). Job uncertainty can persist even where there is no objectively measureable source of uncertainty, for example due to concerns that health problems will make job loss more likely or where opportunities for re-employment are perceived to be limited such as due to economic recession (Burgard et al., 2012; Zheltoukhova et al., 2012). More generally, the 'safety net' offered through policy, employment law, social welfare systems, economic circumstances, trade unions, financial security and social support networks has an important influence on the way that individuals experience work stressors (Burgard and Lin, 2013; Burgard et al., 2012). For example, unemployment benefits and social pensions modify the threat of job loss on material resources thereby lessening the health consequences of job uncertainty as a stressor. Individuals who work at home without health and safety oversight could also be disadvantaged in their occupational health, while the influence of trade unions to appeal for good working conditions (including salary, health and safety, working hours and contract type) has weakened for workers whose jobs could be cost-effectively outsourced (for example manufacturing jobs moved to a different country) (Burgard and Lin, 2013).

1.6.1 Biopsychosocial models of health and work

Poor health (and self-assessed poor health (e.g. Mein et al., 2000)) is a leading cause of early departure from the workforce especially influential in those aged 50 years and over with the age range 55-64 years being key window of early departure (Muszyńska and Rau, 2012; Haan and Myck, 2009). The links between health and work highlight the need to maintain a healthy workforce if policy changes to extend working lives are to be realised. However, translation from measures of health expectancy and health gaps into informative evidence from a working perspective is not straightforward. In the Netherlands, for example, Solinge and Henkens (2010) found that people were frequently not achieving their personal expectations and goals regarding the length of their working lives. These goals were found to relate to individuals' self-assessment of their health through their own subjective life expectancy, which could suggest that being in perceived good health is not simply a universally necessary and sufficient condition for remaining in the workforce. Biopsychosocial models of health and work provide useful frameworks for understanding how a variety of factors (independently and/or through interaction) influence the likelihood of work participation and disability, and can inform joined up policy-making relating to various exposures, risk factors, or potential interventions (Wilkie et al., 2020). As well as increasing the feasibility of extended working lives policies, promoting healthy working lives will benefit businesses with ageing workforces (for example through reduced absenteeism and presenteeism) and people with long-term health problems who may struggle to work until the rising State Pension age, and will promote the accessibility of good work that benefits health and wellbeing (Wilkie et al., 2020; Wilkie et al., 2011; Waddell and Kim Burton, 2006).

There are a number of models of healthy work, each proposing links between theory and the complexity of the real world (Costa-Black et al., 2013). Karasek's (1979) job-demand-control model of job strain through measurement and comparison of job control and psychological demands is a well-known example, which - through its simplicity - is among the most frequently adopted models in research as a theoretical foundation and for empirical analyses (Fila et al., 2017; Luchman and González-Morales, 2013; Griffin and Clarke, 2011; Kain and Jex, 2010). For those who are in paid work, the model characterises expected levels of psychological strain and illness risk based on low or high levels of psychological demands and low or high levels of control at the workplace ("freedom of action" in carrying out work tasks as well as "freedom to engage in informal rituals" such as taking breaks or adopting preferred work habits) (Karasek and Theorell, 1990, p. 34). Categorising jobs into one of four corresponding types allows the implications of low or high job strain and low or high job control to be better understood while the model's simplicity makes widely accessible its practical use both analytically and to support interventions (focused on work factors to improve job outcomes) (Fila et al., 2017).

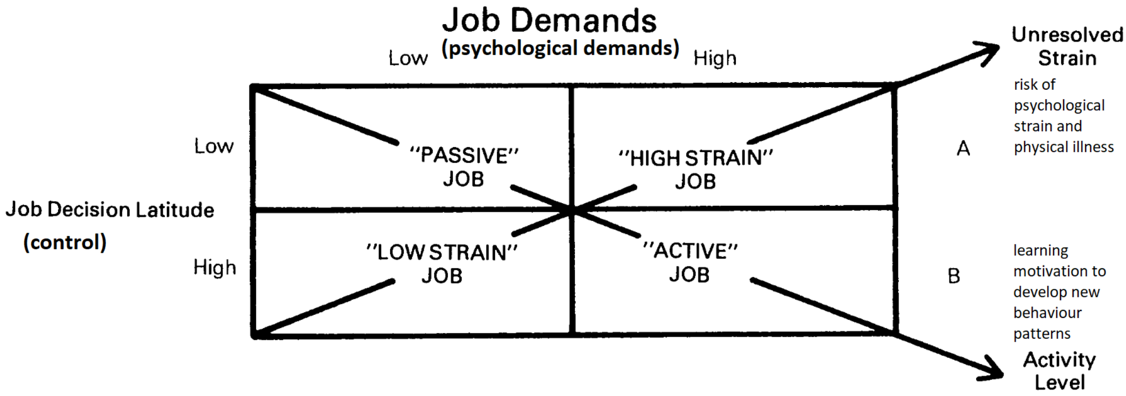


FIGURE 1.4: The Karasek job-demand-control model (Karasek and Theorell, 1990; Karasek, 1979)

High-strain jobs (top right box in figure 1.4) are demanding roles where the stress response to psychological stressors cannot be translated into action to solve or avoid the work-related problem. An individual who is repeatedly constrained from responding optimally to stressors often experiences a "hopeless, long-lasting, and negatively experienced response [to] residual psychological strain" (Karasek and Theorell, 1990, p. 33). Persons working in high-strain job are most likely to experience the most severe effects of psychological strain on their physical and mental health including fatigue, anxiety, depression and heart disease (Karasek and Theorell, 1990).

In active jobs (bottom right in figure 1.4), work involves challenging situations demanding high levels of performance but excess psychological strain is avoided as work stressors can be responded to through effective problem solving, channeling stress energy into action (Karasek and Theorell, 1990). Individuals can learn how to respond to psychological stressors most effectively and adapt to be highly productive in their work. While challenging, high demand and high control jobs are associated with high levels of job satisfaction and people working in such roles are typically the most active and motivated in leisure and other non-work activities.

Low-strain jobs (bottom left in figure 1.4) have fewer psychological stressors than most jobs while high decision lattitude can make work enjoyable and relaxing. People working in low-strain jobs are likely to experience lower levels of residual psychological strain and risk of illness, and may be happier and healthier because of their work (Karasek and Theorell, 1990). However, in their free time, people working in low-strain jobs are less likely to be motivated to participate in work-like activities to promote positive social change in the interest of themselves or others (Karasek and Theorell, 1990).

Passive jobs (top left in figure 1.4) are those with low demands but also low control. Such work is associated with lost skills, lack of job challenges, and loss of motivation and productivity. Risks of psychological strain and illness are present but not as high as in high-strain jobs as low demands mean that stressors are not always confronted. Passive jobs are associated with the least engagement in leisure and other non-work activities.

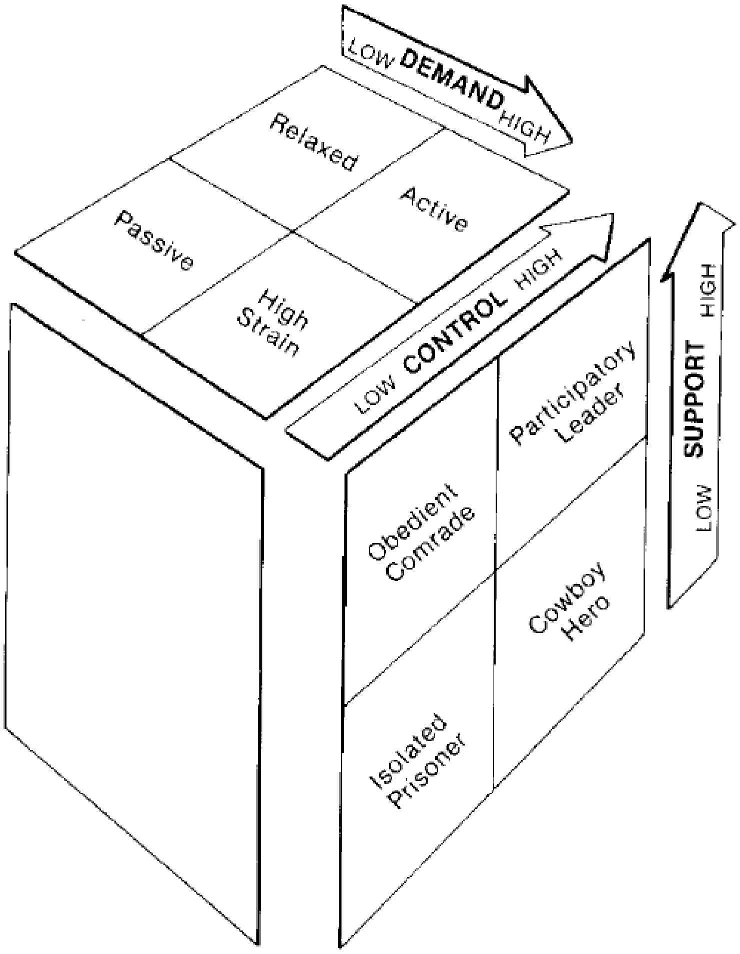


FIGURE 1.5: The Karasek job-demand-control-support model of the psychosocial work environment (Karasek and Theorell, 1990, p. 70). Image reproduced with permission of the rights holder, Hachette Books Group.

Through the inclusion of a workplace support dimension, the demand-control job strain model is expanded into a model of the psychosocial work environment (Karasek and Theorell, 1990). There are two types of social support in the workplace: socioemotional support (social and emotional integration of the work group, co-workers and supervisors and levels of trust) moderates and mitigates against psychological strain of job demands; and instrumental support (practical support with work tasks including extra assistance or resources) alters how demanding work tasks are (Karasek and Theorell, 1990). Workplace support levels can be negative in hostile work environments or where task interdependency, for example, becomes a psychological stressor in itself. In practice, support in the workplace is closely related to levels of control and demand (Häusser et al., 2010; Karasek and Theorell, 1990).

Another leading work model proposed since Karasek's (1990; 1979) job-demand-control and job-demand-control-support model is that of effort-reward imbalance (Schaufeli and Taris, 2014; Siegrist et al., 1997), which characterises job stress as a product of high effort spent and low reward received (Siegrist et al., 2004). Both Karasek's job-demand-control(-support) model (1990; 1979) and the effort-reward imbalance model (Siegrist et al., 1997) have been demonstrated to highlight jobs associated with increased musculoskeletal symptoms (Herr et al., 2015; Siegrist et al., 2004), which may sometimes be a longer-term response to chronic work-related stress preceded by health problems such as fatigue, stomach ache, headache, trouble concentrating, and depression (Lourenço et al., 2015). Among those already living and working with chronic health conditions such as musculoskeletal disorders, however, models of the psychosocial work environment may not be broad enough to capture the main sources of job strain and threats to continuing in employment (Gignac et al., 2007). Instead, experience of job strain among workers with musculoskeletal conditions and other long-term health problems is more likely to relate to experience of pain and workplace activity limitations (Gignac et al., 2007), both of which are highly influenced by workplace structures and broader biospsychosocial factors including biological factors, personal circumstances, economic factors (such as labour market security, interest rates, and labour costs), social factors (such as education, income, and access to health care), and political factors (such as legislation on taxes, wages, pensions, and trade restrictions as well as political stability) (Wilkie et al., 2020; Rugulies, 2019).

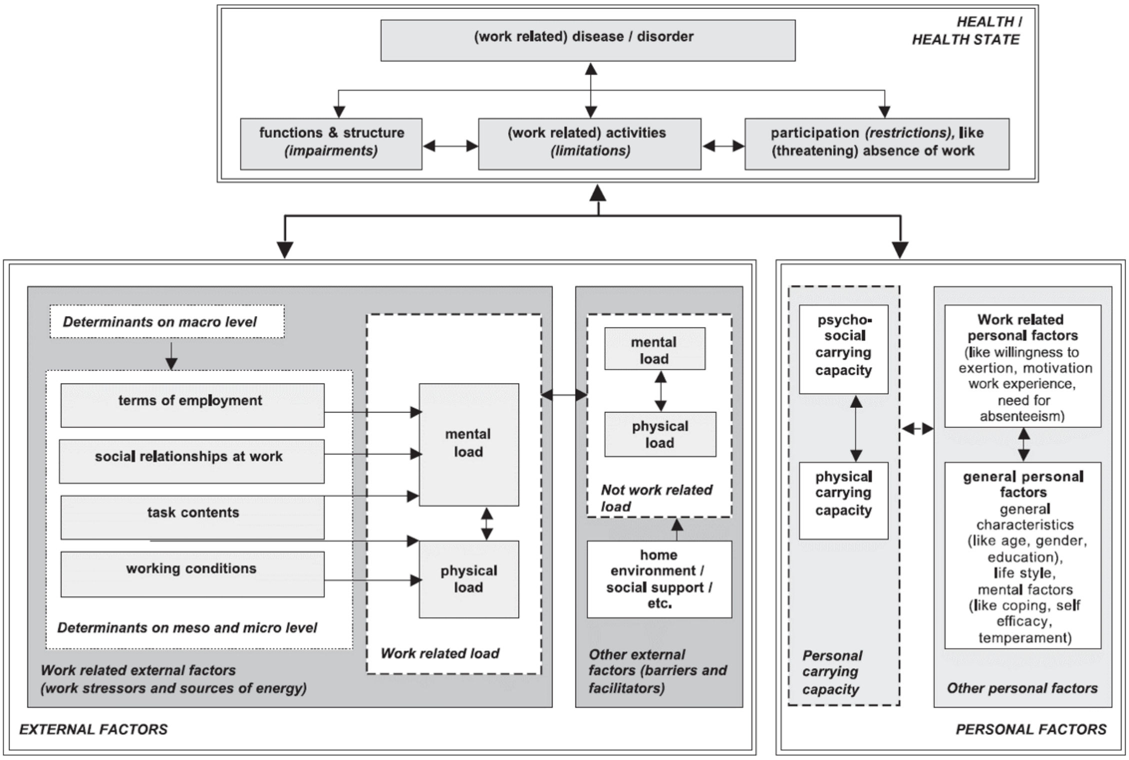


FIGURE 1.6: The expanded ICF-scheme incorporating work related external factors, other relevant external factors and personal factors that influence functioning (including work related activities and participation in work) (Heerkens et al., 2004). Image reproduced with permission of the rights holder, Taylor & Francis.

The extended version of the World Health Organization International Classification of Functioning, Disability and Health (WHO-ICF) model (figure 1.6) is another example of a biopsychosocial model of work (Heerkens et al., 2004). This model highlights the macro-level (upstream) factors that impact work and the mechanisms through which biopsychosocial factors affect limitation in work-related activities (Heerkens et al., 2004), pointing to the roles of both biomedical and psychosocial factors in disability and recovery (Wade and Halligan, 2017). The extended WHO-ICF model is based on the World Health Organization's (WHO) International Classification of Functioning, Disability and Health (ICF) and former International Classification of Impairments, Disabilities and Handicaps (ICIDH) frameworks, which have been widely used (possibly more than any other biopsychosocial model) in research, policy, and practice internationally for a variety of physical and mental health conditions (Wade and Halligan, 2017; Heerkens et al., 2004). Macro-level factors such as political and economic structures impact meso-level workplace structures and micro-level factors such as terms of employment, staffing adequacy, job demands, content of work, and social relationships at work. Experienced psychosocial working conditions can also affect individuals' way of thinking, emotional processes and health-related behaviours, which in turn can affect management of existing health conditions and susceptibility to physical and mental health problems. The Sherbrooke model (another well-known biopsychosocial healthy work model; figure 1.7) (Loisel et al., 2005) expands further on the impact of working conditions. The Sherbrooke model was proposed after workplace interventions were found to be more effective than clinical interventions at achieving earlier return-to-work among workers who had been absent for over four weeks with low back pain (Loisel et al., 1997). A combination of both types of intervention was found to be the most effective. The Sherbrooke model emphasizes the role and importance of engaging multiple stakeholders (including employers, healthcare providers, policy makers, and family members) in addition to the individual themselves to share a common goal of modifying the workplace and societal context in order to reduce and prevent work disability (Loisel et al., 2005). The models highlight the complexity of work-related behaviour and activity limitation, and indicate that improvements to work participation involves a number of factors (and their interactions) and stakeholders (Wilkie et al., 2020).

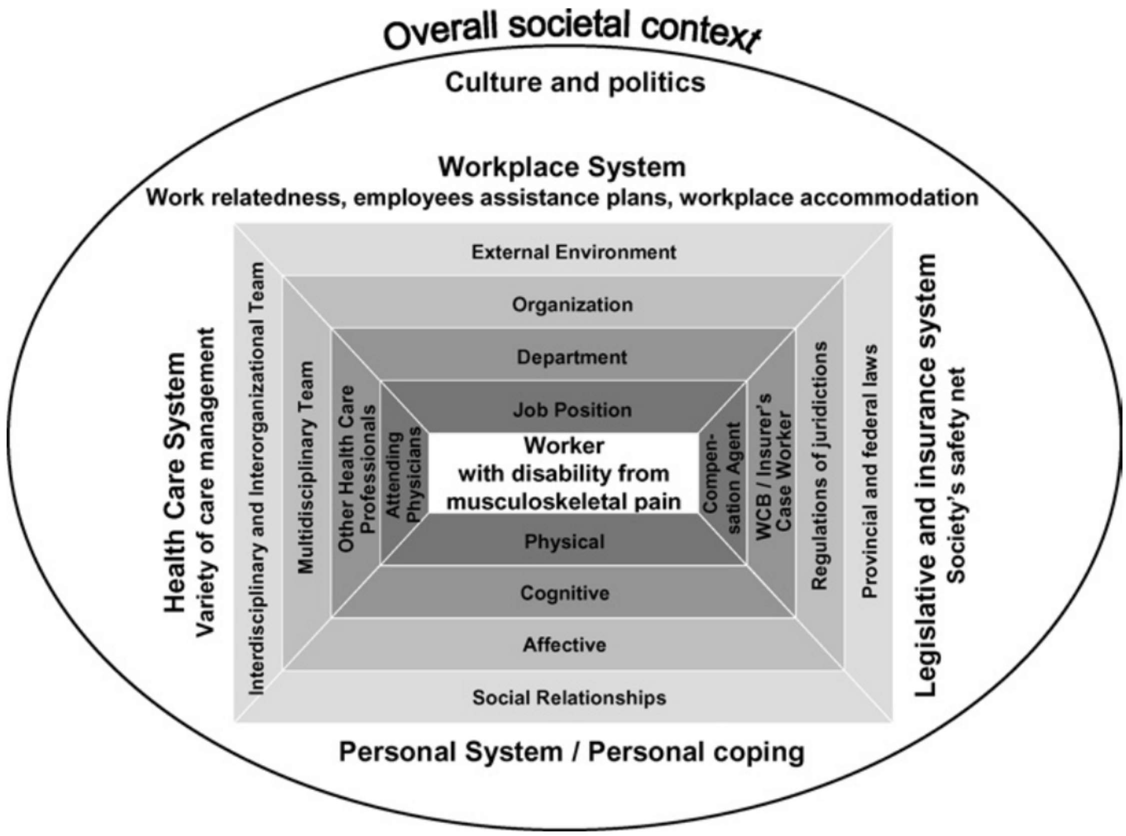


FIGURE 1.7: The Sherbrooke model: the arena in work disability prevention (Loisel et al., 2005). Image reproduced with permission of the rights holder, Springer Nature.

1.7 Systematic review of estimated length of healthy working life

The models introduced in the previous section point to measurement of both population health and work to investigate the possibility extensions to working life. A population indicator of life expectancy in health and work from age 50 has the potential to assess the feasibility of policy changes and guide interventions to improve work participation. The numerical estimates of such a metric would help clarify whether populations are in a position to extend working lives.

A systematic review was conducted to identify estimates of the number of years that adults aged 50 years and over are healthy and participating in paid employment (work). The objectives of this review were to identify and evaluate evidence of estimates of time spent in health and work, how health and work participation has been operationalised, and factors associated with and drivers of reduced health and work participation.

1.7.1 Methods

Evidence was identified using a four-stage protocol for searching and filtering results from literature databases: search strategy and identification of studies (stage 1); study selection (stage 2); data extraction and quality assessment (stage 3); and analysis (stage 4). The systematic review protocol was registered with Prospero (CRD42019122189) and was reported using PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines (Moher et al., 2009).

Search strategy and identification of studies (stage 1)

The following databases were searched on the 5th of March 2018:

- Embase [searched using OVID] (1974 to 2nd March 2018)
- Allied and Complementary Medicine Database (AMED) [OVID] (1985 to February 2018)
- Medline [OVID] (1946 to present)
- Health Management Information Consortium (HMIC) (1979 to present)
- Social Sciences Citation Index and Science Citation Index Expanded (Web of Science) (1970 to present)
- AgeLine [EBSCO] (1978 to present, with some coverage from 1966-1977)
- CINAHL [EBSCO] (1937 to present)
- PsycINFO [EBSCO] (1800s to present)
- Grey literature database Open Grey

These databases were intended to form a comprehensive list containing all relevant literature to fulfil the aims of this review. AgeLine was searched to retrieve recognised ageing research while other databases contributed research published through medical, biomedical, pharmaceutical, social science, psychology, nursing, allied health, complementary medicine and health and social care routes. Science Citation Index Expanded contains significant research from multiple fields and Open Grey was searched to retrieve any material published outside of regular academic channels. To ensure the comprehensiveness of the systematic review, expert advice was obtained from the Systematic Review Team at Keele University's School of Medicine in selecting databases and developing the search strategy.

Key databases were searched for publications matching at least one work-related search term and at least one health expectancy search term. Search terms were selected to be sensitive to any potentially relevant research. A single reviewer (MP - the author of this thesis) conducted the searches in March 2018, adapting the search terms as needed to accommodate differences in database management. The work related search terms used to search Medline (using OVID) were:

- occupation.mp. or Occupations/
- employed.mp.
- employment/ or employment, supported/ or return to work/ or unemployment/ or workplace/
- employment.mp.
- unemployed.mp.
- unemployment.mp.
- retirement/ or exp work/
- retire*.mp.
- pension.mp. or Pensions/

- absenteeism/ or presenteeism/
- absenteeism.mp.
- presenteeism.mp.
- Workers' Compensation/
- incapacity benefit.mp.
- "employment and support allowance".mp.
- workers compensation.mp.
- (long term adj3 sick).mp.
- (longterm adj3 sick).mp.
- Sick Leave/
- sick leave.mp.

The health expectancy search terms used to search Medline were:

- active life expectanc*.mp.
- disability free life expectanc*.mp.
- disease free life expectanc*.mp.
- health* life year*.mp.
- health adjusted life expectanc*.mp.
- health adjusted life year*.mp.
- disability adjusted life expectanc*.mp.
- disability adjusted life year*.mp.
- dependent life expectanc*.mp.

- dependent life year*.mp.
- (life expectancy adj3 disabilit*).mp.
- health* expectanc*.mp.
- work* life expectanc*.mp.
- population indicator*.mp.
- health* life expectanc*.mp.

The majority of search strategy differences across databases were minimal and typically related to the manner in which each database allowed search terms to be combined. However, the strategy used to search Web of Science consisted of fewer terms and avoided complex search rules. The complete OVID search strategy to identify Medline records is included with numbers of results detected in Appendix A. All records identified through the academic database searches were extracted and saved into reference management software. However, because records required individual extraction from search results and since a pre-specified exclusion criterion for non-English language papers existed, only the 59 English language records were extracted from the 93 Open Grey search results.

Inclusion required population-level estimates of combined health and work statuses, where the population age range included 50-60 year olds. Because pension policies are applied to national populations, for study populations to be eligible for the systematic review they were required to be representative of a general population and not defined by health or work status at age 50. Exclusion criteria were that the full text was unavailable, the publishing language was not English, the study was not published as a research article or report, no numerical estimate was given for time spent in health and work, and the research did not investigate duration of combined work participation and health statuses. Studies without abstracts were not excluded in abstract screening.

Study selection (stage 2)

Screening was carried out initially on titles, then abstracts and finally full texts, retaining studies at each stage that did not clearly meet exclusion criteria. Full texts were assessed for eligibility against the same inclusion and exclusion criteria described above. References of the retained results were then manually screened for any studies missed in the database searches. Finally, studies that were not the primary sources of the relevant evidence were excluded. Remaining studies were deemed eligible and included in the review. Records that were in formats other than journal articles (such as conference presentation abstracts or books) were excluded as they were considered unlikely to contain peer-reviewed and/or novel results, or to have available content. Exclusion on the grounds of format was carried out no sooner than the full text screening stage in order for the number of potentially relevant but excluded records to be identified.

Two reviewers were involved in screening to reduce the chance of failing to detect relevant articles through human error. MP carried out all screening and RW was the second reviewer for screening all abstracts and a random sample of 100 titles. The consistency of agreement between the two reviewers in screening decision-making was determined by calculating the inter-rater agreement, using percentage agreement and Kappa statistics.

Inter-rater agreement reflects the proportion of decisions that multiple reviewers took identically (Gisev et al., 2013). The inter-rater percentage agreement was calculated in both screening stages that involved two reviewers. However, chance could affect the percentage of agreement in abstract and full text screening decisions. Therefore, in addition to reporting the agreement percentage, the kappa statistic was also used to compare the proportion of observed agreement to the proportion of agreement that would be expected by chance. Kappa calculations yield a standardized correlation coefficient ranging from -1 to 1 describing the extent of agreement between reviewers (McHugh, 2012) where 1 represents perfect agreement, 0 represents the proportion of observed agreement estimated to be comparable to chance, and -1 represents a complete lack of agreement.

$$\text{kappa } (\kappa) = \frac{\text{observed agreement} - \text{expected chance agreement}}{1 - \text{expected chance agreement}} \tag{1.3}$$

The formula to compute the kappa statistic (equation 1.3) takes the difference between the agreement proportion observed and the proportion expected by chance in the numerator. The expected chance agreement in the denominator is a proportion that varies according to the rate with which reviewers make each decision. That is, if both reviewers frequently favour one decision, the kappa statistic interprets a high likelihood of coincidental (not informed) agreement on the basis that the probabilities of each reviewer making this decision are much higher than 50%.

Using Landis and Koch's (1977) proposed criteria, kappa values of <0.00 can be interpreted as poor agreement, 0.00-0.20 as slight agreement, 0.21-0.40 fair, 0.41-0.60 moderate, 0.61-0.80 substantial, and 0.81-1.00 as almost perfect agreement. The application of the kappa statistic to assess inter-rater agreement assumes independence of the reviewers, independence of each rating, and the independent, exhaustive and mutually exclusive nature of the available rating decision outcomes (Gisev et al., 2013). The abstract and full text screening processes in this systematic review were considered to sufficiently meet these assumptions by the following mechanisms:

- The use of two different reviewers making decisions separately (rater/reviewer independence)
- The prior removal of all duplicate database search results (rating independence is achieved by having only distinct research papers to screen for inclusion)
- The binary decision outcomes (decision outcomes were to either include or exclude the research paper being rated, thus being independent, exhaustive and mutually exclusive)

Opposing screening decisions between the two reviewers (MP and RW) in a large proportion of the randomly selected sample would be indicative of human error and/or decision making complexity. This could suggest a need for screening to be conducted in full by two reviewers to ensure the quality of the systematic review, or decision making training to be carried out. Permissible levels of disagreement might reasonably vary according to context and application; here, kappa scores were used to inform whether the use of one reviewer for title screening might compromise the quality of the review.

Data extraction and quality assessment (stage 3)

Data extracted from eligible studies included study population, study design, sample size, research aim(s), the population summary indicator used and how it was defined, the statistical methodology employed to compute results, the number of years people were estimated to be healthy and in work, and factors identified as being associated with or predictive of the number of years spent healthy and in work. Data were extracted by MP.

The quality of the eligible studies was then assessed. Research findings can be biased by deviations from true representations in sample selection, data collection, statistical analyses, result interpretation and publishing (Simundić, 2013). Types of bias are often generalised into one of three categories: selection bias; information bias; and confounding (Skelly et al., 2012).

Selection bias refers to types of bias that affect the study design, such as recruitment method or sampling frame, that could lead to selecting a sample that is not representative of the target population (Hammer et al., 2009). Bias due to systematic differences in participant non-response and/or attrition threaten the accuracy of any causal conclusions from a study (internal validity) and the generalizability of the findings (external validity) (Gray, 2016; Godwin et al., 2003). Even where data lost to non-response or attrition are missing at random, the reduction in power increases the likelihood of false positive or negative results (Gray, 2016).

Information bias affects the data collection in a study. Recall bias, interviewer bias, misclassification and measurement error are examples of information bias (Hammer et al., 2009). When data are collected through interviews, systematic differences in how questions are asked can introduce bias (interviewer bias) (Pannucci and Wilkins, 2010). For example, individuals known to be diagnosed with or free from a particular medical condition may be probed to different extents about their lifestyle choices (Pannucci and Wilkins, 2010).

Using proxies for exposures of interest - or exposures or outcomes that are not clearly defined - can lead to participants being misclassified (misclassification bias) (Pannucci and Wilkins, 2010). Further, bias can be introduced by measurement error (for example, due to laboratory error) (Cessie et al., 2012). Measurement error could be independent of both the exposure and outcome variables (classic measurement error), or the measurement taken could be affected by the exposure or the outcome (Cessie et al., 2012). Measurement error could also arise from measuring changeable variables at the wrong time (Cessie et al., 2012).

A confounding factor is causally or non-causally associated with the risk factor as well as causally associated with the outcome - but is not on the causal pathway between the risk factor and the outcome (figure 1.8) (Szklo and Nieto, 2014; Pannucci and Wilkins, 2010).

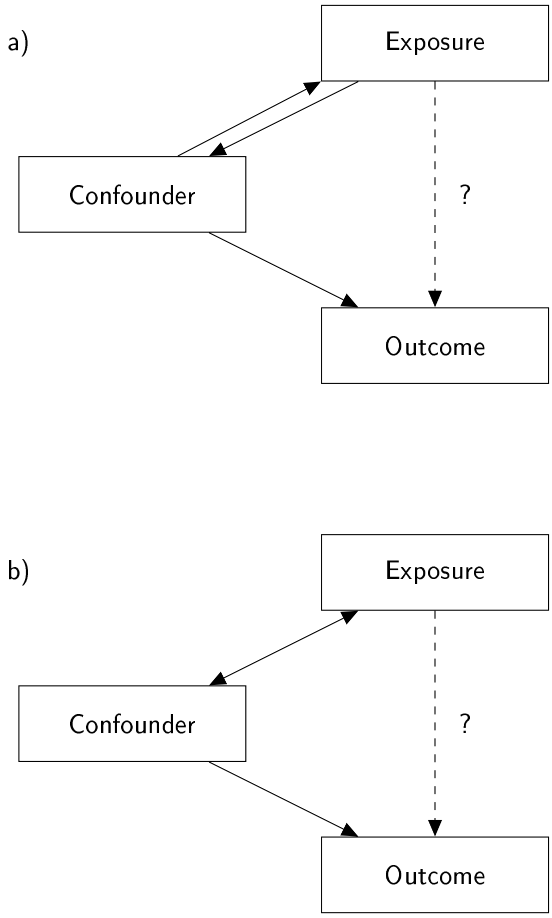


FIGURE 1.8: A confounding variable: is associated causally (a) or non-causally (b) with the exposure of interest; is causally associated with the outcome; and is not on the causal pathway between exposure and outcome (Szklo and Nieto, 2014, p. 156). Unidirectional arrows indicate causal relationships. Noncausal association is indicated by a bidirectional arrow.

Uncontrolled confounding can bias the results and conclusions of study analyses (Skelly et al., 2012). For example, confounding left unaccounted for could lead to an apparent but false statistically significant association between the risk factor and the outcome. Confounding can introduce bias through several mechanisms, including: unmeasured known or suspected confounders; poorly designed selection and recruitment processes; and by secular trends (Cessie et al., 2012; Pannucci and Wilkins, 2010). Potential confounders should be measured and reported in studies, reporting results of both crude analyses and any adjusted analyses carried out (Skelly et al., 2012).

The QUality In Prognosis Studies (QUIPS) tool is designed to support assessment of selection, information, and confounding bias in prognostic research as well as bias relating to (in)appropriate analysis and reporting of results (Hayden et al., 2013). The tool is a template of statements describing high quality research. The researcher must indicate whether these standards are met in the research paper undergoing quality assessment. These points of consideration are grouped into six sections and facilitate informed assessment of six types of bias:

TABLE 1.4: The six types of bias assessed by the QUIPS tool (Hayden et al., 2013) (box).

- Bias related to study participation
- Bias related to study attrition
- Bias related to the prognostic factor of interest
- Bias related to outcome measurement
- Bias related to study confounding
- Bias related to statistical analysis and reporting

Five of the six sections in the QUIPS template were applicable in this review. As research into measures of life expectancy does not involve clinical trials assessing prognostic factors, the QUIPS section assessing bias due to these was instead used to assess bias due to any exposures measured ('bias related to factors associated with the outcome of interest'). Therefore, an adaptation of QUIPS was used to assess the quality of the studies included in the systematic review (see appendix B). For each of the six types of bias, QUIPS provides reviewers a series of questions to answer in order to inform whether the following statements are satisfied:

- "The study sample represents the population of interest on key characteristics, sufficient to limit potential bias to the results"
- "Loss to follow-up (from sample to study population) is not associated with key characteristics (i.e. the study data adequately represents the sample), sufficient to limit potential bias"
- "The prognostic factor of interest is adequately measured in study participants to sufficiently limit potential bias"
- "The outcome of interest is adequately measured in study participants to sufficiently limit potential bias"
- "Important potential confounders are appropriately accounted for, limiting potential bias with respect to the prognostic factor of interest"
- "The statistical analysis is appropriate for the design of the study, limiting potential for presentation of invalid results"

Reviewers mark the extent to which each statement is satisfied as one of: yes; partly; no; unclear; or not relevant. In this review, 'prognostic factor' was replaced by 'factor associated with the outcome of interest'. MP and RW independently carried out quality assessment of the included records.

Analysis (stage 4)

It was not feasible to quantitatively pool study findings of estimates of time spent in health and in work from age 50. There was a low number of eligible studies and a high level of heterogeneity between them. The included studies used different population indicators, statistical methods, and operationalisations of health and work. Additionally, estimates of time spent in health and work required transformation to be comparable from age 50. For these reasons as well as study population differences, a meta-analysis was not appropriate. Instead, a narrative synthesis of the evidence was carried out using textual descriptions, tabulation and data transformation (for example, estimates of time spent in health and work from age 16 were lowered by 34 years to give an approximation of the result from age 50) (Popay et al., 2006).

1.7.2 Results

Applying the search strategy to each of the six databases identified 1409 records in total, reducing to 1029 with exclusion of 34 non-English language Open Grey records and 346 duplicate results. A systematic review study flow diagram (figure 1.9) is presented on page 39. Title screening led to the exclusion of 691 records and a futher 295 records were excluded during abstract screening. Of the 43 papers retained following abstract screening, 39 were found not to be eligible through full text screening. One additional record was included upon reference screening of the remaining records. Finally, one record was excluded due to being a secondary source of evidence (the primary source was the record identified through reference screening).

Four records were identified for inclusion after completion of the search and screening process:

- A Lièvre et al. (2007). "Healthy working life expectancies at age 50 in Europe: a new indicator". *J. Nutr. Health Aging* 11.6, pp. 508–514

- M Mutafova et al. (1996). "Occupational handicap-free life expectancy in Bulgaria 1976-1992 based on the data of the medical expert commissions". *Soc. Sci. Med.* 43.4, pp. 537–542

- J Kaprio et al. (1996). "Total and occupationally active life expectancies in relation to social class and marital status in men classified as healthy at 20 in Finland". *Journal of Epidemiology & Community Health* 50.6, pp. 653–660

- Markku M Nurminen et al. (2004). "Estimating Marginal Cohort Working Life Expectancies from Sequential Cross-sectional Survey Data". *J. Off. Stat.* 20.3, pp. 495–517

Reasons for exclusion at the full text screening stage were as follows:

- Non-English language paper (n = 4)
- No combined health and work expectancy estimate (n = 30)
- Not a journal article (n = 4)
- No full text available (n = 1)

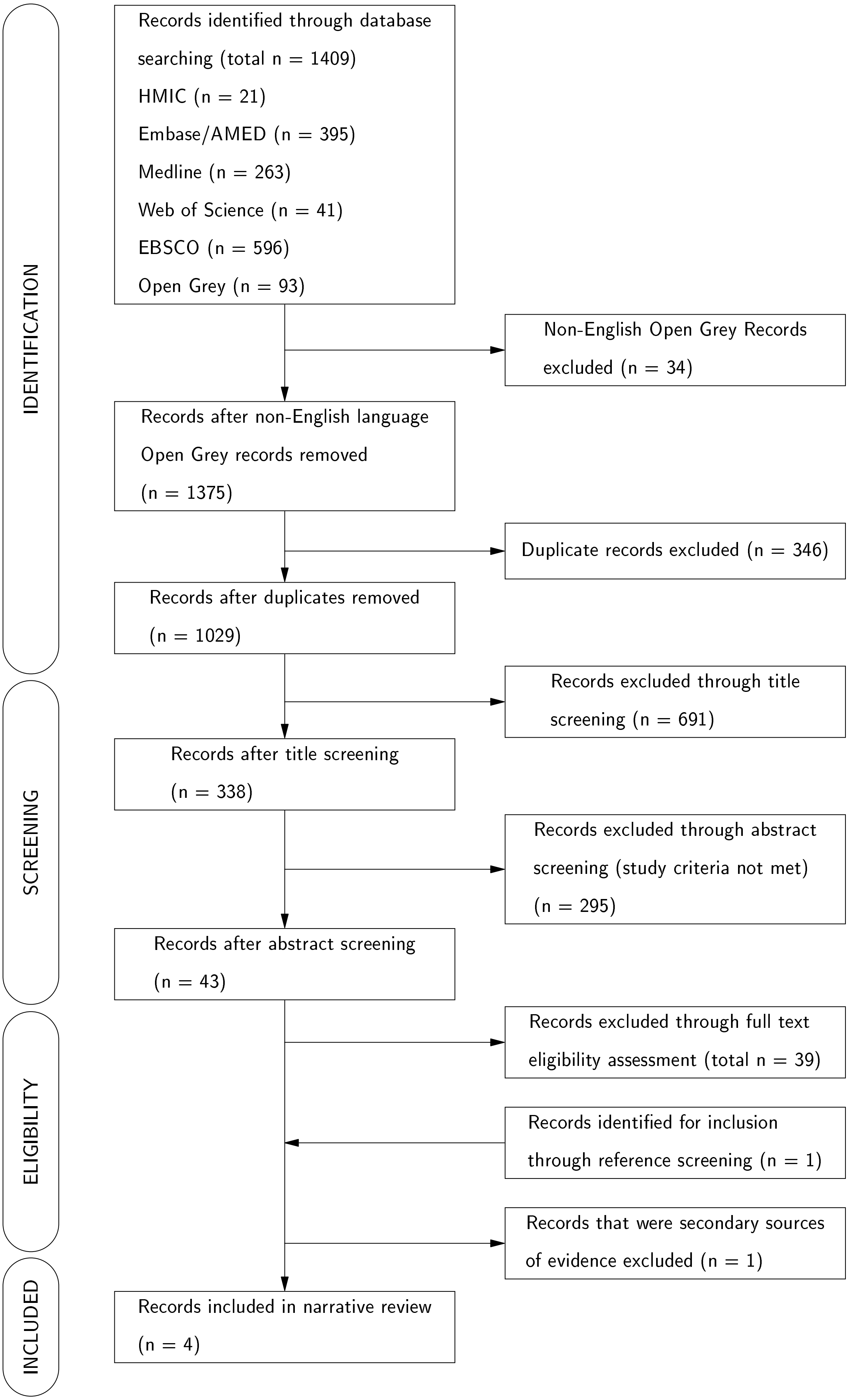


FIGURE 1.9: Systematic review study flow diagram

Inter-rater agreement

MP and RW's title screening decisions agreed in 84 of the 100 cases, deciding to include 25 records and exclude 59 records (table 1.5. In ten cases, MP decided to include a record that RW decided to exclude. In six cases, MP decided to exclude a record that RW decided to include. Percentage of exact agreement was 84%, exceeding the frequently used 80% minimum agreement threshold (McHugh, 2012). The kappa statistic of 0.64 (95% confidence interval 0.48-0.80) (McHugh, 2012) is indicative of a substantial but not perfect level of agreement (Landis and Koch, 1977).

MP and RW jointly reviewed the differences in title screening decisions to identify the reasons for disagreement and determine which discrepancies represented meaningful disagreement that had potential to compromise the quality of the review. Of the ten records originally included by MP but excluded by RW, MP agreed to exclude two. It was found that the remaining eight could be included on the strict application of the inclusion/exclusion criteria (see page 30), but with more extensive research experience RW recognised that they were unlikely to investigate or estimate duration of work capacity (exclusion criteria 3 and 4). RW therefore considered MP's decisions to include acceptable. RW also agreed to exclude one record that was originally only excluded by MP. These 11 disagreements were not considered consequential with regards to the comprehensiveness of the systematic review but highlighted the role of the researcher in shaping the findings of a systematic review thereby evidencing the benefit of dual-review. Five cases of disagreement remained where MP had excluded records that RW included, which all related to either global burdens of diseases or research involving 'elderly' people. These were considered meaningful differences in screening decisions. Percentage inter-rater agreement was recalculated as 95%. As a result, MP reviewed initial screening decisions for all records containing 'elderly' or 'global burden' in their title. Due to

TABLE 1.5: 2x2 table of inter-rater title screening agreement

		MP (first reviewer)	
		include	*exclude*
RW (second reviewer)	*include*	25	6
	exclude	10	59

training MP's decision making it was not considered necessary for a second reviewer to screen all titles.

The two reviewers' (MP and RW) abstract screening decisions agreed in 316 out of 338 cases (94% inter-rater percentage agreement), yielding a kappa score of 0.67 (95% confidence interval 0.42-0.91). The confidence interval for the title screening kappa statistic suggests that the true agreement could be anything from moderate to almost perfect.

Examination of the abstract screening disagreements revealed that RW decided to include seven records that MP decided to exclude, while MP included 15 records that RW excluded. MP and RW reviewed these 22 discrepancies and agreed to include the majority (17 records) for comprehensiveness. Of the five records that were excluded upon shared reevaluation, four had been favoured for inclusion by RW and one had been favoured for inclusion by MP.

During the abstract screening process, one excluded record was a copyright correction note for a different result (which was retained in title screening). Two records lacked available abstracts (including a jounal article for which an abstract had not been published) and these were not excluded at this stage.

Overview of eligible records

Lièvre et al. (2007): Healthy working life expectancies at age 50 in Europe: A new indicator

Lièvre et al. (2007) defined Healthy Working Life Expectancy as the average number of years that individuals in a population are expected to be both healthy and in work. Health was defined subjectively, according to respondents' self-report of chronic physical or mental health problems, illnesses, or disability, and whether they were 'hampered' as a result (Lièvre et al., 2007, p. 509). Survey participants were considered to be employed if they participated in paid employment for 15 hours per week or more. HWLE was estimated for 12 European countries, and for Europe on average, using the multistate life-table method. Mean duration in each state and partial life expectancies were computed using the IMaCh software, based on the self-reported data from individuals who had participated in at least two waves of questionnaires.

The data used by Lièvre et al. (2007) were collected in nationally representative studies of ageing that were carried out in 14 European countries and harmonised for comparability. Two countries (Luxembourg and Ireland) for which data were available were excluded from analyses, reportedly due to insufficient sample size. The survey sample sizes for Luxembourg and Ireland were not stated, but the smallest sample size of male respondents in the included countries was 817 (Denmark) and the smallest sample size of female respondents in the included countries was 844 (Denmark).

Mutafova et al. (1996): Occupational handicap-free life expectancy in Bulgaria 1976-1992 based on the data of the medical expert commissions

Mutafova et al. (1996) calculated the Occupational Handicap-Free Life Expectancy (OHFLE) for Bulgaria (1976-1992). Capacity to work (the absence of work limitation as assessed by a medical commission considering mainly directly medical factors) was presented as an indicator of morbidity and quality of life, measured through Occupational Handicap-Free Life Expectancy. The duration of work capacity was studied in order to more fully quantify population health through a combination of quantity of life (life expectancy) and quality of life (level of occupational handicap). Based on the authors' definition of light occupational handicap as affecting "people who because of their health status are not able to fulfil their previous profession but who are able to work in another profession" (Mutafova et al., 1996, p. 539), the estimated length of healthy working life for the purpose of this review was taken as time spent with no occupational handicap (OHFLE) or light occupational handicap.

The authors defined Occupational Handicap-Free Life Expectancy as the expected number of years lived between the ages of 15 and 69 without 'occupational handicap', which could be severe, moderate, or light. A national system for assessing and recording reduced work capacity of individuals existed during the study period in Bulgaria, with all accounts of occupational handicap determined through expert medical assessment. Severe occupational handicap was defined as having health problem(s) that prevent any form of professional activity. Moderate occupational handicap was defined as having health problem(s) that meant the individual could no longer continue in their previous occupation but who can carry out some activities (for example at home) and who may therefore have the potential to do some professional work under the right circumstances. Light occupational handicap was defined as having health problem(s) that meant that the individual could no longer continue in their previous occupation but could carry out professional activity in a new profession. Mutafova et al. (1996) analysed these national data to determine both life expectancy without occupational handicap during the years of working life in Bulgaria, as well as life expectancy with light, moderate or severe occupational handicap. Numeric results for partial life expectancy were not reported for every level of severity of occupational handicap but can be viewed in graphical form for 16 year olds. For this review the partial life expectancy of years lived with no or light occupational handicap constituted the average number of years that people in Bulgaria were expected to be able to work in some profession. Estimates of partial life expectancies were calculated using the Sullivan method, according to life tables of cumulative person-years per ten-year age interval.

Kaprio et al. (1996): Total and occupationally active life expectancies in relation to social class and marital status in men classified as healthy at 20 in Finland

Kaprio et al. (1996) examined the effects of socio-economic factors on morbidity and mortality during adult life. The authors discussed the complexity and uncertainty surrounding the relationship between changes in life expectancy and changes in lifespan, which were linked conceptually through morbidity and mortality. Work capacity (measured according to receipt of disability pension) was used as an indicator of morbidity, and a partial life expectancy (Occupationally Active Life Expectancy (OALE)) was computed.

Kaprio et al. (1996) studied a cohort of only men, who had all been certified as healthy at age 20 through medical examination for eligibility for military service. Occupationally Active Life Expectancy was defined as the partial life expectancy from age 20 that the men lived, on average, without experiencing one of the following endpoints: early retirement; receipt of disability pension; death; or reaching the national default retirement age of 65 years. Morbidity and mortality data were collected through national records where possible, with some missing data completed using survey questionnaire responses.

Kaprio et al. (1996) stratified the data according to marital status, and separately according to occupational category. Social class was analysed according to the nature of the occupation each man spent the largest portion of his working life in. Occupational groups comprised of: executives (or professionals); clerical workers; skilled workers; unskilled workers; and farmers. Occupationally Active Life Expectancy was the Kaplan-Meier estimate of mean time to event (any defined endpoint) from age 20. Results of these calculations were supported by mortality and morbidity hazard ratios using Cox's proportional hazards model.

Nurminen et al. (2004): Estimating Marginal Cohort Working Life Expectancies from Sequential Cross-sectional Survey Data

Nurminen et al. (2004) computed working life expectancies for employees in municipal workplaces in Finland, as well as working life expectancies in different states of work ability. Concerns over shortages in the labour force amidst unemployment and the retirement of large birth cohorts motivated investigation of the number of years of working life (ages 45-63) spent with good, fair, or poor work ability - or spent not working at all. Reduced work capacity was associated with poor health and disability through common themes of restrictive long standing illness, functional disability, and poor self-rated health.

Health and employment data were collected through responses to survey questionnaires that participants were asked to complete on three occasions (in 1981, 1985 and 1992). These data were supplemented by information retrieved from national disability and mortality records. Work ability states were subjective and defined according to a composite health and work self-assessment score, derived from seven questionnaire items and scaled from 0 to 1 with arbitrary cut-offs: scores $\geq$0.85 were used to define excellent work ability; scores 0.7-$<$0.85 defined good work ability; scores 0.5-$<$0.7 defined fair work ability; and scores $<$0.5 defined poor work ability. The study sample had been recruited for a different study that was designed to be representative of municipal workplaces nationally. Participants were not selected randomly but on the basis of their gender and occupation. Nurminen et al. (2004) estimated the logistic transformation of the conditional probabilities of work ability and work participation. A discrete approximation of the area under the probability curve allowed estimation of working life expectancies in each or any state of work ability.

A strict definition of disability was applied by Mutafova et al. (1996) and Kaprio et al. (1996). The systems of disability pension provision for persons of reduced work capacity in Bulgaria and Finland that provided data for these studies meant that all individuals were considered to be in a state of health unless a medical diagnosis and clinical assessment of reduced work capacity was recorded on national records. Any persons with poor self-rated health but who lacked a diagnosis would have been treated as fully healthy in these data, and it could be that duration of work capacity and duration of working life were equivalent in this context.

Quality assessment

Quality assessment for each record was reviewed in a meeting between MP and RW and the results are shown in table 1.6 below. Where MP and RW did not agree on a quality assessment for whether a type of bias has been convincingly minimised, both assessments are reported.

TABLE 1.6: Quality assessment of included studies using the QUIPS tool

	LIEVRE ET AL. (2007)	**MUTAFOVA ET AL. (1996)**	**KAPRIO ET AL. (1996)**	**NURMINEN ET AL. (2004)**
Outcome measure	Healthy Working Life Expectancy (HWLE)	Occupational Handicap-Free Life Expectancy (OHFLE)	Occupationally Active Life Expectancy (OALE)	Working life expectancy in varying states of work ability
Bias related to:				
study participation	unclear	yes	partly	partly
study attrition	unclear	yes	unclear	unclear (MP)/ partly (RW)
factors associated with the outcome measurement	not relevant	not relevant	yes	not relevant
the outcome measurement	yes	yes	yes	yes
confounding measurement	not relevant	not relevant	no	not relevant
analysis	yes	yes	partly (MP)/ yes (RW)	yes
Research quality	**unclear**	**high**	**acceptable**	**acceptable**

The work undertaken by Lièvre et al. (2007) to estimate Healthy Working Life Expectancy in Europe was not published with sufficient detail to assess the quality of the research. Study populations were assumed to be repressentative but the effect of 'considerable' attrition bias was not discussed. Behr et al. (2005) studied the response rates across waves in the European Community Household Panel (ECHP) (from which Lièvre et al., 2007 calculated HWLE estimates) and found these to be highly variable across the countries in the study. The country most affected by attrition was Ireland, with only 54% response by the fifth wave. However, due to the small sample size, Lièvre et al. (2007) did not use these data to estimate HWLE in Ireland or to contribute to estimation of HWLE in Europe. The ECHP in the UK had lower overall response rates than any other participating country and only collected three waves of data (only two of which were used to estimate HWLE as the study was based on years 1995 onwards) (Lièvre et al., 2007; Behr et al., 2005). Approximately 80% response was achieved in the first wave (1994) in the UK, and of these respondents only 62% participated in the third wave (1996) (Behr et al., 2005, p. 492). Despite these causes to question the national representativeness of the ECHP data, it is worth noting that Behr et al. (2005) found no major bias when analysing income distribution within and income mobility between the participating countries; key determinants of non-response (such as a change of interviewer or moving home) were identified to not be proximally related to variables typically of research interest. Published estimates of HWLE by Lièvre et al. (2007) may not be severely affected by non-response and attrition bias. However, these estimates are no longer up-to-date and results would benefit from data with improved mortality reporting and fewer concerns about national representativeness. Further, the authors indicate that there may be important cross-cultural differences in the construction of a measure incorporating self-assessed health; construct validation work within each country would be necessary to obtain reliable estimates for inter-country comparisons.

Using QUIPS, the Occupational Handicap-Free Life Expectancy research carried out by Mutafova et al. (1996) was found to be of high quality. The use of national records available for all individuals in Bulgaria avoided bias resulting from study participation, attrition and analysis. However, the choice of outcome measurement was specific to Bulgaria and a similar construct is not likely to be achievable in other countries, unless a similar process of assessing and recording work capacity exists.

National records of work disability pension receipt in Finland facilitated the estimation of Occupationally Active Life Expectancy by Kaprio et al. (1996) - a similar outcome measurement methodology as that used by Mutafova et al. (1996) in Bulgaria. However, the representativeness of these estimates may be compromised by the fact that the sample of men was not randomly selected but were matched controls to athletes in a different study (matched by age cohort and residential area). It is possible that the socioeconomic advantages associated with increased physical activity participation both on an individual and neighbourhood level (Eime et al., 2015) led to a sample that underrepresented disadvantaged groups. Research into OALE employed a total sample size of 1662 men who were healthy at age 20. Kaprio et al. (1996) estimated OALE for subgroups of men according to occupation as a proxy for socioeconomic status. The use of subgroups could assist in the generation of representative results. However, the OALE of single men computed from the small number of never-married men in the sample (n=227) was ten years lower (OALE=49.8) than that of ever-married men (OALE=59.42, n=1399) (Mutafova et al., 1996). This non-causal association reflects lifecourse factors relating to and affecting both marital status and work capacity and possible moderating factors affecting the nature of relationship between work and health for ever- or never-married men .

Research into working life expectancy in varying states of work ability (Nurminen et al., 2004) was found to be of acceptable quality through application of the QUIPS tool. Participants were not recruited randomly but efforts were made to generate a sample representative of municipal workplaces in Finland. Nurminen et al. (2004) make the assumption that the study population is approximately representative of Finland's general population. Additionally, bias could be introduced through study attrition. This research into working life expectancy with work ability was published originally in the Journal of Official Statistics (from publisher Statistics Sweden), where it was introduced with a focus on methodology (Nurminen et al., 2004). One month later, the lead author published a further paper (Nurminen, 2004) in the Scandinavian Journal of Work, Environment and Health, discussing the context and application of the same research (Nurminen et al., 2004). In this secondary research paper, studies are cited that validate the use of the work ability index (Tuomi et al. 1998, as cited by Nurminen, 2004, p. 340) to capture clinically assessed health status. These studies suggest the index may perform 'fairly well' at the population level (Nurminen, 2004, p. 340). However, Nurminen (2004) emphasizes that the measure has key limitations due to the unaddressed variation of perceived health and work ability across cultural contexts, with age and with workplace factors.

Data extraction

An overview of the key features of the research identified in the systematic review is given in table 1.7. Due to study heterogeneity, a meta-analysis could not be performed on the numerical findings and extracted quantitative data serve only to indicate general trends in duration of work capacity. To aid the reader's own comparison of the findings, informal adjustments were made to results to anchor each estimate of work capacity to age 50 (see table 1.8). These adjustments do not account for the intrinsic study heterogeneity nor for the studies' designs but are used to present the available answers to the question of duration of healthy working life from age 50, which motivated this systematic review.

TABLE 1.7: Overview of research identified through systematic review

Author(s)	**A. LIEVRE, F. JUSOT, T. BARNAY, C. SERMET, N. BROUARD, J.M. ROBINE, M.A. BRIEU, F. FORETTE**	**M. MUTAFOVA, H.P.A. VAN DE WATER, R.J.M. PERENBOOM, H.C. BOSHUIZEN, C. MALESHKOV**	**J. KAPRIO, S. SARNA, M. FOGELHOLM, M. KOSKENVUO**	**M.M. NURMINEN, C.R. HEATHCOTE, B.A. DAVIS**
Publication year	2007	1996	1996	2004
Research aim(s)	To propose and use Healthy Working Life Expectancy (combining health and productivity information) to assess societal involvement and the absence of disease and/or disability	To find an indicator that combines the different aspects of health (combining morbidity and mortality data) effectively and realistically to understand population health	To investigate how total life expectancy and occupationally active life expectancy differ from each other and in relation to socioeconomic status (using social and marital status and studying men who were healthy as young adults)	To estimate the duration of work life spent in different states of work ability (work capacity) between ages 45 and 63
Study design	Longitudinal data analysis of health and work statuses using a multi-state life table approach was used to estimate HWLE. Mean duration of time occupying each state was calculated from the transition probabilities between states using a Markov chain discrete-time model with IMaCh software (logistic multinomial model estimation of transition probabilities between initial and final work-health state).	Cumulative person-year life tables (Sullivan method) were used to estimate the expected portion of working life (ages 16-49) spent in different states of occupational handicap (ranging from no to severe). OHFLE is calculated from the average number of person years in each occupational handicap state at each age interval.	Retrospective cohort study of men who were healthy at baseline and identified as matched controls for a different study. Occupationally Active Life Expectancy is the Kaplan-Meier estimate of mean time to event according to marital/'social class' status of the study participants.	Cohort marginal probabilities were estimated from sequential cross sectional surveys on ageing and work ability. Weighted least squares regression of log partial odds for prevalences and probabilities was used to estimate expected occupancy times in work ability states (good, fair, poor, not actively employed).

* Continued on next page*

Table 1.7 – continued from previous page

Author(s)	**LIEVRE ET AL. (2007)**	**MUTAFOVA ET AL. (1996)**	**KAPRIO ET AL. (1996)**	**NURMINEN ET AL. (2004)**
Research setting	General population in Europe (Austria, Belgium, Denmark, Finland, France, Germany, UK, Greece, Italy, the Netherlands, Portugal, Spain)	Bulgaria	Finnish male citizens	Municipal workplaces in all 11 provinces of Finland
Sampling frame	European Community Household Panel (ECHP) collected nationally representative household data through national studies of ageing. ECHP waves 1995-2001 were used for this research. (Wave 1 in 1994 was excluded.) Two European countries' data were excluded due to sample size insufficiency.	National data from Expert Medical Commissions on Working Capacity. All persons in Bulgaria with reduced work capacity have consultations where their work capacity is assessed. All long-term reductions in work capacity recorded were used in this study; short term cases were excluded.	Finnish men who had been classified as fully healthy at age 20 upon medical examination for entry into military service (all Finnish men undergo this exam). The subjects used in this study were those selected in a previous study as referents for their research into mortality in top male athletes. The subjects were selected from a register of men liable for military service archived by the Finnish Defense Forces.	Municipal workers born between 1923 and 1936 who had worked in their present occupation for at least five years were sampled from to obtain a cohort that was representative of municipal workplaces regionally with respect to sex and occupational grouping.
Sample size	21,026 men and 22,660 women in total across Europe and with at least two interviews. Male sample size per country range: 817-3037; female sample size range: 844-3140.	267,737 (for study years 1976-1992). Population size in 1976 was 259,285.	1712 men in total; 1662 for survival analyses due to unknown vital status for 50 men.	6257 (excluding people who did not respond to at least one of the three surveys, and excluding 190 respondents who did not meet inclusion criteria).

TABLE 1.8: Estimates of work capacity duration from age 50

	LIEVRE ET AL. (2007)	**MUTAFOVA ET AL. (1996)**	**KAPRIO ET AL. (1996)**	**NURMINEN ET AL. (2004)**
Health assessment	self-rated	clinical examination	clinical examination	self-rated
Outcome measure	Healthy Working Life Expectancy (HWLE)	Occupational Handicap-Free Life Expectancy (OHFLE)	Occupationally Active Life Expectancy (OALE)	Working life expectancy in varying states of work ability
Derivation of estimate of work capacity duration from age 50	N/A (results from age 50 used as published)	Life expectancy with light occupational handicap (unable to continue in current professional duties but able to work in a different profession) was added to OHFLE (life expectancy with no occupational handicap) to derive work capacity expected duration. Estimates for age 16 in 1992 were read from graph and used to calculate age at which work capacity ends. Work capacity duration from age 50 is derived by subtracting 50 from this result.	OALE estimates the age at which work capacity ends. Work capacity duration from age 50 is derived by subtracting 50 from OALE estimate.	The authors estimated life expectancy in states of good work ability, fair work ability, poor work ability, or no longer working. Results are presented for ages 45-62. Work capacity duration form age 50 is derived by summing life expectancy in good and in fair work ability for age 50.
Estimate of duration of work capacity from age 50	Europe average: males 7.5 years; females 4.8. UK: males 8.8; females 5.8. Finland: males 6.3; females: 6.2.	Life expectancy with no or light occupational handicap: 1992 results from graph: males 6.8*; females 8.5*. NB: rates of occupational handicap changed from 1976 to 1992. OHFLE alone at age 50 in 1992: males 8.9 years; females 9.5.	Executives (n=127): 11.91 years*. Clericals (n=314): 9.77*. Skilled workers (n=578): 8.31*. Unskilled workers (n=177): 2.17*. Farmers (n=317): 7.08*.	Males 5.48 years; females 6.06.

Note: * indicates estimates of ableness to work from age 50 that were derived approximately from the expected end of work capacity at age 16.

1.7.3 Evidence synthesis: narrative review

Health was captured by Mutafova et al. (1996) and Kaprio et al. (1996) in the objective medical assessment of reduced work capacity. In both study contexts, a national programme assessed work capacity and provided disability pensions to those deemed unable to continue in paid employment. Both studies assumed that working-age individuals are in work by default unless in receipt of a disability pension. Kaprio et al. (1996) estimated OALE for a cohort of men who had been certified as healthy at age 20 through medical examination for eligibility for military service. The outcome was reported as the age at which occupationally active life was expected to end. By subtracting 50 years from OALE results as presented, estimates ranged from 2.17 to 11.91 years from age 50 according to occupation category. Similarly, relevant analyses by Mutafova et al. (1996) were only available from age 16 (not from age 50) but suggested estimates of 8.9 and 9.5 years of work participation with work capacity ('no occupational handicap' or 'light occupational handicap') from age 50 for males and females respectively. Over the study period in Bulgaria, female OHFLE at age 16 and age 50 decreased slightly despite corresponding life expectancy increases (Mutafova et al., 1996).

The remaining two studies investigated work participation with subjective health or work capacity self-assessment. Estimates of the duration of work participation in health (Lièvre et al., 2007) or good or fair work ability (Nurminen et al., 2004) in these studies ranged from 5.5 years (France – Lièvre et al. (2007); Finland - Nurminen et al. (2004)) to 9.7 (Greece - Lièvre et al. (2007)) for males. The range of estimates for females was 2.9 years (Italy – Lièvre et al. (2007)) to 6.2 (Finland – Lièvre et al. (2007)). Lièvre et al. (2007) estimated UK HWLE as 7.4 years for males and 5.8 years for females, but data were only available for two time points so a correction factor was applied based on trends observed in other European countries studied (table 1.8).

Of all the studies in the review, only Kaprio et al. (1996) presented subgroup analyses to examine factors associated with duration of healthy and working life. Never being married and lower socioeconomic status (measured by occupation) were associated with lower OALE, lower total life expectancy, and a less favourable ratio of OALE to total life expectancy. OALE was 9.42 years from age 50 for ever married men, but men who had never married were not expected to stay in the workforce until they turned 50.

1.7.4 Discussion

The primary aim of this systematic review was to identify estimates of the number of years that adults in their later working lives (from age 50 years) are likely to be both healthy and in work. The systematic search identified four studies, which allowed review of how duration of health and work participation has been operationalised. Only one study reported potential determinants of reduced work capacity. The four included studies were published from 1996-2007, which was prior to the implementation of policies to extend working lives. No theoretical or statistical justification for the definitions of health and work participation were published or cited in the research of Healthy Working Life Expectancy (Lièvre et al., 2007) and no rationale was given for the exclusion of individuals working fewer than 15 hours per week, which will lead to lower estimates of the number of years that people are healthy and in work. Only one study identified a group of people who, on average, would be working until their 60s: male Finnish executives (approximately 8% of the study population, who had all been healthy at 20 years old) (Kaprio et al., 1996).

The research identified in this review was positioned in the contexts of: success in ageing (Lièvre et al., 2007); workforce ageing (Nurminen et al., 2004); and the relationship between life expectancy and quality of life (Kaprio et al., 1996; Mutafova et al., 1996). As more countries experience population ageing, workforce ageing and increasing life expectancy (Gelbard et al., 1999), the key concerns these changes bring must be considered. Knowing whether longer life expectancy is accompanied by longer life span and more years in good health is important for effective planning in policy areas such as retirement and healthcare provision. Given the increased proportion of older adults in workforces and efforts to alleviate burdens associated with population ageing, research is being increasingly targeted towards health-related outcomes experienced during adults' longer lives (Jagger et al., 2007). Measuring and projecting the quality of adults' later lives and later working lives could prove critical in facilitating success in ageing, making evidence-based policy decisions, and projecting the health care and pension needs of adults both in and out of work. To this end, there would be clear benefit in establishing how best to effectively measure health status and work outcomes, and in determining the number of years that adults can be expected to be both healthy and in work.

Lièvre et al. (2007) and Nurminen et al. (2004) used different study populations, sample populations and statistical methodology to compute their estimates of duration of work participation with health/work ability in Finland. Despite this, their estimates were similar: 6.3 and 5.5 years for males from age 50; and 6.2 and 6.1 years for females (Lièvre et al. (2007) and Nurminen et al. (2004) respectively). The range of estimates for males in Finland found by Kaprio et al. (1996), however, varied to a much greater extent: 2.2-11.9 years from age 50 according to occupational grouping. The Kaprio et al. (1996) study differs from other studies of this nature in that it was neither nationally representative nor nationally exhaustive in its data. Kaprio et al. (1996) estimated Occupationally Active Life Expectancy only from age 20 (OALE was not estimated from age 50); for the purposes of this review, an approximation OALE from age 50 was derived by computing the difference between age 50 and the expected end of occupationally active life. A more accurate result would necessitate reanalysing the data including only those who survived to the age of 50. A difference in Occupationally Active Life Expectancy of approximately ten years was detected between ever-married and never-married men; never-married men were estimated to reach the end of their occupationally active life prior to their 50th birthday (age 49.8 years). This comparison should be accompanied by noting the small sample size of never-married men in the research and the potential for sampling bias (see table 1.6 on page 46 for further discussion of quality assessment). Despite the low OALE result amongst never-married men, it can be observed that the distribution of OALE estimates was negatively skewed; most men were expected to continue their occupationally active lives until late in their 50s. This result, which was based on clinical assessment of reduced health capacity, is reminiscent of the high values of Occupational Handicap-Free Life Expectancy obtained for Bulgaria (Mutafova et al., 1996) through data with a similar disability construct. Estimates of duration of work capacity as measured by medical examination (Kaprio et al., 1996; Mutafova et al., 1996) identified in this review typically fell at the upper region of (or exceed) the interval of estimates of work capacity using self-reported health data (Lièvre et al., 2007; Nurminen et al., 2004).

Estimates of OHFLE published by Mutafova et al. (1996) treated all forms of occupational handicap that compromise work capacity as endpoints, even where work capacity was only slightly reduced. OHFLE was given for adults in ten year age intervals from 20 to 50. These estimates were supplemented by life expectancy estimates with light, moderate or severe occupational handicap. Combining the number of years expected to be affected by light occupational handicap (with which working is possible but a change of profession may be required) with estimates of OHFLE may best reflect the number of years that adults are 'able' to work and do so. However, estimates of life expectancy with light occupational handicap were published only for adults at age 16. Approximate estimates of ableness to work from age 50 were derived with the same methodology used to estimate OALE (Kaprio et al., 1996) at age 50 - with the same limitation that persons who died before age 50 were incorrectly included (leading to underestimation of the work-related life expectancy from age 50). OHFLE alone at age 50 in 1992 (males 8.9 years; females 9.5) was higher than the estimate of OHFLE and light occupational handicap life expectancy at age 50 (males 6.8; females 8.5) derived from estimates for 16 year olds in 1992. This is in part due to mortality between ages 16 and 50, but could also be associated with the increase in occupational handicap (of all levels of severity) observed from the beginning to the end of the study period (1976-1992) for both males and females.

Clinically examined and self-assessed measures of health

Two of the four papers included in this review employed clinically assessed health variables (Kaprio et al., 1996; Mutafova et al., 1996) whilst two used subjective self-reported measures (Lièvre et al., 2007; Nurminen et al., 2004). Self-reported health has been shown to be a good proxy for objective clinical health assessment in the past (e.g. Eskelinen et al., 1991) but research generally indicates that self-assessed health measured with a five-point scale may be misleading (Nesson and Robinson, 2019; Black et al., 2017; Greene et al., 2015; Lenderink et al., 2012; Zajacova and Dowd, 2011; Pfarr et al., 2010; Crossley and Kennedy, 2002; Groot, 2000); individuals' subjective health assessment may be more driven by mental well-being and functional limitation while practitioners' reports focus on known risk factors and clinically measurable variables (Smith and Goldman, 2011).

Both methods of measuring health feature in the literature and both have limitations in relation to labour market behaviour (Baker et al., 2004). If the research aim of measuring health is to detect the presence of diagnosed conditions, clinical examination can measure precisely this. However, health is a complex driver of workforce participation, and self-rated health is likely to correlate with this aspect of health more closely than clinical measurement does - for example due to physiological impairment without symptoms that interfere with function (Haan and Myck, 2009; Nurminen, 2004; Bound, 1991). Some self-reported measures of health and ability to work may be a stronger predictors of future health and work outcomes than objective health measurements (Tuomi et al., 2001).

There are systematic differences in the effect of health on work participation detected through the use of objective or subjective measures; observed effects could represent the lower and upper bounds respectively of the true effect (Bound, 1991). There are three main reasons why the effect of health could seem higher using self-report measures than through clinical examination:

1. The definition of self-rated poor health requires no medical diagnosis and is therefore more inclusive than that of clinically assessed poor health (any individual may choose to self-identify as having poor health whereas not everyone has a medically diagnosable or detected condition) (Haan and Myck, 2009).

2. The effect attributed to self-rated health may capture some of the effect of economic factors on work participation decisions (Bound, 1991). There is income-related heterogeneity in reporting of self-assesed health that leads to overestimation of income-related health inequality; small health improvements tend to be rated more favourably among higher-income groups than lower-income groups, and income level itself and education level account for some of the variance in self-assessed health that is not explained by physical or mental health problems (Nesson and Robinson, 2019). This does not necessarily mean that the effects of self-assessed health on work participation are not meaningful, rather that they are incorrectly

attributed to health. Economic factors are determinants of work participation outcomes and measurements of health (subjective and objective) are correlated with economic factors (Johnston et al., 2009; Baker et al., 2004). For example, people living in more disadvantaged neighbourhoods (who may not have the means for, or access to an environment in which to enjoy a healthy lifestyle) may have few suitable paid work options. Vitality (energy, motivation and resilience) - an indicator of psychological well-being with links to economic factors through poverty and socioeconomic status - may be one possible moderating factor between lower self-assessed health ratings and lower socioeconomic status (Lavrusheva, 2020; Mears et al., 2019; Steenbergen et al., 2016; Au and Johnston, 2014; Gary-Webb et al., 2011; Ryan et al., 2010).

3. Some individuals may wish to justify their non-employment through falsely reporting poor subjective health (the 'justification hypothesis') (Cai, 2010; Baker et al., 2004). Some studies report evidence of this while others have found that systematic differences in self-rated health between employed and non-employed persons are not sufficient to imply 'rationalisation' (Cai and Kalb, 2006; Baker et al., 2004; Stern, 1989).

Changes to contextual, societal and economic conditions can have substantial and complex effects on the morbidity and mortality affecting a working-age population (Gronlund, 2014; Wagenaar et al., 2010; Mutafova et al., 1996). The biopsychosocial relationship between health and work strengthens the rationale for subjective health measures, as used by (Lièvre et al., 2007), over objective work capacity assessments (Kaprio et al., 1996; Mutafova et al., 1996) or even subjective assessments of work ability (Nurminen et al., 2004). Incorporating a subjective approach to health measurement recognises that individuals may take decisions for any number of reasons (Ringen, 1995), also providing scope for employers to affect change in how individuals interact with their work environment without any improvement or decline in physical function.

Aspects of the biopsychosocial model of disability - including vocational, educational, psychosocial and financial factors - are not recognised in the medical model of disability but are often key drivers of (in)ability to complete tasks and, therefore, (in)ability to participate in paid work (Chen, 2007). In general, it is hard to predict the extent to which an individual experiences disability solely from medical assessment of physical, psychological or anatomical impairment (Chen, 2007). In a work context this highlights the role of psychosocial working conditions, where workers health is influenced not only by biological factors but macro- and meso-level factors including economic, social, political and workplace structures (Rugulies, 2019). Modelling the health-related workforce participation behaviour of a population is not equivalent to estimating population employment with medically assessed health or work capacity (Nurminen, 2004). These biopsychosocial and medical models (respectively) of health and work are likely to explain some of the variation in results identified in this review, although this is not clear due to the differences between each of the studies.

Healthy Working Life Expectancy

Lièvre et al. (2007) investigated Healthy Working Life Expectancy (HWLE) across Europe. Healthy Working Life Expectancy is associated with markers of successful ageing: health status; productive engagement (through employment); and longevity (Lièvre et al., 2007). In turn, these markers of successful ageing conceptually link the monitoring of HWLE to the ongoing sustainability of national social security systems. HWLE was presented by Lièvre et al. (2007) as a mechanism by which to measure quality of later life, as well as to monitor the extent to which social security policies are affordable and realistic.

Study strengths and limitations

A strength of this review is that the broad scope of the search strategy and dual-review screening process allowed numerical results to be identified despite the variety of individual study aims, designs and approaches to analysis. Although non-English language results were excluded, the majority of these were Open Grey results and no English language papers from this source were found to be eligible for the review.

The systematic review included assessment of the identification of papers by using a second reviewer for all abstract screening and a random sample of title screening and measuring agreement. Agreement in screening decisions for 100 randomly selected titles was substantial (84%, kappa statistic 0.64) and screening decisions were updated after disagreements were resolved in a consensus meeting. Reviewers agreed in 317 of the 338 abstract screening decisions. Despite a modest kappa statistic of 0.67, percentage agreement was high (94%).

The review findings are limited by the number of formal studies that have been carried out in this area. A meta-analysis was not appropriate due to the high level of heterogeneity across several aspects of the studies, and the role of factors driving health and work participation could not be determined as study authors were largely speculative on this matter. Estimates of the number of years in health and work from age 50 transformed from OHFLE (Mutafova et al., 1996) and OALE (Kaprio et al., 1996) are underestimated due to persons who died before age 50 not being excluded. Finally, length of healthy working life using results by Nurminen (2004) may be overestimated as some individuals may have left the workforce prior to age 45 due to poor health.

Implications for policy

Life expectancy and its subdivisions into health state life expectancies have important effects on societies at the individual and population level (Beltrán-Sánchez et al., 2015). Whether death is postponed in favour of extended disability and poor health, or in fact adults are experiencing a proportional (or equal) increase in number of healthy years is a crucial consideration for policy makers and health care providers contending with an ageing population. Adding to existing evidence that morbidity is compressing in some populations and expanding in others (Jagger, 2015), the findings of this review suggest that existing evidence is insufficient to support the feasibility of policies seeking to extend working lives. Valid and reliable estimates of life expectancy in health and work from age 50 are needed to evaluate whether populations are ready to work later in life. Combining working status with health status makes HWLE a well-suited population health indicator for this as policy makers seek to boost work participation in later working life (healthy life expectancy could improve without increased work participation if people prefer not to work or cannot find suitable work) and assess whether policies to extend working lives are 'working' (indicators such as employment rate do not directly measure whether people are spending more years in paid work). HWLE estimates would also serve to highlight where strategic intervention is needed to reduce health and work inequalities and make extended working lives achievable. Work is needed on the development and implementation of a population indicator suitable for this purpose. The benefits of successful ageing (health and productive activity in older age (Jagger et al., 2007; Lièvre et al., 2007)) are not only multifarious but would allow for a new working understanding of the relationship between chronological age and the process of ageing (Spijker and MacInnes, 2013), which through policy making could lead to more equitable and nationally affordable healthcare and pension provision.

Implications for research

The nature of work is changing. Increasingly, workers carry out non-manual, non-industrial work; accompanying this shift has been a decrease in workplace accidents and a rise in work-related mental health problems, stress and job strain (Baumberg, 2012; Vickerstaff et al., 2012). Types of roles available are changing due to automation and redistribution of work, for example the offshoring of not only manufacturing jobs but, increasingly, also skilled professional and technical work (Barley et al., 2017). Further, with the rise of the 'gig economy', growing numbers of people are engaged in temporary and short-term work (Barley et al., 2017). A given illness or disability may be more or less disabling at work depending on the characteristics of the role (Baumberg, 2012). The definition of 'work limiting disability' is tied to context; for example a low number of accessible employment opportunities or a low demand for workers may mean that long term illness has a greater impact on ability to secure employment (Bartley and Owen, 1996). This highlights the importance of measuring both work capacity and participation among older adults and the use of a combined health and work indicator is advantageous in incorporating objective measures of work participation. Prevalence of longstanding limiting illness need not increase in a population for changes in work factors (such as availability and nature of job opportunities) to increase levels of work limiting disability (Baumberg, 2012). There is a need for a healthy working life expectancy indicator that allows for changes in the relationship between health and work (for example due to variation in the availability and nature of work opportunities).

The scarcity of studies that have used a population indicator to measure the number of years that people are healthy and in work identified in this review indicates the need to operationalise this construct to inform policy. Recent studies of working life expectancy with respect to health (Wind et al., 2018) or disability (van der Noordt M. et al., 2019) status were ineligible for the systematic review as study populations were defined by health status at baseline and work status at baseline respectively (within the target age-range of 50-60 years). Additionally, this target age range was not captured in full in either study population where, in both cases, the youngest adults were aged 55 years. Population subgroups affected by poor health and work non-participation lower the average number of years spent in health and work. The review criterion that study populations represent a general population is necessary for the comparison of results to policies applied nationally, to demonstrate that the population indicator can be used for this purpose, and to inform strategic interventions to increase time spent in health and work.

The scarcity of studies identified in this review also suggests there are obstacles to the calculation of healthy working life expectancy. Two studies analysed data that were collected in relation to local policies (in order to monitor and support people with reduced work capacity) which are not routinely collected in other settings (Kaprio et al., 1996; Mutafova et al., 1996). Even in countries where such data sources continue to be available, the assumptions that people are in work unless in receipt of a disability pension are unlikely to be reasonable as societies and their workforces change (including the preferences a high proportion of older workers exercise in working only where jobs offer good-quality working lives (Maltby, 2012)). Nurminen et al. (2004) analysed survey data collected as part of a standalone study, also making strong assumptions about the representativeness of the data to the general population. Of the studies identified in this review, only the analysis carried out by Lièvre et al. (2007) has potential to be updated or replicated in new settings, although there are possible challenges in accessing mortality-linked longitudinal survey data and in the methodological and computational complexity of estimating multi-state life tables using interpolated Markov chain modelling. There is a need to adopt an indicator that can feasibly be estimated and routinely updated; 'Healthy Working Life Expectancy' (Lièvre et al., 2007) may be a good starting point for this although more work is needed on the operationalisation of health and work.

Conclusion

This systematic review identified four studies that estimated the average number of years adults are both healthy and in work in later working-age life (from age 50). The low number of results and the lack of recent studies is indicative of limitations in available data and/or methods for the calculation of healthy working life expectancy. The review was updated in January 2019 and no new eligible records were identified. Some numerical findings identified supported existing evidence that duration of health and work participation does not necessarily maintain a linear relationship with total life expectancy (Nurminen, 2004; Crimmins, 2002; Mutafova et al., 1996). The average number of years that people are healthy and in work therefore requires regular measurement to monitor workforce potential and inform policy making. This review also showed no general adoption of a population indicator for this purpose, and current and reliable estimates of the average duration of health and work participation (in any population and using any metric) were not identified. Evidence from the narrative review draws attention to the need for development of an appropriate population indicator that can be routinely estimated to monitor and guide improvements to population and workforce health and wellbeing.

1.8 Thesis aims

The overarching aim of the work described in this thesis was to examine use of the HWLE indicator to investigate whether the population of England is in a position to extend working life. The objectives of the thesis were to:

1. determine whether HWLE can be measured in England
2. estimate HWLE in England
3. investigate how HWLE is likely to change in future years in England
4. investigate the association between socio-demographic, health, lifestyle and workplace factors and higher or lower HWLE

These objectives were considered in the studies presented in chapters 2 to 5.

The objectives for the work described in **Chapter 2** were to:

- determine whether HWLE can be feasibly estimated for England
- operationalise HWLE using nationally representative data from the English Longidutinal Study of Ageing (ELSA)
- estimate HWLE from age 50 for England overall
- investigate inequalities in HWLE between subpopulations of England according to key demographic factors (sex, deprivation level, occupation type, education level, and region)
- assess the sensitivity of HWLE findings to methodological implementation choices and handling of missing data
- assess the sensitivity of HWLE estimates to operationalisation of health as limiting longstanding illness using alternative health definitions using self-assessed health (SAH) and difficulties with activities of daily living (ADLs)
- compare summed health expectancies to estimates of total life expectancy from standard life tables (including mortality and not health/work ELSA data)
- compare HWLE, health expectancy and total life expectancy findings to official published estimates of healthy life expectancy, working life expectancy and total life expectancy

The objectives for the work described in **Chapter 3** were to:

- identify data and methodology suitable for investigating HWLE trend over time in England
- estimate HWLE annual projections up to the year 2035 for men and women in England using data from the Health Survey for England (HSE) and official mortality rate statistics
- investigate the expected rate of HWLE change for men and women in England in future years up to 2035
- assess the sensitivity of annual HWLE estimates and projected estimates to age-specific mortality rates being the same or different between healthy and working people aged 50-75 compared to unhealthy and/or not working people aged 50-75
- assess HWLE model performance using alternative method (Sullivan approach) HWLE estimates for the observed data years

The objectives for the work described in **Chapter 4** were to:

- examine HWLE in people with a long term health condition using osteoarthritis (OA) as an exemplar
- estimate HWLE for people (in England overall, for men and women, and according to occupation type) with and without self-reported OA at age 50 using nationally representative ELSA data
- for comparison with HWLE estimates based on self-reported OA, estimate HWLE at age 50 for people whose medical records indicate having OA or not having OA within the 50-75 target age range (determined by general practice consultation(s) for OA) using medical record linked survey data collected in North Staffordshire (the North Staffordshire Osteoarthritis Project; NorStOP)
- assess the sensitivity of ELSA results to missing OA data handling through comparison to HWLE estimates presented in chapter 2
- assess the sensitivity of HWLE findings from NorStOP to methodological implementation choices and handling of missing data

- compare summed health expectancies from NorStOP to estimates of total life expectancy from standard life tables (including mortality and not health/work NorStOP data)

The objectives for the work described in **Chapter 5** were to:

- investigate the impact of various health (including OA), lifestyle and workplace factors individually (and for key combinations of factors with OA) on rates of healthy and working people becoming unhealthy and/or stopping working using ELSA data

- estimate the associated HWLE from age 50 of people with and without each health (including OA), lifestyle and workplace factor individually (and for key combinations of factors with OA)

- assess the sensitivity of HWLE findings to use of a reduced ELSA sample size and alternative methodology through comparison to HWLE estimates presented in previous chapters

- assess the sensitivity of HWLE estimates to operationalisation of health as limiting longstanding illness using alternative health definitions using SAH and difficulties with ADLs

Chapter 2

Estimates of Healthy Working Life Expectancy at age 50 in England

The percentage of the global population aged 65 and over is expected to double from the year 2000 to 2045 (UN, 2019). Increases to life expectancy at age 65 are accompanied by rising social pension and healthcare expenditure exacerbated by a decrease in the proportion of the population who are working-age and contributing to national budgets through taxation. Many countries are experiencing population ageing and worsening old age dependency ratios - especially Japan, where the number of people aged ≥65 per hundred working age adults (ages 15-64) increased from 24.9 in 2000 to 46.2 in 2018 (The World Bank, 2019). Similar trends can be observed across Europe. Major changes in national policies and care systems are required to ensure pension funding is sustainable and address growing care needs for complex and long-term health problems (Kingston et al., 2018; WHO, 2015; DWP, 2010).

Policies to defer retirement age are widespread in effort to mitigate against unaffordability of population ageing and improve old age dependency ratios; for example, France, Germany and Spain will increase state retirement age to 67 between 2023 and 2029 and the United Kingdom plan to increase state retirement age to 68 after 2037. In the UK, the schedule for increasing the state retirement age is based on limiting average duration of social pension (the 'State Pension') receipt to no more than one third of adult life (DWP, 2017b). However, the success of such policies depends on the willingness and ability of a substantial proportion of people to work for longer. Health is a strong driver of work outcomes, particularly among adults aged 50 and over (Haan and Myck, 2009). Initiatives to improve population health may be required as ageing workforces and older workers are at increased risk of absenteeism, presenteeism, work disability and early retirement for health reasons leading to productivity losses, employer costs and reliance on state financial support for disability or unemployment (Reeuwijk et al., 2017; Hofäcker et al., 2016).

The systematic review described in chapter 1 (page 26) found that evidence of whether people in later working-age life (age $\geq$50) are able to work for longer is limited and no suitable indicator has been adopted for population monitoring. Key indicators of work participation such as employment rate or working life expectancy do not capture function or work capacity, required for sustainable extension to working life. Similarly, healthy life expectancy indicators are not well-suited to measure extensions to working life as they do not incorporate work status, which is not solely driven by health but also the availability of paid work and the suitability of such opportunities to personal preferences and circumstances (for example chronic health conditions and caring responsibilities). Additionally, increases to healthy life expectancy at age 50 do not necessarily imply more years available for working as they could be due to health improvements at older ages while health levels remain similar for adults in later working life. Healthy Working Life Expectancy (HWLE) is the average number of years people are expected to be healthy and in work from age 50 (Lièvre et al., 2007). The systematic review carried out previously identified HWLE as a suitable indicator to: measure whether adults in later working-age life are able to work for longer; monitor extensions to healthy working life; and identify inequalities in healthy working life.

The objective of the study presented in this chapter was to operationalise HWLE to produce estimates for England overall and by key population subgroups defined by sex, geographic region, occupation type, and individual (educational attainment) and area (Index of Multiple Deprivation (IMD) measuring relative deprivation in neighbourhoods in England) level indicators of socio-economic status. In relation to the objective of operationalising HWLE, findings were assessed for sensitivity to operationalising health as limiting long-standing illness by estimating HWLE using alternative health definitions using self-assessed health and difficulties with activities of daily living. HWLE estimates were also assessed for sensitivity to the number of transitions modelled per each year of age, the approach to inferring the age-specific prevalence of state occupation (from the transition probabilities or using observed prevalences in the study population), and the exclusion of individuals with missing data on subpopulation identifiers.

The following sections present the methodology to estimate HWLE in England. First, an overview is presented of the data source and survey design. The methods of multi-state modelling will then be introduced before their application to HWLE estimation is outlined.

2.1 Data source: The English Longitudinal Study of Ageing (ELSA)

The English Longitudinal Study of Ageing (ELSA) is a longitudinal study of adults aged 50 and over in England (Banks et al., 2016). ELSA collected detailed infomation of the health and lifestyles of participants and was designed to be representative of the English population aged 50 years and older (Steptoe et al., 2013). ELSA was modelled on the Health and Retirement Study that has been ongoing in the United States since 1992 (Sonnega et al., 2014). The three key aims of ELSA were: to describe ageing in England; to investigate the relationships between the various key aspects of later life; and to understand these relationships and patterns observed (Banks et al., 2003). Each of these aims (especially the third) were strategic to support evidence based policy making (Banks et al., 2003). ELSA study data were also linked to mortality data (needed for the calculation of Healthy Working Life Expectancy) from the National Health Service Central Register. Data were collected every two years and (in 2019) there are eight waves of data available (from 2002 to 2017) (table 2.1). Mortality data (year of death) have been linked up to wave 6 (2012/13).

ELSA participants were recruited from respondents to the Health Survey for England (HSE) - an annual survey that began in 1991 and was designed to be representative of England’s community dwelling population. HSE respondents from 1998, 1999 and 2001 who had consented to be recontacted provided the initial sampling frame (‘wave 0’) for

TABLE 2.1: ELSA fieldwork dates for waves 1-6

Wave	Fieldwork years	Range of interview months recorded	Middle month of fieldwork
1	2002/03	03/2002 - 03/2003	08/2002
2	2004/05	06/2004 - 07/2005	12/2004
3	2006/07	05/2006 - 08/2007	12/2006
4	2008/09	06/2008 - 07/2009	12/2008
5	2010/11	07/2010 - 06/2011	12/2010
6	2012/13	05/2012 - 05/2013	11/2012

ELSA in 2002. The sampling frame was refreshed for ELSA waves 3, 4, 6 and 7 so that collected data continued to represent adults from age 50 despite cohort ageing, deaths and attrition. In all but one of these waves the refreshment sample included only adults in their early 50s. The wave 4 refreshment sample included a wider age range (adults aged 50-74 years old). Each ELSA wave of data collection was piloted using samples from HSE respondents from the year 2000. Refreshment samples were recruited from respondents to more recent HSE surveys. Cohort numbers indicate the wave at which individuals joined the ELSA core sample. For ELSA waves 1-6 (the waves linked to mortality data), only cohorts 1, 3, 4 and 6 exist as sample refreshment did not occur at waves 2 or 5. Table 2.2 below gives the birth date ranges for the original ELSA sample (cohort 1) and subsequent refreshment samples as well as the HSE years from which ELSA recruited for waves 1-6.

TABLE 2.2: ELSA sample member birth date range and samping frame HSE year(s) by cohort

Cohort	Date of birth range	HSE year(s) used as sampling frame
1	- 29/02/1952	1998, 1999, 2001
3	01/02/1952 - 29/02/1956	2001-2004
4	01/03/1933 - 29/02/1956	2006
6	01/03/1956 - 28/02/1962	2009-2011

By design, neither HSE nor ELSA took responses from adults living in institutions. As well as core ELSA sample members (comprising the nationally representative ELSA sample), ELSA interviews were carried out with some sample members' partners including those who were under 50 years old. Some partners became core sample members at wave 3. Interviews were carried out in person using Computer-Assisted Personal Interview (CAPI) software and participants were also asked to complete a self-completion questionnaire which was either returned by post or to the interviewer directly. At alternate waves (waves 2, 4, 6), core sample members received a visit from a nurse who asked additional questions, measured height and weight, and collected various other biological samples and measurements (NatCen Social Research, 2018).

2.1.1 Survey design

The ELSA study population structure was inherited from nationally representative Health Survey for England data and used a complex survey design with clustering, stratification, and weighting strategies to account for non-response and survey attrition. Analysing data from complex survey designs is not always appropriate without accounting for the design - usually with survey weights. Weighting increases and decreases the relative 'importance' of individuals in the sample in order to better represent the underlying population. For example, a subgroup of the study population associated with non-response might have weights greater than 1 so that this group is no longer underrepresented in analyses.

Two types of weights exist for ELSA at most waves:

1. **longitudinal weights** for core sample member respondents at each wave who had been responding core members since the first wave (consistent cohort 1 responders)

2. **cross-sectional weights** for all responding core sample members at each wave, and additionally for all respondents to the self-completion questionnaires at each wave (non-response to the self-completion questionnaires was non-random among those who participated in the main interview).

Although ELSA was designed to be nationally representative, weights were calculated because variables associated with non-response were identified at each wave. However, use of the longitudinal weights (for cohort 1 only without refreshment samples) would mean sample size reduces rapidly with survey attrition, and an effect of cohort ageing is that transitions are not observed at the youngest ages at follow up time points. Further, the methodology for estimating HWLE requires that individuals' weights are the same at each survey time point, meaning that adopting the longitudinal weighting strategy (which allocates consistent cohort 1 responders a new weight at each wave as the sample population changes) is impossible. Similarly, to employ cross-sectional weights would require selection of just one survey wave and studying only the individuals who participated in that wave. A key disadvantage of this approach is that the sample at time points for which the cross-sectional weights were not designed will not reflect the national population; whilst the prevalence of state occupation can be observed at the weighted wave, it is the transitions observed either side of this wave that form the basis of the HWLE estimates.

HWLE was therefore estimated without survey weighting using the sample of all ELSA participants who were core sample members in at least one ELSA survey wave (up to wave 6) unless all study and mortality data were missing for the individual. Some individuals who were interviewed originally as partners later joined the core sample; in these cases ($<$ 1% of the final study population), data collected prior to the individual joining the core sample were included to maximise study data for analysis and the earliest observations for some in this group took place when they were younger than 50 years old.

Partners from the HSE interview who were still partners at ELSA interview were 'old' or 'young' partners if they were age-eligible for the study themselves or not respectively. People who became partners (of core sample members) since the HSE interview were termed 'new partners'

A mistake in the cohort 3 sample refreshment algorithm (identified while preparing data for analysis and then checked in ELSA documentation) meant new sample members were recruited with birth dates on or after 1 March 1953 instead of 1 March 1952. To correct for this, young partners from cohort 1 and old partners from cohort 3 who were born in the mistakenly omitted birth date range were reclassified by ELSA as core sample members. This affected 103 people. A further 63 cohort 1 partners also became sample members in cohort 3. Thus, 166 cohort 3 sample members had previously been interviewed while classed as partners of cohort 1 sample members. The 248 individuals born between 1

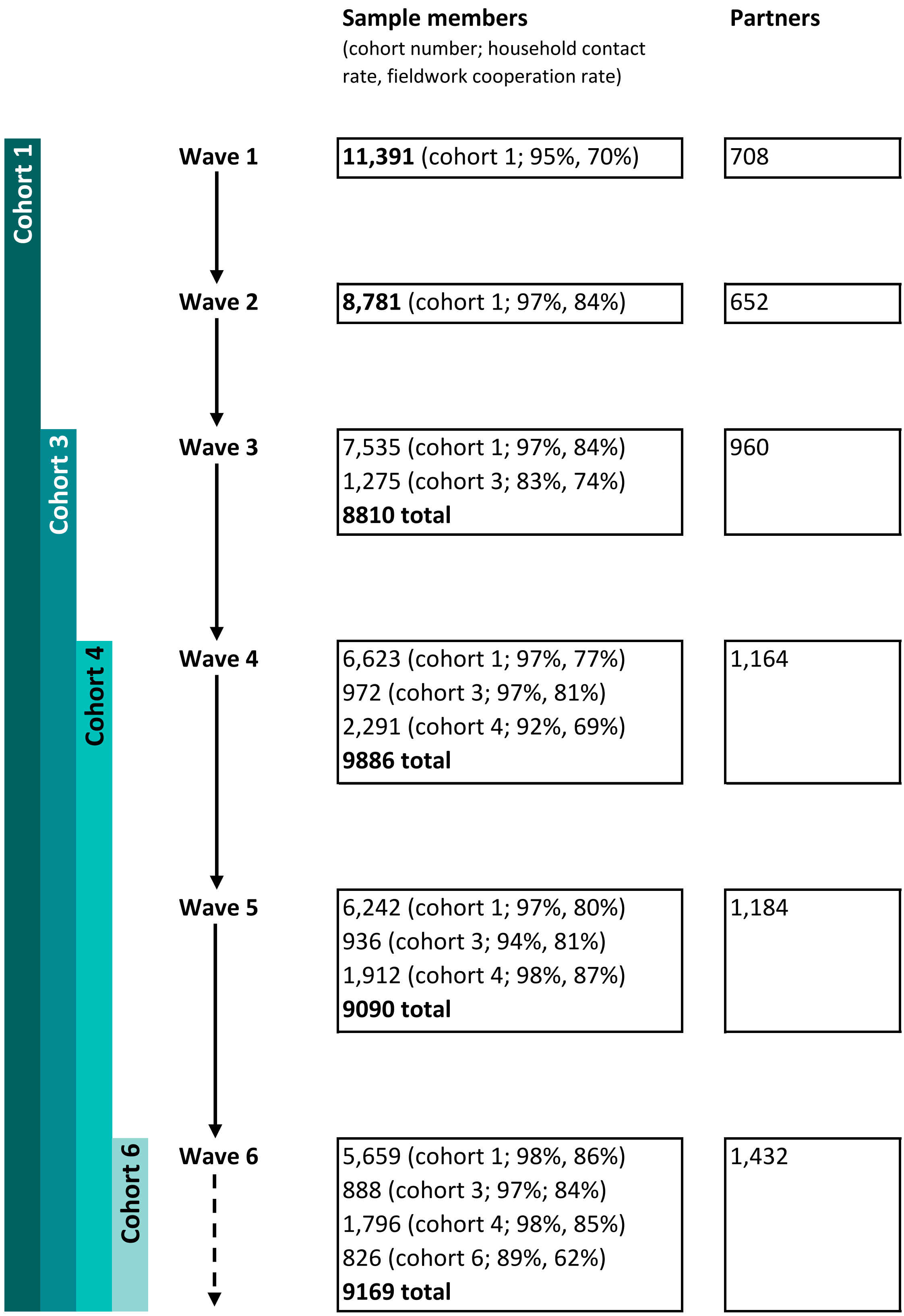


FIGURE 2.1: ELSA achieved samples for waves 1 to 6 compared to cohort baseline response. Household contact rate is the percentage of eligible households where interviewers successfully contacted at least one sample member. Fieldwork cooperation rate is the interviewed percentage of eligible and contacted individuals.

March 1952 and 28 February 1953 who should have been part of the cohort 3 refreshment sample were added to cohort 4.

The ELSA sample flow chart (figure 2.1) shows the achieved sample sizes at each wave compared to the baseline respondents for each cohort (Bridges et al., 2015b). Individuals who did not respond when first contacted as core sample members but who responded at a later wave were not included in ELSA technical reports of achieved sample size at follow up, but were included in the sample for this study. Total achieved sample size among people who were ever core members is discussed in section 2.5.2 and given in table 2.8.

Healthy Working Life Expectancy was estimated for adults age 50 in England using responses to ELSA waves 1-6 (2002/3-2012/13). Wave 6 was the last survey wave that was linked to mortality data. Mortality-linked (year of death from the National Health Service Central Register) ELSA data were obtained from the UK Data Service. Months of death were imputed based on 2010 monthly death rates in England and known vital status at interview date in the year of death.

2.2 Statistical methods

HWLE was estimated using an interpolated Markov chain multi-state modelling approach, which involved individuals making transitions between states defined by health and work status over small periods of time (interpolated Markov chain multi-state modelling).

A multi-state model was defined including the four combinations of health status (healthy or not healthy) and work status (in work or not in work) (figure 2.2). HWLE was the average number of years expected to be spent in both health and work from age 50 and relates to time spent in the state shown top-left of the multi-state model diagram: both healthy and in work.

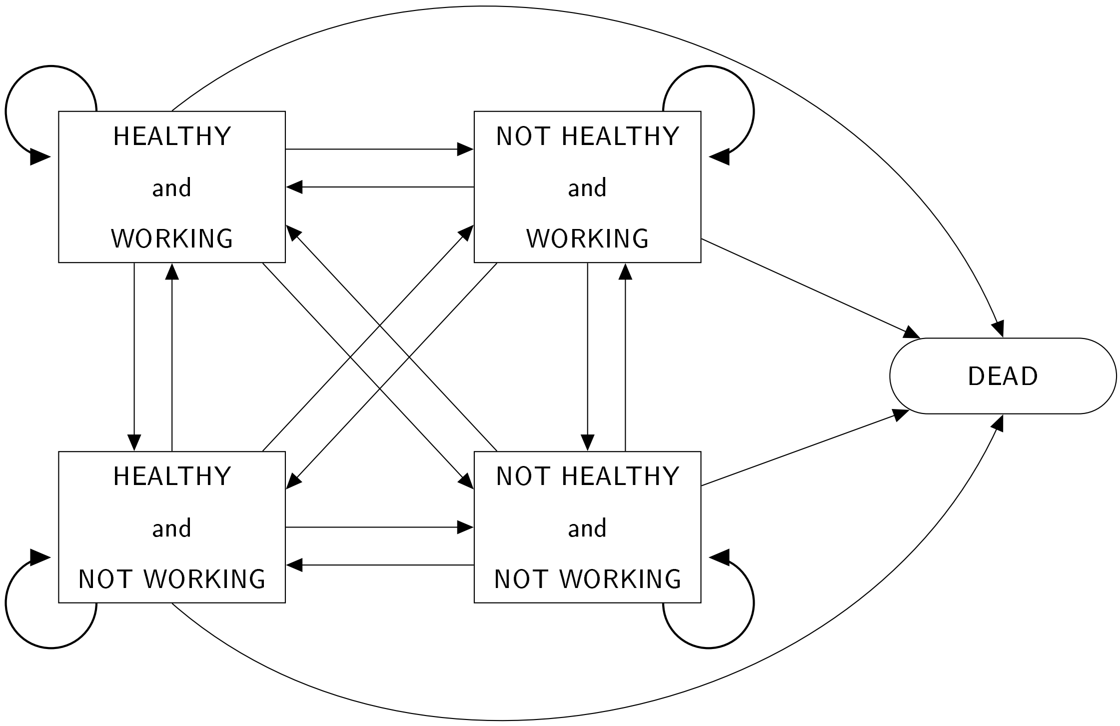


FIGURE 2.2: States and permitted transitions (shown with arrow heads) in the HWLE model. Circular arrows represent occupation of the same state at successive time points.

2.2.1 Introduction to multi-state models

Multi-state processes are discrete-valued stochastic processes. A multi-state process visits a finite set of possible outcomes or states with randomness affecting the transition times and events occurring (Andersen and Keiding, 2002; Hougaard, 1999). For example, two individuals with comparable health and sociodemographic circumstances may make different decisions about whether or when to apply for a job, leave a job, or retire. Multi-state processes often (but not always) evolve over time so we adopt indexing parameter t for measurements in the sequence. The hazards (instantaneous risks) of transitions are referred to as transition rates or intensities.

Definition 2.2.1. A *multi-state process* is a sequence of random variables $\mathbf{X} = \{X_t\}$ with finite state space $S = \{1, ..., N\}$, where $t \in T$ for (time) interval $T = [0, \tau]$ with $\tau < \infty$. The hazard (transition) rate from state i to state j $(i, j \in S)$, $\alpha_{ij}(t)$, is written as

$$\alpha_{ij}(t) = \lim_{\delta t \to 0} \frac{p^{ij}(t, t + \delta t)}{\delta t} \tag{2.1}$$

Multi-state models have been applied in medical research in a wide range of areas (Collett, 2015). The simple survival model is an example of a multi-state model with permitted transitions from the alive state to the dead state, with these transitions occurring with transition rate $\alpha(t)$ (figure 2.3). In a simple survival model, all individuals start in the same initial state (alive).

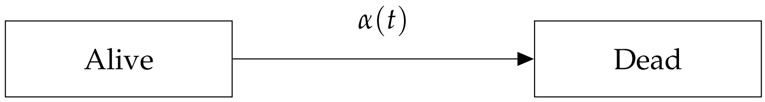


FIGURE 2.3: In the simple survival model individuals move from the alive state to the dead state with transition rate $\alpha(t)$. $\alpha(t) = \alpha_{01}(t)$ where state $0 =$ alive and state $1 =$ dead.

In the simple survival model, mortality is an absorbing state from which no further transitions are possible (the state cannot be exited). Survival analyses are commonly used in medical research to compare outcomes over time between groups (for example, mortality among subpopulations with and without osteoarthritis (Wilkie et al., 2019)) as well as identify factors associated with higher or lower risks of an outcome of interest (for example, to investigate early risk factors or protective factors for death or liver transplantation for patients with bile duct disease (Wang et al., 2019)).

A competing risks model allows multiple routes away from a state. An example is a multi-state model with an alive state and two (or more) absorbing dead states, which could be death due to some specific cause and death due to all other causes (figure 2.4). For example, Gillam et al. (2010) modelled death as a competing risk to prosthesis surgery revision as use of a two state simple survival model led to biased results. In another example of a competing risk multi-state model applied in the medical literature, Jalali et al. (2014) used a model with one starting state (alive) and four outcome states to investigate whether EBMT (The European Society for Blood and Marrow Transplantation) risk score differentiated individuals at higher or lower risks of relapse or death (each with or without graft-versus-host disease) among people treated for acute myelogenous leukemia with allogeneic stem cell transplantation.

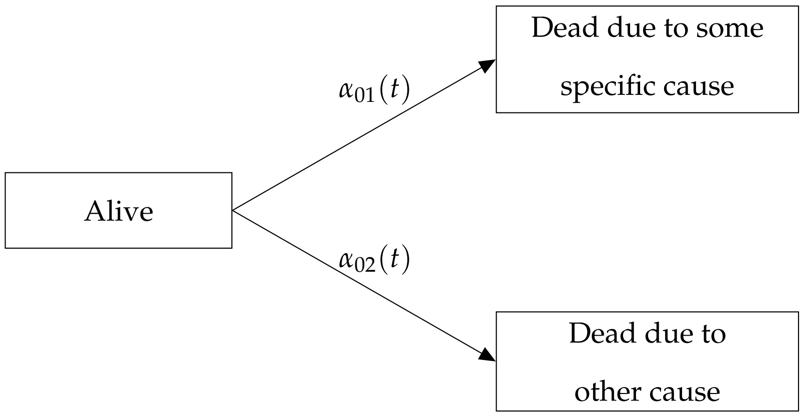


FIGURE 2.4: Example of a competing risks model where individuals move from the alive state to one of two dead states.

Additional non-absorbing states may be included in multi-state models with appropriate permitted transitions, as illustrated in the illness-death model examples below (figure 2.5). Illness-death multi-state models have been used to research a range of medical conditions (especially those that are irreversible), for example degenerative dementia (Xue et al., 2017; Touraine et al., 2016; Harezlak et al., 2003). Examples of usage of more complex multi-state models with reversible transitions include modelling of HIV disease progression among antiretroviral therapy patients in Zimbabwe (Matsena Zingoni et al., 2019) and assessment of treatment cost effectiveness for multiple sclerosis (Palace et al., 2014).

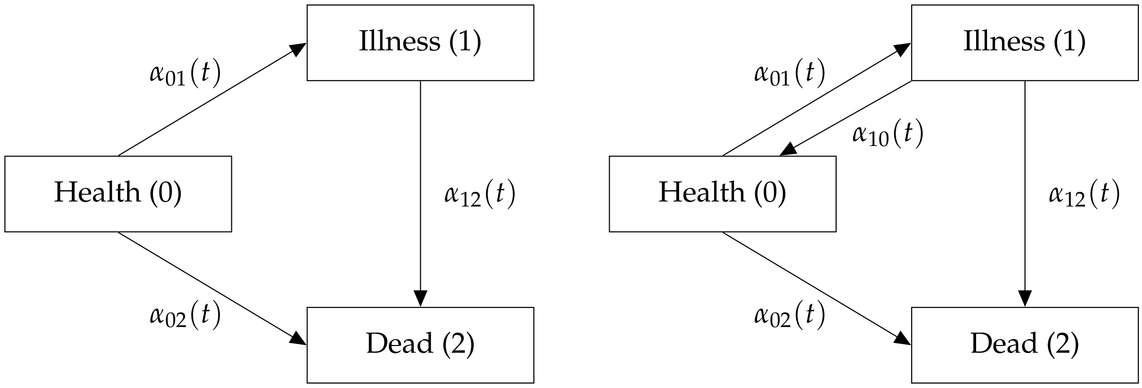


FIGURE 2.5: Progressive illness-death model (left) and model with permitted return from illness to health state (right).

Related to transition intensities are transition probabilities, which can also be used to characterise multi-state processes. Transition probabilities describe movement between states in a multi-state model over a fixed time interval and are therefore suited to discrete-time processes including 'cross-longitudinal' survey data (panel data from repeated cross-sectional surveys of a cohort).

Definition 2.2.2. *Transition probability* is the probability of moving between two specified states $i \to j$ (or remaining in the same state) over a specified time interval (r, s), given the history of the process H_{r-}

$$p^{ij}(r,s) = P(X(s) = j|X(r) = i, H_{r-}) \tag{2.2}$$

where $r < s \leq \tau$ and $i, j \in S$ (τ and S from definition 2.2.1 on page 76). $X(r)$ and $X(s)$ denote the state(s) occupied at times r and s respectively and H_{r-} is the history of the process until time r: $\{X(t); 0 \leq t \leq r\}$.

For a discrete-time process this can be written as

$$p^{ij}(t_n, t_{n+1}) = p(X(t_{n+1}) = j|X(t_n) = i, X(t_{n-1}), ..., X(t_0)) \tag{2.3}$$

where n is in $[1, k-1]$ and $t.$ denotes a discrete time point in a specified continuous time interval. $X(t_0), ..., X(t_k)$ are the states occupied at times $t_0, ..., t_k$ respectively in the discrete-time process.

The mathematics of multi-state models can be (and typically is) simplified by assuming that the process is memoryless (the 'Markov property'), so that transition intensities and transition probabilities can be estimated without consideration of the history of previous state occupation. In multi-state Markov models, the probabilities associated with being in each given state at the next time point depend only on the state currently occupied.

2.2.2 Markov chains

Markov chains are stochastic (random) processes where the next value in the sequence only ever depends on the present value.

Markov chains have finite state spaces of values that may be taken by random variables in the sequence. That is, there is a countable set of states that a process may be in at any given time.

Definition 2.2.3. A *discrete-time Markov chain* is a sequence (set) of random variables $\mathbf{X} = \{X_0, X_1, X_2, ..., X_k\}$ that satisfies the Markov property:

$$P(X_{n+1} = j | X_0, ..., X_n) = P(X_{n+1} = j | X_n) \tag{2.4}$$

for $n \in [1, k-1]$ where each $X_0, X_1, X_2..., X_k \in \mathbf{X}$ takes one of a countable set of values in the finite state space $S = 1, ..., N$.

The examples of multi-state processes given in figures 2.3, 2.4 and 2.5 are Markov chains when the Markov property is assumed. The sequence of random variables $X_0, X_1, X_2, ..., X_k$ in definition 2.2.3 then correspond to $X(t_0), X(t_1), X(t_2), ..., X(t_k)$ from definition 2.2.2.

Transition probability matrices give the probabilities associated with each time 'step' in the discrete-time process. When the transition probability matrix does not vary over time (as the process evolves) the Markov model is said to be (time-)homogeneous. When this is not the case, the Markov model is non-homogeneous. To simplify notation for $p^{ij}(t_n, t_{n+1})$, let $p^{ij}(t)$ denote the probability of moving from state i at time t to state j at the next time point. The transition probability matrix $\mathbf{P}(t)$ for a non-homogeneous discrete-time Markov chain with N states at time t is as follows:

$$\mathbf{P}(t) = \begin{bmatrix} p^{11}(t) & p^{12}(t) & \dots & p^{1N}(t) \\ p^{21}(t) & p^{22}(t) & \dots & p^{2N}(t) \\ \vdots & \vdots & \ddots & \vdots \\ p^{N1}(t) & p^{N2}(t) & \dots & p^{NN}(t) \end{bmatrix} \tag{2.5}$$

where $p^{ij}(t)$ is the ijth entry of $\mathbf{P}(t)$. A transition probability matrix for a homogeneous Markov chain would be the same for any time t and therefore written $\mathbf{P}$.

Each row in a transition probability matrix sums to 1 and represents the state occupation probabilities for the next step in the process, given the currently occupied state (denoted by the row number). The HWLE transition probability matrix has five rows and five columns ($N = 5$) representing the four combinations of health and employment circumstances (binary variables), with the fifth state being mortality. As mortality is an absorbing state, $p^{5j}(t) = 0$ for $j = 1, 2, 3, 4$ and $p^{5j}(t) = 1$ for $j = 5$ at all time points $t \in \{t_0, t_1, t_2, t_3, t_4, t_5\}$ (there are a maximum of six observed time points for each participant in ELSA waves 1-6).

The probability that a Markov chain starting in state i will be in state j two steps later can be found by summing the probabilities of all possible routes between i and j.

$$P(X_{n+2} = j | X_n = i) = \sum_{k=1}^{N} p^{ik}(t_n, t_{n+1}) p^{kj}(t_{n+1}, t_{n+2}) \tag{2.6}$$

For a homogeneous Markov chain (where transition probabilities are constant) this is computed by squaring the transition probability matrix.

$$P(X_{n+2} = j | X_n = i) = \sum_{k=1}^{N} p^{ik} p^{kj} = (p^2)^{ij} \tag{2.7}$$

$(p^2)^{ij}$is the ijth entry of $\mathbf{P}^2$. For a homogeneous Markov chain, state occupation probabilities in m steps are given by $\mathbf{P}^m$ with the ijth entry $(p^m)^{ij}$ giving the probability of moving from state i to state j in m steps. Estimating m-step state occupation for non-homogeneous Markov chains requires the transition probability matrices for every intermediate step.

2.2.3 Method for estimating HWLE

To estimate Healthy Working Life Expectancy in England, this research used the method of health expectancy estimation presented by Lièvre et al. (2003) drawing on the work of Laditka and Wolf (1995; 1998). This involved treatment of the individuals in a population as moving through a discrete-time multi-state process (see figure 2.2 on page 75) and estimation of transition probabilities using interpolated Markov chains. Interpolation refers to the estimation of transition probabilities at regular time intervals, which may be smaller than the duration between the measured survey time points. These interpolation 'step' sizes are multiples of months - for example, one, three, 12 or 24 months. Taking a small time interval for interpolation step size acknowledges and approximates the continuous nature of the true underlying process with the comparative computational ease of working with discrete-time Markov chains.

Transition probability models are specified for each permitted transition in the multistate model using the logit link function. The log odds of each permitted transition over one interpolation step is modelled on an intercept term and age. Transition probabilities from the currently occupied state to that occupied at the next measurement are assumed to be constant over time within each year of age and not to be affected by any history of previous state occupation (the Markov property). Parameters for each model are estimated using maximum likelihood estimation, allowing transition probabilities to be estimated by evaluating the models at each year of age. The transition probabilities then enable estimation of expected lengths of stay in a state, given the individual's starting state, over a specified time interval. Population health expectancies are weighted sums of expected stay-times according to the population prevalence of state occupation at the starting age (the proportions of people starting in each health/work state at age 50) - either using the prevalences observed in the study population, or through estimating the 'stable prevalences' that (eventually) will be observed in any population with the same transition intensities. Observed population prevalences are easily computed using a representative dataset, whereas stable prevalences are computed using transition intensities and usually lead to optimistic health expectancy results (Lièvre et al., 2003).

The steps to calculate population health expectancies with confidence intervals are outlined in table 2.3.

TABLE 2.3: Steps in methodology for estimating HWLE using the state occupation proportions observed in a population

1. Specify the multi-state model with permitted transitions and absorbing state(s)
2. Select the length of time (number of months) for interpolation step size
3. For each non-absorbing state, model the log odds of departure to each other accessible state individually as functions of age
4. Use maximum likelihood estimation to estimate a vector of parameters for the models from the previous step (maximise the log likelihood function)
5. Estimate one-step transition probabilities by evaluating each model at each year of age (e.g. monthly transition probabilities at each year of age if step size is one month)
6. Estimate the expected stay-time in each health state ('health expectancies') given the starting state through a summation of the estimated transition probabilities
7. Using population prevalences of state occupation, take a weighted average of the health expectancies from the previous step to find health expectancies on average irrespective of starting state
8. Estimate the second-order partial derivatives of the log likelihood function at the maximum likelihood parameter estimates (the Hessian matrix)
9. Estimate the variances and covariances for transition probabilities and health expectancies using a Taylor series approximation and the Hessian matrix
10. Present the health expectancy variances and covariances as the covariance matrix, from which standard errors and confidence intervals for health expectancy estimates can be computed.

Specifying the model (steps 1-3)

The Healthy Working Life Expectancy model contains four non-absorbing states with all available transitions permitted (see figure 2.2 on page 75). Transitions are permitted between all non-absorbing states and from all non-absorbing states to an absorbing state of death.

The states in the HWLE model are:

1: Healthy and in work

2: Healthy and not in work

3: Not healthy and in work

4: Not healthy and not in work

5: Dead (absorbing state)

The transition probabilities, including the probability of remaining in the same state, are obtained by modelling the log odds of each possible departure route from each state. For each permitted transition between distinct states, express the natural log of the odds of the transition during a given time interval in terms of an intercept term, age and any other covariates. The length of time interval is one interpolation step z specified as a multiple of months. Let ${}_z\mathbf{P}_x$ denote the matrix of transition probabilities from any state i occupied at age x to any state j occupied at age $x+z$. Let ${}_zp_x^{ij}$ denote the ijth element of ${}_z\mathbf{P}_x$ where ${}_zp_x^{ij}$ is the probability that an individual in state i at age x will be in state j after time z.

Equation 2.8 models the log odds of transition from state i to state j ($i \neq j$) in one step on age x (at the start of the interval) and no other covariates:

$$log \frac{{}_zp_x^{ij}}{{}_zp_x^{ii}} = a_{ij}(z) + b_{ij}(z)x \tag{2.8}$$

Sixteen such models are developed for analysis of HWLE as there are four possible target states j for every non-absorbing state i. For example, if taking state 1 (both healthy and in work) as starting state i, separate models will be required for transitions into states 2, 3, 4 and 5. No models are required for transitions starting in state 5 (dead) as departure from an absorbing state is not possible.

Transition probabilities are assumed to be constant (a homogeneous Markov chain) over time within each year of age. Age-dependent transition probability matrices are achieved by including age as a covariate in the transition probability models.

Because z represents one unit of time (the number of months selected as the interpolation step size), it can be absorbed in the notation to give $log\frac{p_x^{ij}}{p_x^{ii}} = a_{ij} + b_{ij}x$. Then, for example, if z was defined as six months, p_{50}^{12} (entry $(1,2)$ of $\mathbf{P}_{50}$) would be the probability of being in state 2 at age 50 years plus six months, given that state 1 was occupied at age 50 years.

State occupancy probabilities over longer time intervals are found through matrix multiplication of the transition probability matrices at each interpolation step contained in the time interval. ${}_yp_x^{\bullet\bullet}$ for any states • and for some time interval $(x, x+y)$ is the corresponding (••th) entry of the matrix product ${}_y\mathbf{P}_x = \mathbf{P}_x\mathbf{P}_{x+z}\cdots\mathbf{P}_{y-z}$.

Estimating transition probabilities and health expectancies (steps 4-7)

Model parameters (a_{ij} and b_{ij} for all i and j with $i \neq j$; equation 2.8) are estimated using a maximum likelihood estimation process. For a given (joint) probability distribution, the *likelihood function* indicates how probable it would be for proposed values of statistical parameter(s) to generate the data observed. *Maximum likelihood estimation* is used to infer values of the statistical parameters for which the observed data are most likely to be generated.

To find the maximum likelihood estimates of parameters for each of the transition probability models, we first express the likelihood of each transition observed in the data through the likelihood contributions made by each individual sample member. The natural log of these likelihood contributions are then summed to find the total log-likelihood.

Let $\underline{\theta}$ be the vector of model parameters (a_{ij} and b_{ij} for all i and j with $i \neq j$) and let $L(\underline{\theta})$ denote the likelihood. The log-likelihood is $l(\underline{\theta}) = log(L(\underline{\theta}))$.

The likelihood contibution of an individual q observed at state i at age x_1 and state j at age x_2 is ${}_{x_2-x_1}p_{x_1}^{ij}$ (entry (i,j) of ${}_{x_2-x_1}\mathbf{P}_{x_1}$). If this individual were subsequently observed in state h at age x_3, the component of the total likelihood contributed by individual q would be given by $L^{(q)} = {}_{x_2-x_1}p^{ij}_{x_1} \times {}_{x_3-x_2}p^{jh}_{x_2}$.

The total log-likelihood of a sample of size Q is given by

$$l = \sum_{q=1}^{Q} log(L^{(q)}) \tag{2.9}$$

This vector of maximum likelihood parameter estimates $\underline{\widehat{\theta}}$ maximizes the total log-likelihood and defines the model that is most likely to have generated the data observed. The process of maximum likelihood estimation involves proposal of model parameters and calculation of the likelihood of the observed data being generated by the proposed model (the total log-likelihood), where the proposed model is the set of transition probability models specified previously (substituting the proposed parameters for each a_{ij} and b_{ij}). A new set of model parameters is then proposed and the log-likelihood re-evaluated. New models are proposed in an iterative process to identify the model that maximises the log-likelihood, which is selected as the maximum likelihood model. The vector of maximum likelihood model parameters $\underline{\widehat{\theta}}$ is the maximum likelihood estimator of $\underline{\theta}$.

$\underline{\widehat{\theta}}$ contains maximum likelihood parameter estimates $\widehat{a_{ij}}$ and $\widehat{b_{ij}}$ for all transition probability logit models to be estimated. Estimating parameters for all transition probability models simultaneously is necessary to maximise the likelihood of observing the entire dataset as individuals make a series of different transitions over time, and to allow for paths through additional states between observed time points at interviews two (or more) years apart. For example, a step size of three months means modelling individuals to make any permitted transition (including staying in the same state) every three months between survey observations, producing a Markov chain containing any number of the permitted transitions for which log odds are modelled individually (see equation 2.8). It is assumed that transitions (including remaining in the same state) occur exactly once over each interpolation step.

The estimated transition probabilities are found through evaluation of the transition probability models (at the maximum likelihood parameter estimates for each age $\geq$50) to give a transition probability matrix for each interpolated time point in the process.

(Recall that if steps are one month, for example, monthly transition probability matrices will be identical within each year of age). The expected length of stay (in total from all visits) in a state j given that an individual started in state i at age x is denoted e_x^{ij}. The health expectancy e_x^{ij} is estimated by summing the estimated $i \rightarrow j$ transition probabilities for all time intervals $(x, x+y)$, where y increases incrementally in interpolation steps:

$$\widehat{e_x^{ij}} = e_x^{ij}(\widehat{\underline{\theta}}) = \sum_{y=1}^{\infty} {}_y p_x^{ij}(\widehat{\underline{\theta}}) = \sum_{y=1}^{\infty} \widehat{{}_y p_x^{ij}} \tag{2.10}$$

A maximum age of 120 years is assumed and the upper limit of y in practice (shown as ∞ in equation 2.10) is therefore 70 when $x = 50$ and the length of interpolation steps is one year (12 months). The summation ends after $y = 840$ when taking interpolation steps of length one month (12 steps per year $\times$ 70 years from age 50 to age 120). Recall from pages 80 and 84 that transition probabilities over more than one step in a Markov chain (here, $y \geq 2$) are obtained through matrix multiplication of the transition probability matrices at each contained time point (interpolation steps).

The average expected stay in a given state for a population is found by taking the weighted average of starting-state specific health expectancies, weighted according to the observed population prevalence of state occupation. The population health expectancy for HWLE (state 1) is the average number of years a person in the population is expected to be both healthy and in work (from age 50 by definition) by taking a weighted average of $\widehat{e_{50}^{11}}$, $\widehat{e_{50}^{21}}$, $\widehat{e_{50}^{31}}$ and $\widehat{e_{50}^{41}}$.

Computing confidence intervals for health expectancies (steps 8-10)

Taking the second order partial derivatives of the log-likelihood function forms the Hessian matrix from which the information matrix $\mathbf{I}$ (the negative of the Hessian matrix) can be found. The covariance matrix $\mathbf{V}(\widehat{\underline{\theta}})$ is estimated by dividing the inverse of the information matrix (evaluated at the maximum likelihood parameter estimates) by the sample size (equation 2.11).

$$\mathbf{V}(\widehat{\underline{\theta}}) = \frac{\mathbf{I}^{-1}}{samplesize} \tag{2.11}$$

It is then straightforward to estimate standard errors for the health expectancies (that can be used to estimate confidence intervals) using a Taylor series approximation of the transition probabilities (equation 2.12) and the multivariate delta method for estimating the variances and covariances of the parameter estimates (equations 2.13 and 2.14) (Raykov and Marcoulides, 2004).

$$ {}_y p_x^{ij}(\widehat{\underline{\theta}}) \approx {}_y p_x^{ij}(\underline{\theta}) + (\widehat{\underline{\theta}} - \underline{\theta})' \frac{\delta}{\delta\theta} {}_y p_x^{ij}(\underline{\theta}) \tag{2.12} $$

$$ Var({}_y p_x^{ij}(\widehat{\underline{\theta}})) \approx (\frac{\delta}{\delta\underline{\theta}} {}_y p_x^{ij}(\underline{\theta}))' \mathbf{V}(\underline{\theta}) \frac{\delta}{\delta\underline{\theta}} {}_y p_x^{ij}(\underline{\theta}) \tag{2.13} $$

$$ Cov({}_y p_x^{ij}(\widehat{\underline{\theta}}), {}_y p_x^{gh}(\widehat{\underline{\theta}})) \approx (\frac{\delta}{\delta\underline{\theta}} {}_y p_x^{ij}(\underline{\theta}))' \mathbf{V}(\underline{\theta}) \frac{\delta}{\delta\underline{\theta}} {}_y p_x^{gh}(\underline{\theta}) \tag{2.14} $$

$$ Var(\widehat{e_x^{ij}}) = Var(e_x^{ij}(\widehat{\underline{\theta}})) \approx \sum_y \sum_z (\frac{\delta}{\delta\underline{\theta}} {}_y p_x^{ij}(\underline{\theta}))' \mathbf{V}(\underline{\theta}) \frac{\delta}{\delta\underline{\theta}} {}_z p_x^{ij}(\underline{\theta}) \tag{2.15} $$

$$ Cov(\widehat{e_x^{ij}}, \widehat{e_x^{ih}}) = Cov(e_x^{ij}(\widehat{\underline{\theta}}), e_x^{ih}(\widehat{\underline{\theta}})) \approx \sum_y \sum_z (\frac{\delta}{\delta\underline{\theta}} {}_y p_x^{ij}(\underline{\theta}))' \mathbf{V}(\underline{\theta}) \frac{\delta}{\delta\underline{\theta}} {}_z p_x^{ih}(\underline{\theta}) \tag{2.16} $$

Variances and covariances of starting-state specific health expectancies (equations 2.15 and 2.16 above, using equation 2.10 and rules for calculating variance) allow estimation of the variance of average health expectancies regardless of starting state (equation 2.17 for the HWLE model with four alive states).

$$ Var(\widehat{e_x^{\cdot j}}) = Var(\sum_{i=1}^{4} \widehat{e_x^{ij}}) = \sum_{i=1}^{4} Var(\widehat{e_x^{ij}}) + 2 \sum_{i<h}^{i=3,h=4} Cov(\widehat{e_x^{ij}}, \widehat{e_x^{hj}}) \tag{2.17} $$

As the health expectancies are asymptotically normally distributed, confidence intervals are obtained using standard errors $\frac{\sqrt{Var(\widehat{e_x^{\cdot j}})}}{\sqrt{samplesize}}$ and the standard normal distribution.

For a more in depth treatment of the health expectancy estimation methodology, the reader is referred to Lièvre et al., 2003.

2.2.4 IMaCh software for estimating HWLE

The HWLE computation methodology described in the previous section 2.2.3 is implemented in IMaCh (**I**nterpolated **Ma**rkov **Ch**ain) software, which was purpose built by Nicolas Brouard (with previous contributions from Agnes Lievre and Christopher Heathcote) for health expectancy analysis of cross-longitudinal data. Information about IMaCh software and free download links can be found on the IMaCh documentation wiki website: `http://euroreves.ined.fr/imach/wiki/index.php/Documentation`.

Recall from page 83 that IMaCh models the log odds of each permitted transition individually: $log\frac{p_x^{ij}}{p_x^{ii}} = a_{ij} + b_{ij}x$, where i is the starting state, j is the destination state and x is age. This gives the following 16 transition probability models for estimating HWLE.

Transitions starting from state 1 (healthy and in work)

$$log\frac{p_x^{12}}{p_x^{11}} = a_{12} + b_{12}x$$

$$log\frac{p_x^{13}}{p_x^{11}} = a_{13} + b_{13}x$$

$$log\frac{p_x^{14}}{p_x^{11}} = a_{14} + b_{14}x$$

$$log\frac{p_x^{15}}{p_x^{11}} = a_{15} + b_{15}x$$

Transitions starting from state 2 (healthy and not in work)

$$log\frac{p_x^{21}}{p_x^{22}} = a_{21} + b_{21}x$$

$$log\frac{p_x^{23}}{p_x^{22}} = a_{23} + b_{23}x$$

$$log\frac{p_x^{24}}{p_x^{22}} = a_{24} + b_{24}x$$

$$log\frac{p_x^{25}}{p_x^{22}} = a_{25} + b_{25}x$$

Transitions starting from state 3 (not healthy and in work)

$$log\frac{p_x^{31}}{p_x^{33}} = a_{31} + b_{31}x$$

$$log\frac{p_x^{32}}{p_x^{33}} = a_{32} + b_{32}x$$

$$log\frac{p_x^{34}}{p_x^{33}} = a_{34} + b_{34}x$$

$$log\frac{p_x^{35}}{p_x^{33}} = a_{35} + b_{35}x$$

Transitions starting from state 4 (not healthy and not in work)

$$log\frac{p_x^{41}}{p_x^{44}} = a_{41} + b_{41}x$$

$$log\frac{p_x^{42}}{p_x^{44}} = a_{42} + b_{42}x$$

$$log\frac{p_x^{43}}{p_x^{44}} = a_{43} + b_{43}x$$

$$log\frac{p_x^{45}}{p_x^{44}} = a_{45} + b_{45}x$$

IMaCh writes a results file with the maximum likelihood parameter estimates for each transition probability model. IMaCh is a console application and analysis requires writing a text file ('parameter file') specifying instructions and starting conditions for analysis. The filepath for this parameter file is entered into the console to initiate analysis. A description of the IMaCh parameter file for estimating HWLE in England overall is presented in appendix C. The parameter file contains the filename for the dataset, which must also be written as a text file adhering to specific formatting guidelines. IMaCh writes the outputs from the 'run' onto new files created in the same directory as the parameter and data files.

Missing data handling in IMaCh

IMaCh allows for missing health/work status information when individuals are known to be alive. This is denoted with status '-1' and could be used to indicate missing response in a participating survey wave or non-response at a given survey wave (but where the individual is known to be alive). In the case of a -1 status, the log-likelihood contribution is based on transition into any alive state. Where an individual moves to an alive but unknown HWLE status (-1) from a known HWLE status (state i), the transition cannot contribute to estimation of the transition probability for the unknown true transition (${}_y p_x^{ij}$, where x is age, i is the starting HWLE status and j is the true destination HWLE status). Instead, the transition contributes to the estimation of ${}_y p_x^{i1} + {}_y p_x^{i2} + {}_y p_x^{i3} + {}_y p_x^{i4}$. That is, the transition contributes to transition probability estimation of moving from state i into any alive state j despite the loss of HWLE status information. However, if adding additional covariate(s) into the transition probability models, individuals with missing covariate data (at any number of observed time points) will be excluded from analysis. The status '-2' is used where vital status is unknown and instructs IMaCh to ignore the time point.

2.3 Operationalisation of variables for analysis

2.3.1 Definitions of health and work for HWLE in ELSA

Operationalisation of health

Health and its role in workforce participation has often been researched using a SAH question (*"In general, how would you rate your health?"* or similar) (Au and Johnston, 2014; Haan and Myck, 2009; Cai and Kalb, 2006). This item is the first question of 36 in the validated general health questionnaire SF-36 (McHorney et al., 1993) and is also available in ELSA. While this measure has advantages in its ease of use, there are many aspects and interpretations of health; health indicators should therefore correspond to the research context and rationale (Au and Johnston, 2014; Bowling, 2005; Bound, 1991). Although SAH can be informative, disadvantages include cultural differences in reporting behaviour and only weak association with limitations resulting from physical and mental health (SAH is largely driven by perceived vitality) (Au and Johnston, 2014). These disadvantages present key issues to an indicator such as HWLE, which must be suitable for use over time and in multiple study contexts with a high level of interpretability. Health was therefore defined in this study through the presence or absence of limiting long-standing illness as per the definition of disability in the Equality Act 2010 (Equality Act, 2010, p. 4):

A person (P) has a disability if—

(a) P has a physical or mental impairment, and

(b) the impairment has a substantial and long-term adverse effect on P's ability to carry out normal day-to-day activities.

In ELSA, this definition was operationalised using a combination of two survey items:

[Do you / Does [name]] have any long-standing illness, disability or infirmity? By long-standing I mean anything that has troubled [you / [name]] over a period of time, or that is likely to affect [you / [name]] over a period of time.

1 Yes

2 No

IF whether has long-standing illness = yes

(Does this / Do these) illness(es) or disability(ies) limit [your / [name's]] activities in any way?

1 Yes

2 No

Health for HWLE was defined as the absence of a limiting long-standing illness. That is, a person in ELSA was unhealthy if they reported having a long-term health condition that impacted function and activities. Otherwise, they were counted as healthy (including people with long-standing illnesses that did not limit activities).

There are various strengths to this operationalisation of health: the selected self-report items provide some scope for subjective interpretation of one's own health (Jagger et al., 2010); the questions are targeted to a specific aspect of health (global activity restriction); and the use of two survey items could lead to better reporting consistency. Multi-item measures are more precise, reliable and stable than single item measures such as SAH (Bowling, 2005). In addition, this definition has also been adopted by the UK government's strategy for one million more people with disabilities to be in work by 2027 (DWP, 2017c), with long-term defined as 12 months or more in line with the Government Statistical Service's harmonised statistical measure of disability. Similarity with the Government Statistical Service's harmonised statistical measure of disability improves the comparability of HWLE to other published indicators. The differences identified in work engagement levels and rates of movement into and out of work between healthy and disabled people as classified by the Equality Act disability definition (DWP, 2017c) suggest this indicator captures an aspect of health relevant to work capacity and participation.

These survey items are also those that most closely adhere to the conceptual framework for the Global Activity Limitation Indicator (GALI) in the ELSA questionnaires. The GALI is the recommended indicator for global (non-specific) activity restriction (Robine et al., 2003a). Unlike SAH, the GALI captures health similarly in different countries and cultural contexts (Hsiao et al., 2019; Jagger et al., 2010). The GALI is measured through one to three self-reported questions on general long-standing activity limitation and is designed to examine changes in population morbidity (testing the hypotheses of morbidity compression, expansion and dynamic equilibrium) (Robine et al., 2003a).

"**Conceptual criteria for a Global Activity Limitation Indicator (GALI):**

1. A concise set of questions: between one and three questions maximum
2. Presence of long-standing limitations: duration at least 6 months
3. Cause of activity limitation: a general health problem
4. Usual activities: the reference is to activities people usually do
5. Severity of limitations: inclusion of full range in the response with at least three levels
6. No preceding screening for health conditions

Practical criteria for a Global Activity Limitation Indicator (GALI):

1. Questions compact and in simple words
2. Same instrument for total population (including institutionalized population)
3. Same instrument for all age categories
4. To be used without further explanation or instructions
5. To be used in self-administered, face-to-face or telephone survey
6. To be used in general, health and disability surveys
7. No comparison with same age group, sex or with previous periods
8. Validated
9. If necessary the GALI can be extended by sub-questions, indicating specific life situations: school/work, house, leisure time
10. Specific question for identification of the health causes of the activity limitation
11. Specific question for use of devices or assistance"

FIGURE 2.6: Conceptual and practical criteria for a Global Activity Limitation Indicator (GALI) (Robine et al., 2003a, p. 11) (box).

The measurement of health in ELSA does not include limitation severity in the response. However, Jagger et al. (2010) compute Healthy Life Years using the no limitation GALI category and note more consistent reporting behaviour for this category than in rating severity of limitation. Other weaknesses of the ELSA survey items are that the duration of 'long-standing' is not defined, and the wording 'illness, disability or infirmity' may not be as clear as typical GALI wording "health problem" to promote consistent understanding and reporting among respondents.

Operationalisation of work

All forms of paid work were treated as 'work' for the HWLE indicator; voluntary work and other unpaid socially productive activities were excluded. Work was operationalised using a single survey item. Respondents were shown a card listing the following activities: paid work; self-employment; voluntary work; cared for someone; looked after home or family; attended a formal educational or training course; none of these. Respondents were then asked what activities they had participated in within the last month (*"Did you do any of these activities during the last month, that is since [date month ago]?"* If yes, probe: *"Which ones?"*). People who reported participating in employment or self-employment were considered to be in work. Those who did not report participating in employment or self-employment in the month preceding interview were considered not to be in work.

2.3.2 Identifiers of population subgroups

Sub-populations by sex, socio-economic status (IMD quintile and education level), occupational status, and region were identified. Sex (male/female) was identified using self-report as indicated in the ELSA 'harmonised dataset'. (For all participants, the harmonised dataset contains a subset of key variables and derived variables for all waves with responses standardised to account for differences in questions, responses, or coding conventions at each wave.) Educational attainment was identified from the earliest response which was categorised using the ELSA simplification of 1997 International Standard Classification of Education (ISCED-97) codes: less than secondary education, upper secondary education, tertiary education (education level more advanced than upper secondary), or other (where ELSA could not classify education level for example due to foreign qualifications) (OECD, 1999). IMD was defined by the earliest record of quintile of IMD and coded 1 (least) to 5 (most) deprived quintiles of England based on the national distribution (not the sample distribution).

Occupation type was identified from the earliest response to ELSA's National Statistics Socio-economic Classification (NS-SEC) survey items regarding current (or recent/upcoming)

main occupation and categorised by the ELSA project into non-manual, manual and self-employed occupations (Hallqvist et al., 1998) as follows:
Non-manual occupations:

- employers in large organisations
- higher managerial occupations
- higher professional occupations
- lower professional and higher technical
- lower managerial occupations
- higher supervisory occupations
- intermediate
- employers in small organisations

Manual occupations:

- lower supervisory occupations
- lower technical
- semi-routine
- routine

Self-employed:

- own account workers

Occupation was not recorded at wave 1 and was unknown for individuals who did not respond to follow-up interviews. HWLE by occupation was therefore estimated using waves 2-6 to minimise potential bias. HWLE for the group with unknown occupation (most of whom were not reinterviewed in any of waves 2-6) could not be analysed as the statistical method was based on observed transitions between HWLE states.

HWLE by region was examined using Government Office Region (North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, London, South East, South West). Region was treated as missing for individuals who occupied multiple regions during the study period.

2.4 Analysis plan

The average number of years expected to be spent in each of the four alive HWLE model states (healthy and in work, healthy and not in work, not healthy and in work, and not healthy and not in work) was estimated using the method described above. The multi-state model with states and permitted transitions can be seen in figure 2.2 on page 75.

Each health expectancy was estimated according to the state occupied at age 50 (starting-state specific health expectancies) and averaged (weighted by the observed prevalence of state occupation at age 50) to produce estimates for the population of England overall:

- HWLE
- the average number of years spent healthy and not in work
- the average number of years spent not healthy and in work
- the average number of years spent not healthy and not in work

HWLE was also computed at age 65 as well as age 50 for England overall as individuals of this age are now expected to remain in work. Life expectancy was estimated as the sum of all four health expectancies. Healthy Life Expectancy (HLE) and Working Life Expectancy (WLE) were also estimated because of their close relationship to HWLE (both theoretically and empirically) and to allow for comparison with published estimates. HLE found by summing HWLE and the health expectancy for healthy and not in work. WLE was found by summing HWLE and expected time spent not healthy and in work.

2.4.1 Subgroup analyses

Subgroup analyses of HWLE were carried out as length of healthy working life was expected to be affected by regional, socioeconomic, and gender inequalities in life expectancy (an indicator of population health and wellbeing; see section 1.4 on page 8) as well as health and work factors that may vary with local area, socioeconomic status, and sex (see section 1.6.1 on page 19). Individuals with missing data in the identifiers of population subgroups were excluded from the study population, which was used to estimate HWLE for England overall and then stratified to estimate HWLE by population subgroup:

- sex
- educational attainment
- quintile of IMD
- occupation type
- region

2.4.2 Specifications for model estimation

Age was included in the transition probability models and was measured in years from the midpoint of year of birth (taken as month 6 – June) to the month and year of death. Transition probabilities were assumed to be constant over time within each year of age and not to be affected by any history of previous state occupation (the Markov property).

Monthly transition probability models (interpolation step size = 1 month) were developed to estimate HWLE for England overall and by sex. Annual transition probabilities models (permitting only one change in health and/or work status per year of age) were developed for education, IMD, occupation, and region (step size = 12 months) due to smaller sample sizes.

2.4.3 Sensitivity analyses

Additional analyses were carried out to assess the robustness of the HWLE and health expectancy estimates and their sensitivity to various assumptions made in the main models:

- interpolation step size (number of transitions modelled per year)
- exclusion or inclusion in analyses of individuals with missing data in subpopulation identifiers
- operationalisations of health as limiting long-standing illness rather than a more subjective self-assessment or a function-based self-assessment of difficulties with activities of daily living
- approach to estimating prevalence of health and work state occupation in the population

Interpolation step size

The models for estimating HWLE for England overall and for men and women separately allowed for monthly transitions between health and work states, as individuals may begin or exit paid work at any time and may develop or recover from a health problem at any time. As monthly transition probability models could not be estimated for subgroup analyses due to small sample sizes, it was necessary to consider whether HWLE estimates were sensitive to the use of yearly transition probability models (which estimated for subpopulations according to education level, quintile of IMD, occupation type, and region). A sensitivity analysis of HWLE results to interpolation step size was carried out by estimating yearly transition probability models for England overall and stratified by sex.

Individuals with missing data in subpopulation identifiers

In case there were differences between individuals with missing data in subpopulation identifiers and the study population on average that could bias the HWLE results, a sensitivity analysis was carried out of HWLE estimates to the exclusion of individuals with missing data in variables used for stratification. HWLE was estimated for England overall including respondents who were excluded from main analyses due to missing data in identifiers of population subgroups.

Alternative operationalisations of health

The sensitivity of HWLE results to how health is operationalised was investigated by estimating HWLE for England overall using alternative health definitions that have been frequently used to define health or disability for health expectancies: self-assessed health (SAH) and activities of daily living (ADLs).

Self-assessed health (SAH)

SAH is the first question of the SF-36 (36-item Short Form Survey Instrument to measure self-reported health in surveys). Due to its simplicity to collect data for and analyse, it is commonly included in survey questionnaires and studied in research (Meltzer, 2003). SAH measures an important dimension of health, and poor SAH is associated with mortality and work exit (Haan and Myck, 2009; Jylhä, 2009). ELSA respondents were either asked “How is your health in general? Would you say it was very good, good, fair, bad, or very bad?” (wave 3) or “Would you say your health is excellent, very good, good, fair, or poor?” (waves 2, 4, 5 and 6). At wave 1, respondents were asked one of the two SAH questions (randomly determined) at the beginning of the health module of the questionnaire, and the other question at the end of the health module. For consistency with other waves, the first question asked (at the beginning of the health module) at wave 1 was used for the calculation of HWLE using SAH. SAH was defined as good if respondents reported good, very good or excellent when asked about their general health. SAH was poor if respondents reported their general health as fair, bad, very bad or poor (a commonly used cut off, eg ONS, 2019d; Abuladze et al., 2017; Zarini et al., 2014; Eriksen et al., 2013; Haseen et al., 2010; Monden et al., 2006).

Activities of daily living (ADLs)

Measurement of ADLs gives an indicator of functional ability (Edemekong et al., 2020). Difficulty with activities of daily living (function) is associated with work disability (Zhang et al., 2010). The ADL-based health measure distinguished between having no or any difficulties with activities of daily living using an ELSA ADL 'harmonised' indicator (from ELSA 'harmonised' dataset with variables derived for consistency across waves). An individual had difficulty with ADLs if they reported difficulty with at least one of bathing, dressing, eating, getting in/out of bed or walking across a room. HWLE using the ADL-based definition treated as healthy those with no difficulty with ADLs.

Approach to estimating prevalence of health and work state occupation in the population

The sensitivity of HWLE results to the measurement of the prevalence of state occupation (for averaging starting-state specific health expectancy results) was investigated by estimating HWLE for England overall using stable prevalences of state occupation instead of the population prevalence observed in the study sample. In addition, total life expectancies were estimated with the life table method (observing mortality in the population without classifying individuals into health or work states) to allow for comparison with those found by summing the health expectancies from each of the analyses.

2.5 Data management

2.5.1 Variable management

ELSA data were received in 55 datasets from the UK Data Service. Data used for this study were merged from seven datasets:

- 'Harmonised' ELSA waves 1-7 dataset ('h_elsa')
- Wave 1 core dataset ('wave_1_core_data_v3')
- Wave 2 core dataset ('wave_2_core_data_v4')
- Wave 3 core dataset ('wave_3_elsa_data_v4')
- Wave 4 core dataset ('wave_4_elsa_data_v3')
- Wave 5 core dataset ('wave_5_elsa_data_v4')
- Wave 6 core dataset ('wave_6_elsa_data_v2')

Quintile Index of Multiple Deprivation data were Special License data separately obtained through the UK Data Service.

Participant identification number, sex, education level at each wave (for all waves except 4), occupation at each wave (waves 2-6), year of birth, and year of death were identified from the harmonised dataset. Within the harmonised dataset, education at wave 4 was not categorised in what appeared to be an omission by mistake (values of the derived education variable were assigned a 'missing' code despite the data existing in the original variables) so this information was identified in the wave 4 core dataset and categorised using the same conventions (wave 1 was used for this).

Interview status (ELSA indicator of response and vital status), whether had long-standing illness, whether long-standing illness was limiting (if applicable), employment/self-employment information, region, occupation, self-assessed health and number of difficulties with activities of daily living were identified from the wave-specific datasets. Binary health and work variables were constructed at each wave and combined with cleaned vital status/death date into a HWLE 'status' variable for each wave. All variables were checked for apparent missingness that was actually due to 'no' responses at previous filter questions that meant subsequent questions were considered irrelevant and not asked. All variables were recoded to standardise coding differences between waves, extract key information and format for IMaCh analysis.

2.5.2 Data cleaning and sample size

Each individual who responded to the HWLE health and work questions was allocated an alive HWLE status 1, 2, 3 or 4 corresponding to their health and work statuses: 1 (healthy and in work); 2 (healthy and not in work); 3 (not healthy and in work); 4 (not healthy and not in work); or 5 (dead). Individuals who had died prior to interview were allocated the dead HWLE status 5. Individuals known to be alive at the time of interview but who either did not respond to the survey or who did not answer one or both of the HWLE health and work questions were allocated status -1, indicating that the individual was alive at time of interview but that their HWLE status was unknown. Individuals for whom there was no survey or mortality data at a given interview were allocated HWLE status -2 to instruct IMaCh to ignore the time point.

There were 18,489 individuals in the ELSA datasets obtained from the UK Data Service including ELSA waves 1-7. Of these, there were 16,066 individuals who were core sample members at some point during the study period of waves 1-6 (no data were used from wave 7). Individuals who did not respond in any of waves 1-6 were removed, leaving 16,053 individuals. The following data cleaning changes were then made (figure 2.7):

1. Months of birth and death (not available in the ELSA datasets) were imputed to comply with IMaCh requirements (mm/yyyy input). Months of birth were imputed as the sixth month (June) of the birth year. Months of death were imputed based on monthly rates of death for census year 2010 as published by the Office of National Statistics (ONS) (ONS, 2011) within the constraints of any known data (for example, if an individual was alive at the time of an interview in March of the same year as their death, they must have died later in the year).

2. At waves 2-5, non-responding individuals who had responded at both earlier and later waves were assigned status -1 (alive with unknown HWLE status) and interview dates (a time at which the status is considered true) corresponding to the middle of the fieldwork date range (calculated as $m/2$ if the number of interview months m was an even number and $(m+1)/2$ if m was odd). This affected 686 people at wave 2, 730 people at wave 3, 713 at wave 4 and 315 people at wave 5.

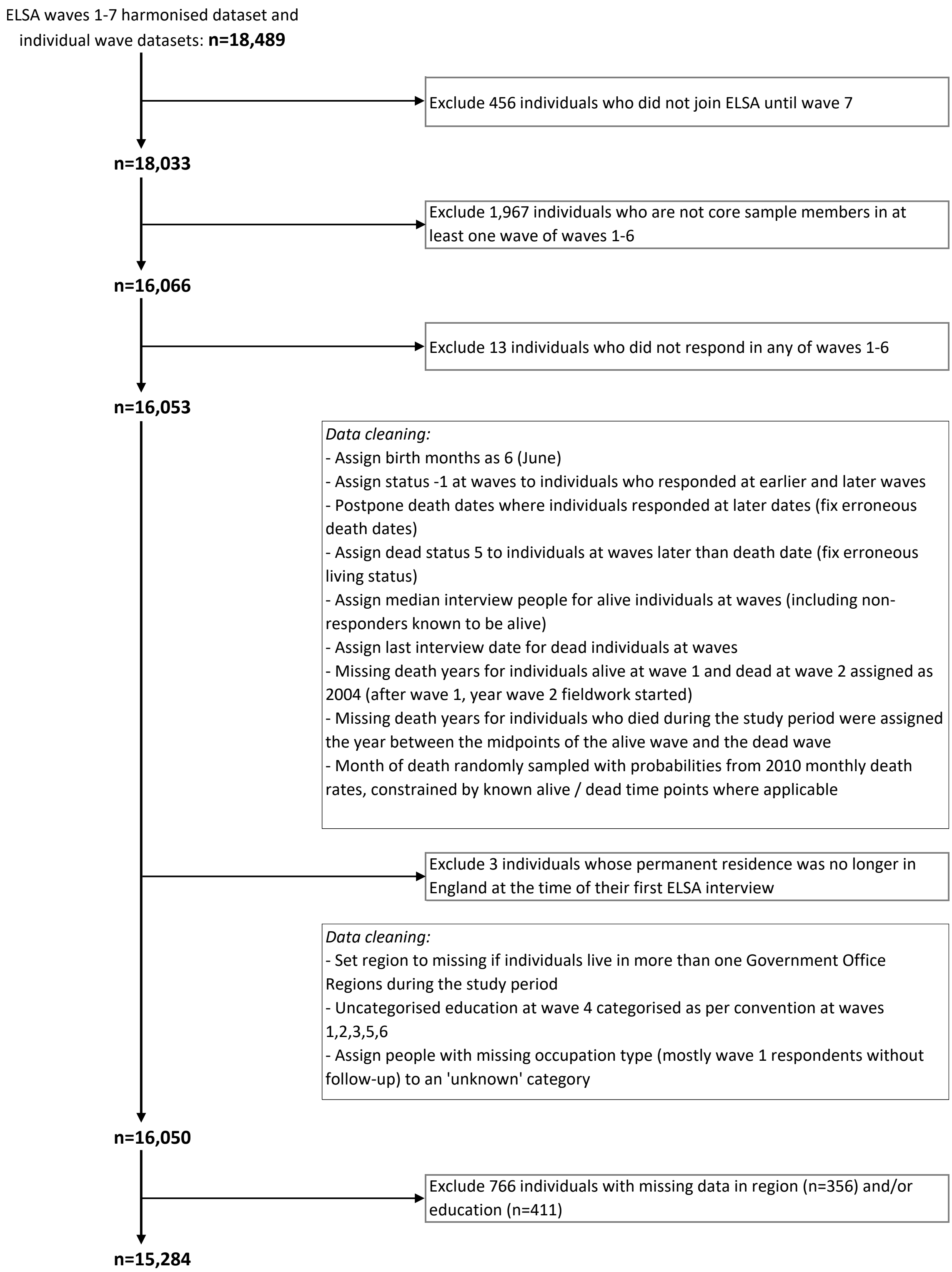


FIGURE 2.7: ELSA sample size for analysis (n=15,284)

3. Any dead statuses for people who responded to a survey at a later date were updated to the correct alive status. This affected two people and both years of death (2000 and 2007) were updated to 2010 after the last known alive time point.

4. Any ELSA alive statuses for people who had a death date prior to fieldwork and did not respond were changed from having status -1 (based on the ELSA interview status indicating they were alive) to the dead status (5). Three changes were made at wave 3, two changes were made at wave 4 and 11 changes were made at wave 5.

5. Using linked mortality data and known vital status during fieldwork, death dates were cleaned as follows:

   (a) Three people recorded as dead at wave 2 were reassigned year of death as 2004 instead of 2006, 2007 and 2009

   (b) Seven people recorded as dead at wave 3 were reassigned year of death as 2006 instead of 2008, 2009 and 2010

   (c) One person recorded as dead at wave 4 was reassigned year of death as 2008 instead of 2010

   (d) Two people recorded as dead at wave 5 were reassigned year of death as 2010 instead of 2012

   (e) 41 people who were dead at wave 2 with unknown death date (and who all responded at wave 1) were assigned year of death 2004

   (f) 63 people who died between waves 2 and 3 with unknown death date were assigned year of death 2005

   (g) 46 people who died between waves 3 and 4 with unknown death date were assigned year of death 2007

   (h) 37 people who died between waves 4 and 5 with unknown death date were assigned year of death 2009

(i) 12 people who died between waves 5 and 6 with unknown death date were assigned year of death 2011

6. Months of death were imputed using a random number generator weighted by the 2010 monthly death rates in England and with restrictions to exclude impossible months of death where necessary.

7. Remaining people who had alive but unknown statuses (-1) without an interview date were allocated the middle fieldwork date. This affected 677 people at wave 2, 648 people at wave 3, 535 people at wave 4 and 382 people at wave 5.

8. People who died in the study period required an interview date for the first wave at which they were recorded with dead status 5. At all waves, individuals with a dead status and an unknown interview date were allocated the last month of fieldwork to allow for any death dates that fell during the fieldwork period (IMaCh requires this interview date for the transition to death to be analysed but the true death date recorded separately in the data file is used for time of death). This affected 506 statuses at wave 2, 1,035 statuses at wave 3, 1,613 statuses at wave 4, 2,211 statuses at wave 5 and 2,706 statuses at wave 6. The number of records updated at each wave strictly does not decrease as all dead statuses without interview dates were updated, not only the first wave at which death was recorded (although only the first recorded dead status is meaningful in IMaCh). There were no records of deaths occuring later than the wave 6 fieldwork period.

Three individuals were then excluded from the sample due to records indicating that they were no longer permanent residents in England at the time of their first ELSA interview. Following this, 766 people with msising data in region (n=356) and/or education (n=411) were excluded from the sample.

After data cleaning, the total sample size for analysis was 15,284 people (8259 females and 7025 males) (figure 2.7). Sample sizes by education, region and occupation are shown in table 2.5. The number of participants for whom data were available was fewer than 15,284 at each wave due to the survey design as well as non-response, survey attrition, and deaths.

Data management was carried out in Stata version 14.2. The Stata '.do' file (appendix D) included commands to write an R script (appendix E) to process month of death imputation (using weighted probabilities from ONS monthly death rates to impute month of death within constraints of dates with known vital status) and call the execution of the script in R (3.6.1) from the command line. Imputed death dates were then merged back into the dataset in Stata memory for further cleaning and preparation of IMaCh datasets.

Using Stata, data to be analysed in IMaCh were saved in a text file (`.txt`) in a wide format according to the specifications given in the IMaCh documentation[1]. Individuals were assigned separate rows with column entries for: an ID number; date of birth (required) and death (if known); any fixed and time-varying covariates with dummy variables for any categorical covariates; the interview date for each interview; and the individual's status at each interview date. For each of the six interview waves, columns were appended to the right of the data file containing the interview date, interview status (HWLE status: 1 (healthy and in work); 2 (healthy and not in work); 3 (not healthy and in work); 4 (not healthy and not in work); or 5 (dead)), and any time-varying covariates.

2.6 Descriptive summaries of the data

The majority of study participants contributed at least two interviews (n=12,232, 80.03%) and 2,667 individuals were recorded to have died throughout the study period (table 2.4).

TABLE 2.4: Number of successful interviews per study participant in ELSA waves 1-6

Number of interviews per study participant (waves 1-6)	Frequency	Percent
1	3,052	19.97%
2	1,825	11.94%
3	3,046	19.93%
4	1,663	10.88%
5	1,039	6.80%
6	4,659	30.48%
Total	15,284	100%

[1] IMaCh documentation available at *http://euroreves.ined.fr/imach/wiki/index.php/Documentation*

Of the 15,284 ELSA participants in the study sample, 8259 were female and 7025 were male (table 2.5). The most common occupation type among sample members was non-manual (40.92%) followed by manual jobs (36.80%). The sample members lived across the nine different regions; the South East was the region occupied by the most respondents (16.37%) and the North East was the region occupied by the fewest respondents (6.37%). Of the national quintiles of IMD, the three least deprived quintiles each accounted for more than 20% of the sample members and the two most deprived quintiles each accounted for fewer than 20% of the sample members.

Table 2.6 shows the number of survey responses (alive sample) with known HWLE status provided at wave 1 and the total number of responses across all waves given by the 15,284 sample members. While the percentages of responses achieved from most population subgroups were generally similar at wave 1 and in total throughout the entire study period, there was evidence of attrition among people with less than secondary or uncategorised ('other', including foreign and uncommon qualifications) education levels (accounting for 43.01% and 8.62% of responses respectively at wave 1, and 37.45% and 6.98% of responses respectively overall across all waves 1-6), and among those living in more deprived areas (accounting for 15.42% of wave 1 responses but 13.65% overall) (table 2.6).

The percentage of individuals who were successfully interviewed at a given wave but who then did not respond (not due to death) at the subsequent wave was generally similar for those who had reported being healthy and in work, healthy and not in work, or neither healthy nor in work (table 2.7). Next-wave non-response was approximately 1% higher on average among those who had reported being not healthy and in work at the previous wave.

2.6.1 Missing health and work data

There were 11,170 survey respondents with complete health and work data at wave 1, 8,658 at wave 2, 8,562 at wave 3, 9,593 at wave 4, 8,868 at wave 5, and 8,735 survey respondents with complete health and work data at wave 6 (table 2.8). There were 55,586 complete health and work observations across all six waves. Cohorts of individuals who

TABLE 2.5: Descriptive statistics of study sample size

		Female	Male	Total (%)
England (whole study population)		8259	7025	15284 (100%)
Education	Less than secondary	3725	2480	6205 (40.6%)
	Upper secondary	3044	3132	6176 (40.41%)
	Tertiary	799	1141	1940 (12.69%)
	Other	691	272	963 (6.3%)
		8259	7025	15284 (100%)
Occupation	Non-manual	3460	2794	6254 (40.92%)
	Manual	3164	2460	5624 (36.80%)
	Self-employed	379	705	1084 (7.09%)
	Unknown	1256	1066	2322 (15.19%)
		8259	7025	15284 (100%)
Region	North East	556	418	974 (6.37%)
	North West	1079	944	2023 (13.24%)
	Yorkshire the Humber	895	778	1673 (10.95%)
	East Midlands	803	726	1529 (10%)
	West Midlands	896	780	1676 (10.97%)
	East of England	973	828	1801 (11.78%)
	London	768	623	1391 (9.1%)
	South East	1364	1138	2502 (16.37%)
	South West	925	790	1715 (11.22%)
		8259	7025	15284 (100%)
IMD	1 (least deprived)	1879	1594	3473 (22.72%)
	2	1915	1640	3555 (23.26%)
	3	1686	1465	3151 (20.62%)
	4	1524	1263	2787 (18.23%)
	5 (most deprived)	1255	1063	2318 (15.17%)
		8259	7025	15284 (100%)

Quintiles of IMD (Index of Multiple Deprivation) measure relative levels of deprivation in neighbourhoods (Lower-layer Super Output Areas) nationally in England

TABLE 2.6: Descriptive statistics of responses at wave 1 and responses at all waves combined given by the 15,284 participants in the study sample

	Wave 1		All waves	
	Responses	% of total	Responses	% of total
Sex				
Male	5077	45.45%	25068	45.10%
Female	6093	54.55%	30518	54.90%
	11170	100%	55586	100%
Education				
Less than secondary	4804	43.01%	20818	37.45%
Upper secondary	4177	37.39%	23143	41.63%
Tertiary	1226	10.98%	7744	13.93%
Other	963	8.62%	3881	6.98%
	11170	100%	55586	100%
Occupation				
Non-manual	4224	46.63%	25942	49.40%
Manual	4108	45.35%	22208	42.29%
Self-employed	727	8.03%	4363	8.31%
Total excluding unknown	9059	100%	52513	100%
Unknown*	2111		3073	
	11170		55586	
Region				
North East	742	6.64%	3540	6.37%
North West	1510	13.52%	7009	12.61%
Yorkshire and the Humber	1232	11.03%	6128	11.02%
East Midlands	1096	9.81%	5826	10.48%
West Midlands	1217	10.90%	6073	10.93%
East of England	1276	11.42%	6760	12.16%
London	1033	9.25%	4908	8.83%
South East	1789	16.02%	9050	16.28%
South West	1275	11.41%	6292	11.32%
	11170	100%	55586	100%
IMD quintile				
1 (least deprived)	2511	22.48%	13218	23.78%
2	2591	23.20%	13498	24.28%
3	2269	20.31%	11393	20.50%
4	2077	18.59%	9890	17.79%
5 (most deprived)	1722	15.42%	7587	13.65%
	11170	100%	55586	100%

* Occupation not measured at wave 1

TABLE 2.7: ELSA non-response according to health and work status at previous wave

	Status at responding wave			
	Healthy and in work (state 1)	H & NW (state 2)	NH & W (state 3)	NH & NW (state 4)
Wave 1 response and wave 2 non-response	17.77	17.79	18.85	19.82
Wave 2 response and wave 3 non-response	13.28	15.45	13.09	14.02
Wave 3 response and wave 4 non-response	16.38	13.39	15.64	14.76
Wave 4 response and wave 5 non-response	10.01	10.25	9.56	10.39
Wave 5 response and wave 6 non-response	8.48	8.4	8.39	10.49

were first interviewed to refresh the sample were assigned status -2 at earlier waves and not -1 so as to ignore the transition and not appear to systematically bias the representativeness of earlier waves.

TABLE 2.8: ELSA sample size for IMaCh analyses by HWLE status

		Wave					
	Status	1	2	3	4	5	6
-2	Unknown vital status	3,990	4,868	4,374	2,888	3,545	3,874
-1	Alive but unknown HWLE status	124	1,254	1,319	1,201	687	8
1	Healthy and in work	3,231	2,312	2,631	2,827	2,287	2,130
2	Healthy and not in work	3,968	3,198	2,920	3,387	3,368	3,374
3	Not healthy and in work	716	466	518	607	477	483
4	Not healthy and not in work	3,255	2,682	2,493	2,772	2,736	2,748
	Total alive with known HWLE status	*11,170*	*8,658*	*8,562*	*9,593*	*8,868*	*8,735*
5	Dead	0	504	1,029	1,602	2,184	2,667
	Total	15,284	15,284	15,284	15,284	15,284	15,284

Respondents with missing health and/or work data were allocated status -1 (alive but unknown HWLE status). All other cases of unknown HWLE statuses (-1 or -2) were due to survey non-participation, either due to non-response or the survey design (for example, the sample member joined during sample refreshment and therefore did not provide data at earlier waves). The total number of people with unknown HWLE statuses due to missing data amongst survey respondents was 8 in wave 1, 7 in wave 2, 8 in wave 3, 10 in wave 4, 14 in wave 5, and 8 in wave 6 (table 2.9).

TABLE 2.9: Missing health and work data for HWLE status at ELSA waves 1-6. The total number of individuals with status -1 (alive but unknown HWLE status) at each wave is shown alongside the number who had this status due to missing response data.

Wave	Status -1 Total	Status -1 Interviewed	Missing data for HWLE status: Health only	Work only	Health and work
1	124	8	3	1	4
2	1,254	7	7	0	0
3	1,319	8	6	2	0
4	1,201	10	4	3	3
5	687	14	7	2	5
6	8	8	6	1	1

Notes:
'Total' is the total number of individuals with status -1 (alive but unknown HWLE status)
'Interviewed' is the number of individuals with status -1 who were successfully interviewed
Status -1 indicates that the individual was alive but either did not participate in the survey or responded with incomplete health and work data

2.6.2 Number of observed transitions for analysis

Among the survey and mortality data given by the 15,284 sample members, there were 42,978 observed 'transitions' (sequential measurements over any length of time interval, which includes remaining in the same state accross the two time points) (table 2.10). Of these, 40,502 transitions both started and ended in known HWLE statuses, where the destination state was that occupied at the measurement following that of the starting state (that is, the subsequent wave, the next participating wave if the participant missed a wave(s), or death record). Participants in more than two waves contributed more than one transition to the contingency table.

There were 2,476 transitions that started in an observed HWLE status and ended in an alive but unknown HWLE state status. There were four individuals for whom HWLE status was never identified (but who responded at least one survey wave) and for whom no death date was recorded. These four individuals therefore did not contribute to the maximum likelihood estimation of transition probability model parameters.

TABLE 2.10: Contingency table of HWLE status transitions observed in ELSA sample

	Destination state					
Starting state	1	2	3	4	5	Total
1	8505	1678	885	361	70	11499
2	394	10755	60	2890	521	14620
3	793	211	944	429	32	2409
4	74	2176	122	8400	1202	11974
Total	9766	14820	2011	12080	1825	40502

Notes:
The 'destination' state is the state occupied at the observation following that of the 'starting state', regardless of the length of time interval between observations or whether the same state is occupied at both time points.

TABLE 2.11: HWLE status transition information loss in ELSA sample

Starting state	Number of observations (excluding final wave)	Transitions to -1	Percentage of transitions with information loss
1	12065	566	4.7%
2	15498	878	5.7%
3	2540	131	5.2%
4	12875	901	7.0%
Total	42978	2476	5.8%

Notes:
Transitions with alive but unknown HWLE statuses (-1) count towards transition probabilities for any alive state
Unknown vital statuses (-2) are ignored and therefore excluded from the sample of observed transitions

2.7 Results

In England overall (based on the full study sample n=15,284 with complete data in subpopulation identifiers), life expectancy (LE) at age 50 was estimated as 31.76 years (95% confidence interval (CI) [31.40,32.12]) and HWLE was 9.42 (9.19, 9.66) years (tables 2.12 and 2.15); that is, from age 50, people in England on average were expected to spend 9.42 years healthy and in work (29.66% of LE) with these years not necessarily lived consecutively but at any time between age 50 and end of life.

TABLE 2.12: Population based average health expectancy results with standard errors at ages 50 and 65 from ELSA sample

Age	Health expectancies: Healthy and in work	Healthy and not in work	Not healthy but in work	Not healthy and not in work	Total life expectancy
50	9.42 (0.12)	11.18 (0.15)	1.84 (0.05)	9.32 (0.13)	31.76 (0.18)
65	1.14 (0.03)	8.92 (0.11)	0.28 (0.01)	7.98 (0.11)	18.31 (0.15)

Notes:
Results are given in years
Parentheses show standard errors

HWLE for England varied by the starting state occupied at age 50 (figure 2.13). People who were healthy and in work at age 50 (state 1) had a HWLE of 10.81 years, corresponding to 33.78% of their LE (32.01 years from age 50). Healthy people who were not working at age 50 (state 2) had a HWLE of 5.92 years, 18.73% of LE (31.62 years). People who were not healthy and who were in work at age 50 were expected to return to the healthy and working state for 7.72 years, with this HWLE corresponding to 24.49% of LE (31.52 years from age 50). Individuals who were neither healthy nor in work at age 50 (state 4) were only expected to spend 2.99 of their remaining years in the healthy and working state (10.04% of the 29.84 years of LE from age 50).

2.7.1 HWLE by sex in England

Compared to HWLE for the entire sample, HWLE was higher for men (10.94 [10.65,11.23] years; n=7,025) and lower for women (8.25 [7.92,8.58] years; n=7,025) (tables 2.14 and 2.15). Men at age 50 were also expected to spend 9.58 years (9.18,9.97) healthy and not

TABLE 2.13: IMaCh health expectancy results (in years) at age 50 by starting state from ELSA sample

Starting state (% of population aged 50)	Health expectancy in state 1 (H&W)	2 (H&NW)	3 (NH&W)	4 (NH&NW)	LE
1 (71.12%)	10.81	10.85	1.67	8.68	32.01
2 (9.48%)	5.92	14.48	1.26	9.96	31.62
3 (12.50%)	7.72	10.57	3.68	9.55	31.52
4 (6.90%)	2.99	11.07	1.07	14.68	29.82

in work, 2.00 (1.85,2.16) years in work but not healthy, and 7.52 (7.19,7.85) years neither healthy nor in work. Women at age 50 were expected to spend 12.58 (12.14,13.00) years in health and not in work, 1.70 (1.56,1.83) years in work but not in health, and 10.97 (10.57,11.36) years neither healthy nor in work. Total LE from age 50 was 30.04 (29.55,30.54) years for men and 33.49 (33.00,33.98) years for women.

TABLE 2.14: Health expectancies with 95% confidence intervals for males and females in England from ELSA data

	Healthy and in work (1)	Healthy and not in work (2)	Not healthy but in work (3)	Not healthy and not in work (4)	Total life expectancy
Males	10.94 (10.65,11.23)	9.58 (9.18,9.97)	2.00 (1.85,2.16)	7.52 (7.19,7.85)	30.05 (29.55,30.54)
Females	8.25 (7.92,8.58)	12.57 (12.14,13.00)	1.70 (1.56,1.83)	10.97 (10.57,11.36)	33.49 (33.00,33.98)

Notes:
Results are given in years
Confidence intervals are shown in parentheses
All results are based on observed state occupancy prevalences ('population based') with monthly interpolation steps

2.7.2 HWLE by deprivation level, occupation type, education level and region in England

The IMD quintile with the highest HWLE was the least deprived quintile (10.53 years [10.06,10.99]) while the lowest HWLE was associated with the most deprived quintile (6.8 [6.18,7.43] years) (figure 2.12, table 2.15). Among population subgroups according to occupation type, HWLE was highest for self-employed people (11.76 [10.76,12.76] years), followed by those with non-manual occupations (10.32 [9.95,10.69] years), and was lowest for people with manual occupations (8.72 [8.25,9.20] years) (table 2.15, figure 2.12). HWLE decreased with decreasing education level; the education level associated with the highest HWLE was tertiary education (HWLE of 11.27 [10.74,11.80] years), while people with less than secondary education had the lowest HWLE (7.68 [7.23,8.14] years) of the subgroups by education level (table 2.5, figure 2.12).

TABLE 2.15: Health expectancy results for England

Population	Sample size	Step size (months)	LE (95% CI)	HWLE (95% CI)	Health expectancies in state 2 (H&NW)	3 (NH&W)	4 (NH&NW)	HLE	WLE
England	15284	1	31.76 (31.40,32.12)	9.42 (9.19,9.66)	11.18 (10.88,11.47)	1.84 (1.74,1.94)	9.32 (9.06,9.58)	20.60	11.26
Sex									
Male	7025	1	30.05 (29.55,30.54)	10.94 (10.65,11.23)	9.58 (9.18,9.97)	2.00 (1.85,2.16)	7.52 (7.19,7.85)	20.52	12.94
Female	8259	1	33.49 (33.00,33.98)	8.25 (7.92,8.58)	12.57 (12.14,13.00)	1.70 (1.56,1.83)	10.97 (10.57,11.36)	20.82	9.95
Education									
Less than secondary	6205	12	30.14 (29.54,30.74)	7.68 (7.23,8.14)	10.08 (9.59,10.57)	1.69 (1.50,1.89)	10.69 (10.21,11.16)	17.76	9.38
Upper secondary	6176	12	33.16 (32.50,33.82)	9.54 (9.21,9.86)	12.62 (12.09,13.14)	1.85 (1.70,1.99)	9.16 (8.72,9.60)	22.15	11.38
Tertiary	1940	12	33.59 (32.38,34.79)	11.27 (10.74,11.80)	12.45 (11.53,13.37)	1.97 (1.74,2.21)	7.90 (7.02,8.77)	23.72	13.24
Other	963	12	31.86 (30.49,33.22)	9.22 (8.14,10.30)	10.9 (9.79,12)	2.19 (1.59,2.78)	9.56 (8.43,10.68)	20.11	11.4
Occupation									
Non-manual (waves 2-6)	6254	12	34.54 (33.92,35.16)	10.32 (9.95,10.69)	13.39 (12.85,13.94)	1.64 (1.49,1.80)	9.19 (8.74,9.64)	23.71	11.96
Manual (waves 2-6)	5624	12	31.66 (31.01,32.31)	8.72 (8.25,9.20)	10.64 (10.10,11.18)	1.85 (1.63,2.07)	10.44 (9.94,10.95)	19.37	10.58
Self-employed (waves 2-6)	1084	12	31.64 (29.95,33.33)	11.76 (10.76,12.76)	9.91 (8.69,11.12)	2.66 (2.16,3.17)	7.31 (6.30,8.32)	21.67	14.42

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Table 2.15 – continued from previous page

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Population	Sample size	Step size (months)	LE (95% CI)	HWLE (95% CI)	Health expectancies in state 2 (H&NW)	3 (NH&W)	4 (NH&NW)	HLE	WLE
Unknown *	2322	N/A							
Region									
North East	974	12	30.49 (29.06,31.92)	7.34 (6.47,8.20)	9.81 (8.65,10.96)	1.60 (1.11,2.09)	11.75 (10.56,12.93)	17.14	8.94
North West	2023	12	29.96 (28.91,31.00)	8.62 (7.93,9.31)	10.69 (9.87,11.52)	1.70 (1.40,1.99)	8.95 (8.26,9.64)	19.32	10.32
Yorkshire the Humber	1673	12	31 (29.93,32.06)	8.93 (8.22,9.65)	10.41 (9.56,11.26)	1.85 (1.55,2.14)	9.80 (8.99,10.61)	19.35	10.78
East Midlands	1529	12	32.16 (31.03,33.29)	8.13 (7.43,8.82)	10.60 (9.71,11.48)	2.33 (1.99,2.68)	11.10 (10.20,12.00)	18.72	10.46
West Midlands	1676	12	32.16 (31.03,33.29)	8.81 (8.04,9.58)	11.37 (10.45,12.28)	1.85 (1.52,2.17)	10.14 (9.26,11.01)	20.17	10.65
East of England	1801	12	33.27 (32.24,34.30)	10.48 (9.83,11.13)	11.31 (10.46,12.16)	1.97 (1.66,2.28)	9.52 (8.74,10.30)	21.79	12.45
London	1391	12	31.95 (30.76,33.15)	9.96 (9.19,10.74)	12.27 (11.22,13.32)	1.31 (1.02,1.60)	8.41 (7.57,9.25)	22.23	11.27
South East	2502	12	32.08 (31.20,32.96)	10.73 (10.16,11.30)	11.56 (10.82,12.29)	1.98 (uncertain CI**)	7.82 (7.26,8.38)	22.29	12.71
South West	1715	12	33.28 (32.25,34.31)	10.51 (9.80,11.22)	12.47 (11.53,13.41)	1.94 (1.59,2.29)	8.36 (7.66,9.06)	22.98	12.45
IMD quintile									
1 (least deprived)	3473	12	33.99 (33.24,34.75)	10.53 (10.06,10.99)	13.16 (12.51,13.82)	1.83 (1.63,2.04)	8.47 (7.93,9.01)	23.69	12.36
2	3555	12	33.56 (32.79,34.32)	9.63 (9.15,10.10)	12.78 (12.13,13.44)	2.05 (1.82,2.28)	9.10 (8.56,9.63)	22.41	11.68

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* **Table 2.15 – continued from previous page** *

Population	Sample size	Step size (months)	LE (95% CI)	HWLE (95% CI)	Health expectancies in state 2 (H&NW)	3 (NH&W)	4 (NH&NW)	HLE	WLE
3	3151	12	31.87 (31.14,32.60)	9.88 (9.34,10.42)	11.25 (10.60,11.89)	1.74 (1.53,1.96)	9.00 (8.46,9.55)	21.13	11.62
4	2787	12	30.81 (29.99,31.63)	9.08 (8.54,9.62)	10.49 (9.81,11.16)	1.54 (1.32,1.77)	9.70 (9.09,10.31)	19.57	10.62
5 (most deprived)	2318	12	27.33 (26.29,28.36)	6.80 (6.18,7.43)	7.20 (6.56,7.83)	1.99 (1.69,2.29)	11.34 (10.56,12.13)	14.00	8.79

Notes:
Abbreviations: Life Expectancy (LE); Healthy Working Life Expectancy (HWLE); Healthy Life Expectancy (HLE); Working Life Expectancy (WLE)
States: Healthy and in work (HWLE) [1]; Healthy and not in work [2]; Not healthy and in work [3]; Not healthy and not in work [4]
Yearly transition probabilities are estimated using interpolation steps of size 12 months
*Health expectancies and total life expectancy not calculated for 'unknown occupation' subgroup (see text)
**Uncertain CI due to poor covariance matrix estimate for this model (due to infrequently observed transitions)

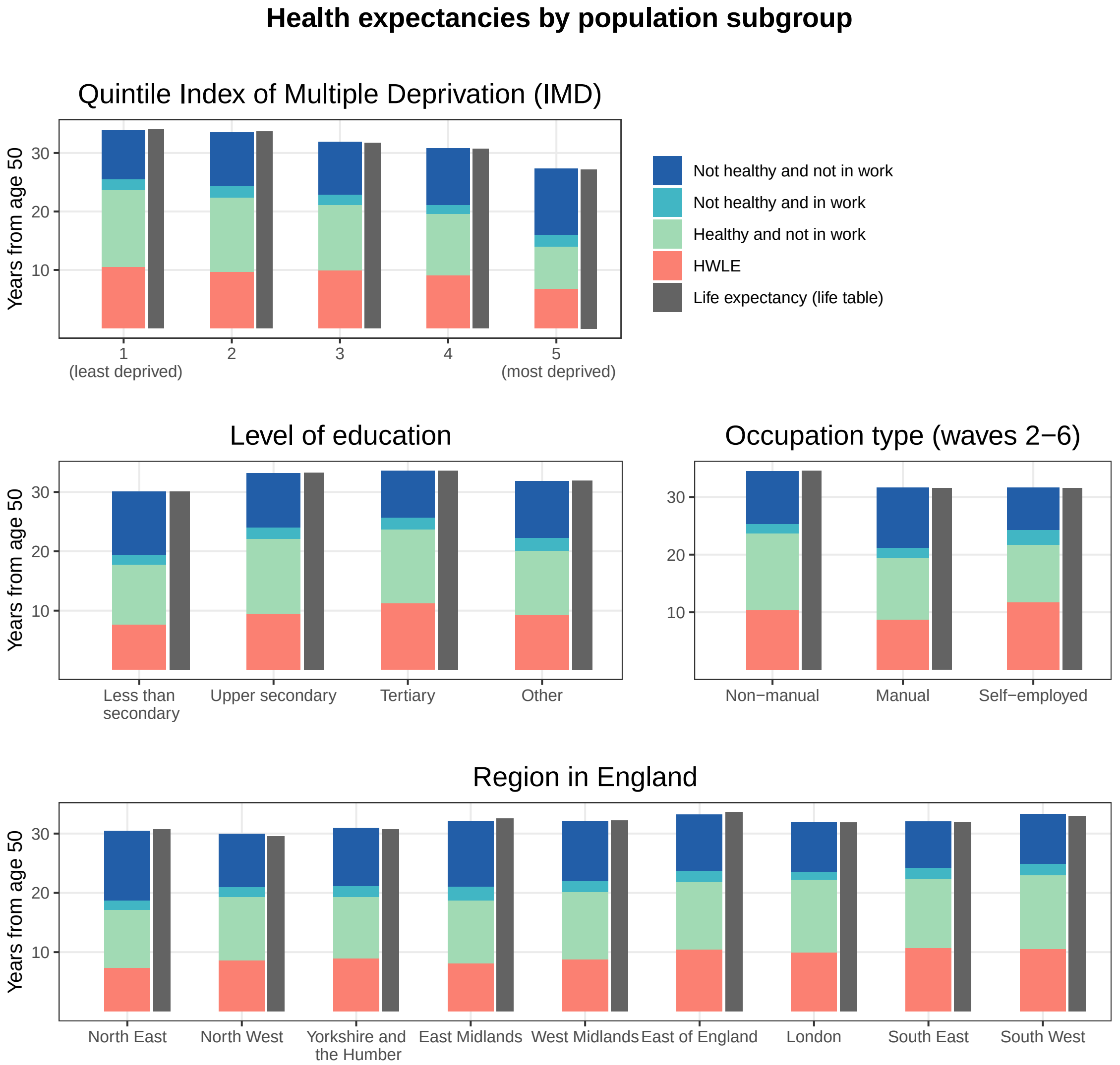

FIGURE 2.8: Barchart of health expectancy and total life expectancy results for England population subgroups by education, occupation and region with life table sensitivity analyses

A geographical pattern was observed in HWLE estimated by region in England. HWLE by region ranged from 7.34 (6.47,8.20) years in the North East to 10.73 (10.16,11.30) years in the South East. Highest HWLE values were observed in the South East, South West, East of England and London (figure 2.9). The median HWLE value was 8.93 years (Yorkshire and the Humber, 95% CI [8.22,9.65]) (table 2.15, figure 2.12).

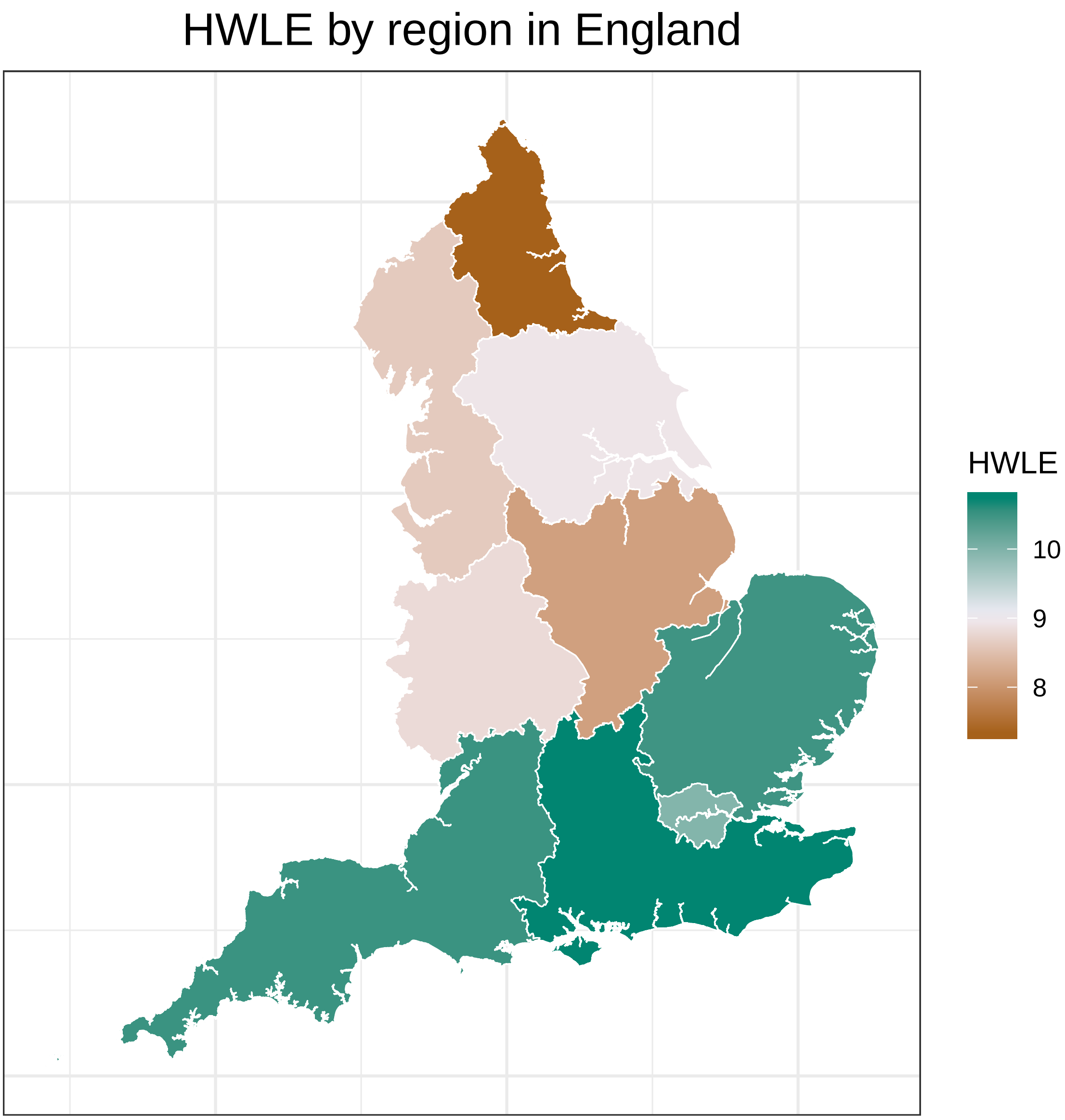

FIGURE 2.9: Map of HWLE in years by region in England

2.7.3 Healthy Life Expectancy, Working Life Expectancy and Total Life Expectancy

LE at age 50 in England overall was estimated as 31.76 (31.40,32.12) years (table 2.15). LE was estimated as 30.05 (29.55,30.54) years for men and 33.49 (33.00,33.98) years for women from age 50. LE from age 50 was lower for people with less than secondary education (30.14 [29.54,30.74] years) than people with upper secondary or tertiary education (33.16 [32.50,33.82] and 33.59 [32.38,34.79] years respectively). LE by occupation type was highest for people with non-manual occupation types (34.54 [33.92,35.16] years) and similar for people with self-employed or manual occupations (31.64 [29.95,33.33] and 31.66 [31.01,32.31] years respectively). LE by region was highest in the South West (33.28 [32.25,34.31] years) and the East of England (33.27 [32.24,34.30] years) and lowest in the North West (29.96 [28.91,31.00] years). Although HWLE, HLE and WLE in London were among the higher regional estimates, the point estimate of LE in London on average (31.95 [30.76,33.15] years) was slightly lower than LE in the East and West Midlands (both 32.16 years with 95% CI [31.03,33.29] and [31.03,33.29] respectively). LE by IMD quintile was highest for people living in the least deprived areas (33.99 [33.24,34.75] years) and reduced with increasing deprivation levels. LE in the most deprived quintile was 27.33 (26.29,28.36) years, which was 6.66 years lower than in the least deprived quintile.

By summing the health expectancies in healthy states 1 (HWLE) and 2 (healthy and not in work) (table 2.15), Healthy Life Expectancy in England at age 50 was estimated as 20.60 years (64.86% of LE). HLE at age 50 was similar for men (20.52 years) and women (20.83 years), which was 68.29% and 62.17% of LE for men and women respectively. HLE followed the same trends among educational groups as HWLE: HLE was highest for people with tertiary education (23.72 years, 70.62% of LE) and lowest for people with less than secondary education (17.76 years, 58.93% of LE). However, whereas HWLE according to occupation type was highest for self-employed people, HLE was highest for people with non-manual occupations (23.71 years, 68.65% of LE). HLE was lower for self-employed people (21.67 years, 68.49% of LE) and lowest for people with manual occupations (19.37 years, 61.18% of LE). HLE was higher in southern regions of England (East of England, London, South East, South West) than the midlands and northern regions (North East, North West, Yorkshire and the Humber, East Midlands, West Midlands). The region with the highest HLE was the South West (22.98 years, 69.48% of LE) and the region with the lowest HLE was the North East (17.14 years, 56.22% of LE). The largest HLE inequality observed between population subgroups was the almost ten years between people living in the least deprived areas (HLE 23.69 years, 69.70% of LE) and people living in the most deprived areas (14 years, 51.23% of LE).

By summing the health expectancies in healthy states 1 (HWLE) and 3 (not healthy and in work) (table 2.15), Working Life Expectancy at age 50 in England was 11.26 years (35.45% of LE). WLE was three years higher for men (12.94 years) than women (9.95 years), corresponding to 43.06% and 29.71% of LE for men and women respectively. The population subgroup analyses with the largest inequalities in WLE were education level and occupation type (table 2.15). WLE by education level ranged from 9.38 years from age 50 for adults with less than secondary education (31.12% of LE) to 13.24 years for adults with tertiary education (39.42% of LE). WLE by occupation type was highest for self-employed people (14.42 years, 45.58% of LE) and lowest for people with manual occupations (10.58 years, 33.42% of LE). WLE by region was lower in the midlands and northern regions (lowest in the North East at 8.94 years, 29.32% of LE) and higher in southern regions (highest in the South East at 12.71 years, 39.62% of LE). The difference of 3.77 years between WLE in the North East and the South East was the largest inequality observed in WLE by population subgroup, followed by the difference of 3.57 years between WLE in the most deprived quintile (8.79 years, 32.16% of LE) and WLE in the least deprived quintile (12.36 years, 36.36% of LE).

2.7.4 Sensitivity analyses

Tables 2.16 and 2.17 show the percentage agreement between the operationalisation of health as limiting long-standing illness with alternative operationalisations SAH and difficulties with ADLs respectively. In total for all respondents at all survey waves, health classification using the applied definition (limiting long-standing illness) and SAH agreed in 78.86% of cases (excluding missing data). At each wave, 20-22% of respondents were classified into HWLE states differently using SAH instead of the main definition.

Missingness in SAH (1635 cases, 2.94%) was much higher than the applied health definition (46 cases in waves 1-6, 0.08%). Among those who reported limiting long-standing illness, 37.9% reported good self-assessed health. Agreement between the main health definition and ADL-based health was 75.85% (excluding missing data), with 55.8% of people with limiting long-standing illness having no difficulties with activities of daily living. Missingness in ADL-based health measurement was 0.34% - higher than limiting long-standing illness but less than missingness in SAH.

TABLE 2.16: Percentage agreement of health as defined for main analyses and self-assessed health (all observations in waves 1-6)

		Self-assessed health			
		Poor	Good	Missing	Total
Health	Not healthy	11437 (57.3%)	7559 (37.9%)	959 (4.8%)	19955
	Healthy	3855 (10.8%)	31130 (87.4%)	655 (1.8%)	35640
	Missing	9 (19.6%)	16(34.8%)	21 (45.7%)	46
	Total	15301	38705	1635	55641

Notes:
Crosstabulation is of health status as defined for HWLE with self-assessed health
1,589 missing cases of SAH were due to proxy responses (question not asked)
Parentheses show row percentages

TABLE 2.17: Percentage agreement of health as defined for main analyses and ADL-based health (all observations in waves 1-6)

		ADL-based health			
		Poor	Good	Missing	Total
Health	Not healthy	8706 (43.6%)	11133 (55.8%)	116 (0.6%)	19955
	Healthy	2249 (6.3%)	33335 (93.5%)	56 (0.2%)	35640
	Missing	4 (8.7%)	26 (56.5%)	16 (34.8%)	46
	Total	10959	44494	188	55641

Notes:
ADL-based health is counted as good if no difficulties were reported with activities of daily living
Parentheses show row percentages

Compared to the main estimate of 9.42 (9.19,9.66) years, HWLE was higher when measuring health according to the presence or absence of difficulties with ADLs (10.62 [10.39,10.85] years) (table 2.18). The health expectancy in state 3 (not healthy and in work) was notably lower with the ADL-based health definition; only 0.64 years were expected to be spent in this state. HWLE was similar when measuring health using SAH (9.63 [9.39,9.87] years) and using the applied health definition of limiting long-standing illness (table 2.18).

TABLE 2.18: Sensitivity analyses of HWLE and other health expectancy results at age 50 using alternative health definitions, using the stable prevalence approach (instead of observed prevalence) to estimating population levels of state occupation, including data for people with missing subpopulation identifiers, and using the life table approach to estimating LE

Health definition	Sensitivity analysis	Sample size	Healthy and in work (1)	Healthy and not in work (2)	Not healthy but in work (3)	Not healthy and not in work (4)	Total life expectancy
Long-standing limiting illness	(Main analysis)	15284	9.42 (9.19,9.66)	11.18 (10.88,11.47)	1.84 (1.74,1.94)	9.32 (9.06,9.58)	31.76 (31.40,32.12)
Long-standing limiting illness	**Stable prevalence***	15284	9.71 (9.38,10.03)	11.06 (10.75,11.36)	1.87 (1.74,2.00)	9.18 (8.90,9.46)	31.81 (31.45,32.17)
Long-standing limiting illness	**Including missing data**	**16050**	9.39 (9.15,9.62)	11.27 (10.98,11.57)	1.83 (1.73,1.93)	9.41 (9.15,9.66)	31.90 (31.54,32.25)
Long-standing limiting illness	**Life table**	15284					31.78
Self-assessed	Health definition	15284	9.63 (9.39,9.87)	12.89 (12.56,13.22)	1.54 (1.44,1.64)	7.71 (7.47,7.95)	31.77 (31.40,32.14)
Activities of daily living	Health definition	15284	10.62 (10.39,10.85)	15.17 (14.83,15.5)	0.64 (0.58,0.70)	5.56 (5.36,5.76)	31.99 (31.63,32.35)

Notes:
Results are given in years
Confidence intervals are shown in parentheses
All results are based on monthly interpolation steps
*Main results are based on observed state occupancy prevalences (population based results) while non-population based use stable prevalences (see page 81)
Main results are given in the first row and results sensitivity analyses are shown in subsequent rows
Differences between sensitivity and main analyses are indicated in bold type

Sensitivity analysis of HWLE to population based or observed state occupation prevalence

Estimated HWLE was slightly higher, and LE and other health expectancy results were similar, when using stable prevalences to calculate the of average starting-state specific health expectancies (table 2.18). Compared to the main estimate of HWLE using the observed population prevalence of state occupation (9.42 [9.19,9.66] years), HWLE was estimated as 9.71 (9.38,10.03) years from age 50 using the stable prevalence approach.

Sensitivity analysis of HWLE to exclusion of missing region and education data

All health expectancy results for England overall were similar when analysing the full dataset including the observations with missing region and education. HWLE was 9.39 (9.15,9.62) years when including people with missing region or education data compared to the main result of 9.42 (9.19,9.66) years (table 2.18).

Sensitivity analysis of HWLE results to IMaCh interpolation step size

Population-based estimates of HWLE for England through modelling monthly transitions (9.42 [9.19,9.66] years) and yearly transitions (9.43 [9.19,9.66] years) were very similar (table 2.19). There were also no significant differences in health expectancies from monthly and yearly models estimated using the stable prevalence of state occupation (table 2.19).

TABLE 2.19: Sensitivity analyses of health expectancies to interpolation step size using ELSA data

Population based	Length of interpolation units	Healthy and in work (1)	Healthy and not in work (2)	Not healthy but in work (3)	Not healthy and not in work (4)	Total life expectancy
yes	1 month	9.42 (9.19,9.66)	11.18 (10.88,11.47)	1.84 (1.74,1.94)	9.32 (9.06,9.58)	31.76 (31.4,32.12)
yes	**12 months**	9.43 (9.19,9.66)	11.24 (10.94,11.53)	1.83 (1.73,1.93)	9.33 (9.07,9.59)	31.83 (31.47,32.18)
no	1 month	9.71 (9.38,10.03)	11.06 (10.75,11.36)	1.87 (1.74,2.00)	9.18 (8.90,9.46)	31.81 (31.45,32.17)
no	**12 months**	9.77 (9.41,10.12)	11.11 (10.75,11.47)	1.85 (1.72,1.99)	9.15 (8.80,9.50)	31.88 (31.25,32.51)

Notes:
Results are given in years
Confidence intervals are shown in parentheses
Population based results are based on observed state occupancy prevalences while non-population based use stable prevalences
Primary results are given in the first row and results sensitivity analyses are shown in subsequent rows
Differences between sensitivity and primary analyses are indicated in bold type

Life expectancy sensitivity analyses using the life table method

For all analyses, LE (the sum of all health expectancies) were consistent with those calculated using the life table method, suggesting that health expectancies were not overestimated or underestimated (table 2.20, figures 2.10, 2.11 and 2.12).

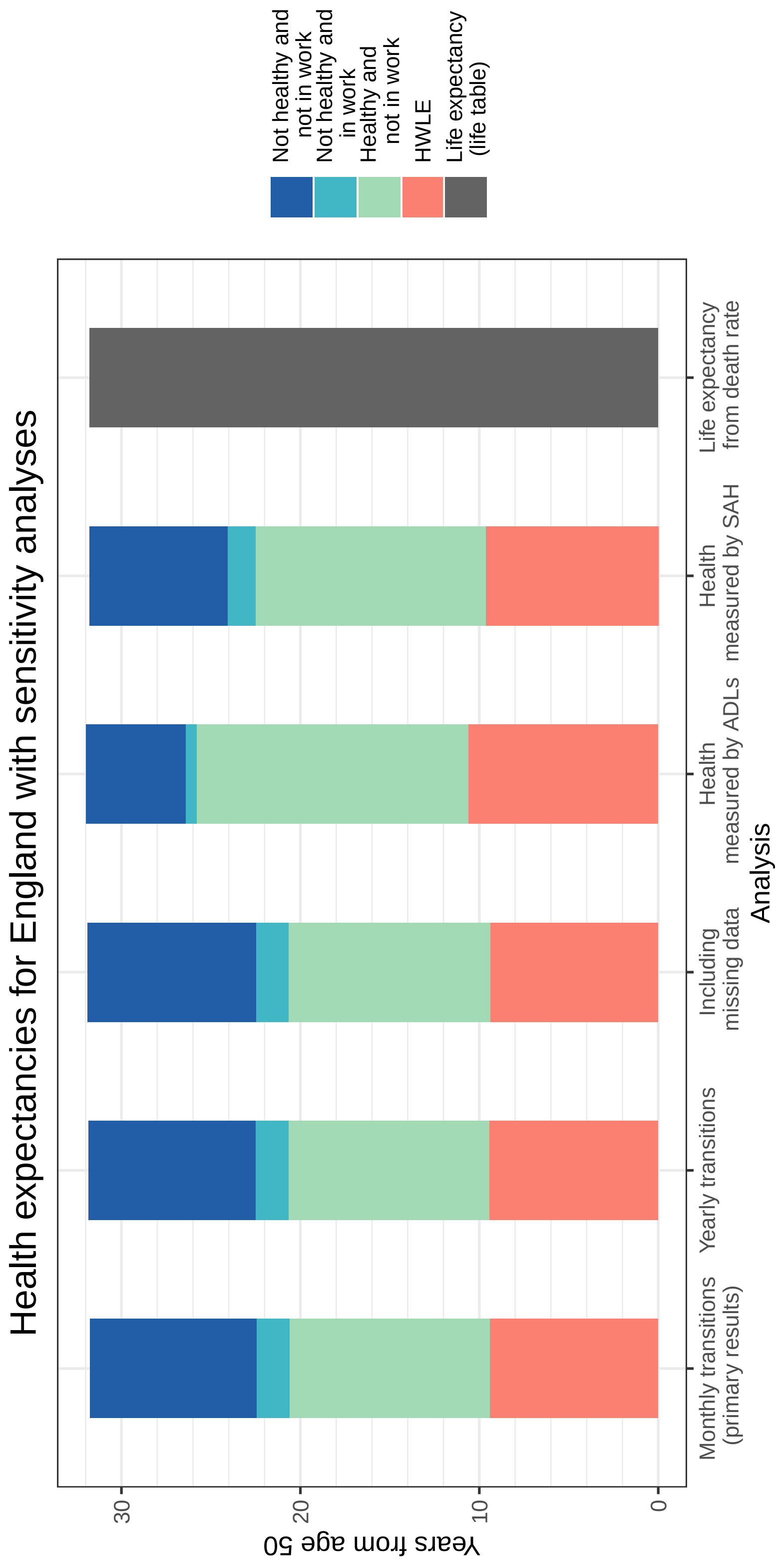

FIGURE 2.10: Barchart of health expectancy and total life expectancy results for England with sensitivity analyses

TABLE 2.20: Sensitivity analyses of health expectancy results for England

Population	Sample size	Step size (months)	LE (95% CI)	HWLE (95% CI)	Health expectancies in state 2 (H&NW)	3 (NH&W)	4 (NH&NW)	HLE	WLE
England: Yearly transitions	15284	12	31.83 (31.47,32.18)	9.43 (9.19,9.66)	11.24 (10.94,11.53)	1.83 (1.73,1.93)	9.33 (9.07,9.59)	20.67	11.26
England: Including all missing data	16050	1	31.90 (31.54,32.25)	9.39 (9.15,9.62)	11.27 (10.98,11.57)	1.83 (1.73,1.93)	9.41 (9.15,9.66)	20.66	11.22
England: Mortality*	15284	N/A	31.78						
England: Health measured by ADLs	15284	1	31.99 (31.63,32.35)	10.62 (10.39,10.85)	15.17 (14.83,15.5)	0.64 (0.58,0.70)	5.56 (5.36,5.76)	25.79	11.26
England: Health measured by SAH	15284	1	31.77 (31.40,32.14)	9.63 (9.39,9.87)	12.89 (12.56,13.22)	1.54 (1.44,1.64)	7.71 (7.47,7.95)	22.52	11.17
Sex									
Male: Yearly transitions	7025	12	30.13 (29.62,30.64)	10.95 (10.60,11.30)	9.65 (9.25,10.05)	1.99 (1.83,2.15)	7.53 (7.2,7.86)	20.60	12.94
Female: Yearly transitions	8259	12	33.55 (33.06,34.04)	8.26 (7.95,8.56)	12.62 (12.2,13.04)	1.70 (1.57,1.83)	10.97 (10.58,11.36)	20.88	9.96
Male: Mortality	7025	N/A	29.75						
Female: Mortality	8259	N/A	33.70						
Education									
Less than secondary: Mortality	6205	N/A	30.11						
Upper secondary: Mortality	6176	N/A	33.29						
Tertiary: Mortality	1940	N/A	33.59						
Other: Mortality	963	N/A	31.98						
Occupation									
Non-manual (w2-6): Mortality	6254	N/A	34.56						
Manual (w2-6): Mortality	5624	N/A	31.54						

*

Continued on next page*

* **Table 2.20 – continued from previous page** *

Population	Sample size	Step size (months)	LE (95% CI)	HWLE (95% CI)	Health expectancies in state 2 (H&NW)	3 (NH&W)	4 (NH&NW)	HLE	WLE
Self-employed (w2-6): Mortality	1084	N/A	31.56						
Unknown**: Mortality	2322	N/A	N/A						
Region									
North East: Mortality	974	N/A	30.68						
North West: Mortality	2023	N/A	29.53						
Yorkshire the Humber: Mortality	1673	N/A	30.72						
East Midlands: Mortality	1529	N/A	32.53						
West Midlands: Mortality	1676	N/A	32.21						
East of England: Mortality	1801	N/A	33.60						
London: Mortality	1391	N/A	31.84						
South East: Mortality	2502	N/A	31.94						
South West: Mortality	1715	N/A	32.98						
IMD quintile									
1 (least deprived): Mortality	3473	N/A	34.06						
2: Mortality	3555	N/A	33.67						
3: Mortality	3151	N/A	31.74						
4: Mortality	2787	N/A	30.74						
5 (most deprived): Mortality	2318	N/A	27.19						

Notes:
Abbreviations: Life Expectancy (LE); Healthy Working Life Expectancy (HWLE); Healthy Life Expectancy (HLE); Working Life Expectancy (WLE)
States: Healthy and in work (HWLE) [1]; Healthy and not in work [2]; Not healthy and in work [3]; Not healthy and not in work [4]
Yearly transition probabilities are estimated using interpolation steps of size 12 months
*Mortality only total life expectancy estimates were calculated with the life table method using observed mortality rates
Footnotes continue on next page

Notes (continued):
Health based on Activities of Daily Living (ADLs) was good if there were no difficulties with ADLs. Health was poor if difficulty was reported with at least one of: bathing; dressing; eating; getting in/out of bed; and walking across a room.
Self-Assessed Health (SAH) was good if respondents reported good, very good or excellent general health. SAH was poor if fair, bad, very bad or poor general health was reported (question phrasing varied across ELSA waves).
**Health expectancies and total life expectancy not calculated for ’unknown occupation’ subgroup (see text)

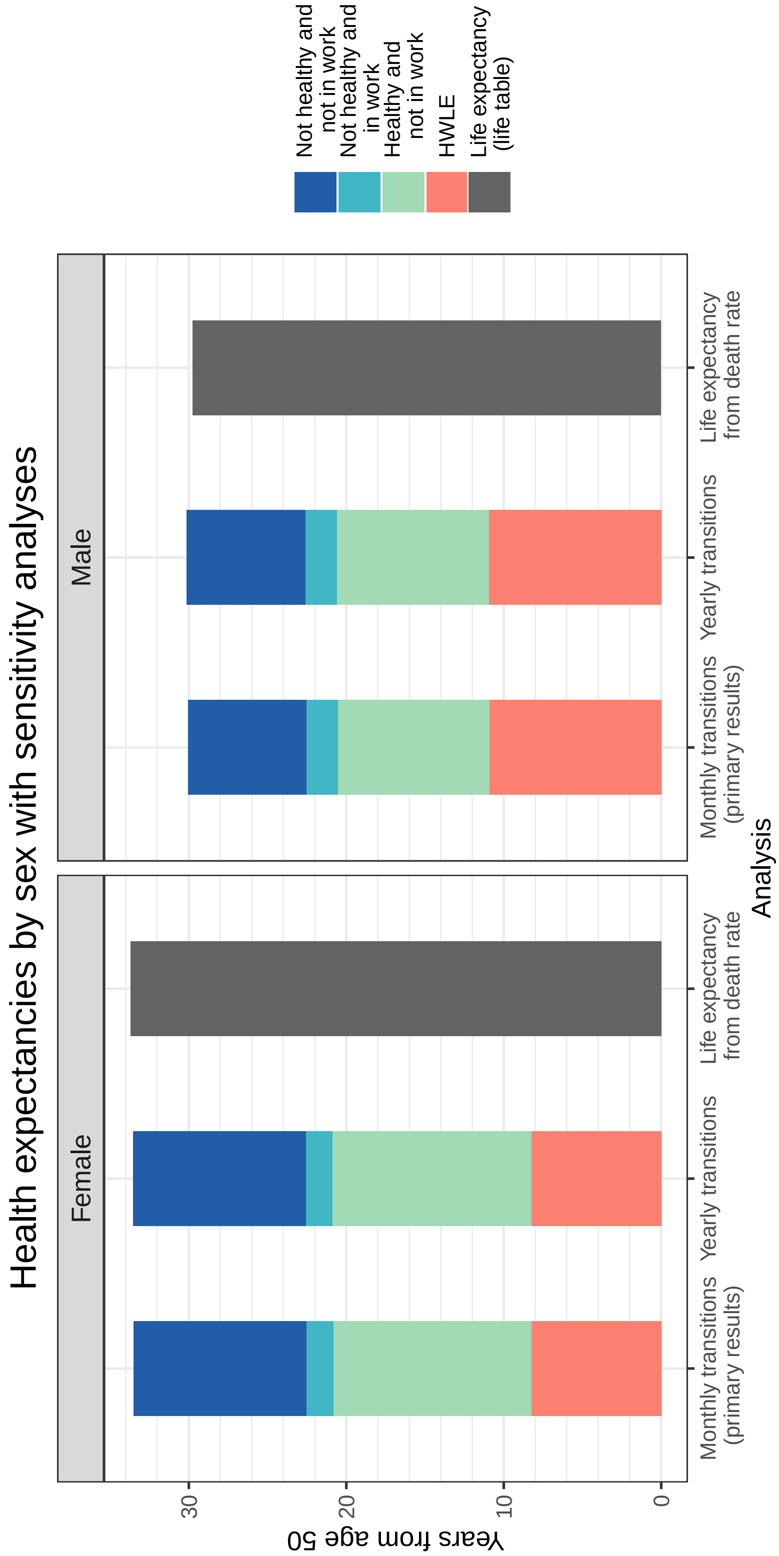

FIGURE 2.11: Barchart of health expectancy and total life expectancy results for males and females in England with life table sensitivity analysis

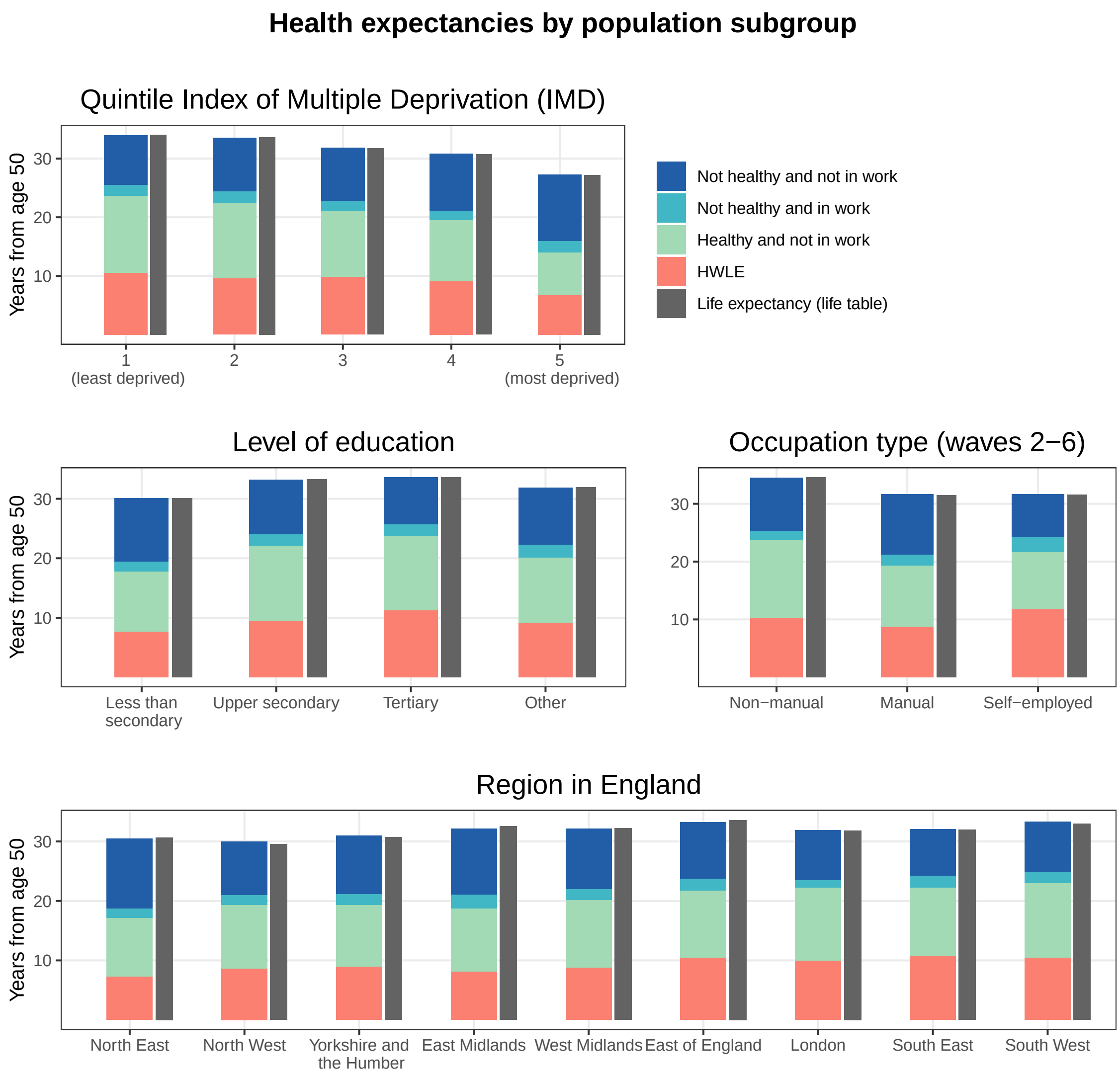

FIGURE 2.12: Barchart of health expectancy and total life expectancy results for England population subgroups by education, occupation and region with life table sensitivity analyses

2.8 Discussion

This chapter has presented analyses of length of healthy working life from age 50 for England as well as subpopulations by sex, geographic region, occupation type and indicators of socio-economic status at the individual level (educational attainment) and area level (quintile of IMD). The results of this large observational study demonstrate that it is possible to operationalise HWLE and reveal a discrepancy between HWLE and proposed extensions to retirement age; on average in England, people aged 50 years are not expected to be healthy and in work for the number of years to State Pension age (SPa) (66 at the end of 2020).

HWLE results for women compared to men reflect that SPa was lower for women than for men until late 2018 and women were less likely to be in work. SPa for women was due to increase from 60 to 65 gradually from 2010, however this equalisation for men and women was accelerated in the Pensions Act 2011 towards the end of the study period (DWP, 2017b). Having reached 66 for men and women in September 2020, SPa will increase to 67 by the end of 2028 with further increases planned. Further monitoring of HWLE for men and women is needed to understand the effect of rising SPa on expected length of healthy working life.

The study findings showed inequalities in HWLE as well as HLE and WLE experienced in England by deprivation level, education level, region and occupation type. People living the longest healthy and working lives on average are those who are highly educated, those who work for themselves or in non-manual occupations, and those who live in less deprived areas or more affluent regions. Inequalities between population subgroups are notable; HWLE in the least deprived quintile of England's population was over 1.5 times higher (3.73 years more) than observed in the most deprived quintile. Analysis of HWLE by region demonstrated a north-south divide. All regions of England contain areas of lower and higher deprivation and further work is needed to investigate whether regional HWLE disparities persist within each deprivation quintile.

Differences observed in HWLE and other health expectancies by region may be due to geographical differences in health as well as in economic development between northern and southern parts of England (Marmot, 2020; Pugalis, 2011; Bachtler, 2004). The North East has higher unemployment rates and lower economic competitiveness than any other region in England, while the country's economic growth is driven by London and the South East (Huggins et al., 2019; ONS, 2019l). There are also substantial regional differences in all cause mortality with persistent excess mortality in the North (Hacking et al., 2011). Geographic health gaps are widening despite a redistribution of health resources to help tackle inequalities (Hacking et al., 2011; House of Commons Health Committee, 2009).

Lower estimates of HWLE among population subgroups with higher deprivation levels may result from poorer health outcomes associated with deprivation throughout the lifecourse, from poorer child health (such as higher rates of low birth weight, infant mortality and excess weight) to premature mortality due to specific causes such as cancer, cardiovascular disease and suicide (PHE, 2018). Behavioural risk factors such as smoking, physical inactivity and poor diet are also more prevalent in the most deprived areas (PHE, 2018). Educational attainment is linked to deprivation (Banerjee, 2016) and higher levels of education are also associated with achieving healthier lifestyles (Cutler and Lleras-Muney, 2006). A further reason for higher HWLE among those with higher education levels relates to access to employment opportunities, especially non-manual and self-employed work which were associated with higher HWLE. The nature of work undertaken is likely to be a key driver of HWLE as workplace accommodations, job control and support at work can remove barriers to participation and function in paid work (for example barriers due to chronic health conditions) (Wilkie, 2012).

Sensitivity analyses showed that HWLE estimates were similar using SAH to operationalise health despite this definition categorising the health status of almost a quarter of the study population differently at each time point. This highlights the importance of health operationalisation if results of health-related research are used to guide targeted interventions, even where estimates are comparable using alternative definitions. ADL-based poor health was a restrictive definition of poor health that identified people with more severe disability resulting in low numbers of years expected to be spent not healthy and in work; higher HWLE estimates using this definition may arise from classifying people with other limiting health problems as healthy (this definition captures a higher level of disability). Compared to operationalising health using limiting long-standing illness, ADL-based poor health may fail to capture individuals whose health problems may affect work behaviour (for example osteoarthritis with pain interference) but not necessarily ability to carry out basic ADLs. The life table sensitivity analyses were indicative of robust health expectancy results even where subgroup analyses were carried out using yearly transitions on data with infrequently observed transitions.

2.8.1 Comparison of results with offical published estimates

Estimated WLE at age 50 (12.94 years for men and 9.95 years for women) compares to higher published estimates of average retirement age of 65.1 years for men and 63.1 years for women in 2018 (table 2.21) (DWP, 2018). This comparison suggests that, on average, men and women do not participate in paid work consistently from age 50 until retirement. Of those years spent working, few are spent without good health suggesting that HWLE may be an important driver of WLE. The difference in years between HWLE and average retirement age (4.2 years for men and 5.6 years for women) has social and financial implications relevant to policy making as people are expected to work for longer.

Estimated HLE at age 50 for men (20.52 years) and women (20.82 years) were slightly higher than ONS published estimates of period HLE from 2009-2011 from age group 50-54 (19.5 years for men and 20.5 years for women) (ONS, 2019e). HLE estimated at age 65 for men (9.71 years) and women (10.38 years) was similar to published estimates by the ONS (9.9 and 10.6 years for men and women respectively from age 60-64) (table 2.21) (ONS, 2019e). LE estimates for men and women at ages 50 and 65 were similar to ONS published estimates from single year life tables averaged over the study period 2002-2013 (table 2.21) (ONS, 2019n), which may suggest that the differences between estimated HLE and ONS estimates of HLE at age 50 reflect the different approach to measuring HLE. That HLE (measured by limiting long-standing illness) at age 50 was estimated to be higher than ONS published estimates (measured using SAH) is unlikely to be due to differences in defining health as sensitivity analyses using SAH produced higher estimates of HLE (by almost two years) than the main results using limiting long-standing illness.

Instead the difference could be due use of different data sources and different methodology; ONS health state life expectancies were estimated using the Sullivan method performed on data from the Annual Population Survey with adjustments based on health data collected in the 2011 Census (ONS, 2018).

TABLE 2.21: HWLE and Healthy, Working and Total Life Expectancy results with published ONS statistics

	Age	HWLE	HLE	HLE* (ONS)	WLE	Average retirement age (ONS)	LE	LE (ONS)
Males	50	10.94	20.52	19.5	12.94	65.1	30.05	30.13
	65	1.56	9.71	9.9	1.93		16.77	17.53
Females	50	8.25	20.82	20.5	9.95	63.9	33.49	33.47
	65	0.77	10.38	10.6	0.97		19.76	20.23

Notes:
*ONS Healthy Life Expectancy estimates from ages 50-54 and 60-64 for males and females
Published statistics sources: HLE for England 2009-2011 estimates (ONS, 2019e); Average retirement age for England 2018 (DWP, 2018); averaged period LE from 2002-2013 single year life tables (ONS, 2019n)

2.8.2 Study strengths and limitations

Strengths of this study include the large sample size with six survey time points and the operationalisation of health as limiting long-standing illness, which enhances the comparability of HWLE to other indicators. Self-reported health status may be affected by biases with unclear directionality, although these may be insignificant at the population level (Benítez-Silva et al., 2004). Sensitivity analyses showed that health expectancies summed to total life expectancy consistent with estimates from life tables, HWLE estimates were similar using SAH to operationalise health, and HLE estimates at age 65 were similar to estimates published by the Office for National Statistics.

However, information bias could affect health measurement if responders were unsure of whether a condition is ‘long-standing’ or whether mental health problems should be reported. The operationalisation of work was inclusive and did not differentiate full time workers from people who work part time and/or for low earnings. Therefore, not all healthy and working years are spent contributing towards national budgets; some individuals counted as being in work may not earn enough to pay tax and may receive government financial support for maintenance.

Despite the large study population, this study was limited by less common transitions being rarely observed. It was not possible to perform all analyses using monthly transition probability models, which led to the use of yearly models for subgroup analyses by educational attainment, IMD, occupation, and region. Analysis of monthly transition probability models is computationally intensive and models may be weakly identifiable where less common health and work transitions are infrequently observed (Cassarly et al., 2017; Jackson et al., 2003). In this case the maximum likelihood estimation procedure may fail to converge on finite and consistent model parameter estimates (in some cases, one or more model parameter estimates may diverge to infinity in some or all maximum likelihood estimation attempts) (Hutchinson et al., 2015; Jackson et al., 2003). Although sensitivity analyses of HWLE for England overall and by sex did not indicate sensitivity of results to monthly or yearly transition probability models, the statistical assumption that transitions between health and work states are permitted once annually less closely approximates the continuous nature of the underlying process.

Results for occupation were affected by the lack of an occupation measurement at ELSA wave 1 leading to analysis using only waves 2-6. Observed transitions from wave 1-2 were therefore not analysed leading to compromised study sample comparability with the England overall and subgroup analyses. Occupation type was also assumed to remain the same over time but some individuals may have changed occupation type before or after reporting it, which could mean differences in HWLE between subpopulations by occupation type are larger than estimated.

The study was also limited by the absence of linked mortality data for more recent ELSA waves 7 and 8. HWLE could be higher than estimated because of more recent policy changes encouraging longer working lives, but it is also worth noting that life expectancy trends in the UK have plateaued since the end of the study period in 2013 making HWLE increases driven by life expectancy gains less likely.

Finally, the ELSA sample is intended to be representative of the community-dwelling population in England but may suffer recruitment and attrition bias as well as inherited bias from the Health Survey for England used as a representative sampling frame. Although ELSA recruited refreshment samples to maintain representativeness, descriptive statistics of the study population by IMD quintile indicate underrepresentation of the most deprived quintiles (table 2.5). In this case, overall HWLE is likely to be lower than estimated.

2.9 Conclusion

Using freely accessible ELSA data and interpolated Markov chain multi-state modelling, this study has demonstrated an operationalisation of HWLE as a population indicator and found that HWLE in England is less than the number of years to SPa. Subgroup analyses highlighted inequalities in HWLE by sex, socioeconomic status (captured through education level and area-level deprivation), occupation, and region.

Living for longer presents new opportunities for societal engagement and personal growth. Those who age healthily are often assets in communities and workplaces and older adults' physical and mental capabilities can equal that of young adults' (WHO, 2015). However, ageing trajectories are diverse and the results of this study demonstrate that, on average, adults in England are not living extended healthy working lives. Factors such as sex, education, psychological support, having resources to meet basic needs and the interaction between environment and personal characteristics are key determinants of healthy ageing and functional ability and may affect length of healthy working life (Allen and Daly, 2016). The success of policies to defer retirement may depend on initiatives to promote healthy ageing as well as the provision workplace accommodations, lifelong training opportunities and inclusive hiring practices to facilitate increased work participation in later working-age life (Walker, 2002; Wilkie, 2012). For this, there is a need for factors associated with higher or lower HWLE to be clearly identified in further research. HWLE projections for men and women in England are also needed - especially because legislated SPa increases from 67 to 68 years have been proposed to be brought forward to 2037-2039. How HWLE might change in the coming years as the State Pension age rises is unknown. Biopsychosocial interventions to tackle widening inequities and improve population health may be necessary for many people in the population to be able to work for longer.

Chapter 3

Projections of Healthy Working Life Expectancy in England to 2035

3.1 Introduction

UK State Pension age is rising in response to life expectancy gains (DWP, 2017b). However, health improvements may not be keeping pace with life expectancy gains - especially at older ages when additional working years will be expected (Jagger, 2015). Used as an indicator of whether people in England are able to work for longer, healthy working life expectancy (HWLE, the average expected number of remaining healthy working years) from age 50 may be over six years lower on average than the number of years to the State Pension age of 66 in late 2020 (HWLE from age 50 in England is 10.94 years for men, 8.25 years for women, and 9.42 years overall - see chapter 2).

If State Pension age rises but HWLE gains do not keep pace, individuals (especially those with chronic health problems) may increasingly face challenges securing suitable employment or engaging productively and healthily at work, to the detriment of their health and wellbeing and that of their families (Wilkie et al., 2020; Van Aerden et al., 2016; Burgard and Lin, 2013; Siegrist et al., 2007; Johri, 2005). Consideration of how levels of population health and work engagement in later working life are likely to change in the coming years allows insight into whether policy objectives are likely to be achieved without national pension expenditure savings being accompanied by additional (possibly health-related) costs to financial support people in or out of work prior to retirement age. The aim of the study presented in this chapter was to estimate HWLE in future years in order to better understand the expected future trajectory of HWLE for men and women in England, and to demonstrate whether it is possible to apply standard statistical forecasting methods to project HWLE. To do this, the application of standard statistical forecasting to project HWLE was examined.

3.2 Statistical methods

HWLE projections were estimated up to 2035 separately for men and women using a combination of methods (Cao, 2016; Majer et al., 2013): the intercensal approach to estimating health expectancies (Guillot and Yu, 2009), and the Lee Carter forecasting approach (Lee and Carter, 1992). In this study, HWLE estimation required a simpler approach than carried out previously (see chapter 2) for use in conjunction with forecasting methodology. The intercensal method for estimating health expectancies was proposed to meet the need for an approach with less restrictive data requirements than the IMaCh multi-state approach while maintaining the multi-state framework lost in the widely-used Sullivan method (which calculates life expectancy or a health expectancy from cross-sectional data with the assumption that the proportion of people alive or healthy at each age does not change over time) (Guillot and Yu, 2009). The intercensal method incorporates cross-sectional observations of the proportion of the population occupying each health state from successive time points to estimate transition probabilities and transition intensities (transition rates).

A 3-state model was used to estimate and project HWLE for men and women in England: healthy and working (state 1); unhealthy and/or not working (state 2); dead (state 3) (figure 3.1). HWLE was estimated and forecasted based on a progressive illness-death model (see page 78) in which individuals can transition from the 'healthy' state 1 to the 'unhealthy' or dead states 2 or 3, and from the 'unhealthy' to dead state (transition 2-3), but cannot return from the 'unhealthy' state 2 to the 'healthy' state 1. As the 'healthy' and 'unhealthy' states here refer to more complex health and work states (which can in reality be exited and re-entered), this approach assumes to model net transitions from healthy and working state 1 to the unhealthy and/or not working state 2.

Notation used throughout this chapter:

- HW denotes 'healthy and working' (state 1)
- nHW denotes 'not both healthy and working' (that is, unhealthy and/or not working, state 2)

- m denotes transition rates
- x = age
- t = time (calendar year)
- $m_{x,t}$ = age specific mortality rates
- $m_{x,t}^{HW}$ = age specific mortality rates from the healthy working HW state (state 1)
- $m_{x,t}^{nHW}$ = age specific mortality rates from the unhealthy and/or not working nHW state (state 2)
- $m_{x,t}^{HWnHW}$ = age specific transition rates from state 1 (HW) to state 2 (nHW)
- $R_{x,t}$ = the ratio of mortality rates from being unhealthy and/or not working (nHW) compared to being healthy and working (HW)

- q denotes transition probabilities
- $q_{x,t}^{HW}$ = age specific probability of death from the healthy working HW state (state 1)
- $q_{x,t}^{nHW}$ = age specific probability of death from the unhealthy and/or not working nHW state (state 2)
- $q_{x,t}^{HWnHW}$ = age specific transition probability from state 1 (HW) to state 2 (nHW)

- Π denotes prevalence
- $\Pi_{x,t}^{HW}$ = age specific prevalence of being healthy and working

- $\Pi_{x,t}^{nHW}$ = age specific prevalence of being unhealthy and/or not working

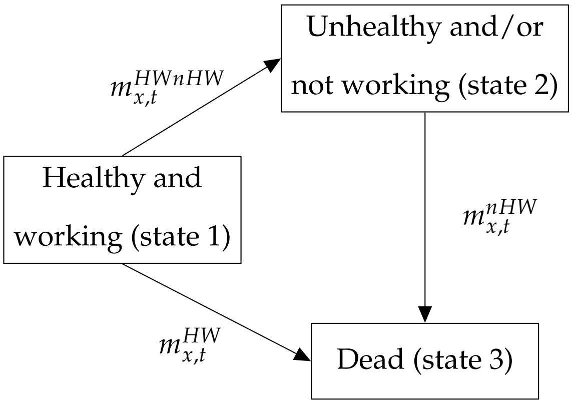

FIGURE 3.1: 3-state multistate model for HWLE projections with permitted transitions shown with arrows and transition rates: $m_{x,t}^{HW}$ (mortality rate from healthy and working state); $m_{x,t}^{nHW}$ (mortality rate from not being healthy and working); and $m_{x,t}^{HWnHW}$ (transition intensity from healthy and working state to unhealthy and/or not working)

To estimate HWLE projections, transition rates were forecasted using the Lee Carter approach (Lee and Carter, 1992). Using the intercensal approach, HWLE was then estimated (both for the observed years and the forecasted years) from the transition probabilities and the proportion of people in each health state at the youngest age (age 50 by HWLE definition) by calculating the number of people alive and in each health state at each age and in each year. Data required for HWLE estimates and projections using the combined intercensal health expectancy and Lee Carter forecasting approach included: the prevalence of being healthy and in work at each year of age from 50 upwards; mortality rates; and data from which the ratio of mortality rates from the HW state (1) and nHW state (2) can be estimated.

The steps to estimate health expectancy projections are summarized in table 3.1.

TABLE 3.1: Steps in methodology for estimating HWLE projections.

1. Estimate transition probabilities and transition intensities for each permitted transition at each age and calendar year using observed data 2. Forecast the overall population mortality rate and the transition rate from the healthy and working state to the unhealthy and/or not working state using the Lee Carter approach 3. Forecast the population prevalence of being healthy and in work at age 50 (the starting age for HWLE) using univariate ARIMA time series methods 4. Estimate the transition probabilities and transition rates for each permitted transition (including mortality rates from each alive state) using the forecasted overall population mortality rate, transition rate from the healthy and working state to the unhealthy and/or not working state, and population prevalence of being healthy and in work at age 50 5. Estimate HWLE for the observed and forecasted years using observed and forecasted estimates of transition probabilities and the population prevalence of being healthy and in work at age 50 6. Estimate lower and upper bounds for HWLE 95% confidence intervals by taking the lowest and highest combinations of results estimated using 95% confidence intervals of Lee Carter vectors of change over time for the overall mortality rate and the transition rate from healthy and working to unhealthy and/or not working, as well as the 95% confidence interval for ARIMA forecasted population prevalence of being healthy and in work at age 50

Estimation of transition probabilities and transition rates (step 1)

Mortality rates from each alive state ($m_{x,t}^{HW}$ and $m_{x,t}^{nHW}$) are estimated from the known overall population mortality rates $m_{x,t}$, the prevalence of being unhealthy and/or not working $\Pi_{x,t}^{nHW}$, and the ratio of mortality rates from being unhealthy and/or not working compared to being healthy and working $R_{x,t}$ as specified in equations 3.1 and 3.2 below. $R_{x,t}$ is assumed not to change with age or time (Cao, 2016; Majer et al., 2013) and can therefore be referred to as R.

$$m_{x,t}^{HW} = \frac{m_{x,t}}{R\Pi_{x,t}^{nHW} + (1 - \Pi_{x,t}^{nHW})} \tag{3.1}$$

$$m_{x,t}^{nHW} = m_{x,t}^{HW} R \tag{3.2}$$

The relationship between the prevalence of being healthy and in work ('HW') at age x and time t ($\Pi_{x,t}^{HW}$) and the same prevalence at the subsequent age one calendar year later is expressed through transition probabilities and the prevalence of *not* being healthy and in work ('nHW') (Cao, 2016; Majer et al., 2013):

$$\Pi_{x+1,t+1}^{nHW} = \frac{\Pi_{x,t}^{nHW}(1 - q_{x,t}^{nHW}) + (1 - \Pi_{x,t}^{nHW})q_{x,t}^{HWnHW}}{1 - (1 - \Pi_{x,t}^{nHW})q_{x,t}^{HW} - \Pi_{x,t}^{nHW}q_{x,t}^{nHW}} \tag{3.3}$$

where $\Pi_{x,t}^{HW}$ and $\Pi_{x,t}^{nHW}$ are the prevalences of being healthy and working (HW, state 1) or unhealthy and/or not working (nHW, state 2) respectively at age x and time t, $q_{x,t}^{HW}$ and $q_{x,t}^{nHW}$ are the age and time specific transition probabilities of death from the HW (state 1) and nHW (state 2) states respectively, and $q_{x,t}^{HWnHW}$ is the age and time specific probability of transition from HW (state 1) to nHW (state 2).

For feasibility when working with cross-sectional data with small sample sizes, it is helpful to calculate period health expectancies for each calendar year thereby replacing the left-hand side of equation 3.3 above ($\Pi_{x+1,t+1}^{nHW}$) with $\Pi_{x+1,t}^{nHW}$ (Majer et al., 2013), to give the following formula:

$$\Pi_{x+1,t}^{nHW} = \frac{\Pi_{x,t}^{nHW}(1 - q_{x,t}^{nHW}) + (1 - \Pi_{x,t}^{nHW})q_{x,t}^{HWnHW}}{1 - (1 - \Pi_{x,t}^{nHW})q_{x,t}^{HW} - \Pi_{x,t}^{nHW}q_{x,t}^{nHW}} \tag{3.4}$$

Equation 3.4 can then be populated using data collected in a single year and rearranged to estimate the transition rate transition $m_{x,t}^{HWnHW}$ and then transition probabilities ($q_{x,t}^{HW}$, $q_{x,t}^{nHW}$, and $q_{x,t}^{HWnHW}$) using equations 3.5, 3.6, and 3.7.

$$q_{x,t}^{HWnHW} = \frac{m_{x,t}^{HWnHW}}{(1 + \frac{m_{x,t}^{HWnHW}}{2} + \frac{m_{x,t}^{HW}}{2})(1 + \frac{m_{x,t}^{nHW}}{2})} \tag{3.5}$$

$$q_{x,t}^{nHW} = \frac{m_{x,t}^{nHW}}{1 + \frac{m_{x,t}^{nHW}}{2}} \tag{3.6}$$

$$q_{x,t}^{HW} = \frac{m_{x,t}^{HWnHW} + m_{x,t}^{HW}}{(1 + \frac{m_{x,t}^{HWnHW}}{2} + \frac{m_{x,t}^{HW}}{2})} - q_{x,t}^{HWnHW} \tag{3.7}$$

Calculation of $m_{x,t}^{HWnHW}$ requires a complex rearrangement of equation 3.3 using equations 3.5 and 3.7 for substitution (equation 3.8), where $q_{x,t}^{nHW}$ is calculated from equation 3.6. After $m_{x,t}^{HWnHW}$ has been found, computation of the remaining transition probabilities is straightforward.

$$m_{x,t}^{HWnHW} = \frac{\begin{array}{c} -(m_{x,t}^{nHW}+2)(\Pi_{x,t}^{nHW}((\Pi_{x+1,t}^{nHW}-1)q_{x,t}^{nHW}(m_{x,t}^{HW}+2) \\ -2\Pi_{x+1,t}^{nHW}m_{x,t}^{HW}+m_{x,t}^{HW}+2) \\ +\Pi_{x+1,t}^{nHW}(m_{x,t}^{HW}-2)) \end{array}}{\begin{array}{c} \Pi_{x,t}^{nHW}((\Pi_{x+1,t}^{nHW}-1)q_{x,t}^{nHW}(m_{x,t}^{nHW}+2) \\ -2\Pi_{x+1,t}^{nHW}m_{x,t}^{nHW}+m_{x,t}^{nHW}-2) \\ +\Pi_{x+1,t}^{nHW}(m_{x,t}^{nHW}-2)+4 \end{array}} \tag{3.8}$$

Forecasting of transition rates and the population prevalence of being healthy and working at age 50 (steps 2-3)

The Lee Carter approach to forecasting was intended for forecasting mortality rates. Here, the Lee Carter approach is used to forecast the overall population mortality rate $m_{x,t}$ and the transition rate from being healthy and in work to being unhealthy and/or not working $m_{x,t}^{HWnHW}$. (Mortality rates from each alive state are derived after forecasting.) For each of the forecasted transition rates $m_{x,t}$ and $m_{x,t}^{HWnHW}$, the natural log of the transition rate at age x and time t is expressed as a model on age and time profiles of the transition rate to derive a time series vector $\mathbf{k}$ capturing the transition rate trend over time as a random walk with drift. The Lee Carter approach is described here in relation to forecasting overall mortality rates; the same process applies to forecasting the transition rate $m_{x,t}^{HWnHW}$. Equation 3.9 below shows the expression of the mortality rate modelled on the average age profile of mortality **a**, mortality changes over time **k**, and the age specific impact of time trends on mortality rates **b** at age x and time t.

$$log(m_{x,t}) = a_x + b_x k_t + e_{x,t} \tag{3.9}$$

Vector **a** is obtained by averaging the age-sepecific log mortality rates. Subtracting **a** from each column of the matrix M of log mortality rates for each year of age (rows) and calendar year of time (columns) then allows computation of **b** and **k** through matrix Singular Value Decomposition (SVD) (equation 3.10).

$$M = UDV^T \tag{3.10}$$

where D is a diagonal matrix with diagonal values **d** giving the vector of singular values of M. U and V are orthonormal column matrices (each of unit length and orthogonal [perpendicular] to one another) containing the left-singular vectors and right-singular vectors of M respectively.

b is found by normalizing V to sum to 1 (each element of V is divided by the sum all elements of V). **k** is the column matrix U multiplied by the sum of all elements of V and the first singular value of M ($\mathbf{d}[1]$). The time index for the observed mortality rates **k** is forecasted as a random walk with drift δ (equation 3.11) by taking δ as the average change in consecutive values of **k** (that is, the mean of values $k_2 - k_1, k_3 - k_2, k_4 - k_3, ...$).

$$k_{t+1} = k_t + \delta + e_t \tag{3.11}$$

k_t for future calendar years are then straightforward to estimate from equation 3.11 and forecasted mortality rates are calculated by $exp(a_x + b_x * k_t)$ for future year t (equation 3.9) based on the observed rates in the final observed year. 95% confidence intervals for the projected mortality rates are given by the same exponential for $k_t \pm 1.96 * \sigma$, where the variance σ^2 is found by multiplying the squared standard error of the mean for observed **k** by the number of years into the future of the forecast ($t-$last observed year).

These steps are repeated to forecast the transition rate from being healthy and in work to being unhealthy and/or not working $m_{x,t}^{HWnHW}$.

As HWLE and life expectancy are estimated from age 50, the prevalence of being healthy and in work at age 50 must also be forecasted (unlike in the Lee Carter approach to forecasting mortality (a two state model) wherein the whole population is alive at age 0). This prevalence of being healthy and in work is forecasted for future years (for men and women separately) using ARIMA models.

Estimation of HWLE and life expectancy for observed and forecasted years (steps 4-6)

The forecasted overall mortality rates, the ratio of mortality rates R, and the prevalence of being healthy and in work at age 50 are used to iteratively estimate all transition rates and probabilities at age 50 and subsequent ages in the first and subsequent forecasted years. Let $l_{x,t}^{HW}$ and $l_{x,t}^{nHW}$ denote the number of living people at age x and time t who are healthy and working (HW) or not healthy and working (nHW) respectively, and let $l_{x,t}$ be the total number of living people at age x at time t. The number of people in each alive state (HW (1), nHW (2)) are estimated using equations 3.12 and 3.13 where $q_{x,t}^{HW}$ is the probability of a healthy working person dying at age x and time t, $q_{x,t}^{nHW}$ is the probability of an unhealthy and/or not working person dying at age x and time t, and $q_{x,t}^{HWnHW}$ is the probability of a healthy working person becoming unhealthy and/or stopping working at age x and time t.

$$l_{x+1,t}^{HW} = l_{x,t}^{HW}(1 - q_{x,t}^{HWnHW} - q_{x,t}^{HW}) \tag{3.12}$$

$$l_{x+1,t}^{nHW} = l_{x,t}^{nHW}(1 - q_{x,t}^{nHW}) + l_{x,t}^{HW} q_{x,t}^{HWnHW} \tag{3.13}$$

The person-years lived in the healthy and working state (1) and in the unhealthy and/or not working state (2) are estimated as follows (equations 3.14 and 3.15):

$$L^{HW}_{x,t} = \frac{l^{HW}_{x,t} + l^{HW}_{x+1,t}}{2} \tag{3.14}$$

$$L^{nHW}_{x,t} = \frac{l^{nHW}_{x,t} + l^{nHW}_{x+1,t}}{2} \tag{3.15}$$

For each year t, cumulative person-years lived in each state (T^{HW}_t and T^{nHW}_t) from age 50 are estimated by summing the person-years lived in each state ($L^{HW}_{x,t}$ and $L^{nHW}_{x,t}$ respectively) from $x = 50$ to the maximum age of 75 for T^{HW}_t for HWLE (because transition rates between states could not be estimated at later ages and prevalence of being healthy and working was therefore assumed to be negligible beyond age 75) and 100 for T^{nHW}_t for life expectancy (the maximum age in ONS life tables from which mortality rates were obtained). Then HWLE for each year t (observed or forecasted) is life expectancy from age 50 in the healthy working state (equation 3.16), and life expectancy from age 50 $LE_{50,t}$ is the sum of HWLE and life expectancy in the unhealthy and/or not working state (equations 3.17 and 3.18).

$$HWLE_t = LE^{HW}_{50,t} = \frac{T^{HW}_t}{l_{50,t}} \tag{3.16}$$

$$LE^{nHW}_{50,t} = \frac{T^{nHW}_t}{l_{50,t}} \tag{3.17}$$

$$LE_{50,t} = LE^{HW}_{50,t} + LE^{nHW}_{50,t} \tag{3.18}$$

Confidence intervals for HWLE and life expectancy are estimated using 95% confidence interval upper and lower bounds of ARIMA estimates of the prevalence of being healthy and in work at age 50 (for forecasted years) and 95% confidence interval upper and lower bounds of transition rates (mortality rates and the transition rate from being healthy and working to unhealthy and/or not working).

3.3 Data sources: Health Survey for England (HSE) and age specific mortality rates from national life tables

The Health Survey for England (HSE) was one of the data sources used for this study. HSE data were used to identify the prevalence of being healthy and working at each year of age from age 50 upwards. HSE is an ongoing annual survey intended to represent the community-dwelling general population of all ages in England (Bridges et al., 2015a). HSE began in 1991 and survey weighting was introduced in 2003. HSE data were collected through household questionnaires, personal interviews and self-completion questionnaires and were obtained from the UK Data Service. Yearly HSE data were available from 1996 to 2014 with information about limiting long-standing illness (to identify health status), work participation status, and year of age for survey respondents. More recent HSE data (2015 onwards) could not be used due to providing only grouped age variables. Labour Force Survey data could not be used as the relevant health question was only asked up to State Pension age (which until recently was lower than age 65 for women). English Longitudinal Study of Ageing (ELSA) data (used in the previous chapter) has fieldwork periods extending over two years and could not be used as, for the forecasting component of HWLE projections, health and work data were required to have time intervals consistent with mortality rates. At some ELSA survey waves there were also no respondents aged in their early 50s.

Age specific mortality rates for males and females separately were identified from the UK Office for National Statistics (ONS) single year life tables from 1996 (to correspond to the start of HSE data used) to 2018 (the most recent year available) (ONS, 2019n). In the literature, the ratio of mortality rates from the 'healthy' model state and the 'unhealthy' model state has been estimated by simple calculation from both rates observed separately or using proportional hazards regression survival analysis (Majer et al., 2013). However, no data were known of to facilitate such analyses due to health and work participation statuses in reality being states that can be repeatedly exited and entered (although modelled in this chapter as one-way transitions), with only (repeated) cross-sectional observations typically collected. Instead, a result presented in chapter 5 was used to estimate the ratio of mortality rates. Chapter 5 presents hazard rate ratio analyses of transitions between states in the 3-state HWLE model (but with two-way transitions permitted between the two alive states) using ELSA data. Results of the study presented in chapter 5 were used to estimate the approximate ratio of mortality rates from the unhealthy and/or not working state (state 2) compared to the healthy working state (state 1) as 1.04 (taken as the ratio of hazard rate ratios for transitions 2-3 and 1-3 that were associated with each additional year of age: 1.10/1.06) (table 5.7 on page 261).

3.4 Operationalisation of health and work for HWLE

Health and work statuses were identified from responses to individual HSE interviews. Health was defined as the absence of limiting long-standing illness captured through two survey items, which were revised in HSE from 2012 onwards.

HSE 1996-2011

Do you have any long-standing illness, disability or infirmity? By long-standing I mean anything that has troubled you over a period of time, or that is likely to affect you over a period of time?

1 Yes

2 No

IF YES

Does this illness or disability (do any of these illnesses or disabilities) limit your activities in any way?

1 Yes

2 No

HSE 2012-2014

Do you have any physical or mental health conditions or illnesses lasting or expected to last 12 months or more?

1 Yes

2 No

> *IF YES*
>
> Do any of your conditions or illnesses reduce your ability to carry out day-to-day activities? Please consider whether you are affected while receiving any treatment or medication for your condition or illness and/or using any devices such as a hearing aid, for example.
>
> 1 Yes, a lot
>
> 2 Yes, a little
>
> 3 Not at all

Respondents were considered to have a limiting long-standing illness if they responded yes to both questions (with activity restriction 'yes, a little' or 'yes, a lot' in 2012-2014). Respondents were considered healthy otherwise.

Work was defined as employment or self-employment as measured in a single survey item. Respondents were shown a card listing the following activities:

- Going to school or college full-time (including on vacation)
- In paid employment or self-employment (or away temporarily)
- On a Government scheme for employment training *(1998 onwards)*
- Doing unpaid work for a business that you own, or that a relative owns *(1998 onwards)*
- Waiting to take up paid work already obtained
- Looking for paid work or a Government training scheme
- Intending to look for work but prevented by temporary sickness or injury (CHECK MAX 28 DAYS)

- Permanently unable to work because of long-term sickness or disability (USE ONLY UP TO STATE PENSION AGE FOR MEN/WOMEN)
- Retired from paid work
- Looking after the home or family
- Doing something else (SPECIFY)

Respondents were then asked what activities they had participated in within the last week (*"Which of these descriptions applies to what you were doing last week, that is in the seven days ending (date seven days ago)?"*). Respondents were considered to be in paid work if they reported being 'in paid employment or self-employment (or away temporarily)' within the past week.

3.5 Components of the HWLE projections

In order to estimate HWLE for the study period and project future values, data requirements included: the prevalence of being healthy and in work (separately for males and females) at each year of age and each calendar year; forecasts of the prevalence of being healthy and in work (separately for males and females) at age 50 for the HWLE projected years (2015-2035); calculated estimates of the transition rate from the healthy working state (state 1) to the unhealthy and/or not working state (state 2) $m_{x,t}^{HWnHW}$; age specific mortality rates m_x (separately for males and females); Lee Carter forecasts of transition rates $m_{x,t}^{HWnHW}$ and mortality rates m_x; the ratio of mortality rates from the two alive states (taken as 1.04 with death more likely from the unhealthy and/or not working state).

3.5.1 Age specific prevalence of being healthy and in work (state 1) (HSE data)

The age specific prevalence of being healthy and in work (separately for men and women) was estimated by dividing the number of HSE respondents who reported good health and paid work participation over the total sample size at each year of age. Survey weights were included in calculations in years 2003-2014. The number of respondents for each sex at each year of age within the range 50-75 ranged from 21 to 160 for men and 21 to 193 for women. The numbers of respondents at each age 50-75 at each HSE survey from 1996-2014 (and 2015-2018 by age group) can be seen in appendix F. Because of small sample sizes at each age and some very small sample sizes at older ages, it was assumed that all healthy and working people became unhealthy and/or stopped working after age 75. Each calendar year, the age-trend in prevalence of being healthy and working required data smoothing; small sample sizes resulted in higher variance between age specific prevalence estimates making modelling using the intercensal and Lee Carter method impossible (and, because mortality rates presented a smooth trend over age, violating the assumption that transitions were only permitted one-way from HW (state 1) to nHW (state 2)). For each calendar year, the population prevalence of being healthy and in work was taken as loess (locally weighted smoothing) smoothed values of the HSE observed prevalence of being healthy and in work (separately for males and females). For loess smoothing, data were used for ages 50-79 with values at age 76, 77, 78, and 79 set to zero. Including ages $76-79$ improved smoothing at later ages in the 50-75 age window for modelling, mitigating against failed calculations (the natural log of transition rates) at later stages. Appendix G shows HSE observed and loess smoothed values for the age specific prevalence of being healthy and in work for men and women for years 1996-2014. Other smoothing approaches were considered (including splines, monotonic polynomials, and loess smoothing with smaller spans of data either side of each data point used for smoothing) but loess smoothing resulted in the fewest complications in calculations at later stages and lead to trend curves in the transition from HW to nHW that most resembled that of mortality rates, for which the Lee Carter method was designed. Loess smoothing was carried out using function `loess` in R package 'stats' (Team and Others, 2013) with default span 0.75. For males in some calendar years, loess smoothing produced prevalences that increased at younger ages before decreasing. This did not affect the feasibility of HWLE estimation. Problems with subsequent calculations that arose for males were not avoided by switching to a monotonic smoothing approach.

3.5.2 Prevalence of being healthy and in work (state 1) at age 50 for HWLE projected years 2015-2035 (HSE data)

The prevalence of being healthy and in work at age 50 for future years was forecasted using ARIMA models of the HSE 1996-2014 data (smoothed values) for males and females separately. ARIMA(0,1,1) was the best fitting model for the female time series, identified from autocorrelation function (ACF) and partial autocorrelation (PACF) plots of the differenced series as well as the automatic model selection function `auto.arima` (from R package 'forecast' (Hyndman et al., 2020; Hyndman and Khandakar, 2008)) and manual testing of various models. A white noise model ARIMA(0,0,0) was automatically detected as the preferred model for the male time series but visual inspection of the trend indicated that this could be an artefact of the length of the time series. Manual testing of various models supported selection of the same model used for the female time series (ARIMA(0,1,1)). Both male and female time series were differenced to achieve stationarity. The female time series was not stationary (visually or using the Dickey-Fuller test) without differencing. Dickey-Fuller tests indicated that the male time series was stationary with or without differencing, but visual inspection suggested differencing was appropriate. Figures 3.3 and 3.2 show the forecasted prevalence of being healthy and working at age 50 for 2015-2035 for men and women respectively.

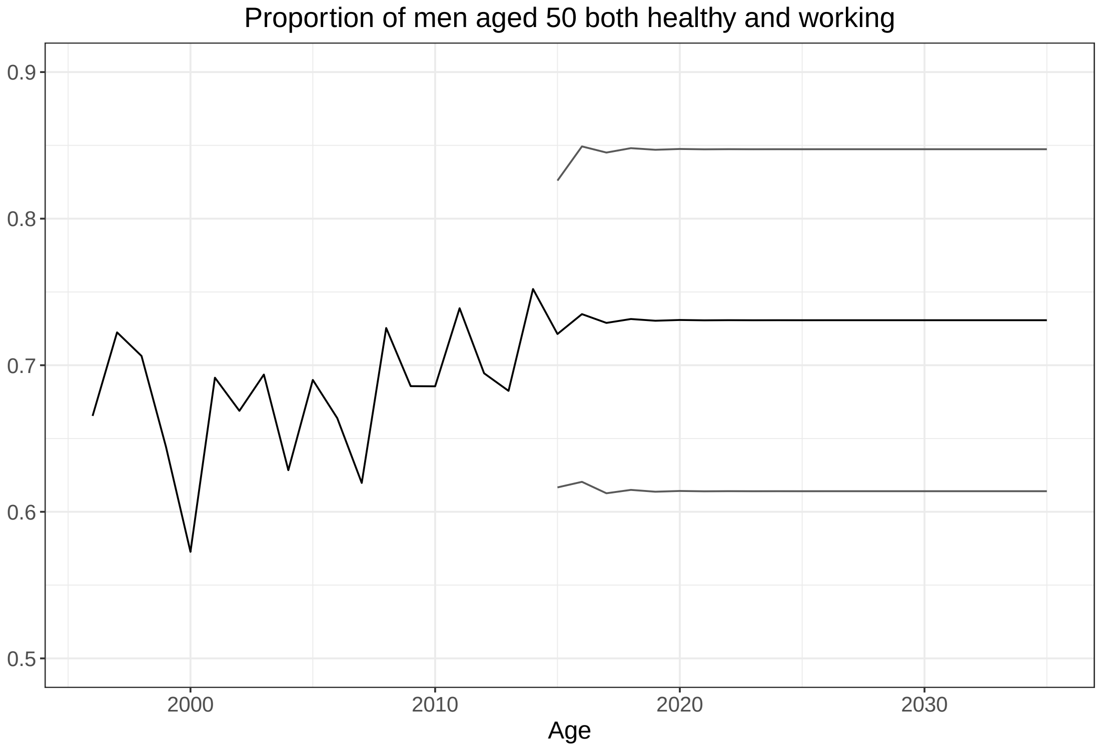

FIGURE 3.2: HSE data time series forecast of prevalence of being healthy and in work among males at age 50 (observed 1996-2014, projected 2015-2035) with 95% confidence interval (grey lines)

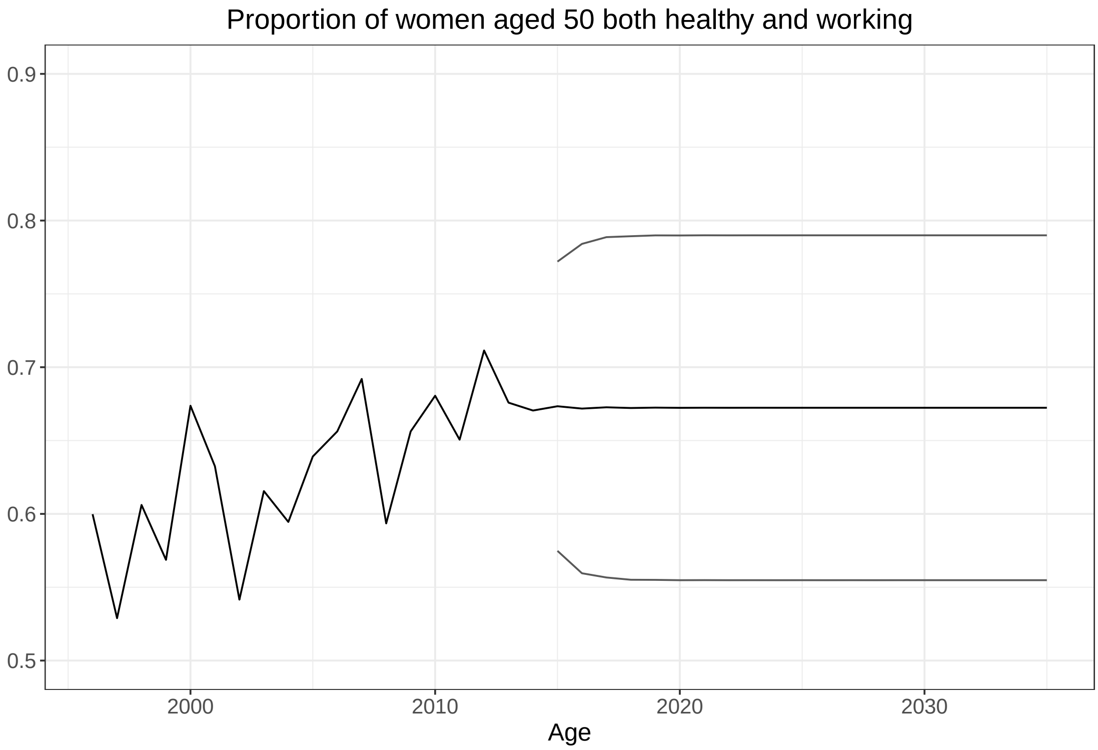

FIGURE 3.3: HSE data time series forecast of prevalence of being healthy and in work among females at age 50 (observed 1996-2014, projected 2015-2035) with 95% confidence interval (grey lines)

3.5.3 Calculation of the projected transition rate from healthy and working to unhealthy and/or not working

Lee Carter forecasting for mortality rates is available pre-programmed in the 'demography' R package (Booth and Hyndman, 2019) but, due to the more complex 3-state model with transitions permitted between alive states, formulae for estimation of transition rates and other variables were coded manually in R software version 3.6.2 (Rodríguez, 2017). Forecasted mortality rates were checked for consistency with those identified using the 'demography' package.

Over all ages 50-75 and all observed years 1996-2014 of the transition rate from the healthy and working state to unhealthy and/or not working, the natural log could not be taken for 15 values for men. All 15 NA values occured after age 50; these missing values were imputed as the value for the preceding age of the same year. There were no such issues in the female data. The upper and lower estimated bounds for projections of the same transition rate were extremely high for a small number of years in the early 50s for men; figures 3.4, 3.5, and 3.6 show the main fit and lower and upper bounds respectively for transition $m_{x,t}^{HWnHW}$ for men in the year 2035 (the latest projected year and therefore the year with the most extreme values). Figure 3.7 shows the same upper bound on a restricted y-axis. To avoid confidence intervals of HWLE with negative values, upper and lower bounds for the projected transition rate $m_{x,t}^{HWnHW}$ for men at ages 52, 53, and 54 were replaced with values from linear interpolation between $m_{x,t}^{HWnHW}$ at ages 51 and 55.

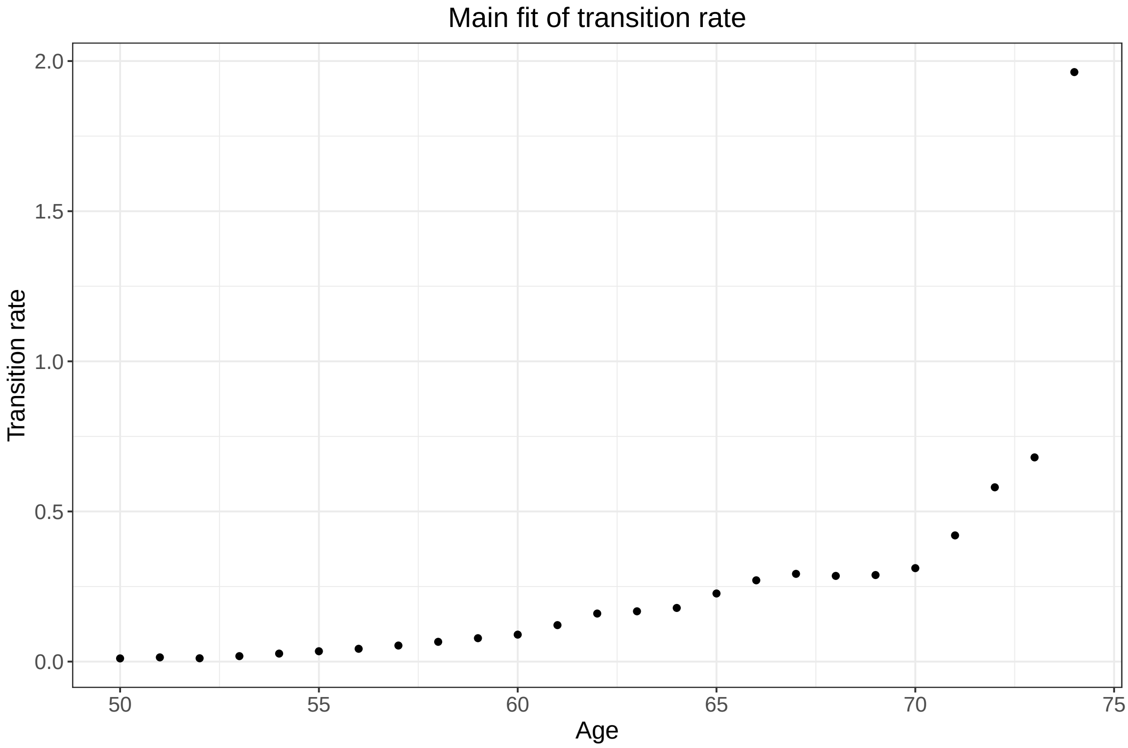

FIGURE 3.4: Main fit estimate of transition rate from healthy and working to unhealthy and/or not working for males in 2035 using HSE data

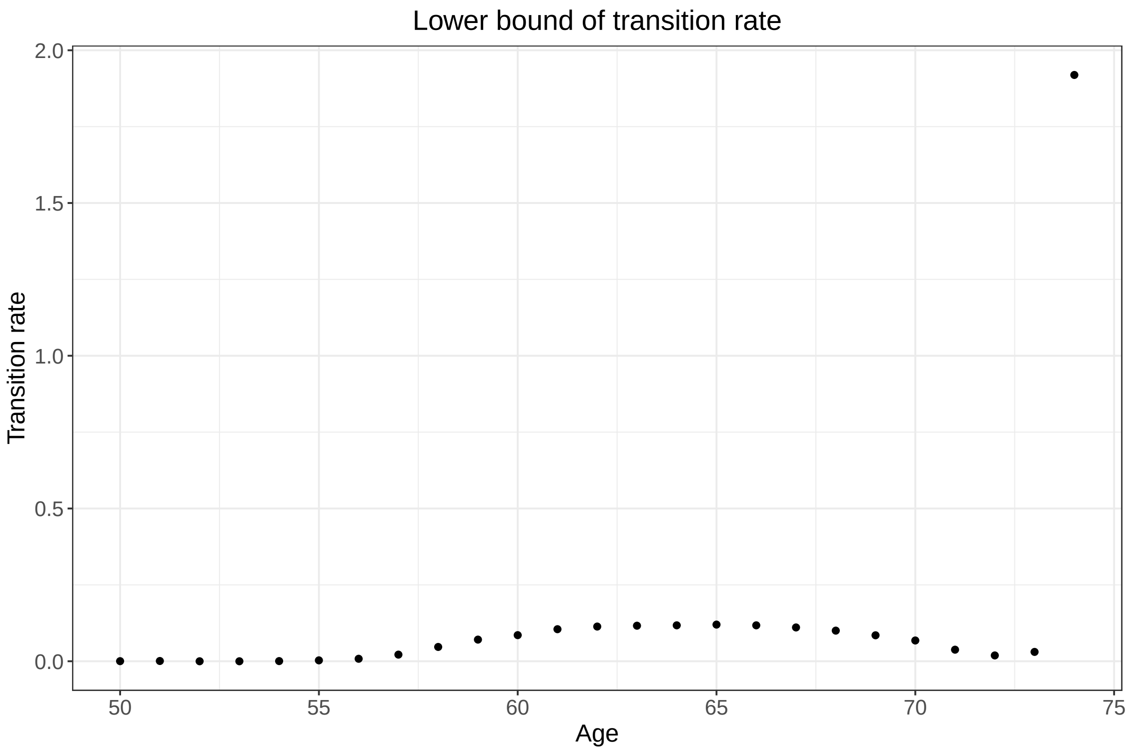

FIGURE 3.5: Lower bound estimate of transition rate from healthy and working to unhealthy and/or not working for males in 2035 using HSE data

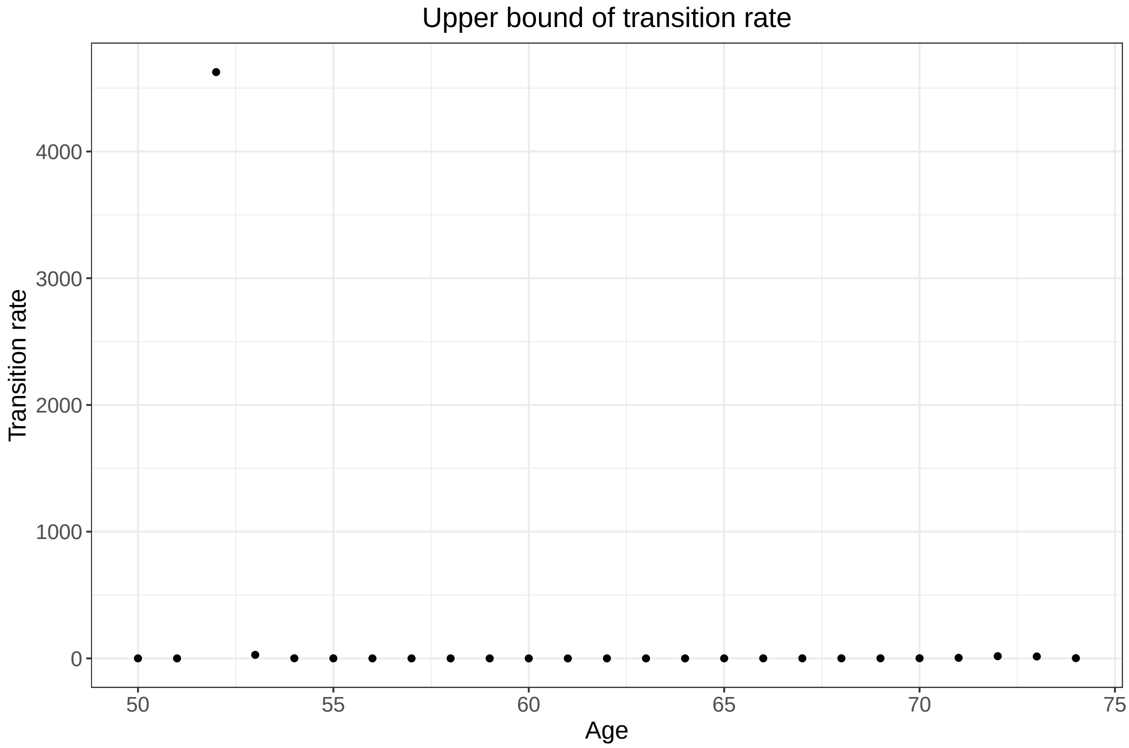

FIGURE 3.6: Upper bound estimate of transition rate from healthy and working to unhealthy and/or not working for males in 2035 using HSE data

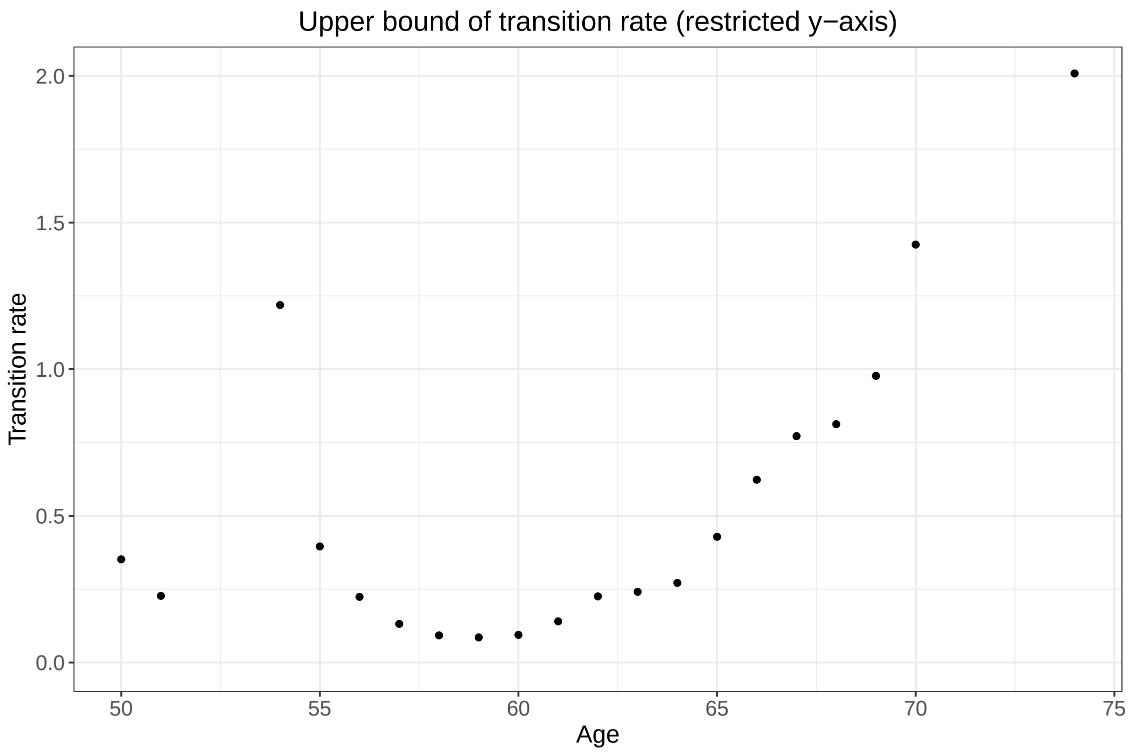

FIGURE 3.7: Upper bound estimate of transition rate from healthy and working to unhealthy and/or not working for males in 2035 using HSE data shown on restricted y-axis

3.6 Sensitivity analyses

As the number of years of HSE data available for forecasting was low compared to mortality data availability for typical Lee Carter forecasting uses, all years of data were used for modelling and forecasting instead of splitting the data for back-forecasting to validate the model. Instead, observed HWLE (1996-2014) and forecasted HWLE (2015-2017) were separately estimated using the Sullivan method (Jagger et al., 2014). (Most recent HSE years 2015-2017 could be used in this sensitivity analysis as - unlike the intercensal approach - grouped ages can be analysed using the Sullivan method.)

Sensitivity analyses used to examine the potential impact on HWLE estimates and projections of taking 1.04 as the ratio of mortality rates from being HW (state 1) or nHW (state 2) were carried out by taking the ratio of mortality rates R as 1 (mortality rates are the same from state 1 and state 2) and taking R as 2 (mortality rates are twice as high from state 2 compared to state 1).

3.7 Missing data

At each calendar year, missing health and/or work responses in the HSE survey were excluded from calculations of the age specific prevalence of being healthy and in work. No more than ten health and/or work responses among respondents aged 50-75 were missing each year (table 3.2).

TABLE 3.2: Number of missing health and/or work responses among respondents aged 50-75 in HSE surveys 1996-2014

Year	Missing health/work statuses among respondents aged 50 and 75
1996	0
1997	3
1998	8
1999	3
2000	7
2001	9
2002	3
2003	9
2004	6
2005	8
2006	5
2007	3
2008	9
2009	2
2010	2
2011	3
2012	9
2013	3
2014	10

3.8 Results

3.8.1 Life expectancy projections

Life expectancy (LE) for men from age 50 was estimated as 26.20 years in 1996, 30.60 years in 2015 (the final year of observed data for HWLE estimation), and 31.60 years from age 50 in 2018 (the most recent year with observed mortality data) (table 3.3). LE for men was projected as 31.78 (95% CI [31.77,31.78]) years from age 50 in 2019, 31.97 (31.71,32.22) years in 2020, and 34.70 (33.75,35.56) years in 2035 (table 3.3). LE for men in 2035 was projected to be 4.10 years higher than that observed in 2015 (the first year for which HWLE was projected), implying an average annual gain in LE of 10.66 weeks (0.21 years) per calendar year.

LE for women from age 50 was estimated as 30.39 years in 1996, 33.65 years in 2015, and 34.51 years in 2018 (table 3.4). LE for women was projected as 34.66 (34.66,34.66) years in 2019, 34.79 (34.51,35.08) years in 2020, and 36.72 (35.69,37.70) years in 2035 (table 3.4). LE for women in 2035 was projected to be 2.46 years higher than that observed in 2015 - an average gain of 6.4 weeks per year (0.12 years).

3.8.2 HWLE projections

For men, HWLE during the observed years was estimated to increase from 6.93 in 1996 to 8.94 in 2014 (table 3.3). Projected HWLE for men was 8.67 (6.57,10.73) years from age 50 in 2015, increasing to 8.85 (4.98,12.03) years in 2020 and 9.05 (2.16,13.28) years in 2035 (table 3.3).

For women, HWLE during the observed years was estimated to increase from 4.94 in 1996 to 6.85 in 2014 (table 3.4). Projected HWLE for women was 7.49 (5.61,9.62) years from age 50 in 2015 increasing to 7.74 (4.50,11.53) years in 2020 and 8.57 (3.28,13.87) years in 2035 (table 3.4).

Throughout 1996 to 2014, the average estimated HWLE gain per calendar year was 5.8 weeks for men (0.11 years) and 5.5 weeks for women (0.11 years) (figures 3.8 and 3.9). From 2015 to 2035, HWLE gains were projected to slow to an average of one week per year for men (0.02 years) and 2.8 weeks per year for women (0.05 years). That average HWLE gains are not expected to keep pace with average LE gains implies a decreasing percentage over time of LE from age 50 spent healthy and in work.

TABLE 3.3: HWLE observed (1996-2014) and projected (2015-2035) for men; life expectancy observed (1996-2018) and projected (2019-2035) for men; Sullivan method HWLE estimates (1996-2017) for men; official published life expectancy estimates (1996-2019) and projections (2020-2035) for men

MALES		*Intercensal method + Lee Carter projections*			*Sullivan method*	*ONS past and 2018-based LE projections*			
Year	Observed HWLE	Projected HWLE (95% CI)	Observed LE	Projected LE	HWLE (95% CI)	Past LE	Projected LE	Low variant	High variant
1996	6.93		26.20		7.74 (7.38,8.10)	27.1			
1997	7.11		26.48		7.88 (7.40,8.37)	27.4			
1998	7.21		26.69		8.15 (7.79,8.50)	27.6			
1999	7.04		26.92		8.05 (7.56,8.55)	27.8			
2000	6.59		27.30		7.56 (7.07,8.06)	28.2			
2001	7.12		27.60		7.95 (7.59,8.31)	28.5			
2002	7.39		27.76		8.26 (7.72,8.80)	28.7			
2003	7.48		27.92		8.33 (7.97,8.70)	28.8			
2004	7.30		28.38		8.25 (7.71,8.79)	29.3			
2005	7.78		28.64		8.70 (8.23,9.17)	29.6			
2006	7.96		28.92		9.06 (8.69,9.43)	29.8			
2007	7.48		29.16		8.67 (8.13,9.21)	30.1			
2008	8.13		29.33		9.19 (8.83,9.55)	30.2			
2009	8.21		29.71		9.25 (8.59,9.91)	30.6			
2010	8.02		29.89		8.83 (8.33,9.32)	30.8			
2011	8.69		30.25		9.60 (9.10,10.10)	31.2			
2012	8.58		30.33		9.72 (9.23,10.21)	31.3			
2013	8.27		30.36		9.22 (8.73,9.72)	31.3			
2014	8.94		30.60		9.95 (9.45,10.46)	31.5			
2015		8.67 (6.57,10.73)	31.33		9.82 (9.31,10.33)	31.4			
2016		8.85 (6.22,11.35)	31.51		9.83 (9.34,10.33)	31.6			
2017		8.79 (5.81,11.51)	31.57		10.10 (9.60,10.59)	31.6			
2018		8.82 (5.53,11.72)	31.60			31.6			
2019		8.83 (5.24,11.87)		31.78 (31.77,31.78)			32.0	31.9	32.1
2020		8.85 (4.98,12.03)		31.97 (31.71,32.22)			32.0	31.8	32.2

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Table 3.3 – continued from previous page

MALES		*Intercensal method + Lee Carter projections*			*Sullivan method*	*ONS past and 2018-based LE projections*			
Year	Observed HWLE	Projected HWLE (95% CI)	Observed LE	Projected LE	HWLE (95% CI)	Past LE	Projected LE	Low variant	High variant
2021		8.86 (4.73,12.15)		32.17 (31.80,32.52)			32.1	31.9	32.3
2022		8.88 (4.49,12.27)		32.36 (31.90,32.79)			32.2	32.0	32.4
2023		8.89 (4.27,12.38)		32.55 (32.03,33.04)			32.3	32.1	32.5
2024		8.91 (4.05,12.48)		32.73 (32.16,33.28)			32.4	32.2	32.7
2025		8.92 (3.84,12.57)		32.92 (32.29,33.51)			32.5	32.3	32.8
2026		8.94 (3.63,12.66)		33.10 (32.43,33.74)			32.6	32.3	32.9
2027		8.95 (3.44,12.74)		33.29 (32.57,33.96)			32.7	32.4	33.0
2028		8.96 (3.25,12.82)		33.47 (32.72,34.17)			32.8	32.5	33.1
2029		8.98 (3.07,12.89)		33.65 (32.86,34.38)			32.9	32.5	33.3
2030		8.99 (2.90,12.96)		33.83 (33.01,34.59)			33.0	32.6	33.4
2031		9.00 (2.74,13.03)		34.01 (33.16,34.79)			33.1	32.6	33.5
2032		9.01 (2.58,13.10)		34.18 (33.30,34.99)			33.2	32.6	33.7
2033		9.03 (2.44,13.16)		34.36 (33.45,35.18)			33.3	32.7	33.8
2034		9.04 (2.29,13.22)		34.53 (33.60,35.38)			33.4	32.7	33.9
2035		9.05 (2.16,13.28)		34.70 (33.75,35.56)			33.5	32.7	34.1

Notes:
States: Healthy and in work (HWLE) [1]; Not healthy and/or not in work (including: healthy and not in work, not healthy and in work, not healthy and not in work) [2]; Dead [3]
Data for estimation of HWLE were observed from 1996 to 2014 (1996 to 2017 for Sullivan method estimates) and data for estimation of life expectancy were observed from 1996 to 2018
ONS low and high variants reflect less optimistic and more optimistic future demographic scenarios respectively based on trend calculations and expert opinions

TABLE 3.4: HWLE observed (1996-2014) and projected (2015-2035) for women; life expectancy observed (1996-2018) and projected (2019-2035) for women; Sullivan method HWLE estimates (1996-2017) for women; official published life expectancy estimates (1996-2019) and projections (2020-2035) for women

FEMALES		*Intercensal method + Lee Carter projections*			*Sullivan method*	*ONS past and 2018-based LE projections*			
Year	Observed HWLE	Projected HWLE (95% CI)	Observed LE	Projected LE	HWLE (95% CI)	Past LE	Projected LE	Low variant	High variant
1996	4.94		30.39		5.57 (5.25,5.89)	31.3			
1997	4.94		30.52		5.62 (5.17,6.06)	31.5			
1998	5.28		30.71		6.00 (5.68,6.31)	31.7			
1999	5.16		30.82		5.89 (5.44,6.34)	31.8			
2000	5.17		31.15		5.82 (5.39,6.26)	32.1			
2001	5.51		31.35		6.26 (5.94,6.58)	32.3			
2002	5.27		31.42		6.00 (5.52,6.48)	32.4			
2003	5.81		31.44		6.65 (6.32,6.97)	32.4			
2004	5.82		31.94		6.71 (6.24,7.19)	32.9			
2005	6.02		32.04		6.68 (6.24,7.12)	33.0			
2006	6.20		32.34		6.99 (6.66,7.33)	33.3			
2007	6.49		32.45		7.25 (6.76,7.73)	33.4			
2008	6.13		32.52		7.05 (6.72,7.38)	33.5			
2009	7.07		33.00		7.95 (7.30,8.59)	34.0			
2010	6.51		33.08		7.25 (6.80,7.69)	34.1			
2011	6.55		33.38		7.37 (6.93,7.81)	34.4			
2012	7.08		33.29		7.84 (7.39,8.30)	34.3			
2013	7.14		33.37		8.17 (7.74,8.61)	34.3			
2014	6.85		33.65		7.76 (7.30,8.22)	34.6			
2015		7.49 (5.61,9.62)	34.26		8.10 (7.64,8.55)	34.3			
2016		7.52 (5.19,10.23)	34.43		8.05 (7.58,8.52)	34.5			
2017		7.59 (4.96,10.67)	34.52		8.18 (7.72,8.65)	34.6			
2018		7.63 (4.78,10.99)	34.51			34.6			
2019		7.69 (4.63,11.27)		34.66 (34.66,34.66)			35.0	34.9	35.1
2020		7.74 (4.50,11.53)		34.79 (34.51,35.08)			34.8	34.7	35.0

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* **Table 3.4 – continued from previous page** *

FEMALES		*Intercensal method + Lee Carter projections*			*Sullivan method*	*ONS past and 2018-based LE projections*			
Year	Observed HWLE	Projected HWLE (95% CI)	Observed LE	Projected LE	HWLE (95% CI)	Past LE	Projected LE	Low variant	High variant
2021		7.80 (4.38,11.76)		34.93 (34.53,35.32)			34.9	34.7	35.1
2022		7.85 (4.27,11.97)		35.06 (34.58,35.54)			35.0	34.8	35.2
2023		7.91 (4.17,12.17)		35.20 (34.64,35.74)			35.1	34.9	35.3
2024		7.96 (4.07,12.35)		35.33 (34.71,35.93)			35.1	34.9	35.4
2025		8.02 (3.98,12.52)		35.46 (34.79,36.12)			35.2	35.0	35.5
2026		8.08 (3.89,12.69)		35.59 (34.87,36.29)			35.3	35.0	35.6
2027		8.13 (3.81,12.84)		35.72 (34.95,36.46)			35.4	35.1	35.7
2028		8.19 (3.73,12.99)		35.85 (35.04,36.63)			35.5	35.1	35.8
2029		8.24 (3.66,13.13)		35.98 (35.13,36.79)			35.5	35.2	35.9
2030		8.30 (3.59,13.27)		36.11 (35.22,36.95)			35.6	35.2	36.0
2031		8.35 (3.52,13.40)		36.23 (35.31,37.11)			35.7	35.3	36.1
2032		8.41 (3.46,13.52)		36.36 (35.41,37.26)			35.8	35.3	36.2
2033		8.46 (3.40,13.64)		36.48 (35.50,37.41)			35.9	35.3	36.3
2034		8.52 (3.34,13.76)		36.60 (35.59,37.55)			35.9	35.3	36.4
2035		8.57 (3.28,13.87)		36.72 (35.69,37.70)			36.0	35.4	36.6

Notes:
States: Healthy and in work (HWLE) [1]; Not healthy and/or not in work (including: healthy and not in work, not healthy and in work, not healthy and not in work) [2]; Dead [3]
Data for estimation of HWLE were observed from 1996 to 2014 (1996 to 2017 for Sullivan method estimates) and data for estimation of life expectancy were observed from 1996 to 2018
ONS low and high variants reflect less optimistic and more optimistic future demographic scenarios respectively based on trend calculations and expert opinions

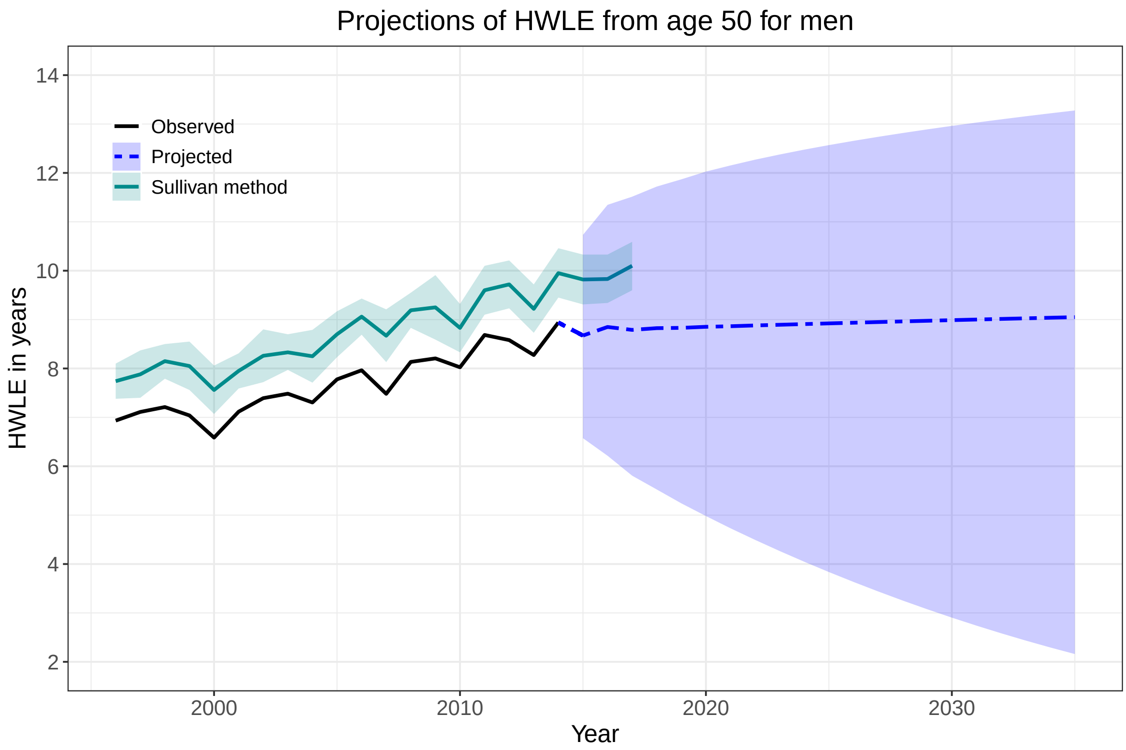

FIGURE 3.8: HWLE observed (1996-2014, black line) and projected (2015-2035, blue dashed line with 95% CI) for males shown with Sullivan method estimates (green) with 95%CI

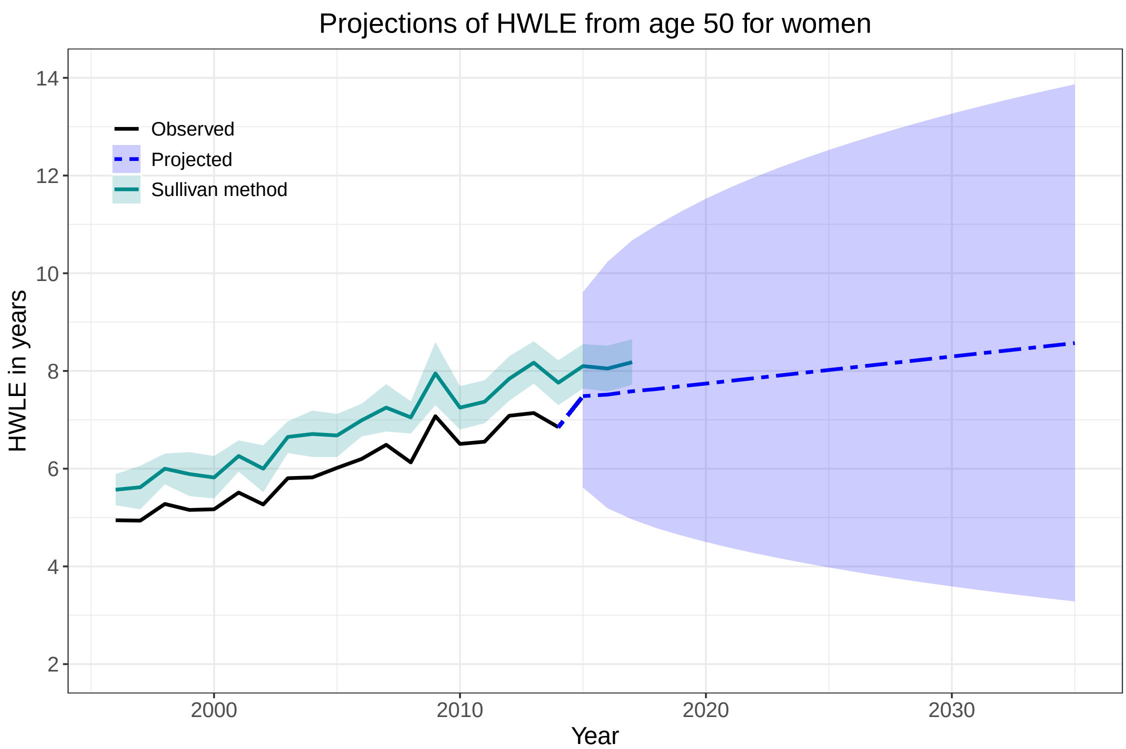

FIGURE 3.9: HWLE observed (1996-2014, black line) and projected (2015-2035, blue dashed line with 95% CI) for females shown with Sullivan method estimates (green) with 95%CI

3.8.3 Sensitivity analyses results

HWLE point estimates obtained using the Sullivan method were almost one year higher on average for men and 0.78 years higher for women from 1996 to 2014 than the main estimates obtained using the intercensal method (tables 3.3 and 3.4). The intercensal observed HWLE estimates for men and women were also consistently lower than the 95% confidence interval lower bounds of Sullivan method estimates. Estimated HWLE trends appear visually similar using both methods suggesting that the intercensal approach may provide a useful reflection of HWLE trends while underestimating the true length of healthy working life from age 50. From 1996 to 2014, Sullivan method HWLE estimates increased by an average of 6.4 weeks per year for men (0.12 years) and 6.3 years for women (0.12 years) compared to average yearly gains of 5.8 weeks (0.11 years) and 5.5 weeks (0.11 years) respectively in intercensal HWLE estimates.

Estimates of HWLE using both the intercensal and Sullivan approaches were lower than HWLE estimates using the interpolated Markov chains approach (chapter 2). Compared to IMaCh estimates of HWLE presented in the previous chapter of 10.94 years for men and 8.25 years for women from age 50, the average HWLE estimated using the intercensal approach throughout the same study period 2002-2013 (ELSA waves 1-6; see chapter 2) was three years lower for men (7.94 years) and two years lower for women (6.34 years). Averaged Sullivan method HWLE estimates from 2002 to 2013 were two years lower than IMaCh estimates for men (8.92 years) one year lower than IMaCh estimates for women (7.16 years).

HWLE estimates in observed and projected years were similar in sensitivity analyses of the ratio of mortality rates R between the two alive states (tables 3.5 and 3.6). Taking R to be 1.04, main HWLE estimates in 1996, 2014, 2015, and 2035 were 6.93, 8.94, 8.67 (6.86,10.48), and 9.05 (4.27,12.57) years respectively for men and 4.94, 6.85, 7.49 (6.06,9.03), and 8.57 (5.58,11.97) years respectively for women. Taking R instead to be equal to 1 (assuming age specific mortality rates are the same for healthy working people as for unhealthy and/or not working people), estimates in 1996, 2014, 2015, and 2035 were 6.94, 8.95, 8.68 (6.58,10.72), and 9.07 (2.08,13.16) years respectively for men and 4.95, 6.85, 7.49 (5.61,9.62), and 8.57 (3.28,13.86) years respectively for women. When R was taken to be equal to 2 (assuming age specific mortality rates are twice as high for unhealthy and/or not working people compared to healthy working people), estimates in 1996, 2014, 2015, and 2035 were 6.81, 8.83, 8.71 (6.84,10.89), and 8.86 (4.44,14.10) years respectively for men and 4.90, 6.80, 7.48 (5.61,9.62), and 8.57 (3.35,13.94) years respectively for women. In 2020, HWLE projected for men was 8.85 (5.92,11.54) years from age 50 in the main analysis (R =1.04) compared to 8.86 (4.97,11.97) when R =1 and 8.83 (5.94,12.48) when R =2 (table 3.5). The main HWLE projection for women (R =1.04) in 2020 was 7.74 (5.60,10.20) years from age 50 and was the same when R =1 (7.74 [4.50,11.52] years) and R =2 (7.74 [4.51,11.56]) (table 3.6).

TABLE 3.5: Sensitivity analyses of male HWLE observed and projected estimates to ratio of mortality rate from being healthy and working compared to mortality rate from being unhealthy and/or not working

MALE		*Main analysis*		*Sensitivity analyses of HWLE*	
Year	HWLE	LE		HWLE (R =1)[1]	HWLE (R =2)[2]
Observed HWLE and LE					
1996	6.93	26.20		6.94	6.81
1997	7.11	26.48		7.12	7.00
1998	7.21	26.69		7.22	7.10
1999	7.04	26.92		7.05	6.95
2000	6.59	27.30		6.59	6.50
2001	7.12	27.60		7.12	7.01
2002	7.39	27.76		7.40	7.28
2003	7.48	27.92		7.49	7.38
2004	7.30	28.38		7.31	7.21
2005	7.78	28.64		7.78	7.68
2006	7.96	28.92		7.97	7.86
2007	7.48	29.16		7.49	7.39
2008	8.13	29.33		8.14	8.03
2009	8.21	29.71		8.21	8.10
2010	8.02	29.89		8.03	7.92
2011	8.69	30.25		8.69	8.58
2012	8.58	30.33		8.59	8.48
2013	8.27	30.36		8.28	8.17
2014	8.94	30.60		8.95	8.83
Projected HWLE and LE					
2015	8.67 (6.86,10.48)	31.33		8.68 (6.58,10.72)	8.71 (6.84,10.89)
2016	8.85 (6.66,11.01)	31.51		8.86 (6.22,11.32)	8.87 (6.64,11.58)
2017	8.79 (6.38,11.13)	31.57		8.80 (5.81,11.48)	8.80 (6.36,11.81)
2018	8.82 (6.23,11.29)	31.60		8.84 (5.53,11.67)	8.83 (6.22,12.08)
2019	8.83 (6.07,11.41)	31.78 (31.78,31.78)		8.84 (5.24,11.82)	8.82 (6.07,12.27)
2020	8.85 (5.92,11.54)	31.97 (31.65,32.29)		8.86 (4.97,11.97)	8.83 (5.94,12.48)
2021	8.86 (5.78,11.64)	32.17 (31.71,32.60)		8.88 (4.72,12.09)	8.83 (5.81,12.64)
2022	8.88 (5.65,11.74)	32.36 (31.81,32.89)		8.89 (4.48,12.20)	8.84 (5.69,12.80)
2023	8.89 (5.53,11.83)	32.55 (31.91,33.15)		8.91 (4.24,12.30)	8.84 (5.58,12.94)
2024	8.91 (5.41,11.91)	32.73 (32.03,33.41)		8.92 (4.02,12.40)	8.84 (5.47,13.07)
2025	8.92 (5.29,11.98)	32.92 (32.15,33.65)		8.94 (3.80,12.48)	8.84 (5.37,13.19)
2026	8.94 (5.18,12.05)	33.10 (32.28,33.89)		8.95 (3.59,12.57)	8.85 (5.26,13.30)
2027	8.95 (5.07,12.12)	33.29 (32.42,34.12)		8.97 (3.40,12.64)	8.85 (5.16,13.41)
2028	8.96 (4.96,12.19)	33.47 (32.55,34.34)		8.98 (3.20,12.72)	8.85 (5.07,13.51)
2029	8.98 (4.85,12.25)	33.65 (32.69,34.56)		8.99 (3.02,12.79)	8.85 (4.97,13.61)
2030	8.99 (4.75,12.31)	33.83 (32.83,34.77)		9.01 (2.84,12.86)	8.85 (4.88,13.70)
2031	9.00 (4.65,12.36)	34.01 (32.97,34.98)		9.02 (2.68,12.92)	8.86 (4.79,13.79)
2032	9.01 (4.55,12.42)	34.18 (33.11,35.18)		9.03 (2.52,12.99)	8.86 (4.70,13.87)
2033	9.03 (4.46,12.47)	34.36 (33.25,35.38)		9.04 (2.36,13.05)	8.86 (4.61,13.95)
2034	9.04 (4.36,12.52)	34.53 (33.40,35.58)		9.06 (2.22,13.10)	8.86 (4.52,14.03)
2035	9.05 (4.27,12.57)	34.70 (33.54,35.77)		9.07 (2.08,13.16)	8.86 (4.44,14.10)

[1] Mortality rate ratio=1 (mortality rates among healthy working adults are the same as among unhealthy and/or not working adults)
[2] Mortality rate ratio=2 (mortality rates among healthy working adults are twice as high as among unhealthy and/or not working adults)

TABLE 3.6: Sensitivity analyses of female HWLE observed and projected estimates to ratio of mortality rate from being healthy and working compared to mortality rate from being unhealthy and/or not working

FEMALE		*Main analysis*		*Sensitivity analyses of HWLE*	
	Year	HWLE	LE	HWLE (R =1)[1]	HWLE (R =2)[2]
Observed HWLE and LE					
	1996	4.94	30.39	4.95	4.90
	1997	4.94	30.52	4.94	4.89
	1998	5.28	30.71	5.28	5.23
	1999	5.16	30.82	5.16	5.11
	2000	5.17	31.15	5.17	5.12
	2001	5.51	31.35	5.52	5.46
	2002	5.27	31.42	5.27	5.21
	2003	5.81	31.44	5.81	5.76
	2004	5.82	31.94	5.83	5.77
	2005	6.02	32.04	6.02	5.96
	2006	6.20	32.34	6.20	6.15
	2007	6.49	32.45	6.49	6.43
	2008	6.13	32.52	6.13	6.07
	2009	7.07	33.00	7.08	7.01
	2010	6.51	33.08	6.51	6.45
	2011	6.55	33.38	6.56	6.50
	2012	7.08	33.29	7.09	7.02
	2013	7.14	33.37	7.14	7.09
	2014	6.85	33.65	6.85	6.80
Projected HWLE and LE					
	2015	7.49 (6.06,9.03)	34.26	7.49 (5.61,9.62)	7.48 (5.61,9.62)
	2016	7.52 (5.80,9.41)	34.43	7.52 (5.19,10.23)	7.51 (5.19,10.25)
	2017	7.59 (5.72,9.68)	34.52	7.59 (4.96,10.67)	7.58 (4.97,10.69)
	2018	7.63 (5.66,9.86)	34.51	7.63 (4.78,10.98)	7.63 (4.79,11.01)
	2019	7.69 (5.63,10.03)	34.66 (34.66,34.66)	7.69 (4.63,11.26)	7.69 (4.64,11.30)
	2020	7.74 (5.60,10.20)	34.79 (34.48,35.10)	7.74 (4.50,11.52)	7.74 (4.51,11.56)
	2021	7.80 (5.58,10.35)	34.93 (34.49,35.36)	7.80 (4.38,11.76)	7.80 (4.40,11.80)
	2022	7.85 (5.56,10.50)	35.06 (34.53,35.58)	7.85 (4.27,11.97)	7.85 (4.29,12.01)
	2023	7.91 (5.55,10.64)	35.20 (34.58,35.79)	7.91 (4.16,12.16)	7.91 (4.19,12.21)
	2024	7.96 (5.55,10.77)	35.33 (34.65,35.99)	7.96 (4.07,12.35)	7.96 (4.10,12.40)
	2025	8.02 (5.54,10.89)	35.46 (34.72,36.17)	8.02 (3.98,12.52)	8.02 (4.01,12.58)
	2026	8.08 (5.54,11.02)	35.59 (34.79,36.36)	8.08 (3.89,12.68)	8.08 (3.93,12.74)
	2027	8.13 (5.54,11.13)	35.72 (34.87,36.53)	8.13 (3.81,12.84)	8.13 (3.85,12.90)
	2028	8.19 (5.54,11.25)	35.85 (34.96,36.70)	8.19 (3.73,12.99)	8.19 (3.78,13.05)
	2029	8.24 (5.54,11.36)	35.98 (35.04,36.86)	8.24 (3.66,13.13)	8.24 (3.71,13.19)
	2030	8.30 (5.54,11.47)	36.11 (35.13,37.03)	8.30 (3.59,13.26)	8.30 (3.64,13.33)
	2031	8.35 (5.55,11.57)	36.23 (35.22,37.18)	8.35 (3.52,13.39)	8.35 (3.58,13.46)
	2032	8.41 (5.55,11.68)	36.36 (35.31,37.34)	8.41 (3.46,13.52)	8.41 (3.52,13.59)
	2033	8.46 (5.56,11.78)	36.48 (35.40,37.49)	8.46 (3.39,13.64)	8.46 (3.46,13.71)
	2034	8.52 (5.57,11.88)	36.60 (35.49,37.64)	8.51 (3.34,13.75)	8.52 (3.41,13.83)
	2035	8.57 (5.58,11.97)	36.72 (35.58,37.78)	8.57 (3.28,13.86)	8.57 (3.35,13.94)

[1] Mortality rate ratio=1 (mortality rates among healthy working adults are the same as among unhealthy and/or not working adults)
[2] Mortality rate ratio=2 (mortality rates among healthy working adults are twice as high as among unhealthy and/or not working adults)

3.9 Discussion

Based on the intercensal approach, healthy working life expectancy is expected to be 9.05 (2.16,13.28) years from age 50 for men and 8.57 (3.28,13.87) years for women by 2035. While life expectancy gains of 2.73 years for men and 1.93 years for women are expected between 2020 and 2035, expected HWLE gains are much lower with 0.2 additional healthy working years expected for men and 0.83 additional healthy working years expected for women. The length of healthy working life from age 50 has been extending for both men and women in England but gains appear to be slowing - especially for men, who may gain only one additional healthy working week per calendar year on average (20 weeks in total) between 2015 and 2035. In contrast, the State Pension age of 65 years in 2015 is increasing to 67 by 2028 and further increases to 68 are planned between 2037 and 2039.

Larger expected gains for women than men is consistent with evidence that working life expectancy at older working ages is increasing more rapidly for women than men in the UK and across Europe (Loichinger and Weber, 2016) as well as in India, where it has been suggested that life expectancy gains will lead to working life expectancy gains for women but not for men - possibly due to lower current work participation rates among women and increasing opportunities for women to work (Dhillon and Ladusingh, 2013). The projected narrowing of the gap between length of healthy working life from age 50 for men and women in England is in keeping with lessening gender differences in working life expectancy from age 50 across Europe (Loichinger and Weber, 2016). It may therefore be a possible scenario that women continue to see HWLE gains tending towards male HWLE, after which little improvement is achieved in length of healthy working life for any gender. This - and the small HWLE gains projected - could be due to the impact on jobs later in the study period of the financial crisis of 2007–2008 and austerity measures introduced in the UK from 2010 reducing the number of jobs or job quality (Taylor, 2017; Dhillon and Ladusingh, 2013; Reeves et al., 2013; Barr et al., 2012). If so, efforts to create good work opportunities for older workers could help to avoid the projected stalling of HWLE in the future. Loichinger and Weber (2016) found that, from age 50, working life expectancy was more strongly correlated with healthy life expectancy than with life expectancy - with these relationships weaker for women than for men. While life expectancy improvements have been widespread across Europe and worldwide (Jagger, 2015) and have been the basis for raising the State Pension age in the UK (DWP, 2017b), smaller improvements in population health at older ages (Jagger, 2015) may be a barrier to increasing both employment at older ages and length of healthy working life (Robroek et al., 2013; Schuring et al., 2007; Schuring et al., 2013; Wagenaar et al., 2012). Women's shorter observed and projected HWLE compared to men despite longer life expectancy reflects historically lower State Pension age and employment rates for women compared to men (DWP, 2014b). This difference - as well as the weaker correlation between female working life expectancy and both life expectancy and healthy life expectancy identified by Loichinger and Weber (2016) - also highlights the role of various lifestyle, biological, workplace and social factors in the broader biopsychosocial model that may influence work engagement and length of healthy working life.

3.9.1 Comparison of life expectancy estimates and projections to official statistics

Prior to 2015, life expectancy estimates from age 50 were lower than official estimates for both men and women published by the Office for National Statistics (ONS) (ONS, 2019n) (figures 3.11 and 3.10). Life expectancy estimates from 2015 to 2018 were the same as those obtained by ONS. Projections were similar but slightly higher than ONS projections. Figures 3.11 and 3.10 show life expectancy projections with confidence intervals and official published estimates with low and high variants, which reflect less optimistic and more optimistic future demographic scenarios respectively based on trend calculations and expert opinions (ONS, 2019g; ONS, 2019h).

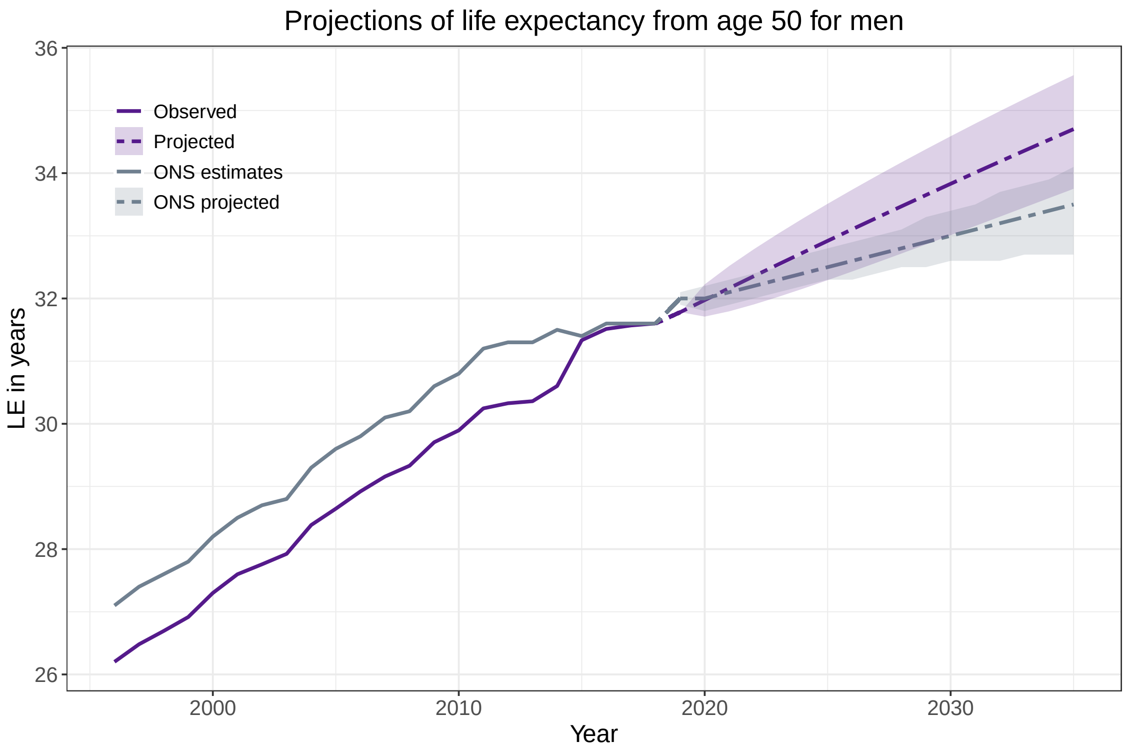

FIGURE 3.10: Observed life expectancy (1996-2018, solid purple line) and projected life expectancy (2019-2035, dashed purple line) for males with ONS published past life expectancy estimates (1996-2018, solid grey line) and projected life expecancy estimates (2019-2035, dashed grey line) with low and high variants (ONS, 2019a; ONS, 2019b; ONS, 2019k)

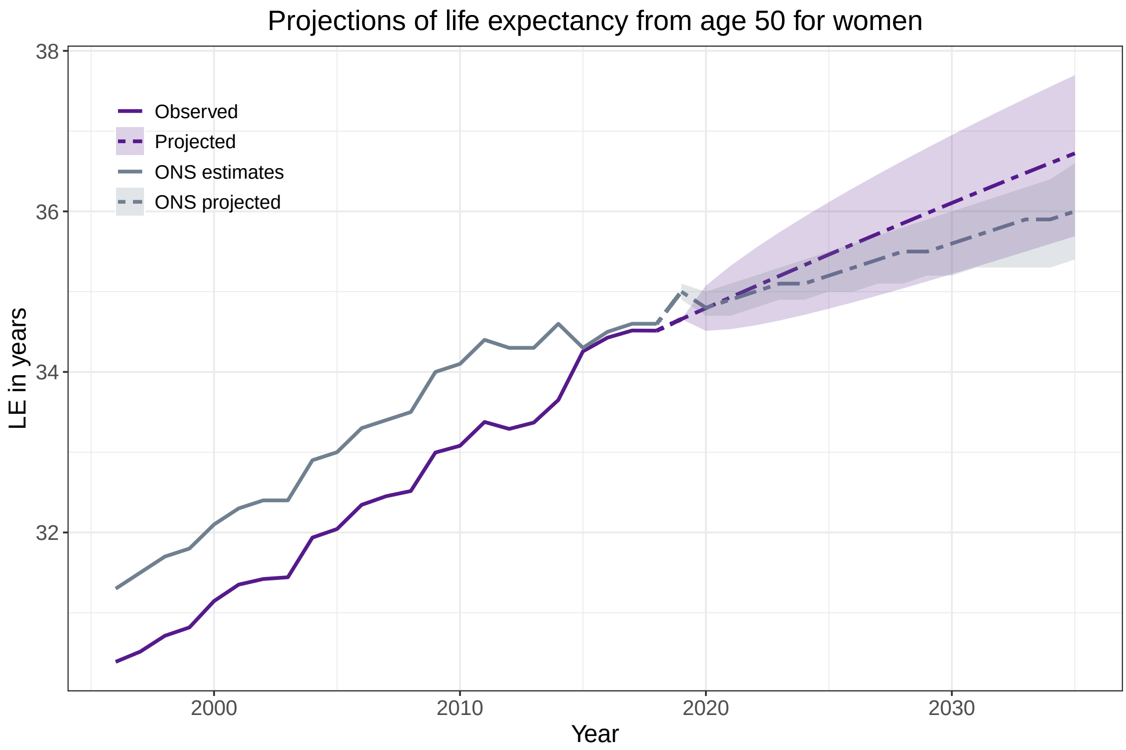

FIGURE 3.11: Observed life expectancy (1996-2018, solid purple line) and projected life expectancy (2019-2035, dashed purple line) for females with ONS published past life expectancy estimates (1996-2018, solid grey line) and projected life expecancy estimates (2019-2035, dashed grey line) with low and high variants (ONS, 2019a; ONS, 2019b; ONS, 2019k)

3.9.2 Strengths and limitations

The opportunity to combine different data sources was a strength of this study, which enabled the use of official mortality statistics and avoided the need to estimate mortality rates from a survey dataset (which may be affected by various types of biases with the potential to compromise representativeness of the general population - for example only sampling from the community-dwelling population). Incorporating the most recent mortality data into the analysis (up to 2018) despite HSE data only used up to 2014 was also a study strength to avoid overestimation of life expectancy projections, official estimates of which for England have been down revised in recent years (ONS, 2019i). The unavailability of age specific HSE data after 2014 meant that years since then which have already passed at the time of this study had to be projected, adding additional uncertainty to the projections in the future.

Life expectancy projections were higher than official projections by ONS, which base lower and upper estimates on expert judgement rather than 95% confidence intervals from statistical methods. If the life expectancy projections obtained in this study are overestimated, the gap between life expectancy gains and HWLE gains may be narrower than observed (although HWLE would also be reduced by increased mortality in the 50-75 age range). Sensitivity analyses demonstrated that HWLE estimates were robust to the ratio of mortality rates from each of the two alive states (healthy and working [state 1] and unhealthy and/or not working [state 2]), likely reflecting lower mortality rates in the 50-75 age group (compared to those older than age 75) and in particular at younger ages in this range where being healthy and in work is more prevalent. This sensitivity analysis is a key strength of this study as the true ratio is difficult to estimate due to the impermanence of people's transitions between health and work statuses.

A limitation of this study is the selection of HWLE estimation method based on feasibility instead of taking a Markov chain approach (see table 2.21 on page 137 and table 2.20 on page 129 for comparisons and sensitivity analyses demonstrating robustness of the IMaCh interpolated Markov chain multi-state modelling approach) (Guillot and Yu, 2009). The implications and possible biases of using the intercensal method (and the Sullivan method) for health expectancy estimation are not well understood. Both the intercensal method and the Sullivan method appear to markedly underestimate HWLE by up to two to three years compared to the preferred interpolated Markov chain approach, which could not be used for this application. Despite this, the clear resemblence of plotted (intercensal) HWLE over time to the Sullivan method HWLE estimates indicates a robustness of HWLE estimation and projection to the use of the newer and more complex multi-state modelling intercensal approach compared to the widely used Sullivan method. There is a lack of consensus on biases affecting estimates obtained using the Sullivan method, but repeated estimates provide a useful indication of trend (Bagavos, 2013; Nurminen, 2013; Guillot and Yu, 2009). The relationship that can be observed visually between the intercensal and Sullivan estimates of HWLE may suggest that the same caution should be applied to values estimated using the intercensal approach, while (like the Sullivan method) time trends could be reasonably robust. Although downward biased, it is therefore a strength of this study that these HWLE projections for men and women provide insight into expected change in HWLE over time as sensitivity analyses using the Sullivan method gave no indication that the projected changes in HWLE are over or underestimated.

The absence of confidence intervals associated with each point estimate is a limitation of the intercensal approach. This method also assumes that the age pattern for the transition rate from healthy and working to unhealthy and/or not working as well as the overall population mortality rate are well described by an exponential function. A further limitation is the modelling of net transition rates instead of the two-way transitions in and out of health and work states possible in reality; this could be a reason why estimates using both the intercensal approach and the Sullivan method differ from earlier IMaCh results (see chapter 2).

Estimation of HWLE observed and projected HWLE was limited by low sample sizes in the HSE datasets for health and work prevalence data to the extent that smoothing was essential. Due to low sample sizes it was also necessary to examine period life expectancy and HWLE because sequential cross-sectional measurements of the age specific prevalence of being healthy and in work were too varied to be feasibly and meaningfully analysed using a cohort approach. (Cohort HWLE estimates using the intercensal approach may be less biased than Sullivan estimates due to avoiding the assumption of stationary mortality rates and population prevalence of being healthy and in work throughout the lifecouse for each calculated year (Guillot and Yu, 2009).) HSE data are intended to be representative of England's community dwelling population, which may be healthier on average than that of the non-community dwelling population and could therefore lead to overestimation of the age specific prevalence of being healthy and work as well as resulting HWLE estimates.

3.9.3 Implications for future research

The Lee Carter forecasting approach does not attempt to anticipate policy changes or other interventions but bases projections on an observed age-period pattern in transition rates. Expected changes in HWLE assume that all variables remain unchanged in future years (previously unvarying variables are assumed to remain constant and those factors that have varied throughout the period of observed data are assumed to sustain these trends). The rising State Pension age may therefore drive larger increases in HWLE over the coming years through extending working life. However, factors such as increasing obesity and inactivity levels could hamper HWLE increases in the future (Kohl et al., 2012; Wang et al., 2011), and changes to the nature of work and types of job roles available could also have an (as of yet unclear) effect. For example, manual jobs may become less common, which could lead to HWLE improvements or could cause HWLE reductions if these jobs are not replaced. The changing nature of work in future years and the potential implications for HWLE is discussed in more depth in chapter 6 (see page 301). More work is needed to examine the biopsychosocial drivers of HWLE that may require targeted intervention to enable people in the population to meet policy goals by working for longer - and doing so in a healthy manner that benefits themselves and their employers as well as wider communities and national budgets. An improved understanding of biopsychosocial drivers of HWLE could also lead to future work projecting HWLE based on expected changes in these factors through modelling plausible scenarios.

There is also a research need to further develop the methodology for estimation and projection of HWLE as the results of this study cannot be updated without updated methodology and/or available data on age specific prevalences of being healthy and in work (or through collapsing all components of the model into grouped age bands, which may severely compromise model fit and feasibility). That HWLE results differ using IMaCh (using different data), the intercensal method, and Sullivan method implies that estimates of HWLE may depend on methodological approach (see page 296 in chapter 6 for further discussion of this). More research and methodological development is also needed to better understand biases in the intercensal (and Sullivan) method and improve the feasibility and accuracy of observing and projecting HWLE as well as other health expectancy indicators (especially those that measure irreversible transitions for comparision, because a source of bias could be the conceptual simplification that net transition rates describe reversible health and work transitions).

3.10 Conclusion

The aim of this study was to estimate HWLE projections for men and women in England. This was achieved using a combination of the intercensal approach to estimating health expectancies and the Lee Carter forecasting approach, with national mortality rate data and survey data from the Health Survey for England. Because the Lee Carter forecasting approach did not take into account the role on HWLE of other factors that may change, the HWLE projections presented in this chapter suggest future trends based on relevant factors remaining the same (or continuing the same trends) as observed in the study period. A key challenge affecting the analysis was the decreasing HSE sample size in more recent calendar years, which precluded the use of the most recent survey years' data (as these were not published with age in years but only in grouped age bands). A larger sample size may also help to promote the feasibility of empirical implementation of the methods. Although difficulty identifying a suitable data source may be a barrier to updating the HWLE projections using these methods in the future, the findings presented in this chapter provide useful insight into the likely trajectory of future HWLE change for men and women in England. Recognising the possibility that HWLE estimates and projections are likely to have been underestimated in this study, there remains a gap between expected levels of working (until the State Pension age on average) and achieved length of healthy working life among men and women in England. There is a need to monitor current and projected HWLE to examine the impact of policy changes in the coming years as State Pension age continues to rise and people are expected to work for longer. The projected slowing of HWLE gains compared to life expectancy indicates a need to better understand the factors that drive or are barriers to extending healthy working life as well as how HWLE varies between subpopulations affected by key age-associated health conditions; initiatives to improve population health and wellbeing, reduce inequalities, and improve access to suitable job opportunities may be essential to continue the upward trajectory of HWLE for men and women as life expectancy and State Pension age rise.

Chapter 4

Examining HWLE in people with a long term health condition using osteoarthritis as an exemplar

4.1 Introduction

As life expectancy increases and populations age in many countries, people are expected to remain in paid work until they are older. However, population ageing is also associated with increasing prevalence of age-associated diseases. Osteoarthritis (OA), the most common form of arthritis, is a leading cause of years lived with disability and is expected to become one of the most common diseases (Hunter and Bierma-Zeinstra, 2019). OA is a degenerative arthritis with irreversible structural changes including cartillage loss and bone remodelling (Hunter and Bierma-Zeinstra, 2019). OA is most prevalent from the age of 50 and is often accompanied by pain, joint stiffness and functional limitation (Loeser, 2013). Pain (including mechanical pain, neuropathic pain, painful structural changes, and flare-ups) is the most disabling symptom of OA with biopsychosocial factors including comorbidities, biological factors, and lifestyle factors driving its presentation (figure 4.1) (Hunter and Bierma-Zeinstra, 2019).

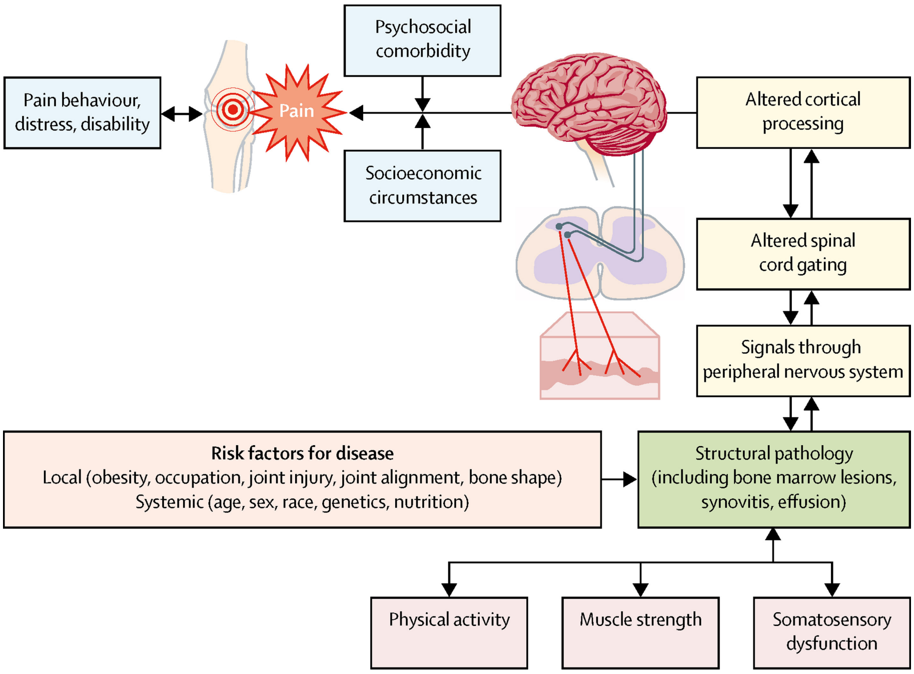

FIGURE 4.1: Biopsychosocial model of osteoarthritis pain (Hunter and Bierma-Zeinstra, 2019). Image reproduced with permission of the rights holder, Elsevier.

The economic burden of OA is high. Annual direct and indirect costs of musculoskeletal disorders were estimated to exceed £30 billion in 2008 (Oxford Economics, 2010). Direct healthcare costs in the UK attributable to OA are driven by joint replacements (for end-stage OA) costing over £850 million annually (Chen et al., 2012). However, indirect costs far exceed direct costs with UK economy production losses estimated to exceed £3.2 billion per year (Chen et al., 2012). In the UK in 2018, musculoskeletal problems accounted for 27.8 million days of sickness absence, which was 19.7% of all 141.4 million working days lost to sickness absence (ONS, 2019m). Minor illnesses (such as colds and flu) was the only reason for sickness absence that claimed more days (38.5 million days, 27.2% of all days lost) (ONS, 2019m). By comparison, mental health problems accounted for 17.5 million days (12.4% of all days lost) (ONS, 2019m). More work is needed to understand the effect of OA on length of working life and work outcomes such as absenteeism and presenteeism in the UK (Chen et al., 2012; Hunter and Eckstein, 2009).

Chapter 2 presented estimates of Healthy Working Life Expectancy (HWLE) in England for the general population and by subgroups according to sex, deprivation level, occupation type, education level and region, and chapter 3 described an investigation of how

HWLE is changing in England. Using OA as an exemplar of a common long term health condition, the study presented in this chapter investigated differences in HWLE between population with and without OA. This chapter presents estimates of HWLE in the English population for adults with and without OA at age 50 (and estimates at each year of age up to 75) using nationally representative survey data, and presents overall estimates of HWLE at age 50 for people with and without OA at any age using a regional survey dataset linked to medical records.

Estimates of HWLE were generated using two datasets using two definitions for OA: self-report of doctor diagnosis, and medical records showing OA as a reason for general practice consultation. Using data from the English Longitudinal Study of Ageing (ELSA) - the same dataset as used in chapter 2 - it was possible to estimate HWLE at age 50 and subsequent years of age according to 'objective self-reported' OA status (individuals' report of whether a doctor has told them that they have OA). ELSA was chosen as a data source with which to estimate age-specific HWLE for people with/without OA because of its intended national representativeness and because of the scope for comparison of findings with previous estimates of HWLE for England overall using the same data source (chapter 2). As there can be considerable differences between objective self-report of arthritis - and other specific health conditions - and diagnoses in medical records (Baker et al., 2004), a second dataset was introduced for analysis: the North Staffordshire Osteoarthritis Project (NorStOP). Unlike ELSA data, which were collected across all regions of England by sampling households, NorStOP data were collected regionally in North Staffordshire using General Practices as a sampling frame and as a source of medical record data enabling identification of OA cases diagnosed by a general practitioner (GP) or other primary care clinician. Clinicians may have different approaches to diagnosing OA (for example the importance placed on whether radiographic changes are observed) but is often based on physical examination and risk factors, whereas self-reported OA may be more closely linked with pain severity (Dueñas et al., 2016; Taruc-Uy and Lynch, 2013). The main reason for analysing NorstOP data in addition to ELSA data was that it allowed examination of whether any HWLE differences detected among ELSA participants who self-reported having or not having OA were also present when defining OA using clinician diagnosis. Additionally, NorStOP data were analysed to demonstrate an approach to estimating HWLE using survey data linked to electronic health records, which is a continual source of big data with potential uses in evidence-based medicine and population health surveillance (Sim, 2016). Because of medical record linkage, NorStOP data also allowed for estimation of HWLE for the population subgroup who have or develop OA at any point from age 50 (the 'OA-group') and for the population subgroup who do not have OA at any point from age 50 (the 'non-OA group').

The aim of the study presented in this chapter was to estimate HWLE in populations with and without OA. This was in order to identify the size of the potential impact on HWLE of one example of a common long-term musculoskeletal condition. Analysis of two datasets determined whether how OA was defined had a major impact on HWLE, which has implications for further research as medical record data could allow for HWLE to be estimated (and monitored for surveillance) in populations with health conditions for which data are not collected in longitudinal surveys.

4.2 Data source: The English Longitudinal Study of Ageing (ELSA)

Longitudinal survey data (with linked mortality data) from adults aged 50 and over who participated in ELSA waves 1-6 were used in this study. ELSA was introduced in section 2.1 with operationalisation of health and work for HWLE described in 2.3.1.

4.2.1 Measurement of variables and identification of OA status

Sex and occupation type were time invariant variables. Measurement of these items was explained in chapter 2 (see 2.3.2 on page 94).

Individuals were considered to have OA if, at that wave or at an earlier wave, they self-reported having been told by a doctor that they have osteoarthritis (or arthritis without knowing the type). (As a gradually progressive chronic condition, it was assumed that OA would continue to be present (to some extent) following self-reported doctor diagnosis (Wilkie et al., 2014a, p. 2).) At each wave, participants were shown a card listing health conditions including 'arthritis (including osteoarthritis, or rheumatism)' and asked whether a doctor had ever told them they had any of the conditions on the card. If the participant reported arthritis, they were asked whether this was osteoarthritis, rheumatoid arthritis or some other kind of arthritis. Missing data where respondents had reported having arthritis but who did not know which type or refused to answer the question were considered to have OA. Differences in ELSA coding of arthritis variables across the datasets for each wave required construction of a new OA variable using wave-specific variables:

- Wave 1: 'heart1', 'heart2', 'heart2', 'hedib01'
- Wave 2: 'heart1', 'heart2', 'bheart1', 'bheart2', 'bheart3', 'hedib01'
- Wave 3: 'heartoa', 'dhedibar'
- Wave 4: 'heartoa', 'hedibar'
- Wave 5: 'heartoa', 'hedibar'
- Wave 6: 'heartoa', 'hedibar'

All incidences of self-reported OA were carried forward to all subsequent waves. Then, self-reported no-OA statuses were carried backwards into earlier missing values. Arthritis of an unknown type was assumed to be OA as this is the most common form of arthritis (Loeser et al., 2012).

4.3 Data source: The North Staffordshire Osteoarthritis Project (NorStOP)

The North Staffordshire Osteoarthritis Project (NorStOP) was a longitudinal observational study of older adults (defined as adults aged 50 years and over) registered at eight General Practices in North Staffordshire (Thomas et al., 2004a). The data were considered representative of the local area (North Staffordshire) due to high rates of GP registration among the general population in England (Lacey et al., 2015; Bowling, 2014)

NorStOP had three primary aims (Thomas et al., 2004a). The first aim was to investigate the impact of radiographic OA and/or the clinical syndrome of joint pain and stiffness on activity and participation levels of adults aged 50 and over. The second aim was to identify factors predictive of changes in pain, activity and participation levels over time in older adults. The final general aim was to determine frequency of health care use and factors that predicted increased health care usage among older adults with radiographic OA and/or the clinical syndrome of joint pain and stiffness. Ethical approval for NorStOP was granted by the North Staffordshire Research Ethics Committee (REC reference numbers 1351 and 1430) (Lacey et al., 2015; Thomas et al., 2004a).

4.3.1 Survey design

Three cohorts of community-dwelling older adults adults aged 50 and above in North Staffordshire were invited to participate in the prospective study of OA and the impact of pain (Lacey et al., 2015; Thomas et al., 2004a). The three cohorts are referred to as NorStOP 1, NorStOP 2 and NorStOP 3. All adults aged 50 and above registered at three general practices belonging to the North Staffordshire General Practice Research Network were invited to join NorStOP 1 and complete baseline questionnaires in April 2002. Baseline questionnaire responses for NorStOP 2 were collected in July and August 2002 and July and August 2003 from a further three general practices in the research network. NorStOP 3 baseline questionnaire data were provided from March 2004 to April 2005 by older adults registered at two further research network general practices. In addition to the baseline 'health survey' questionnaire, all participants were sent follow-up health survey questionnaires at three years and six years after baseline. At all time points, the health survey was followed by mailing of 'regional pain survey' questionnaires if individuals reported pain in the hands, hips, knees or feet and had consented to be recontacted. In addition, participants were asked for consent to access medical records from 12 months prior to recruitment to the end of the study - or until three year follow-up if responses were given to the baseline questionnaire only. Number of respondents and response date ranges for baseline, three year follow-up and six year follow-up for NorStOP 1, 2 and 3 are given in table 4.1.

TABLE 4.1: NorStOP number of respondents and response dates at baseline, three year follow-up and six year follow-up by cohort

Cohort	Questionnaire	Response date range	Midpoint response date	Number of respondents
NorStOP 1	Baseline	25/03/2002-18/09/2002	21/06/2002	7878
NorStOP 1	Three year follow-up	25/04/2005-18/01/2006	06/09/2005	4234
NorStOP 1	Six year follow-up	14/04/2008-22/07/2008	02/06/2008	2831
NorStOP 2	Baseline	08/07/2002-31/07/2003	18/01/2003	6108
NorStOP 2	Three year follow-up	24/10/2005-11/12/2006	18/05/2006	3059
NorStOP 2	Six year follow-up	19/01/2009-03/09/2009	12/05/2009	1944
NorStOP 3	Baseline	23/02/2004-31/05/2005	11/10/2004	4511
NorStOP 3	Three year follow-up	16/04/2007-13/03/2008	29/09/2007	2412
NorStOP 3	Six year follow-up	19/07/2011-02/10/2012	24/02/2012	1648

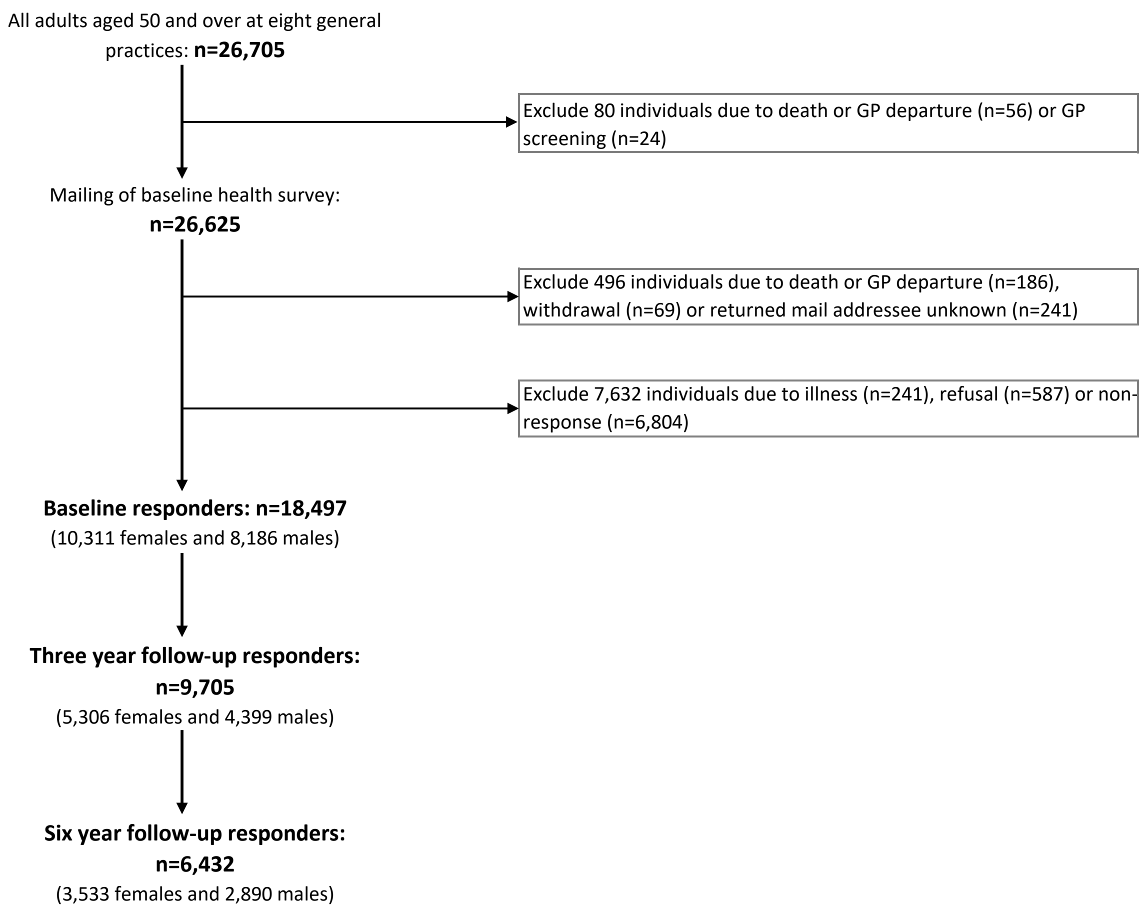

FIGURE 4.2: NorStOP study participant flow chart

Individuals were excluded from the study if they had previously opted out of research project participation or if they were known to have a severe psychiatric or terminal illness or a severe learning disability (Lacey et al., 2015). A study flow chart is shown in figure 4.2.

4.3.2 Definitions of health and work for HWLE in NorStOP

Health was defined as the absence of limitations due to physical health or emotional problems using two survey questions. The physical health question was *"During the past 4 weeks, have you had any of the following problems with your work or other regular daily activities as a result of your physical health?"* and respondents were asked to tick 'yes' or 'no' to sub-items: *"Were limited in the* ***kind*** *of work or other activities"*, and *"**Accomplished less** than you would like"* (bold in original). The mental health question was *"During the past 4 weeks, have you had any of the following problems with your work or other regular daily activities as a result of any emotional problems (such as feeling depressed or anxious)?"* and respondents were asked to tick 'yes' or 'no' to sub-items: *"Didn't do work or other activities as **carefully** as usual"*, and *"**Accomplished less** than you would like"* (bold in original). Individuals were considered to have poor health if they responded 'yes' to at least one of these items and were healthy otherwise.

Work was defined from self-reported employment status. At each time point, respondents were asked to respond to the survey question *"What is your employment status?"* by selecting the single most applicable option from a list. At baseline and three year follow-up, participants were considered to be in work if they reported their employment status as 'employed' (other options were: not working due to ill health; retired; unemployed/seeking work; housewife; other). At six year follow-up, participants were considered to be in work if they reported their employment status as 'in full-time paid work', 'in part-time paid work but not retired' or 'in part-time paid work and partly retired'. There were nine other employment status options available at six year follow-up: off work due to ill health for more than 1 week but less than 6 months; off work due to ill health for 6 months or more; full retired due to reaching retirement age; fully retired due to taking early retirement; fully retired due to taking early retirement because of ill health; not working due to looking after/caring for dependants or family; not working due to attending a full-time formal education or training course; unemployed or seeking work; housewife or looking after the home.

4.3.3 Measurement of variables and identification of OA and non-OA groups

Sex and date of birth were identified from general practice population registers and confirmed using responses to the baseline survey. OA and non-OA groups were identified among participants who had consented to sharing records based on having an N05 "Osteoarthritis and allied disorders" Read code (clinical record of patient findings) in linked medical records (Healey et al., 2018). Individuals were considered to have OA if their medical records indicated that they had consulted general practice for OA (that is, had an N05 Read code) from two years prior to baseline (baseline date varied by cohort, see table 4.1 on page 187) up to six year follow-up, or up to three year follow-up if there was no response to follow-up questionnaires. If no relevant consultation was identified in medical records, individuals were considered not to have OA. As OA is a long-standing, gradually progressive chronic condition, it was assumed that a clinician-established diagnosis at some point during the study period implied that OA was most likely present (at least to some degree) during the entire period of observation (Wilkie et al., 2019).

4.3.4 Data management

NorStOP data were received in multiple datasets in a clean format (an OA variable had already been constructed, missingness was clearly organized, and individuals who did not respond at baseline were already identified and excluded). Datasets were merged and wave-specific identifiers (response status, health, work, HWLE status) were constructed for each time point (baseline, three year follow-up, six year follow-up). Responding individuals were assigned status 1-4 at each time point as determined by their self-reported health and work statuses (healthy and in work (state 1), healthy and not in work (2), not healthy and in work (3), not healthy and not in work (4)). Status was assigned as '-1' (the individual was known to be alive at the data collection time point but their HWLE status was unknown) if there was missingness in the health and/or work variables for a respondent, or where an individual did not respond but was known to be alive at the time of the survey (either through known death dates or through responding at the next survey). Unlike in ELSA, death dates following the study period were known for some NorStOP participants (n=266). This required the addition of a fourth survey time point in IMaCh with status 5 for people with known death dates and status '-2' (unknown vital status / ignore transition) for others. Data management was carried out in Stata version 14.2.

4.4 Methods

HWLE with respect to OA status was investigated using the same HWLE multi-state model and IMaCh software described previously and implemented in the previous chapter (see figure 2.2 on page 75, table 2.3 on page 82 and section 2.2.4 on page 88).

Study objectives were carried out in two parts:

1. Use ELSA data to estimate HWLE by sex, occupation type, and OA status to explore the impact of these factors on HWLE at each year of age from 50-75.

2. Use medical record linked NorStOP data to estimate the overall association with HWLE of having clinician diagnosed OA by estimating HWLE at age 50 for people without OA and HWLE at age 50 for people with OA (at any age).

All models were estimated with transitions permitted once per year (interpolation step size of 12 months) following sensitivity analyses in chapter 2, which suggested that health expectancies were robust to the use of yearly transition probability models compared to more computationally intensive monthly transition probability models. Health expectancies were estimated by taking the weighted average starting-state specific health expectancies using the observed prevalence of state occupation in the study sample ('population-based' estimates).

4.4.1 Analysis plan

Part 1: ELSA

ELSA data were used to estimate transition probability models in IMaCh for each permitted transition with an intercept term, age, and each individual covariate/ covariate combination: sex (male or female), occupation type (non-manual, manual or self-employed) (Polvinen et al., 2014; Hallqvist et al., 1998), and age-specific OA (self-reported doctor diagnosed OA) status. The transition probability models were used to:

- estimate HWLE at age 50 in the overall population and for subpopulations according to sex, occupation type, and age-specific OA status (and for each combination of these three variables) by adding these variables as model covariates (compared to stratification as used in chapter 2)
- estimate HWLE at age 65 for men and women because of the rising State Pension age (beyond age 65) and the historically different State Pension ages for men and women
- estimate remaining HWLE at each year of age from 50-75 for men and women, people with different occupation types (non-manual, manual or self-employed), and those with/without self-reported doctor diagnosed OA at that age in England.

Part 2: NorStOP

Linkage of NorStOP data to medical records allowed OA status to be determined by evidence of a GP or primary care clinician diagnosis. In order to estimate HWLE for the NorStOP population overall and for each of the OA and non-OA population subgroups, transition probability models were estimated using IMaCh software and NorStOP data (the whole study population with linked medical records and, separately, stratified into the OA and non-OA subpopulations).

4.4.2 Sensitivity analyses

ELSA

In chapter 2, ELSA data were analysed in IMaCh and individuals with missing health or work status data but who were known to be alive were assigned HWLE status '-1', which was sometimes due non-response at a given survey wave and sometimes due to missing question response data among people who were successfully interviewed. However, the IMaCh analyses of ELSA data presented in this chapter included additional covariates, of which OA was time-varying and only measured at interviews. IMaCh cannot analyse time points or individuals with missing covariate data, which meant that HWLE status '-1' could not be used in this study when OA status was unknown. Non-responders at a given wave were therefore handled differently in this chapter compared to previous analyses of HWLE using ELSA in chapter 2 if OA status was not known (status '-2' was assigned to instruct IMaCh to ignore the time point). Health expectancies for the overall population (with no added covariates) were therefore compared to estimates from the previous chapter to examine whether the results from the two samples from the same study (ELSA) were similar.

To assess the sensitivity of HWLE estimates to the addition of variables as covariates (instead of stratifying the data), HWLE at age 50 for England overall and according to sex and occupation type was compared with the corresponding results obtained through stratification of the ELSA data, which were presented in chapter 2.

NorStOP

Monthly transition probability models were estimated for the NorStOP overall study population to investigate sensitivity of HWLE estimates to length of interpolation step size. A further sensitivity analysis was performed to check for bias from excluding people without linked medical records by estimating HWLE for the whole sample (without stratifying into OA and non-OA groups) including those without linked medical records. In addition, total life expectancies were estimated with the life table method (observing mortality in the population without classifying individuals into health or work states) to allow for comparison with the life expectancy (LE) estimates found by summing the health expectancies from each of the analyses.

4.5 Results

4.5.1 Sample size and missing data

ELSA

The starting sample size for this study was outlined in 2.5.2. Missingness in health and work response data was described on page 107 (table 2.8).

In chapter 2, missingness in the occupation variable was treated as a separate category that was not analysed; results were computed through data stratification and wave 1 data were not used to contribute to occupation results. In this chapter, occupation was analysed in the same transition probability models with variables sex and OA. All analyses were therefore performed on the same sample (waves 1-6) for consistency. Occupation type (non-manual, manual, self-employed or unknown occupation) was coded as binary dummy variables and results were not generated for the unknown occupation category. Missing OA status among respondents at each wave was imputed with 0 (no OA), affecting four people at wave 1, one person at wave 2, three people at wave 3, 12 people at wave 4, eight people at wave 5 and 13 people at wave 6. People with missing OA status because of not responding to the interview at a given wave (and who had status -1 indicating that they were alive with unknown HWLE status) were assigned status -2 and therefore made no contribution to the likelihood at that time. This affected 488 people at wave 2, 531 people at wave 3, 452 people at wave 4 and 260 people at wave 5. There was complete data for sex.

The number of people observed in each status at each wave is shown in table 4.2. Numbers occupying known states (alive states 1-4 or dead state 5) were the same as in the previous study in chapter 2. Differences in numbers of people with -1 and -2 statuses

TABLE 4.2: ELSA sample size for IMaCh analyses with covariates by HWLE status

	Status	Wave 1	2	3	4	5	6
-2	Unknown vital status*	3,990	5,315	4,864	3,313	3,791	3,874
-1	Alive but unknown HWLE status*	124	807	829	776	441	8
1	Healthy and in work	3,231	2,312	2,631	2,827	2,287	2,130
2	Healthy and not in work	3,968	3,198	2,920	3,387	3,368	3,374
3	Not healthy and in work	716	466	518	607	477	483
4	Not healthy and not in work	3,255	2,682	2,493	2,772	2,736	2,748
	Total alive with known status	*11,170*	*8,658*	*8,562*	*9,593*	*8,868*	*8,735*
5	Dead	0	504	1,029	1,602	2,184	2,667
	Total	15,284	15,284	15,284	15,284	15,284	15,284

*The entries in these lines differ from the sample used in the previous study of HWLE using ELSA data in chapter 2 (see table 2.8 on page 110)

were necessary as result of the addition of covariates in the models; IMaCh allows for missing HWLE status (recorded as -1) but covariates must be known otherwise all data for the individual are excluded from analysis.

TABLE 4.3: ELSA descriptive statistics for time invariant variables sex and occupation

Variable		Number (% of total)
Sex	Male	7025 (45.96%)
	Female	8259 (54.04%)
Occupation	Self-employed	1084 (7.09%)
	Non-manual	6254 (40.92%)
	Manual	5624 (36.80%)
	Unknown	*2322 (15.19%)*
Total		15,284

The study sample included 7025 men and 8269 women (table 4.3). The most commonly reported occupation type was non-manual (n=6254, 41%) followed by manual (n=5624, 37%). Self-employment was reported by 7% of participants (n=1084).

The number of people with OA at each wave is shown in table 4.4. The percentage of the study population with alive statuses (1,2,3,4, or -1) at each wave with OA ranged from 22.46% (wave 1) to 38.82% (wave 6).

TABLE 4.4: ELSA descriptive statistics of osteoarthritis status per wave 1-6

	Wave					
Osteoarthritis status	1	2	3	4	5	6
Has OA	2537	2553	2814	3402	3504	3394
No OA	8757	6912	6577	6967	5805	5349
Dead (status 5)	0	504	1029	1602	2184	2667
Ignore transition (status -2)	3990	5315	4864	3313	3791	3874
Total	15284	15284	15284	15284	15284	15284

NorStOP

The NorStOP study sample used data from all cohorts 1, 2 and 3. The full NorStOP sample achieved responses from 18,497 individuals who all responded to the baseline survey but attrition affected three year and six year follow-up. Birth dates were missing for 84 people who were therefore excluded from the study sample, leaving 18,413 individuals. Of these, 13,774 (74.8%) had consented to sharing medical records and therefore comprised the main study sample (table 4.5). There were 3260 participants who had OA and 10,514 participants who did not have OA (table 4.6). There were 13,016 respondents with complete health and work data at baseline, 8,151 at three year follow-up, and 1,369 at six year follow-up (table 4.6).

TABLE 4.5: NorStOP population with linked medical records compared to the total group of NorStOP participants (with or without linked medical records) by HWLE status

	Status	Time point: Baseline Total	Baseline With medical records (%)	3 year follow-up Total	3 year follow-up With medical records(%)	6 year follow-up Total	6 year follow-up With medical records(%)
-2	Unknown vital status	0	0 (0%)	0	0 (0%)	0	0 (0%)
-1	Alive but unknown HWLE status	1180	758 (64.24%)	7931	4536 (57.19%)	10386	6723 (64.73%)
1	Healthy and in work	2925	2238 (76.51%)	1448	1302 (89.92%)	907	823 (90.74%)
2	Healthy and not in work	3936	2903 (73.76%)	2279	2076 (91.09%)	1665	1528 (91.77%)
3	Not healthy and in work	1814	1490 (82.14%)	828	743 (89.73%)	396	353 (89.14%)
4	Not healthy and not in work	8558	6385 (74.61%)	4371	4030 (92.2%)	2851	2651 (92.98%)
	Total alive with known status	*17233*	*13016 (75.53%)*	*8926*	*8151 (91.32%)*	*5819*	*5355 (92.03%)*
5	Dead	0	0 (0%)	1556	1087 (69.86%)	2208	1696 (76.81%)
	Total	18413	13774 (74.81%)	18413	13774 (74.81%)	18413	13774 (74.81%)

TABLE 4.6: NorStOP sample size (and sample size with OA) for IMaCh analyses by HWLE status

		Time point							
		Baseline		3 year follow-up		6 year follow-up		Extra time point	
	Status	Total	OA (%)	Total	OA (%)	Total	OA (%)	Total	OA (%)
-2	Unknown vital status	0	0 (0%)	0	0 (0%)	0	0 (0%)	11821	2786 (23.57%)
-1	Alive but unknown HWLE status	758	200 (26.39%)	4536	905 (19.95%)	6723	1487 (22.12%)	0	0 (0%)
1	Healthy and in work	2238	253 (11.3%)	1302	162 (12.44%)	823	103 (12.52%)	0	0 (0%)
2	Healthy and not in work	2903	520 (17.91%)	2076	403 (19.41%)	1528	261 (17.08%)	0	0 (0%)
3	Not healthy and in work	1490	284 (19.06%)	743	163 (21.94%)	353	74 (20.96%)	0	0 (0%)
4	Not healthy and not in work	6385	2003 (31.37%)	4030	1396 (34.64%)	2651	931 (35.12%)	0	0 (0%)
	Total alive with known status	*13016*	*3060 (23.51%)*	*8151*	*2124 (26.06%)*	*5355*	*1369 (25.56%)*	*0*	*0 (0%)*
5	Dead	0	0 (0%)	1087	231 (21.25%)	1696	404 (23.82%)	1953	474 (24.27%)
	Total	13774	3260 (23.67%)	13774	3260 (23.67%)	13774	3260 (23.67%)	13774	3260 (23.67%)

As the NorStOP study only followed individuals who responded at baseline, there were no -1 statuses at baseline that were due to individuals not responding to the survey and all cases of -1 statuses (n=758) at baseline were due to missing response data to the health questions and/or the work questions (see table 4.7). Of the 4,536 -1 statuses at three year follow-up, 687 were due to missing health and/or work responses. There were 6,723 alive but unknown HWLE state (-1) status at six year follow-up, of which 537 were due to missing health and/or work responses.

TABLE 4.7: Missing health and work data for HWLE status at each NorStOP time point. The total number of individuals with status -1 (alive but unknown HWLE status) at each wave is shown alongside the number who had this status due to missing response data.

Time point	Total (status -1)	Responded to survey (status -1)	Missing data for HWLE status		
			Health only	Work only	Health and work
Baseline	758	758	305	432	21
3 year	4536	687	220	395	72
6 year	6723	537	115	353	69

Notes:
'Total' is the total number of individuals with status -1 (alive but unknown HWLE status)
'Interviewed' is the number of individuals with status -1 who were successfully interviewed
Status -1 indicates that the individual was alive but HWLE status was unknown (either due to non-response at that survey time point or incomplete health and work responses)

Of the 13,774 sample members (all of whom responded at baseline), 8,838 responded at 3 year follow-up (64.16%; males 63.43%, females 64.80%) and 5,892 responded at 6 year follow-up (42.78%; males 42.06%, females 43.40%) (table 4.8). The mean follow-up time was 3.21 years with 21.40% of participants providing response at two time points (baseline and one follow-up) and 42.77% of participants responding to all three surveys (table 4.9). Response rates at follow-up interviews were higher among participants with OA compared to those without (table 4.8).

TABLE 4.8: NorStOP responses to 3 year and 6 year follow-up according to OA status and sex

Survey responses		Female	Male	Total
Has OA	Baseline	2068 (100%)	1192 (100%)	3260 (100%)
	3 year follow-up	1478 (71.47%)	877 (73.57%)	2355 (72.24%)
	6 year follow-up	967 (46.76%)	577 (48.41%)	1544 (47.36%)
No OA	Baseline	5305 (100%)	5209 (100%)	10514 (100%)
	3 year follow-up	3300 (62.21%)	3183 (61.11%)	6483 (61.66%)
	6 year follow-up	2233 (42.09%)	2115 (40.6%)	4348 (41.35%)
Total	Baseline	7373 (100%)	6401 (100%)	13774 (100%)
	3 year follow-up	4778 (64.8%)	4060 (63.43%)	8838 (64.16%)
	6 year follow-up	3200 (43.4%)	2692 (42.06%)	5892 (42.78%)

Notes:
'Total' includes all study participants with OA and without OA
Percentages compare follow-up to baseline for the same category

TABLE 4.9: Number of achieved surveys among NorStOP participants

Number of completed surveys per person	Frequency	Percentage
1 (baseline only)	4,935	35.83%
2	2,948	21.40%
3	5,891	42.77%
Total	13,774	100%

4.5.2 Number of observed transitions for analysis

ELSA

The number of observed transitions between known states can be seen in table 2.10 on page 112.

NorStOP

There were 14,655 transitions observed in the NorStOP data with complete HWLE information and 354 transitions from a known alive state into an unknown alive state (total 15,009) (table 4.10).

TABLE 4.10: Contingency table of HWLE status transitions observed in NorStOP study sample

	Destination state						
Starting state	1	2	3	4	5	-1	Total
1	1410	467	362	209	62	34	2544
2	139	2050	33	1073	287	82	3664
3	459	163	586	363	42	28	1641
4	51	753	82	4667	1397	210	7160
Total	2059	3433	1063	6312	1788	354	15009

There were 3828 transitions (112 with incomplete data) observed among NorStOP participants with OA (table 4.11) and 11,181 transitions (242 with incomplete data) among NorStOP participants without OA (table 4.12).

TABLE 4.11: Contingency table of HWLE status transitions observed in NorStOP population with OA

Starting state	Destination state 1	2	3	4	5	-1	Total
1	144	68	67	38	4	6	327
2	20	349	8	282	36	15	710
3	81	28	130	103	5	6	353
4	11	188	18	1751	385	85	2438
Total	256	633	223	2174	430	112	3828

TABLE 4.12: Contingency table of HWLE status transitions observed in NorStOP population without OA

Starting state	Destination state 1	2	3	4	5	-1	Total
1	1266	399	295	171	58	28	2217
2	119	1701	25	791	251	67	2954
3	378	135	456	260	37	22	1288
4	40	565	64	2916	1012	125	4722
Total	1803	2800	840	4138	1358	242	11181

4.5.3 Estimates of HWLE at age 50 in England (ELSA data)

HWLE at age 50 in England was estimated as 9.43 years (95% CI [9.19, 9.66]) (table 4.16).

HWLE for males and females over ages 50-75

HWLE at age 50 was 11.00 (10.67,11.34) years for men and 8.19 (7.90,8.48) years for women, which was 32.28% and 24.57% of LE from age 50 respectively (table 4.13). The remaining number of years expected to be spent healthy and in work was consistently higher for men than women over ages 50-75 (figure 4.3). At age 65, men on average are expected to spend fewer than two remaining years healthy and in work while women are expected to spend less than one remaining year healthy and in work (figure 4.3, table 4.13).

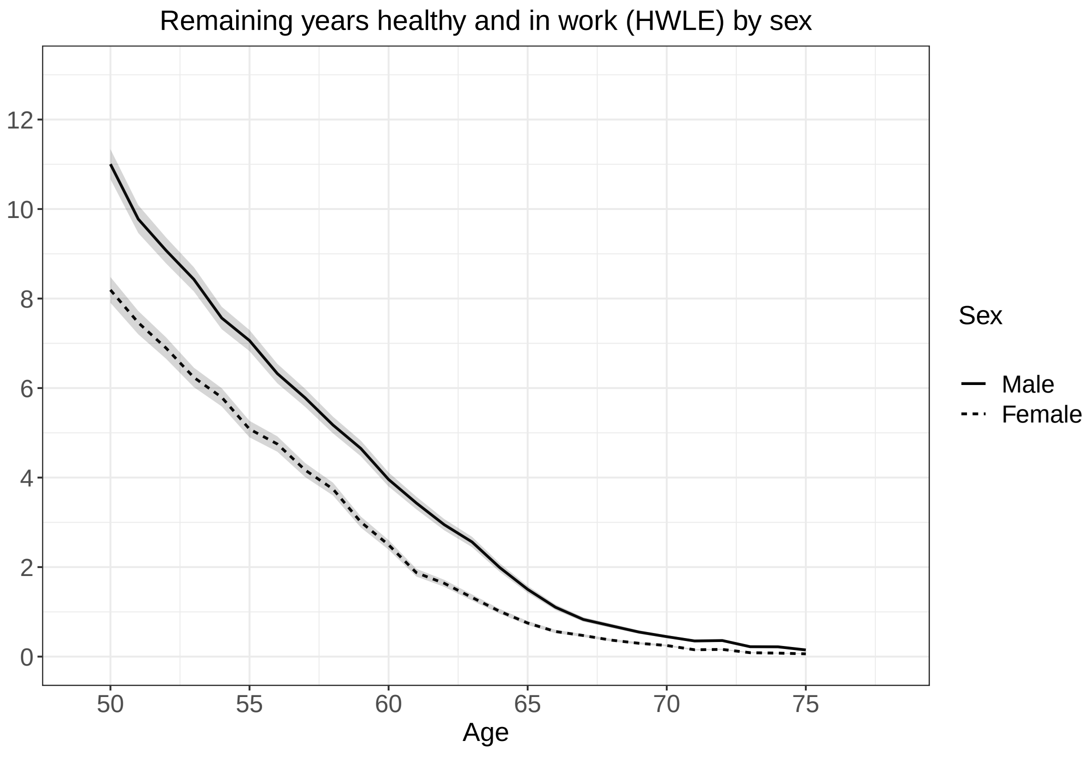

FIGURE 4.3: Plot of remaining years expected to be spent healthy and in work (HWLE) by sex at ages 50-75 with 95% confidence intervals

HWLE for people with non-manual, manual and self-employed occupations over ages 50-75

At age 50, HWLE was estimated as 10.98 (10.23,11.74) years for self-employed people (32.83% of LE), 10.06 (9.74,10.38) years for people with non-manual occupations (27.61% of LE), and 8.59 (8.24,8.93) years for people with manual occupations (25.41% of LE) (table 4.13). At all ages 50-75, the average number of remaining years expected to be spent healthy and in work was highest for people with self-employed occupations, followed by non-manual occupations and lowest for people with manual occupations. Confidence intervals for self-employed HWLE and non-manual HWLE overlapped at ages 50 and 56 (figure 4.4).

FIGURE 4.4: Plot of remaining years expected to be spent healthy and in work (HWLE) by occupation at ages 50-75 with 95% confidence intervals

HWLE for people with and without osteoarthritis over ages 50-75

For all ages 50-75, HWLE was higher for people without OA than those with OA. Estimates at each age apply to people who have/do not have OA *at that age*. That is, HWLE at age 50 for people with OA is the average number of remaining years expected to be spent healthy and in work for people who have OA at age 50 (and, by definition, never stop having OA). HWLE at age 50 for people without OA is the average number of remaining years expected to be spent healthy and in work for people who do not have OA at age 50 (but who may develop OA at a future age). HWLE was 10.00 (9.74,10.26) years at age 50 for people without OA at age 50 (31.01% of LE), compared to 5.68 (5.29,6.07) years for people who have OA at age 50 (18.14% of LE) (table 4.13).

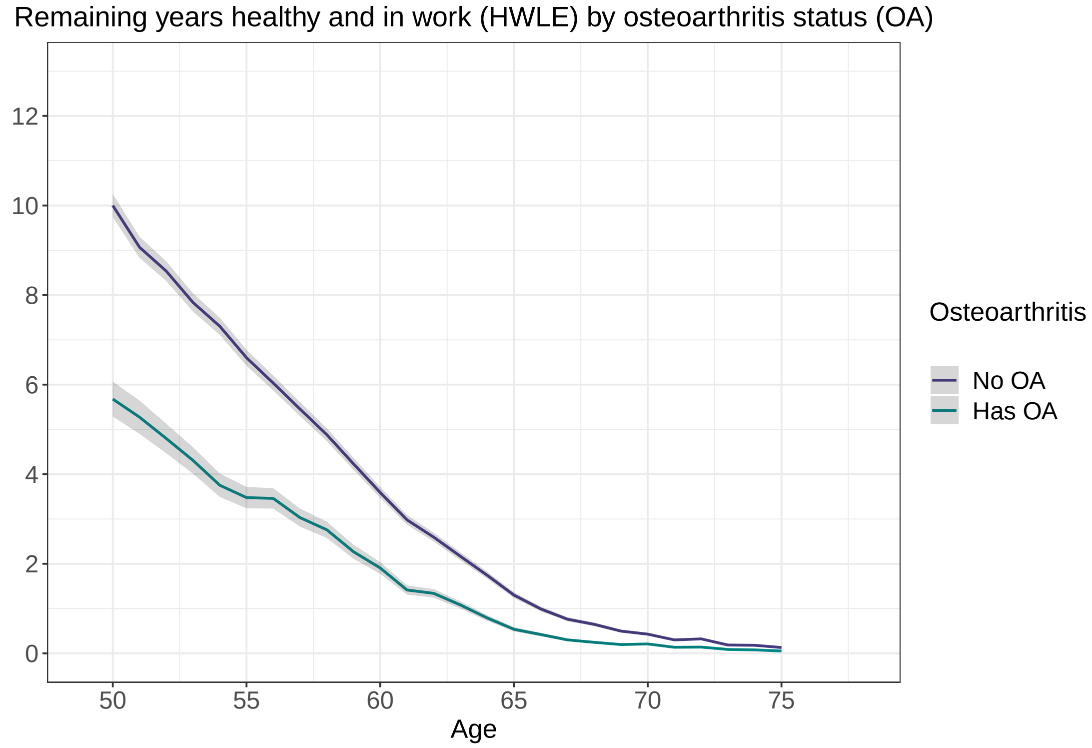

FIGURE 4.5: Plot of remaining years expected to be spent healthy and in work (HWLE) by osteoarthritis status at ages 50-75 with 95% confidence intervals

HWLE for males and females with and without osteoarthritis over ages 50-75

In general, the average number of remaining years expected to be spent healthy and in work at ages 50-75 was highest for men without OA, followed by women without OA, then men with OA, and lowest for women with OA. At age 50, HWLE was 11.41 (11.06,11.75) years for men without OA (37.94% of LE), 8.77 (8.45,9.09) years for women without OA (26.70% of LE), 6.56 (5.99,7.12) years for men with OA (21.59% of LE), and 5.28 (4.90,5.65) years for women with OA (15.74% of LE) (table 4.13). From age 59, remaining HWLE was similar for women without OA and men with OA. It can be seen visually in figure 4.6 that results for men with OA did not produce as smooth a trend as men and women without OA and women with OA, with wider confidence intervals reflecting less certainty in the estimates.

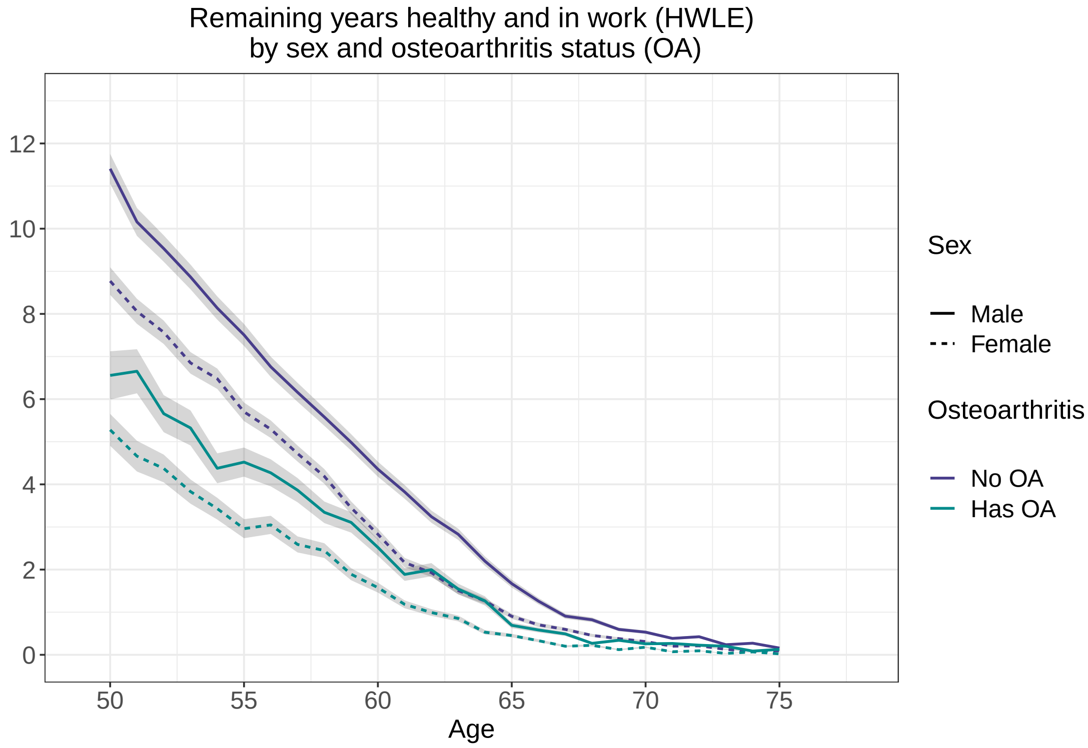

FIGURE 4.6: Plot of remaining years expected to be spent healthy and in work (HWLE) by sex and osteoarthritis status at ages 50-75 with 95% confidence intervals

HWLE for people with manual, non-manual and self-employed occupations with and without osteoarthritis over ages 50-75

At each age 50-75, expected remaining years healthy and in work was higher for people without OA (highest for people with self-employed then non-manual then manual occupations) than people with OA (figure 4.7). Among people with OA, HWLE at each age was generally higher for people with non-manual occupations than manual occupations. Within groups with and without OA, remaining years healthy and in work were similar for people with non-manual and manual occupations from age 62-75. From age 65 onwards, being self-employed (regardless of OA status) was found to be clearly associated with longer remaining healthy working lives than work as a manual or non-manual employee.

Estimates of remaining years healthy and in work for self-employed people with OA had wide confidence intervals and fluctuation in numerical HWLE results that crossed results lines for people with OA and non-manual and manual occupations. Trends in point estimates over age fluctuated less in later ages where self-employed people with OA were estimated to have more expected remaining years healthy and in work than people with or without OA who had non-manual or manual occupations. The number of ELSA participants who were self-employed with OA may not be sufficient (especially in younger ages) to support this model ($log \frac{_z p_x^{ij}}{_z p_x^{ii}} = a_{ij}(z) + b_{ij}(z) * age + c_{ij}(z) * occupation + d_{ij}(z) * sex$).

At age 50, the average number of remaining years expected to be spent healthy and in work was 12.00 (11.23,12.78) years for people with self-employed occupations without OA (36.05% of LE), 10.48 (10.14,10.82) years for people with non-manual occupations without OA (28.93% of LE), 9.33 (8.94,9.71) years for people with manual occupations and no OA (27.85% of LE), 7.29 (6.80,7.78) years for people with non-manual occupations who have OA (20.06% of LE), 5.81 (4.86,6.76) years for people with self-employed occupations who have OA (17.36% of LE), and 4.86 (4.46,5.25) years for people with manual occupations who have OA (14.45% of LE) (table 4.13).

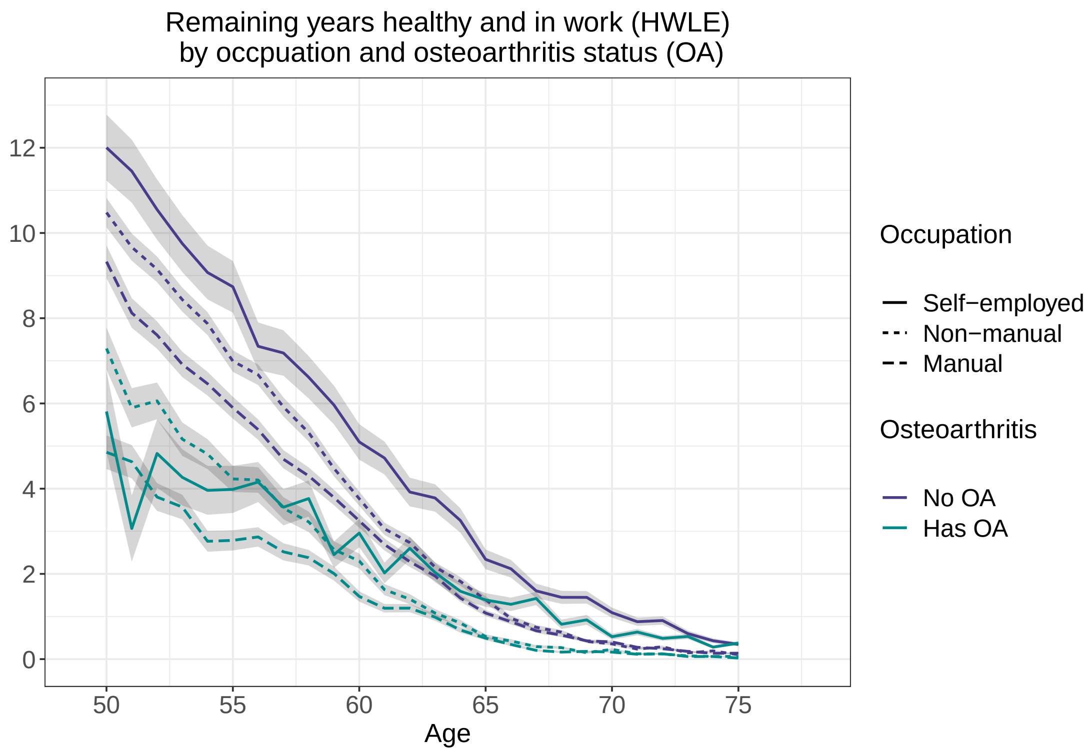

FIGURE 4.7: Plot of remaining years expected to be spent healthy and in work (HWLE) by occupation and osteoarthritis status at ages 50-75 with 95% confidence intervals

HWLE for males and females with manual, non-manual and self-employed occupations, with and without osteoarthritis over ages 50-75

The ranking trend of OA and occupation combinations described above persisted within groups of women and men (figure 4.8), with men generally having higher estimates of remaining years expected to be spent healthy and work than women for the corresponding OA status and occupation category across ages 50-75 (figure 4.8, table 4.13). Fluctuation of HWLE estimates with each year of age previously observed among people with self-employed occupations who have OA was more severe when adding sex to the model (see figures 4.7 and 4.8), and also affected estimates for men with manual occupations with OA at younger ages 50-56.

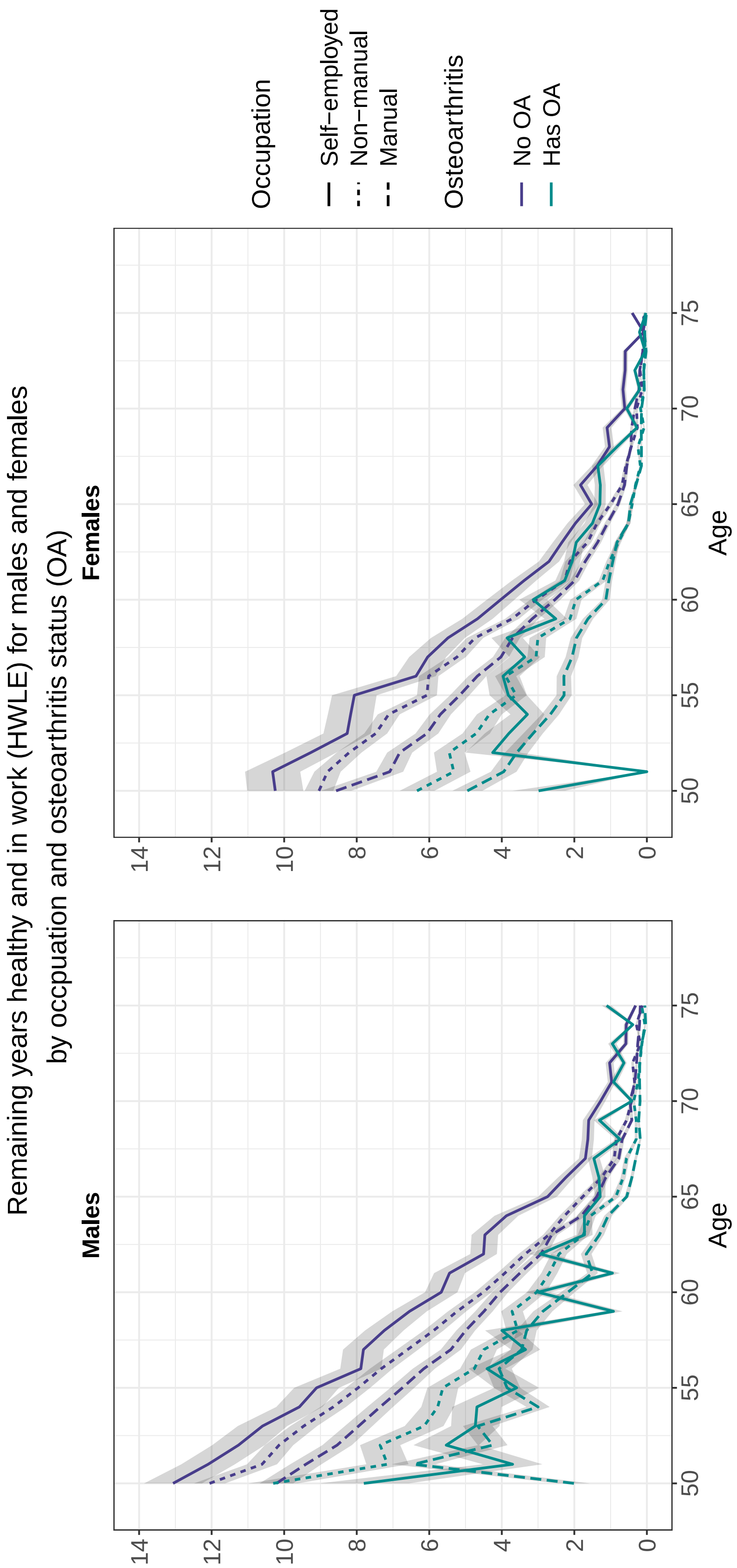

FIGURE 4.8: Plot of remaining years expected to be spent healthy and in work (HWLE) by sex, occupation and osteoarthritis status at ages 50-75 with 95% confidence intervals

TABLE 4.13: Remaining years expected to be spent healthy and in work (HWLE) at ages 50, 55, 60, 65, 70 and 75 with covariate combinations sex, osteoarthritis and occupation

Model	Age (95% CI) 50	55	60	65	70	75
Sex						
Male	11.00 (10.67,11.34)	7.06 (6.83,7.30)	3.96 (3.80,4.11)	1.50 (1.42,1.58)	0.45 (0.41,0.48)	0.15 (0.14,0.16)
Female	8.19 (7.90,8.48)	5.08 (4.90,5.27)	2.50 (2.39,2.60)	0.75 (0.70,0.80)	0.25 (0.23,0.27)	0.06 (0.05,0.07)
Osteoarthritis						
Has OA	5.68 (5.29,6.07)	3.48 (3.24,3.72)	1.91 (1.77,2.04)	0.54 (0.49,0.58)	0.21 (0.19,0.23)	0.05 (0.05,0.06)
No OA	10.00 (9.74,10.26)	6.60 (6.42,6.78)	3.59 (3.47,3.71)	1.30 (1.24,1.37)	0.43 (0.40,0.46)	0.13 (0.12,0.14)
Occupation						
Self-employed	10.98 (10.23,11.74)	7.92 (7.36,8.49)	4.61 (4.24,4.99)	2.14 (1.94,2.34)	0.94 (0.84,1.03)	0.35 (0.31,0.39)
Non-manual	10.06 (9.74,10.38)	6.51 (6.29,6.73)	3.41 (3.27,3.55)	1.16 (1.09,1.22)	0.30 (0.28,0.33)	0.09 (0.08,0.10)
Manual	8.59 (8.24,8.93)	5.15 (4.93,5.37)	2.77 (2.64,2.90)	0.92 (0.86,0.98)	0.30 (0.28,0.33)	0.10 (0.09,0.10)
Sex + osteoarthritis						
Male + has OA	6.56 (5.99,7.12)	4.52 (4.18,4.86)	2.52 (2.33,2.72)	0.69 (0.63,0.76)	0.26 (0.23,0.28)	0.13 (0.11,0.14)
Male + no OA	11.41 (11.06,11.75)	7.51 (7.25,7.76)	4.36 (4.18,4.53)	1.67 (1.58,1.76)	0.53 (0.49,0.57)	0.16 (0.14,0.17)
Female + has OA	5.28 (4.90,5.65)	2.96 (2.74,3.18)	1.58 (1.46,1.69)	0.45 (0.41,0.49)	0.18 (0.16,0.20)	0.02 (0.02,0.03)
Female + no OA	8.77 (8.45,9.09)	5.70 (5.48,5.92)	2.83 (2.70,2.96)	0.90 (0.84,0.96)	0.31 (0.28,0.34)	0.09 (0.08,0.10)
Osteoarthritis + occupation						
Has OA + self employed	5.81 (4.86,6.76)	3.98 (3.43,4.54)	2.96 (2.63,3.29)	1.39 (1.23,1.55)	0.53 (0.46,0.59)	0.38 (0.33,0.42)
Has OA + non-manual	7.29 (6.80,7.78)	4.23 (3.92,4.54)	2.30 (2.13,2.48)	0.53 (0.48,0.58)	0.23 (0.21,0.25)	0.07 (0.06,0.07)
Has OA + manual	4.86 (4.46,5.25)	2.79 (2.55,3.02)	1.47 (1.35,1.59)	0.49 (0.44,0.54)	0.17 (0.15,0.18)	0.03 (0.02,0.03)
No OA + self employed	12.00 (11.23,12.78)	8.74 (8.13,9.34)	5.10 (4.68,5.51)	2.34 (2.11,2.57)	1.09 (0.97,1.21)	0.35 (0.30,0.39)
No OA + non-manual	10.48 (10.14,10.82)	6.99 (6.74,7.24)	3.77 (3.60,3.93)	1.39 (1.31,1.48)	0.36 (0.32,0.39)	0.10 (0.09,0.12)
No OA + manual	9.33 (8.94,9.71)	5.90 (5.64,6.16)	3.25 (3.08,3.41)	1.08 (1.01,1.15)	0.40 (0.37,0.44)	0.14 (0.13,0.15)
Sex + osteoarthritis + occupation						
Male + has OA + self employed	7.80 (6.57,9.04)	3.59 (2.97,4.21)	3.00 (2.66,3.34)	1.29 (1.14,1.43)	0.42 (0.35,0.48)	1.11 (0.98,1.24)
Male + has OA + non-manual	10.30 (9.62,10.98)	5.63 (5.20,6.05)	3.04 (2.78,3.30)	0.86 (0.76,0.95)	0.36 (0.32,0.40)	0.14 (0.13,0.16)
Male + has OA + manual	2.01 (1.57,2.46)	3.85 (3.49,4.22)	2.18 (1.98,2.37)	0.56 (0.49,0.62)	0.19 (0.16,0.21)	0.06 (0.05,0.06)
Male + no OA + self employed	13.06 (12.27,13.86)	9.11 (8.49,9.72)	5.67 (5.22,6.12)	2.74 (2.48,3.00)	1.28 (1.14,1.41)	0.31 (0.26,0.36)

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* **Table 4.13 – continued from previous page** *

	Age (95% CI)					
Model	50	55	60	65	70	75
Male + no OA + non-manual	12.06 (11.63,12.49)	7.96 (7.63,8.30)	4.51 (4.28,4.74)	1.77 (1.65,1.88)	0.42 (0.38,0.46)	0.13 (0.11,0.14)
Male + no OA + manual	10.22 (9.75,10.68)	6.74 (6.41,7.07)	4.05 (3.82,4.27)	1.38 (1.28,1.48)	0.46 (0.42,0.51)	0.18 (0.16,0.20)
Female + has OA + self employed	2.99 (2.26,3.71)	3.82 (3.30,4.34)	3.13 (2.75,3.52)	1.30 (1.14,1.45)	0.55 (0.48,0.63)	0.03 (0.01,0.04)
Female + has OA + non-manual	6.34 (5.86,6.82)	3.61 (3.31,3.90)	1.96 (1.80,2.11)	0.41 (0.36,0.45)	0.18 (0.16,0.19)	0.04 (0.03,0.04)
Female + has OA + manual	4.95 (4.54,5.36)	2.28 (2.07,2.49)	1.13 (1.03,1.23)	0.45 (0.41,0.50)	0.15 (0.13,0.16)	0.01 (0.01,0.01)
Female + no OA + self employed	10.25 (9.47,11.02)	8.07 (7.45,8.68)	4.03 (3.65,4.41)	1.52 (1.33,1.71)	0.61 (0.53,0.69)	0.41 (0.35,0.46)
Female + no OA + non-manual	9.04 (8.65,9.43)	6.06 (5.79,6.34)	3.05 (2.88,3.22)	1.00 (0.92,1.07)	0.28 (0.25,0.31)	0.07 (0.06,0.08)
Female + no OA + manual	8.57 (8.15,8.99)	5.16 (4.89,5.43)	2.54 (2.38,2.69)	0.80 (0.73,0.86)	0.33 (0.30,0.36)	0.10 (0.08,0.11)

TABLE 4.14: Health expectancies and life expectancy from age 50 with covariate combinations sex, osteoarthritis and occupation

Model	Health expectancies (95% CI)				
	HWLE	State 2 (H&NW)	State 3 (NH&W)	State 4 (NH&NW)	LE
Sex					
Male	11.00 (10.67,11.34)	9.73 (9.34,10.13)	1.99 (1.84,2.15)	7.59 (7.26,7.92)	30.32 (29.84,30.80)
Female	8.19 (7.90,8.48)	12.54 (12.12,12.96)	1.69 (1.56,1.82)	10.91 (10.52,11.30)	33.33 (32.83,33.84)
Osteoarthritis					
Has OA	5.68 (5.29,6.07)	12.17 (11.80,12.53)	1.62 (1.51,1.72)	7.53 (7.25,7.80)	31.31 (30.89,31.73)
No OA	10.00 (9.74,10.26)	8.82 (8.36,9.29)	2.74 (2.48,3.00)	15.00 (14.43,15.58)	32.25 (31.59,32.90)
Occupation					
Self-employed	10.98 (10.23,11.74)	10.70 (9.58,11.82)	2.78 (2.37,3.19)	8.99 (7.94,10.05)	33.45 (31.89,35.02)
Non-manual	10.06 (9.74,10.38)	14.32 (13.78,14.85)	1.79 (1.65,1.93)	10.27 (9.80,10.75)	36.44 (35.74,37.14)
Manual	8.59 (8.24,8.93)	11.40 (10.93,11.88)	1.76 (1.61,1.92)	12.05 (11.55,12.55)	33.80 (33.16,34.45)
Sex + osteoarthritis					
Male + has OA	6.56 (5.99,7.12)	7.36 (6.83,7.88)	3.73 (3.33,4.12)	12.75 (12.06,13.44)	30.39 (29.60,31.17)
Male + no OA	11.41 (11.06,11.75)	10.41 (9.97,10.84)	1.78 (1.64,1.93)	6.47 (6.16,6.79)	30.07 (29.55,30.59)
Female + has OA	5.28 (4.9,5.65)	9.65 (9.12,10.18)	2.38 (2.12,2.64)	16.23 (15.58,16.88)	33.54 (32.81,34.26)
Female + no OA	8.77 (8.45,9.09)	13.96 (13.44,14.47)	1.46 (1.33,1.59)	8.66 (8.27,9.05)	32.85 (32.27,33.42)
Osteoarthritis + occupation					
Has OA + self employed	5.81 (4.86,6.76)	8.21 (7.10,9.31)	5.16 (4.35,5.97)	14.28 (12.72,15.85)	33.46 (31.60,35.31)
Has OA + non-manual	7.29 (6.80,7.78)	11.10 (10.45,11.76)	2.93 (2.61,3.25)	15.02 (14.26,15.78)	36.34 (35.41,37.26)
Has OA + manual	4.86 (4.46,5.25)	8.61 (8.05,9.17)	2.19 (1.92,2.46)	17.98 (17.18,18.78)	33.63 (32.73,34.53)
No OA + self employed	12.00 (11.23,12.78)	11.62 (10.40,12.83)	2.32 (1.95,2.68)	7.36 (6.44,8.28)	33.29 (31.71,34.88)
No OA + non-manual	10.48 (10.14,10.82)	15.75 (15.11,16.38)	1.58 (1.45,1.72)	8.42 (7.96,8.88)	36.23 (35.47,36.99)
No OA + manual	9.33 (8.94,9.71)	12.68 (12.12,13.24)	1.58 (1.43,1.73)	9.91 (9.42,10.40)	33.50 (32.79,34.20)
Sex + osteoarthritis + occupation					
Male + has OA + self employed	7.80 (6.57,9.04)	6.91 (5.94,7.87)	6.46 (5.46,7.46)	11.22 (9.78,12.65)	32.38 (30.68,34.09)
Male + has OA + non-manual	10.30 (9.62,10.98)	9.31 (8.62,10.00)	2.92 (2.50,3.35)	11.67 (10.90,12.44)	34.20 (33.26,35.15)
Male + has OA + manual	2.01 (1.57,2.46)	7.27 (6.58,7.95)	1.32 (0.94,1.71)	19.00 (17.98,20.01)	29.60 (28.48,30.71)
Male + no OA + self employed	13.06 (12.27,13.86)	10.27 (9.13,11.40)	2.62 (2.20,3.04)	6.39 (5.56,7.23)	32.35 (30.81,33.88)
Male + no OA + non-manual	12.06 (11.63,12.49)	13.55 (12.89,14.22)	1.64 (1.47,1.81)	7.19 (6.73,7.65)	34.44 (33.66,35.23)

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Table 4.14 – continued from previous page

	Health expectancies (95% CI)				
Model	HWLE	State 2 (H&NW)	State 3 (NH&W)	State 4 (NH&NW)	LE
Male + no OA + manual	10.22 (9.75,10.68)	10.73 (10.14,11.32)	1.76 (1.56,1.95)	8.82 (8.30,9.34)	31.52 (30.77,32.27)
Female + has OA + self employed	2.99 (2.26,3.71)	10.11 (8.65,11.57)	2.60 (1.66,3.54)	19.50 (17.52,21.49)	35.20 (33.05,37.34)
Female + has OA + non-manual	6.34 (5.86,6.82)	12.19 (11.45,12.93)	2.86 (2.53,3.19)	16.73 (15.87,17.59)	38.11 (37.09,39.13)
Female + has OA + manual	4.95 (4.54,5.36)	9.39 (8.77,10.01)	2.22 (1.95,2.50)	18.98 (18.10,19.86)	35.54 (34.57,36.52)
Female + no OA + self employed	10.25 (9.47,11.02)	14.55 (13.04,16.07)	1.82 (1.45,2.18)	9.49 (8.35,10.64)	36.11 (34.30,37.92)
Female + no OA + non-manual	9.04 (8.65,9.43)	18.12 (17.32,18.93)	1.50 (1.35,1.65)	9.82 (9.22,10.41)	38.48 (37.55,39.41)
Female + no OA + manual	8.57 (8.15,8.99)	14.47 (13.77,15.17)	1.47 (1.31,1.63)	11.17 (10.55,11.79)	35.67 (34.82,36.53)

4.5.4 Estimates of HWLE at age 50 in the NorStOP population (NorStOP data)

HWLE (at age 50) for the overall NorStOP population was estimated as 6.58 (6.28,6.87) years, which was 22.51% of LE from age 50. In addition to spending 6.58 years healthy and in work from age 50, on average people age 50 were expected to spend 6.96 (6.63,7.30) years healthy and not in work, 3.32 (3.09,3.54) years not healthy and in work, and 12.38 (11.95,12.80) years not healthy and not in work (table 4.15, figure 4.9). Total LE was 29.23 (28.77,29.69) years.

TABLE 4.15: Health expectancies for adults in the NorStOP population overall and by osteoarthritis status

Population	Sample size	Healthy and in work (1)	Healthy and not in work (2)	Not healthy and in work (3)	Not healthy and not in work (4)	Total life expectancy
North Staffordshire	13774	6.58 (6.28,6.87)	6.96 (6.63,7.30)	3.32 (3.09,3.54)	12.38 (11.95,12.80)	29.23 (28.77,29.69)
OA group	3260	4.31 (3.68,4.94)	5.35 (4.72,5.98)	3.47 (2.94,4.01)	18.69 (17.65,19.72)	31.82 (30.98,32.67)
Non-OA group	10514	6.90 (6.57,7.24)	7.43 (7.04,7.83)	3.22 (2.98,3.47)	10.83 (10.38,11.28)	28.39 (27.86,28.92)

HWLE for people with and without OA in the NorStOP population

When stratifying the data according to whether medical records showed consultation(s) relating to OA from two years prior to baseline to the end of the study period, HWLE was similar (point estimate was slightly higher) for people without OA and approximately two years lower for the OA group compared to the overall NorStOP population (figure 4.9). HWLE for the OA group was 4.31 (3.68,4.94) years (13.54% of LE). People with OA were also expected to spend 5.35 (4.72,5.98) years not healthy and in work, 3.47 (2.94,4.01) years not healthy and in work, and 18.69 (17.65,19.72) years not healthy and not in work from age 50 (table 4.15). Total LE from age 50 for people who consulted primary care for OA was 31.82 (30.98,32.67) years. HWLE for the non-OA group was 6.90 (6.57,7.24) years (24.30% of LE). People without OA were also expected to spend 7.43 (7.04,7.83) years healthy and not in work, 3.22 (2.98,3.47) years not healthy and in work, and 10.83 (10.38,11.28) years not healthy and not in work from age 50 (table 4.15). Total LE from age 50 for the non-OA group was 28.39 (27.86,28.92) years.

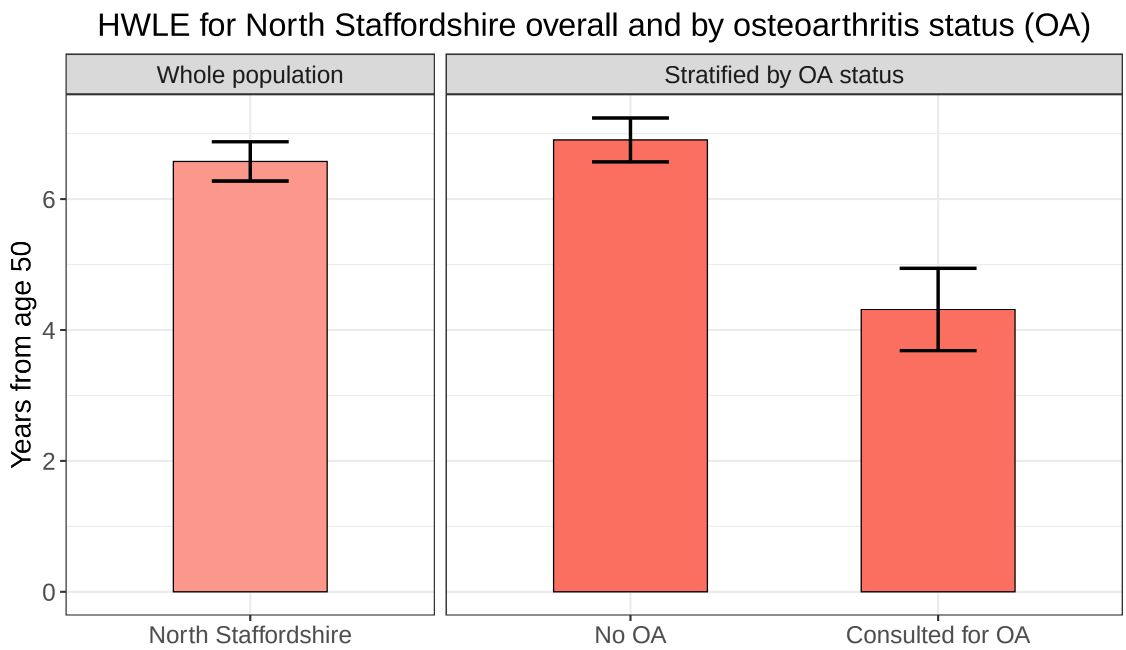

FIGURE 4.9: HWLE for adults in the NorStOP population overall and for the OA and non-OA subpopulations

4.5.5 Sensitivity analyses

ELSA

Despite differences in the numbers of transitions observed from known alive states into an alive but unknown state (-1 status), health expectancy results for England overall using the ELSA sample as defined for this study were identical to results using yearly transition probabilities in the previous study (chapter 2; see lines one and two in table 4.16), indicating that results of the analyses presented in this chapter were not sensitive to the exclusion of survey time points where non-responding individuals who were known to be alive but without known OA status (assigning status '-2' to this group to ignore the time point instead of '-1' to indicate that the individual was alive but the status at that time point was unknown).

TABLE 4.16: Sensitivity of health expectancy results for England overall population to status reassignment from -1 (alive but unknown status) to -2 (unknown vital status / ignore transition) due to missing osteoarthritis status

Health expectancy results	Length of interpolation steps	Healthy and in work (1)	Healthy and not in work (2)	Not healthy and in work (3)	Not healthy and not in work (4)	Total life expectancy
Current chapter 4 study sample	12 months	9.43 (9.19, 9.66)	11.24 (10.94, 11.53)	1.83 (1.73, 1.93)	9.33 (9.07, 9.59)	31.83 (31.47, 32.18)
Previous chapter 2 sensitivity analysis	12 months	9.43 (9.19,9.66)	11.24 (10.94,11.53)	1.83 (1.73,1.93)	9.33 (9.07,9.59)	31.83 (31.47,32.18)
Main analysis in previous chapter 2	1 month	9.42 (9.19,9.66)	11.18 (10.88,11.47)	1.84 (1.74,1.94)	9.32 (9.06,9.58)	31.76 (31.4,32.12)

Notes:
Results are given in years
Confidence intervals are shown in parentheses
Results are based on observed state occupancy prevalences
Sample size for all analyses is 15,284
All results are estimated using population-based (observed) state occupation prevalences

Examining the HWLE estimates from two ELSA samples (described in this chapter and chapter 2)

HWLE at age 50 for males (11.00 [10.67,11.34] years) and females (8.19 [7.90,8.48] years) was consistent with estimates calculated in chapter 2 through the alternative method of data stratification (males: 10.93 [10.58,11.28] years, females: 8.25 [7.93,8.57] years) (table 2.15 on page 116).

Total LE estimates from age 50 for non-manual (36.44 [35.74,37.14] years) and manual (33.80 [33.16,34.45] years) occupation types were higher than (self-employed point estimate 33.45 [31.89,35.02] years was similar to) the average LE for England estimated in the previous study of HWLE using ELSA data (31.76 [31.40,32.12] years; chapter 2, see page 116) and LE estimated by sex (men 30.32 [29.84,30.80] years; women 33.33 [32.83,33.84] years) (table 4.14). LE estimates were also high in models including occupation type and other covariate(s), suggesting that some health expectancies are overestimated (and some may be underestimated) using the models including occupation type. It was expected that including occupation type as a variable in analysis of ELSA waves 1-6 would lead to bias in results due to occupation type not being measured at wave 1, as estimation of health expectancies and total LE by occupation category was only carried out for individuals who survived until and responded at subsequent wave(s). The estimates of total LE according to occupation type compare to lower estimates 34.54 (33.92,35.16) years (non-manual), 31.66 (31.01,32.31) years (manual), and 31.64 (29.95,33.33) years (self-employed) found in chapter 2 (table 2.15 on page 116). Despite higher estimates of LE, estimates of HWLE at age 50 for manual and non-manual occupation types were similar but slightly lower than those calculated through stratification in the previous chapter: 10.06 (9.74,10.38) years for people with non-manual occupations compared to 10.32 (9.95,10.69) years previously estimated; and 8.59 (8.24,8.93) years for people with manual occupations compared to 8.72 (8.25,9.20) years previously estimated. Estimates for people with self-employed occupations were lower (10.98 [10.23,11.74] years) than those previously estimated through stratification (11.76 [10.76,12.76] years).

NorStOP

Health expectancy results estimates from the main NorStOP study sample were similar to (with slightly higher point estimates) estimates found when including people with missing medical record data (table 4.18, figure 4.10). Total LE from the main study sample using the life table method was lower than that found by summing the health expectancies, and was closer to estimates found using the larger sample. The larger sample (including people with missing medical record data) included 16,666 transition observations (16,287 from and to known states) compared to 15,009 in the main study sample (of which 14,655 had both initial and destination states known) (table 4.17 and table 4.10 on page 200).

HWLE point estimates were higher when estimated using monthly transition probability models than yearly transition probability models in both the main study sample (6.90 [6.12, 7.68] years compared to 6.58 [6.28, 6.87] years) and the larger sample including people with missing medical record data (6.93 [6.31, 7.55] compared to 6.52 [6.24, 6.80]).

TABLE 4.17: Contingency table of HWLE status transitions observed in whole NorStOP sample (including people without linked medical record data)

	Destination state						
Starting state	1	2	3	4	5	-1	Total
1	1567	515	410	232	76	40	2840
2	151	2244	35	1165	380	88	4063
3	510	177	647	396	50	29	1809
4	52	820	89	5034	1737	222	7954
Total	2280	3756	1181	6827	2243	379	16666

TABLE 4.18: Health expectancies from NorStOP sample at age 50 with results of sensitivity analyses

Population	Interpolation step size	Sample size	Healthy and in work (1)	Healthy and not in work (2)	Not healthy and in work (3)	Not healthy and not in work (4)	Total life expectancy
Medical record data available (main analysis)	12	13774	6.58 (6.28, 6.87)	6.96 (6.63, 7.30)	3.32 (3.09, 3.54)	12.38 (11.95, 12.80)	29.23 (28.77, 29.69)
Medical record data available	**1**	13774	6.90 (6.12, 7.68)	6.87 (6.53, 7.21)	3.39 (3.12, 3.65)	12.11 (11.29, 12.93)	29.27 (28.78, 29.76)
Medical record data available	**Life table**	13774					28.99
Including people with missing medical record data	12	18413	6.52 (6.24, 6.80)	6.86 (6.54, 7.17)	3.29 (3.08, 3.50)	12.20 (11.81, 12.60)	28.87 (28.44, 29.30)
Including people with missing medical record data	**1**	18413	6.93 (6.31, 7.55)	6.76 (6.44, 7.09)	3.38 (3.14, 3.62)	11.86 (11.20, 12.52)	28.93 (28.48, 29.38)
Including people with missing medical record data	**Life table**	18413					28.59

Notes:
Results are given in years
Confidence intervals are shown in parentheses
Primary results are given in the first row and results sensitivity analyses are shown in subsequent rows
Differences between sensitivity and primary analyses are indicated in bold type

Health expectancy estimates for the NorStOP population subgroup with OA were based on fewer observed transitions than estimates for the subgroup without OA (see tables 4.11 and 4.12). Total life expectancies from summed health expectancies for population subgroups with and without OA were similar to estimates found with the life table method (table 4.18, figure 4.10). The estimate of total LE for the OA group was found to be higher than for people without OA and higher than the general population estimate (figure 4.10).

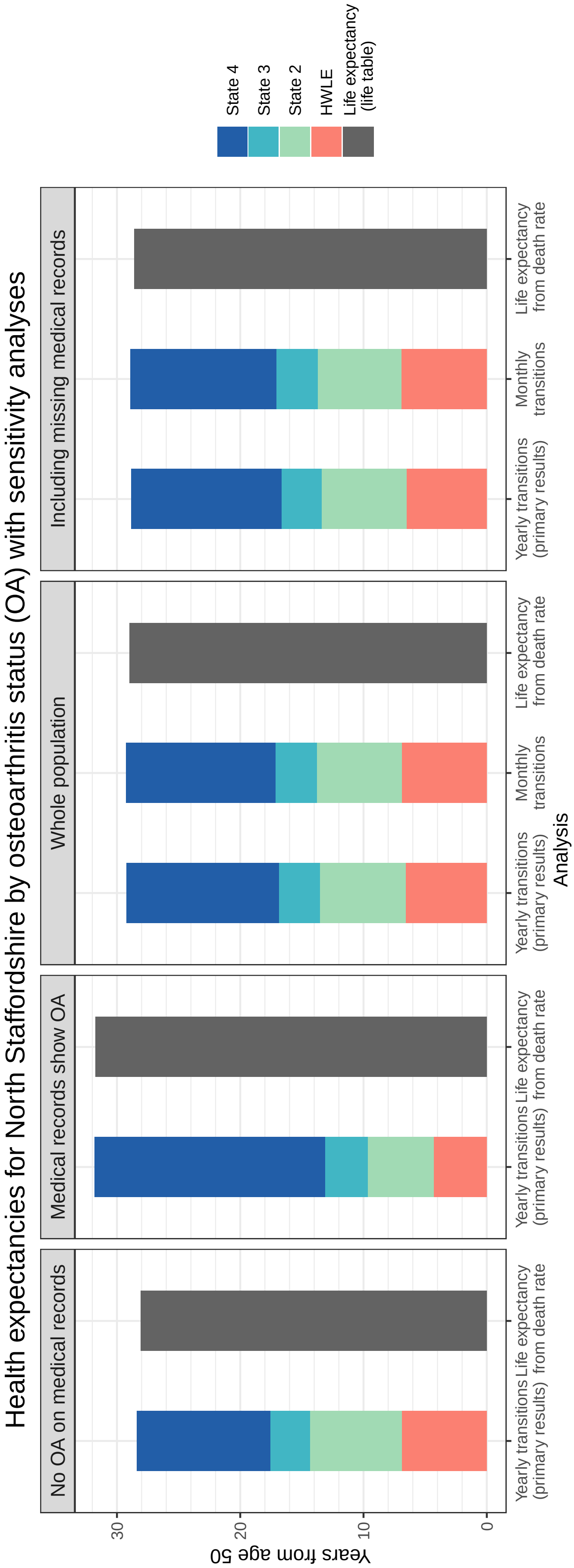

FIGURE 4.10: Barchart of health expectancy and total life expectancy results for the NorStOP population (overall and stratified by osteoarthritis status) with total life expectancy estimates using the life table method

4.6 Discussion

This study has presented HWLE estimates for people with and without OA in England as well as subpopulations by sex and occupation type. Using two different approaches to defining OA (self-reported doctor diagnosis and medical record of OA consultation), this study of HWLE in study populations ELSA (representative of England) and NorStOP (North Staffordshire) found clear and persistent differences in length of healthy working life in later working life for people who have or develop OA compared to those who do not. Although sample characteristics and health definitions differed between the two data sources in addition to different OA measurements, both ELSA and NorStOP results indicated that HWLE is reduced by over a third for people with OA.

In England on average, people who have developed OA by age 50 are expected to spend fewer than six years of their remaining life expectancy both healthy and in work. HWLE at age 50 was ten years for people who do not have OA at age 50 compared to 5.68 years for people with OA at age 50. Within groupings by occupation and sex, people with OA have lower HWLEs than their non-OA counterparts. The effect of OA on HWLE can be seen at all years of age from 50-77. Although a higher number of people may have OA and reduced HWLE at older years in the age range, the inequality at age 50 highlight the impact of OA on working-age adults who have over 15 years remaining until they become eligible for the State Pension.

Estimates of life expectancy and healthy life expectancy at age 50 were lower in the NorStOP population than in England on average (NorStOP HWLE: 6.58 [6.28, 6.87] years; ELSA: 9.43 [9.19, 9.66] years). Differences in health outcomes and employment factors (including work opportunities) in North Staffordshire compared to England overall likely lead to lower HWLE estimates from NorStOP data than observed using the ELSA data. This highlights the importance of local level conditions affecting population health and work opportunities (for example deprivation levels) and could mean that inequalities affect HWLE in local areas to an even greater extent than implied by the regional variation observed previously in chapter 2. Another important reason for population health measurement in sub-regional areas (including estimation of HWLE) is that health inequalities policy is devolved to local areas in the UK (Katikireddi et al., 2017).

Results from NorStOP suggested a 2.6 year difference in HWLE at age 50 by OA status, which was lower for people who have OA (who develop OA at any age) compared to those who do not. Differences in HWLE by OA status suggest an important detrimental effect of this common disease on a large number of people's access to or ability to participate in paid work. The smaller difference in HWLE between the OA and non-OA groups in NorStOP compared to ELSA suggests that the impact of OA on HWLE in a deprived area is less because the average length of healthy working life is already lower. This highlights the importance of upstream factors and deprivation; health conditions such as OA may be associated with lower HWLE but broader social factors also influence health and work outcomes. The higher estimates of HWLE for self-employed people compared to those of other occupation types using ELSA data indicates higher levels of functional health; people in self-employed work likely have more control over their activities and may therefore be able to more effectively manage their health conditions (which could also be a reason for choosing self-employment).

As well as reducing HWLE, OA was found to be associated with reduced healthy life expectancy and reduced working life expectancy. Reductions to healthy life expectancy and associated HWLE reductions may be linked to physical OA symptoms of pain and reduced physical mobility, which may become worse with time and age, and are likely to be influenced by various lifestyle, socioeconomic, workplace, and social factors (Wilkie et al., 2020; Hunter and Bierma-Zeinstra, 2019; Farr et al., 2013). For example, having support in the workplace can improve return to work, sickness absence, and presenteeism outcomes for people with chronic conditions (Wilkie et al., 2020; Sabariego et al., 2018). Health-related quality of life is closely related to pain severity, which can also be improved through surgical intervention in some cases but this carries higher surgical risks due to comorbidities and factors such as obesity (Farr et al., 2013). There is evidence that weight loss if needed and exercise can reduce risks of symptomatic OA and reduce pain severity among overweight adults with OA (Farr et al., 2013; Zhang and Jordan, 2010). Pain that interferes with everyday life is more prevalent and impactful with increasing age (Thomas et al., 2007) and pain interference is strongly associated with work disability and premature work loss (Wynne-Jones et al., 2018; Wilkie et al., 2014b). However, fluctuations in the severity of pain experienced can mean variation in the extent of pain interference (Farr et al., 2013; Zhang and Jordan, 2010), and workplace accommodations such as flexible work arrangements could allow people with OA to remain active in paid work who may otherwise feel unable to continue. Furthermore, whether a workplace is supportive can determine the extent of pain interference thereby influencing the timing of work exit among workers with OA (Wilkie et al., 2014b). This is consistent with the findings of this study in which models of HWLE that included OA and occupation type suggested that, by age 60, people with OA who are self-employed (and who are therefore likely to have more control over their work) are able to achieve similar HWLE outcomes as people without OA in non-manual or manual occupations. This highlights the importance of measuring HWLE as an indicator as not only medical diagnoses but also factors from the wider biopsychosocial model of health and work can drive ability to engage in paid work.

4.6.1 Strengths and limitations

There are various strengths and limitations to this study. A strength of this study is the analysis of nationally representative ELSA data to explore trends in HWLE over ages 50-75 according to OA status, sex and occupation type in order to reflect the average healthy working life outcomes experienced accross England. That ELSA HWLE results in this study for England overall and for men and women separately were similar to those found in chapter 2 suggests that the sample sizes were sufficient and indicates sufficient accuracy of estimates of HWLE among study participants. Although NorStOP data reflect health and work behaviour in a local area instead of nationally, the linked medical records allowed for improved identification of OA cases as diagnosed by a clinician, leading to results that demonstrate a significant effect of OA throughout the lifecourse on HWLE at age 50. The consistency of LE estimates from summed health expectancies with LE from the life table method across all ELSA analyses and NorStOP HWLE analyses indicates that the samples were sufficiently large for the chosen analysis approach and suggests that HWLE estimates are a realistic representation of the health and work outcomes experienced by the study participants.

A limitation of NorStOP data analyses was the exclusion of study participants without linked medical records. The life table estimate of LE when including people with missing medical record data was lower than the main life expectancy estimate (summed health expectancies) and life table estimate for the study population with linked medical record data). This suggests that there is some sensitivity of LE estimates to the exclusion of data from participants who declined to allow access to medical records; there may be differences between participants who chose to allow or not allow access to medical records and there may also be an effect on estimates of analysing only a subset of the transitions observed in the NorStOP study. As a result, one or more of the health expectancies may be overestimated (and some could be underestimated) although it is not clear which health expectancies may be affected and there were no significant differences between health expectancies estimated including and excluding participants without linked medical records using yearly transition probability models. The percent of NorStOP participants who consented to sharing medical records was similar for people in each HWLE statuses (healthy and working (1), healthy and not working (2), not healthy and working (3), not healthy and not working (4)) at all time points, except at baseline where a higher rate of consent to sharing medical records was found among not healthy and working (status 3) individuals. This possible selection bias means population-based HWLE estimates may assume a disproportionately high percentage of people to be unhealthy and working, thereby potentially overestimating HWLE (see table 2.13 on page 114). However, HWLE estimates were similar across analyses of the main study sample and the sample including participants without linked medical records, indicating that HWLE was not overestimated as a result of sensitivity to the exclusion of participants without linked medical record data. Sensitivity analyses HWLE estimates using monthly transition probability models rather than yearly transition probability models - in both the NorStOP main study sample as well as the larger NorStOP sample including people with missing medical record data - suggest that the analyses of NorStOP data may have some sensitivity to interpolation step size. The reason for this sensitivity (which was not detected for ELSA data) is unclear but could be due to the frequency of data collection (every three years in NorStOP and every two years in ELSA), sample size or characteristics, or the number or distribution of transitions.

The total life expectancy of the NorStOP OA group was found to exceed the total life expectancy of the non-OA group, which is unlikely to reflect the true difference in the North Staffordshire population as an association between OA and increased mortality has previously been found using data from the same study after adjusting for confounding (Wilkie et al., 2019). The similarity of LE estimates between summed health expectancies estimated with the multi-state model and the total life expectancy estimated using the life table method suggests that the health expectancies were not over- or underestimated for the study population, implying that the higher LE observed among the OA group is an artefact of the sample data and that the sample size was not insufficient for modelling HWLE. The higher LE in the OA group compared to the non-OA group could be due to low numbers of questionnaires completed by the oldest old adults (≥85 years), with data collected relatively more commonly in the OA group than the non-OA group compared to the proportion of the overall NorStOP population these groups comprise (survey attrition was lower among participants with OA, possibly due to the questionnaire content relating to OA symptoms). This suggests a need either for more data to be collected at older ages and/or for a longer follow-up period for mortality data (death dates were known for 1,953 [14.18%] of the 13,774 study sample members with linked medical record data) in order to accurately represent and estimate life expectancy for North Staffordshire using a (multi-state) life table approach. In this case, one or more health expectancies for an unhealthy and/or not working state may be overestimated for the North Staffordshire population; HWLE is unlikely to be affected as healthy and working years are typically lived at younger ages with transitions to death from the healthy working state being less common.

Self-report of doctor diagnosed OA may have been a limitation to the use of ELSA data, which is likely to have introduced information bias as there were inconsistencies in self-reported diagnoses across waves. Variation in whether OA was reported at each wave was ignored as it was assumed that OA is not reversible clinically (OA causes irreversible structural changes). However, the presence of conflicting OA responses indicated potential misclassification bias (a quarter of OA reports in waves 1 to 5 were disputed at a later wave). Identification of OA cases in the data was inclusive wherein all reports of having OA (or arthritis of an unknown type) were acknowledged as OA, and therefore any misclassification is more likely to affect incorrect reporting of OA leading to overestimation of HWLE for people with OA. Similarly, the first available record of occupation type was used as an indicator of main employment type throughout the life course, but participants may have changed job type later in their working life (for example if unable to continue in a previous job for health reasons). The direction of this misclassification bias is not clear and is further compounded by survivorship bias affecting participants in the original sample (starting at wave 1) as occupation type was only measured from wave 2. Models including occupation type were therefore affected by the limitation that this was not measured at wave 1, with resulting subgroup estimates of total life expectancy higher than the overall population and higher than occupation type subpopulation estimates using waves 2-6 only presented in chapter 2. However, HWLE estimates according to occupation type were not higher in the study presented in this chapter. This could be due to low rates of transition to death directly from from the healthy and working state, resulting in only a small effect (if any) of analysing all waves 1-6 on estimates of HWLE, and could indicate that HWLE is less likely to have been over- (or under) estimated than the health expectancies in the three other states. Results shown in table 4.14 and table 2.15 indicate that models including occupation in this chapter are more likely to have overestimated the health expectancy in state 2 (healthy and not in work) and to some extent state 4 (not healthy and not in work). Finally, an important limitation affecting more complex models used to analyse ELSA data is the presence of infrequently observed transitions particularly among the lower numbers of people with OA (compared to those without and to the whole study sample), which can be seen in plots of HWLE over ages 50-75 to result in uncertain HWLE estimates without smooth trends across the years of age. Such models with multiple added covariates are likely to require larger datasets for analysis.

In addition to different measurements of OA, study differences between ELSA and NorStOP as well as local level conditions affecting the NorStOP sampling frame reduced the comparability of the results. Whereas ELSA carried out interviews every two years and sought to include all invited participants (including those who missed earlier waves or the first wave), NorStOP collected information every three years and only included participants who responded at baseline. This could lead to differences in attrition that compound existing differences due to participation rates in each study, sample refreshment (in ELSA and not in NorStOP), study type (interview or postal questionnaire), and regional (NorStOP) compared to national conditions (ELSA) captured in the estimates. However, although the data sources were different, the presentation of HWLE results for both of the study populations is a strength of the study to highlight subnational HWLE differences as the NorStOP results may better represent English subpopulations living in more deprived areas. While ELSA data underrepresent people living in more deprived areas, North Staffordshire includes several of England's most deprived local areas (see table 2.6 on page 109 in chapter 2) (Noble et al., 2019; Mallen et al., 2005).

4.6.2 Implications for policy and research

This study has implications for policy and employers in that an increasing effect of osteoarthritis on the workforce and in workplaces should be anticipated as the workforce ages and retirement is deferred. As the prevalence of osteoarthritis among workers increases (through population and workforce ageing, deferred retirement age, and increasing obesity and physical inactivity), the association between osteoarthritis and reduced HWLE may make extensions to working life difficult for many people with this common musculoskeletal condition. However, there is also a need to better understand the causal pathways between osteoarthritis and work exit/ poor health, and investigate the role of factors within the broader biopsychosocial model of osteoarthritis pain interference; despite the clear overall effect of osteoarthritis on population HWLE, findings such as longer healthy working lives for self-employed people caution against an interpretation of inevitability. An important implication for research is therefore the need to understand how biopsychosocial factors drive work participation and work outcomes such as absenteeism and presenteeim in the general population and in particular among those with osteoarthritis. Achieving extended working lives policies may require changing perceptions around work disability as a likely consequence of osteoarthritis and other musculoskeletal disorders. Further work is needed to determine the extent that interference of symptomatic osteoarthritis with everyday activities such as work and social engagement may be lessened with supportive workplaces and a higher degree of individual control of work responsibilities and arrangements.

The demonstration of the use of medical record-linked NorStOP data to estimate HWLE for English subpopulations with and without osteoarthritis also has implications for further research and population surveillance. Survey data linked to medical records could be used in the future for HWLE surveillance for people with osteoarthritis or any other health condition, as questions asked in general population surveys may not provide the detail and coverage needed to facilitate this for many health conditions. HWLE may also become more difficult to estimate using survey data alone as longitudinal studies are expensive to run and may not be continuously available. This issue of sustainable HWLE estimation is discussed further in the final chapter of this thesis on page 306.

4.6.3 Conclusion

This study found consistent evidence from two large longitudinal studies that people with osteoarthritis are expected to spend fewer years healthy and in work from age 50 compared to people without osteoarthritis. The population subgroup identified by sex, osteoarthritis and occupation type that was best placed to work extended working lives were self-employed men without osteoarthritis at age 50 - who were expected to be healthy and in work for just over 13 years. Tackling HWLE inequalities and improving work outcomes for people with osteoarthritis will lead to overall improvements in average HWLE at the national level, which will require an understanding of the links between reduced HWLE and key (modifiable and non-modifiable) factors that are potential drivers of health, wellbeing, and work participation.

Chapter 5

Investigating factors associated with reduced Healthy Working Life Expectancy

Observational results presented in the previous chapters highlighted inequalities in Healthy Working Life Expectancy (HWLE) at age 50 for population subgroups by sex, socioeconomic status (measured by educational attainment and Index of Multiple Deprivation quintile), region and occupation type. HWLE was also found to be lower for people with osteoarthritis (OA), which is the most common form of arthritis and is associated with premature work exit. The Karasek job-demand-control(-support) model introduced in chapter 1 (figure 1.5 on page 22) highlighted the role of working conditions and psychological factors on health and work outcomes (Karasek and Theorell, 1990; Karasek, 1979). The extended WHO-ICF model (figure 1.6 on page 24) pointed to the importance of personal and broader external factors and their interplay (Heerkens et al., 2004). Models of health and work have also been developed for specific health conditions (such as those shown for OA in figures 5.1 and 5.2) (Mobasheri and Batt, 2016; Suri et al., 2012). Together, these models imply links between a large number of variables in different domains and health and work outcomes. The models indicate that work outcomes are a result of the interaction between health, socio-demographic, lifestyle and workplace factors. By selecting variables as exemplars from these domains, the study presented in this chapter aimed to estimate the strength of association between health, socio-demographic and workplace factors and transitions out of health and work, and to estimate the extent that these associations impact HWLE.

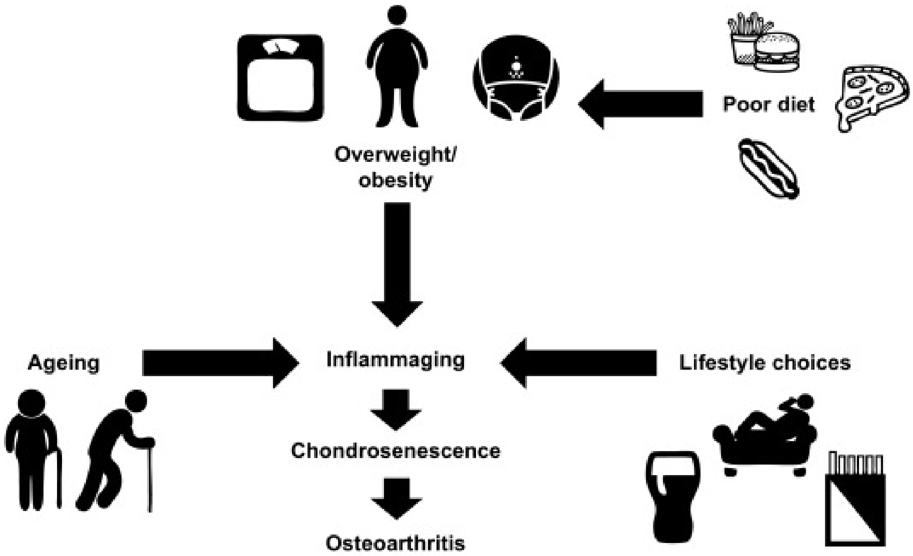

FIGURE 5.1: The convergence of ageing, obesity and lifestyle choices in the development of age-related cartilage dysfunction in OA (Mobasheri and Batt, 2016). Image reproduced with permission of the rights holder, Elsevier.

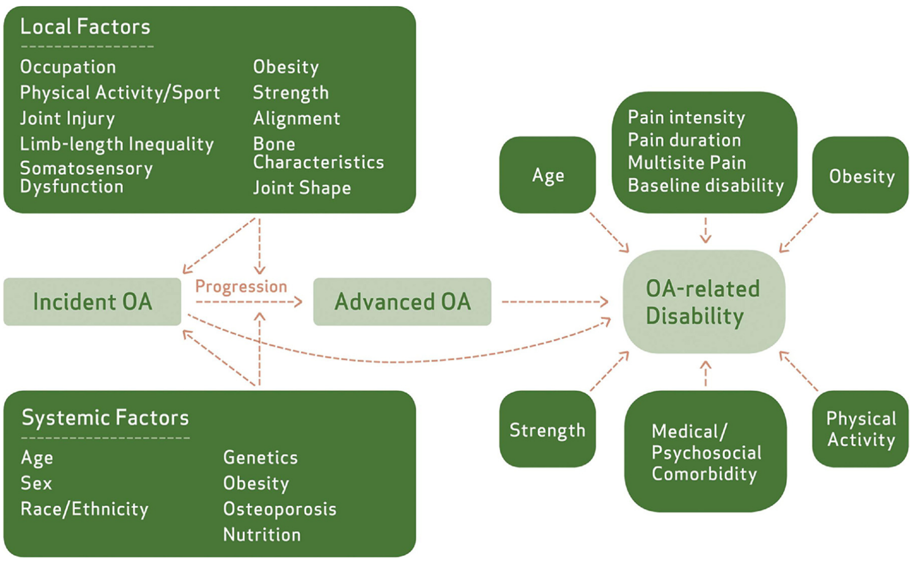

FIGURE 5.2: Risk factors for OA and OA-related disability (Suri et al., 2012). Image reproduced with permission of the rights holder, John Wiley and Sons.

5.1 Aims and objectives

The aim of this study was to investigate the strength and direction of association between health, socio-demographic and workplace factors and reduced HWLE. The original aim of this study was to develop a model of biopsychosocial drivers of reduced HWLE in people with OA. However, it was not possible with the methods and data available to estimate complex models involving numerous factors and it was not feasible to use the full 5-state HWLE model implemented in chapters 2 and 4 (some 5-state models with variables age and one additional covariate could successfully be estimated - typically taking days or weeks to run - while others could not). Instead, theory drove the selection of a restricted set of key biopsychosocial factors for analysis.

The objectives of this study were to:

1. Estimate the hazard rates of transitions (transition intensities) between healthy and working states in adults aged 50 and over in England and the corresponding HWLE
2. Estimate age-adjusted hazard rate ratios (HRRs) into and away from the healthy and working state associated with OA, pain interference, comorbidity and health factors, lifestyle and workplace factors
3. Estimate HWLE at age 50 associated with the presence or absence of each factor (OA, pain interference, comorbidity and health factors, lifestyle and workplace factors)

5.2 Methods

In order to investigate transition intensities into and away from the healthy and working state, the 5-state HWLE model previously introduced was simplified into a 3-state model (figure 5.3): healthy and working (state 1); unhealthy and/or not working (state 2) (including healthy but not in work, not healthy and in work, and not healthy and not in work); and dead (state 3). The use of a 3-state model reduced the computational intensity of analysis and mitigated against convergence failure where transitions were infrequently observed, thereby making the analyses feasible in terms of successful convergence and computation time. While IMaCh software (used for analyses in chapters 2 and 4) uses discrete-time Markov multi-state models, the approach taken in this study was based on a continuous-time model. The continuous-time approach was used as this is implemented in R software packages that were used as an alternative to IMaCh in order to estimate the association of different factors with transitions out of the healthy and working state.

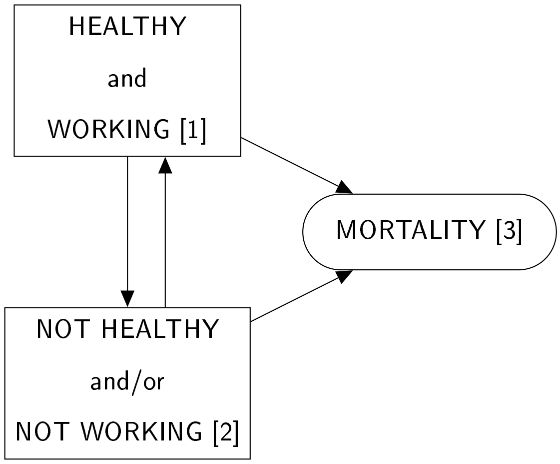

FIGURE 5.3: States and permitted transitions (shown with arrow heads) in the 3-state HWLE model

Transition intensities (hazard rates) were estimated using the 'msm' R package (Multi-State Modelling) (Jackson, 2011). This software package estimates transition probabilities using a Markov multi-state model approach (described in chapter 2). The multi-state model is defined by specifying a transition intensity matrix of starting values. The size of the matrix reflects the number of states and zero entries indicate non-permitted transitions. Rows of the transition intensity matrix sum to zero with diagonal entries defined as equal to the sum of the same row's off-diagonal entries.

Definition 5.2.1. *Transition intensities* α_{ij} give the instantaneous risk (hazard) of moving from state i to state j depending on values taken by any explanatory variables $v(t)$ (covariates) which may be fixed or time-varying. $X(t)$ denotes the state occupied at time t.

$$\alpha_{ij}(t, v(t)) = \lim_{\delta t \to 0} \frac{P(X(t+\delta t) = j | X(t) = i)}{\delta t} \tag{5.1}$$

Transition intensities modelled using the 'msm' package are time homogeneous. The transition intensity matrix $\mathbf{A}$ for the 3-state HWLE model is a matrix with three rows and three columns:

$$\mathbf{A} = \begin{pmatrix} -(\alpha_{12}+\alpha_{13}) & \alpha_{12} & \alpha_{13} \\ \alpha_{21} & -(\alpha_{21}+\alpha_{23}) & \alpha_{23} \\ 0 & 0 & 1 \end{pmatrix}$$

The R 'msm' software estimates the transition intensity by carrying out a maximum likelihood estimation procedure on transition probabilities estimated from the transition intensity matrix $\mathbf{P}(t) = \exp(t\mathbf{A})$. The matrix exponential is computed to give the transition probability matrix over time interval of length t, $\mathbf{P}(t)$, using eigensystem decomposition or, if eigenvalues are not distinct, the scaling and squaring method (Jackson, 2011; Moler and Van Loan, 2003). Maximum likelihood estimation is carried out on the sum of each individual's full likelihood contributions evaluated as the product of the likelihood contributions for each observed transition (pair of states observed).

The likelihood contrbution for each observed transition is $p_{X(t_n)X(t_{n+1})}(t_{n+1} - t_n)$ where $X(t_n)$ and $X(t_{n+1})$ are the states occupied at successive observed time points t_n and t_{n+1}. This is the $X(t_n)X(t_{n+1})$th entry of $\mathbf{P}(t)$ where $t = t_{n+1} - t_n$.

Individual-level covariates $v(t)$ were added to the Markov multi-state model in order to adjust for age and investigate the effect of factors of interest. The effect of covariates is modelled by 'msm' software using proportional intensities. Transition intensities α_{ij} in transition intensity matrix $\mathbf{A}$ are replaced by $\alpha_{ij}(v(t)) = \alpha_{ij}^{(0)}\exp(\beta_{ij}^T v(t))$ where $\alpha_{ij}^{(0)}$ is the baseline transition intensity from state i to state j and $\beta_{ij}^T v(t)$ is the linear combination of explanatory variables (covariates) applicable to a given individual at the observed time and transition. When covariates are included the likelihood is maximised over $\alpha_{ij}^{(0)}$ and β_{ij}.

The function `crudeinits.msm` was used to obtain values for the transition intensity matrix, which were used as starting values for the maximum likelihood estimation process. Sampling times were assumed to be non-informative except for death dates, which were handled by summing the likelihood contributions resulting from occupying any alive state in the instant before death.

Hazard rate ratios (HRR) describe the estimated ratio of transition intensities (hazard rates) with each additional year of age (for the modelled age variable) or when a binary variable (0 or 1) is equal to 1 (for modelled binary variables). HRRs were estimated for each modelled covariate combination.

Models used to estimate health expectancy from transition intensities must allow transition intensities to change with age (that is, age must be included in the model). While such a model can be fitted within 'msm' (through including age in the model as a covariate), in-built functionality to infer time spent in each state is only suitable for simpler models. The 'elect' R package (Estimation of Life Expectancies using Continuous-Time multi-state models) (van den Hout and Sum Chan, 2019; van den Hout and Matthews, 2019) facilitates estimation of health expectancies using results from 'msm' models fitted with age as a covariate to allow transition intensities to change with age. In this approach, a piecewise-constant approach is taken to model age as a time-dependent covariate within a smooth model. The 'elect' package then uses the same piecewise grid (years of age) to compute a numerical approximation of the following integral to derive starting-state based health expectancies:

$$e_t^{ij}(\mathbf{v}) = \int_0^\infty P(X(t+z) = j | X(t) = i, \mathbf{v}) dz \tag{5.2}$$

where $e_t^{ij}(\mathbf{v})$ is the expected total length of stay in alive state j given that state i was occupied at time (age) t, $X(t)$ is the state occupied at age t, and $\mathbf{v}$ is the vector of covariate values which are assumed not to depend on time or age. $P(X(t+z) = j|X(t) = i, \mathbf{v})$ is the probability that state j is occupied at time (age) $t + z$ given that state i was occupied at age t with covariate values $\mathbf{v}$.

The health expectancy in state j regardless of starting state at age t is denoted $e_t^{\cdot j}(\mathbf{v})$ and is calculated by averaging the starting-state based health expectancies using the probability of occupying each of the alive states at age t.

$$e_t^{\cdot j}(\mathbf{v}) = \sum_{i \neq D} P(X(t) = j|\mathbf{v}) e_t^{ij}(\mathbf{v}) \tag{5.3}$$

for each alive state i in the finite state space S (excluding the dead state D).

The distribution of state occupation at age t is estimated by specifying a multinomial logistic regression model of state occupied on the covariates included in the 'msm' model. The probability of occupying state i at age t given the vector of covariate values $\mathbf{v}$ is then

$$P(X(t) = i|\mathbf{v}) = \frac{\exp(\gamma_i(t))}{1 + \sum_{i \neq D} \exp(\gamma_i(t))} \tag{5.4}$$

where $\gamma_i(t)$ is the log odds of occupying a given state i evaluated at age t and covariate values $\mathbf{v}$.

5.2.1 Data source: The English Longitudinal Study of Ageing (ELSA)

This study used data from the English Longitudinal Study of Ageing (ELSA), introduced in chapter 2. The study data were collected in ELSA waves 2-6 (wave 6 was the most recent survey wave linked to mortality data). Wave 1 data were not used in this study as questions about work factors were not asked until wave 2.

5.2.2 Health, socio-demographic and workplace factors

Following from the results of the study presented in the previous chapter, OA was also selected for analysis in this study as an exemplar of a common long-term health condition in addition to other health, socio-demographic and workplace factors. Guided by models of OA (figures 5.1 and 5.2; figure 4.1 on page 182) and work (figure 1.5 on page 22), pain interference, obesity, physical inactivity, mental health, and work factors of support and control at work were variables included in the study in addition to osteoarthritis status and sex (Hunter and Bierma-Zeinstra, 2019; Mobasheri and Batt, 2016; Karasek and Theorell, 1990). Pain is the most prominent symptom of OA, and female sex is a risk factor for OA and pain interference (Mobasheri and Batt, 2016; Thomas et al., 2007). With the exception of age, obesity is the main risk factor for OA through excessive joint loading (a mechanical process) and disturbances in fat metabolism (non-mechanical) (Thijssen et al., 2015). Independently from obesity, physical inactivity is also an important risk factor for OA (Hunter and Bierma-Zeinstra, 2019; Mobasheri and Batt, 2016). Not only does exercise help to preserve health and wellbeing, regular exercise is a prominent aspect of recommended OA management for the improvement of pain and joint stiffness (Hunter and Bierma-Zeinstra, 2019; Mobasheri and Batt, 2016). Mental health problems were of interest as an example of a comorbidity (two thirds of people with OA also have comorbidities) and because mental health problems are a leading reason for sickness absence and have been linked to early retirement (ONS, 2019m; Swain et al., 2019; Olesen et al., 2012). Work factors of interest were the main modifiable factors in Karasek's 1990 influential job-demand-control-support model: support at work and control at work (see page 1.5).

5.2.3 Operationalisation of variables for analysis

HWLE states were defined using the definitions of health (absence of limiting long-standing illness) and work (employment or self-employment) introduced previously in chapter 2 (page 90). Individuals were classed as healthy and working (state 1) if they reported no limiting long-standing illness and reported participating in paid work within the month prior to interview. Individuals were classed as unhealthy and/or not working (state 2) if they did not meet both the healthy and working criteria. Individuals were classed as dead (state 3) based on linked mortality records.

Table 5.1 gives the definition used to identify each variable included in the models in the ELSA data. For each of the binary variables (with values 0 and 1), value 1 was assigned to the level hypothesized to be associated with less favourable health and/or work outcomes.

TABLE 5.1: Variable definitions

Variable	Definition	Coding
Sex	As coded in ELSA datasets (obtained in the Health Survey for England and confirmed (asked or coded) at each interview (Bridges et al., 2015b))	Male (0), female (1)
Osteoarthritis	Self-report at present or previous interview of having doctor diagnosed osteoarthritis (or arthritis of an unknown type) (Wilkie et al., 2014a; Loeser et al., 2012)	No OA (0), has OA (1)

Mental health problem(s)	Having a mental health problem was defined as scoring 3 or higher on the CESD-8 (Center for Epidemiologic Studies Depression) depression scale (comprising eight yes/no questions about depressive symptoms) and/or reporting having an emotional, nervous or psychiatric problem during the last two years (Kozlov et al., 2020; Moon et al., 2017; White et al., 2016; NCCMH, 2011)	No mental health problem (0), has mental health problem (1)
Obesity	Obesity was defined as BMI$\geq$30 as measured in nurse visits (waves 2, 4 and 6 only) (NICE, 2014)	Not obese (0), obese (1)
Pain interference	Individuals were classified as having pain interference if they reported often being troubled with pain ("Are you often troubled with pain?" yes/no) (Smith et al., 2018)	No pain (0), has pain (1)
Physical inactivity	Individuals were considered to be physically active if they reported exercising at moderate or vigorous intensity at least twice per week (Poole and Jackowska, 2018; González et al., 2017)	Physically active (0), physically inactive (1)
No control at work	Self-report of 'agree' or 'strongly agree' to a statement relating to paid employment in the last month "At work, I feel I have control over what happens in most situations" in the self completion questionnaire (wave 2 onwards) (Carr et al., 2016; Häusser et al., 2010)	Has control (0), no control (1)
No support at work	Self-report of 'agree' or 'strongly agree' to a statement relating to paid employment in the last month "I receive adequate support in difficult situations" in the self completion questionnaire (wave 2 onwards) (Baidwan et al., 2019; Häusser et al., 2010)	Has support (0), no support (1)

As in the previous chapter (chapter 4), it was assumed that OA would continue to be present (to some extent) following self-reported doctor diagnosis (Wilkie et al., 2014a, p. 2); self-reported OA (self report of having ever been told by a doctor that the respondent has OA) was carried forward to all subsequent waves before self-reported no-OA statuses were carried backwards into earlier time waves with missing values. Arthritis of an unknown type was assumed to be osteoarthritis as this is the most common form of arthritis (Loeser et al., 2012).

A single indicator of mental health problems of any type was used. Mental health problems were identified from depression symptoms (measured on the CESD-8 scale) and/or self-report of ever receiving a doctor diagnosis of emotional, nervous or psychiatric problems (including anxiety) unless the respondent reported having no emotional, nervous or psychiatric problems within the last two years. Generalised anxiety disorder is one of the most common mental health problems (NCCMH, 2011) but no instrument was included in the ELSA survey to detect symptoms of anxiety, and the survey questionnaires did not contain sufficient detail to identify whether the emotional, nervous or psychiatric problems recently experienced were the same as (or different to, or a selection of) the emotional, nervous or psychiatric problems for which a doctor diagnosis has been received at some point in the past. The combination of CESD-8 and self-reported doctor diagnosis variables was considered to reflect any mental health problem and was selected as a single indicator of mental health, which was preferred over a depressive symptoms indicator as other mental health problems may also affect health and work participation.

5.2.4 Analysis plan

Transition intensities between the three states in the 3-state HWLE model were modelled using R package 'msm' and multiply imputed ELSA data (due to missingness in covariates and HWLE status for some idividuals at some time points) to estimate baseline hazards (transition intensities between the states at age 50) and HRRs associated with each increasing year of age. HRRs with 95% confidence intervals associated with each factor of interest individually were estimated in 'msm'. HRRs were also estimated in 'msm' for a small number of more complex models with more than one factor included as covariates. Age was included as an explanatory variable in all models.

For each of the models estimated in 'msm', the hazard and HRR results were then used with the prevalence of state occupation at each individual's first data time point in the

ELSA data to estimate health expectancies with 95% confidence intervals in ‘elect’. These health expectancies were calculated for each possible combination of the binary covariate(s) that were included in the corresponding ‘msm’ model in addition to age. For example, a model was specified in ‘msm’ of transition intensities on age and OA. Baseline hazards and HRRs were estimated using ‘msm’. Then, using the prevalence of state occupation (healthy and working [state 1] or unhealthy and/or not working [2]) according to OA status observed in the data (using each individual’s first observation only), health expectancies including HWLE were estimated in ‘elect’ for each covariate combination (here, OA or no OA) based on the covariate(s) (here, OA status) remaining constant from age 50 to the end of life (maximum age 120 years). All ‘msm’ and ‘elect’ analyses were performed on each imputed dataset before HRR and health expectancy results were pooled.

Transition hazard rate ratios associated with osteoarthritis and health, socio-demographic and workplace factors

Whether osteoarthritis and health, socio-demographic and workplace factors reduce HWLE was considered by investigating the association between these factors and higher or lower rates of healthy and working people becoming unhealthy and/or stopping working (transitions from healthy and working [state 1] to unhealthy and/or not working [state 2]). Health and work transition rates and associations with osteoarthritis as well as the other health, socio-demographic and workplace factors were estimated for each factor modelled individually with age as a single additional covariate. Ageing is strongly linked to onset and severity of health conditions and multimorbidity, and osteoarthritis is an age-related disease (Fabbri et al., 2015; Shane Anderson and Loeser, 2010). Work participation behaviour (for example retirement) also depends on age. Age was adjusted for in all models in order to estimate real associations between the health, socio-demographic, and workplace factors and transitions between the health and work states - rather than some or all of these variables serving to an extent as proxy measures of age. Age-adjusted models were also necessary for subsequent estimation of health expectancies and life expectancy (as in IMaCh models presented in chapters 2 and 4); R ‘elect’ software was written for the purpose of estimating stay-times in states from ‘msm’-fitted models that include age as a covariate precisely because transition hazards that do not change with age are unsuitable for life expectancy or health expectancy estimation. Age-adjusted hazard rate ratios of transitions between HWLE states were estimated for variables:

- sex
- OA
- mental health
- obesity
- pain interference
- physical inactivity
- control at work
- support at work

Work factors were only applicable for people who were in work. When modelling work factors, control and support at work variables were therefore only included as covariates for transitions out of the healthy and working state (transitions 1-2 and 1-3).

A small number of more complex models with more than one additional covariate (in addition to age) were specified based on adding additional health, socio-demographic and workplace variables to the age-adjusted OA model. Variables with established important causal links with OA were not included in this as there was limited scope to adjust for confounding variables and other relevant risk factors because of the time taken to run each model (minutes for some models and hours or days for others, multiplied by 20 for analysis of each imputed dataset and increasing for more complex models), non-convergence of some models on some imputed datasets (and failure of complex models on all imputed datasets), and because 'elect' software is intended for use with covariates that do not change over time. Instead, models were specified to estimate associations rather than to identify variables that explained these links. Models were specified with explanatory variables age and OA as well as additional covariates mental health, work factors (control at work, support at work) and sex individually (table 5.2).

TABLE 5.2: Covariate combinations to be modelled

Variable 1	+ Variable 2	+ Variable 3
- *(age only)*		
Sex		
Osteoarthritis		
Mental health		
Obesity		
Pain interference		
Physical inactivity		
Control at work		
Support at work		
Osteoarthritis	Sex	
Osteoarthritis	Mental health	
Osteoarthritis	Control at work	
Osteoarthritis	Support at work	
Osteoarthritis	Sex	Control at work
Osteoarthritis	Sex	Support at work

No model was specified with OA, sex and mental health as a covariate combination as some infrequently observed transitions provided insufficient data, particularly for the transition from healthy and working to dead (1-3) among adults with OA and mental health problems.

Estimating the effect on HWLE of hazard rate ratios associated with osteoarthritis and health, socio-demographic and workplace factors

Using the HRRs associated with each variable of interest, which indicate whether people with or without each factor are at a higher or lower risk of transition into different states (in particular, the transition 1-2 from healthy and working [state 1] to unhealthy and/or not working [state 2]), HWLE was estimated for each modelled covariate combination to demonstrate the overall effect (there are four transitions with HRRs estimated for each) on length of healthy working life.

5.2.5 Sensitivity analyses

Sensitivity of results to use of the simplified 3-state HWLE model

To assess whether the 3-state HWLE model was an appropriate simplification of the original 5-state model, the sensitivity of health expectancy results to the number of states in the model was investigated. This was done by computing health expectancies using hazard rate ratios modelled on age and no other covariates using a 5-state model as well as the 3-state model.

Sensitivity of results to the operationalisation of health using limiting long-standing illness

To assess the robustness of hazard rate ratio and health expectancy estimates with respect to operationalisation of health, HWLE was estimated from hazards of transitions (modelled on age and no other covariates) using health determined by no limitations with activities of daily living (ADLs) and separately using health determined by self-assessed health (SAH) to estimate HWLE (see page 99 for definitions of the ADL-based and SAH health measures).

5.2.6 Missing data

For some individuals in the study sample, values of covariate(s) or health or work status were missing at some ELSA wave time points. It was necessary to impute missing data in order to analyse all observed transitions. Missing data was handled using multiple imputation by predictive mean matching (PMM), which imputes missing observations by sampling values from similar cases (‘neighbours’) (De Silva et al., 2019; Morris et al., 2014). In this approach, missing observations are imputed for each variable in turn using each other variable and this process is repeated to achieve convergence; the final iteration produces an imputed dataset. In order for analyses to reflect the uncertainty due to missing data, twenty imputed datasets were generated (White et al., 2011; Graham et al., 2007). The results of analysing all imputed datasets were pooled to produce the final results.

Health status or work status (which were later combined to determine HWLE status) were treated as two variables for multiple imputation. OA missingness was examined after OA had been defined as per the description on page 239 (that is, carrying data forward and backwards as applicable based on the assumption that OA could be developed but not lost throughout the study period). The percentage of complete observations of variables to be modellled was 79.48% (tables 5.3 and 5.4). Most cases of missingness affected BMI (6251 missing observations, 14.65%) and work factor measurements (support at work and control at work combined had 2571 missing observations, 6.03%); BMI was not measured in waves 2 and 4, and work factors were measured in self-completion questionnaires with lower response rates than the main interviews. Unmeasured work factors for individuals who were not in work at a given time point were not treated as missing.

TABLE 5.3: Patterns of missingness in modelling variables (ELSA)

Combinations of variables with missing data	Number of variables with missingness	Count (missing observations)	Percentage of observations missing
(complete)	0	33904	79.48%
BMI	1	5498	12.89%
control at work and support at work	2	1927	4.52%
BMI, control at work and support at work	3	465	1.09%
depression	1	318	0.75%
depression and BMI	2	198	0.46%
support at work	1	80	0.19%
psychiatric problem	1	50	0.12%
pain interference	1	25	0.06%
depression, control at work and support at work	3	24	0.06%
depression, BMI, control at work and support at work	4	24	0.06%
health status	1	20	0.05%
OA	1	18	0.04%
BMI and support at work	2	15	0.04%
control at work	1	14	0.03%
psychiatric problem and BMI	2	13	0.03%
33 other combinations (observed < 10 times)	varies (range 1-9)	64	0.15%

Notes:
Missingness is shown for all combinations (observed at least 10 times) of model variables

There are three key missing data scenarios (Morris et al., 2014):

1. Missing completely at random (MCAR): All observations have the same probability of being missing (missingness does not depend on measured or unmeasured data)

2. Missing at random (MAR): The probability of being missing is the same for all observations in groups defined by measured variables (missingness is random conditional on measured data)

3. Missing not at random (MNAR): Missingness in observations is not random and the probability of being missing depends on unmeasured data

The MAR assumption is that data are considered to be missing at random based on all variables that affect missingness being included in the imputation model. The MAR assumption was plausible for the study sample with the inclusion of key variables reported in the ELSA technical reports as associated with response and non-response (Banks et al., 2014; Banks et al., 2012; Banks et al., 2010; Scholes et al., 2008; Taylor et al., 2007; Scholes et al., 2006):

- sex
- number of people living in household
- health status
- occupation type
- cohort number (baseline sample or refreshment sample)
- response at previous interview(s)
- white or non-white ethnicity
- whether owns own home
- smoking status
- education level

- exercise (physical inactivity)

Variables that were additional to those for modelling were added into the imputation model as auxilliary variables. The three work factors not selected for modelling (pressure at work, security at work, and recognition at work) were also included as auxilliary variables. An urban/rural variable was also identified in ELSA technical reports as associated with response however this is not available in the main ELSA datasets.

TABLE 5.4: Number and percentage of missing observations in ELSA variables for modelling across waves 2-6 (missingness in auxilliary variables shown in italics)

Variable	Count (missing observations)	Percentage of observations missing
BMI	6251	14.65
securityatwork	2588	6.07
supportatwork	2554	5.99
pressureatwork	2518	5.90
controlatwork	2475	5.80
recognitionatwork	2461	5.77
socialclass	709	1.66
depression	592	1.39
ahown	194	0.45
raeducl	105	0.25
psychiatricproblem	74	0.17
pain interference	48	0.11
OA	32	0.08
health	31	0.07
physical inactivity	18	0.04
work	10	0.02
smoker	9	0.02
mstat	6	0.01
sex	0	0.00
ethnicitywhite	0	0.00
hhres	0	0.00

Missing data imputation was performed separately using alternative SAH and ADL-based health indicators in order to carry out the sensitivity analyses of hazard rate and HWLE results to the operationalisation of health (section 5.2.5).

5.2.7 Implementation in R

Missing data were imputed using a wide dataset with wave-specific variables for measured variable (health, work, OA status etc.) at wave 2, 3, 4, 5 and 6 (for example health, denoted health_2, health_3, health_4, health_5, and health_6). The imputation model included variables to construct the outcome (HWLE status, derived from health and work statuses), variables to be analysed as predictor variables for HWLE transitins, and auxilliary variables identified in ELSA technical reports as predictive of non-response (table 5.5). All variables were binary except for BMI category (underweight: BMI less than 18.5, normal weight: BMI 18.5-24.9, overweight: BMI 25.0-29.9, obese: BMI 30 or higher), cohort (four categories), education category (less than secondary education, upper secondary and vocational training, tertiary education, other), occupation category (non-manual occupation, manual occupation, self-employed), smoking status (never smoker, current smoker, ex-smoker), marital status (eight categories), and number of residents in household (numeric ranging from 1-11). For the purpose of imputation, work factors (including those that were auxilliary variables) were assigned value 1 (no control at work, no support at work, etc.) at time points where individuals were not in work.

BMI was only measured at every second wave (waves 2, 4 and 6). In order to avoid completely missing variables, BMI category at waves 3 and 5 were carried forward from waves 2 and 4 respectively where possible and remaining missing values were carried backwards from waves 4 and 6 respectively. Because BMI at waves 3 (BMI_3) and 5 (BMI_5) consisted of values primarily from waves 2 (BMI_2) and 4 (BMI_4) respectively, BMI_2 and BMI_4 were not used to predict other variables in the imputation model. The decision to use BMI_3 and BMI_5 for prediction instead of BMI_2 and BMI_4 was taken as this avoided collinearity issues. Cohort number was not used to predict BMI_2 as participants who joined ELSA in refreshment cohorts were not yet in the sample at wave 2.

The inital approach was multiple imputation by chained equations in Stata (used initially for data management) using standard fully conditional specification with a series of univariate imputation models. However, this was not feasible due to multicollinearity and several counts of perfect prediction. Non-convergence persisted in tests that dropped problematic terms from models, excluded auxilliary variables, modified the specified univariate models, and used the Stata 'force' and 'augment' options to avoid missing imputed values and perfect prediction. Non-convergence and other problems in imputation of longitudinal panel data with many variables (especially categorical variables) is well-documented (e.g. De Silva et al. (2019), White et al. (2011)). Multiple imputation was therefore carried out using predictive mean matching (PMM) (De Silva et al., 2019). This was not possible in Stata due to the large number of variables and was instead carried out in R using type 1 matching, which finds nearest neighbours based on the distance between the predicted value of the observation and drawn values (Morris et al., 2014). Missing values were imputed with an observation randomly selected from the ten nearest neighbours (Morris et al., 2014). Twenty iterations of imputations were generated for each of the twenty imputed datasets. Trace plots were visually inspected for convergence, indicated by no clear trends in the later iterations (Buuren and Groothuis-Oudshoorn, 2010). The twenty imputed datasets were cleaned to correct impossible imputed values for variables with restrictions; if a person (who had an OA status later in the study) was imputed to have OA before a time point where they were imputed not to have OA, the earlier imputed OA value was carried forward. All observations at time points that had no interview (or had a proxy interview) were then removed. Composite variables for HWLE status and mental health were constructed, and BMI category was used to generate a binary variable for obesity.

Models fitted in 'msm' included age as a variable in order to estimate age-adjusted hazard rate ratios and facilitate health expectancy analyses in 'elect'. The model of HWLE status on age and OA was specified as follows:

```
for(i in 1:length(electdat)){
  OA_age[[i]]<-msm(state~age,subject=id,data=electdat[[i]],
                     center=FALSE,qmatrix=Qcrude[[i]],deathexact=3,
                     control=list(fnscale=60000,maxit=500000,reltol = 1e-16),
                     covariates=~age+OA)
}
```

Fitting the models was computationally intensive and time consuming, but use of the

TABLE 5.5: Variables in the imputation model for ELSA data waves 2-6. There were five variables for each item listed (for observations at waves 2, 3, 4, 5 and 6) except items in bold, which were constant for the study period.

Outcome	Variables used in models	Auxilliary variables for imputation
health status*	**sex**	**cohort**
work status*	OA	**education category**
	depression***	**ethnicity white**
	psychiatric problem***	marital status
	BMI category**	number of residents in household
	pain interference	**occupation category**
	physical inactivity	pressure at work
	control at work	recognition at work
	support at work	security at work
		smoking
		whether owns home
		response at each wave

Notes:
Observations at each of the five waves were contained in five variables for each item listed (e.g. health_2, health_3, health_4, health_5, and health_6 give health status at waves 2, 3, 4, 5, and 6 respectively) except for bold items which were not wave-specific
*These items were used to construct a variable for HWLE status
**This item was used to construct a variable for obesity
**These items were used to construct a variable for mental health

3-state model reduced the time to run one model on all 20 datasets from approximately three weeks to several days when running in parallel. It was not possible to run analysis of a given model in parallel when convergence failed on any imputed dataset and analysis of affected models took longer to complete.

After model fits from 'msm' were obtained, 'elect' was used to estimate health expectancies for each covariate combination using age on a shifted scale (0 indicates 50), assuming a maximum alive age of 120 (70 years from age 50) and simulating 500 individual trajectories to estimate confidence intervals.

```
for(i in 1:length(OA_age3)){
  LEs_OA1_age3[[i]]    <- elect(x = OA_age3[[i]],
                                        b.covariates = list(age=0,OA = 1),
                                        statedistdata = sddata_OA_age3[[i]],
                                        h = 0.5, age.max = 70, S = 500)
  LEs_OA0_age3[[i]]    <- elect(x = OA_age3[[i]],
```

```
                                              b.covariates = list(age=0,OA = 0),
                                              statedistdata = sddata_OA_age3[[i]],
                                              h = 0.5, age.max = 70, S = 500)
}
```

Following analysis in each of the R packages, 'msm' hazard rate ratio results and 'elect' health expectancy results from analysing each imputed dataset were pooled using Rubin's Rules (Marshall et al., 2009). As there is no linked functionality between the 'mice' R package for imputation and the 'msm' or 'elect' packages, a function was written to pool HRRs for each year of age from 50 to 75 from each imputed dataset analysed with 'msm' and pool health expectancy results from each imputed dataset analysed with 'msm' then 'elect' (for each covariate combination at age 50). The functions implemented 'mice' (Buuren and Groothuis-Oudshoorn, 2011) source code functions `barnard.rubin` and `pool.scalar` for pooling univariate parameters. In the cases where 'msm' convergence failed, results were pooled from the successfully estimated models.

5.2.8 Data management

In preparation for analysis using the 'msm' and 'elect' R packages, the imputed datasets were converted to a long format containing only the data (observed or imputed) associated with a successful interview. A variable for age on a shifted scale (measured as time from age 50) was constructed for each observation. A baseline variable was constructed to indicate the first observation for each individual in the dataset. These twenty imputed datasets were saved for use in the sensitivity analysis with the 5-state HWLE model. The HWLE states were then collapsed into three states: healthy and working (state 1); other alive (state 2, comprised of people who were unhealthy or not in work or both); and dead (state 3). These twenty imputed datasets were used for the main analysis.

5.3 Results

5.3.1 Sample size

The starting sample was originally prepared for the study described in chapter 2. There were 16,050 adults in the initial sample who had participated in any of waves 1-6 (including participants with missing data - see page 2.5.2). As this study only used data from waves 2-6, 1,968 individuals who had only responded at wave 1 were excluded. Data collected from participants who were aged less than 50 at time of response (for example due to being a younger partner prior to joining the core sample) were excluded as the age scale started at age 50. Data provided by a proxy interview were used in imputation and then these observations were removed. Participants without multiple observations (either at least two interviews or at least one interview as well as recorded date of death) were then excluded. The final sample size was 11,540 adults (5,251 males and 6,289 females) (figure 5.4). Table 5.6 shows the 32,791 transitions observed in one of the imputed datasets in the whole study population and according to covariate values at the start of each transition; a small number of starting/destination states may vary (due to missing health/work responses) across imputed datasets as well as some covariate values (those that were missing in the ELSA survey data).

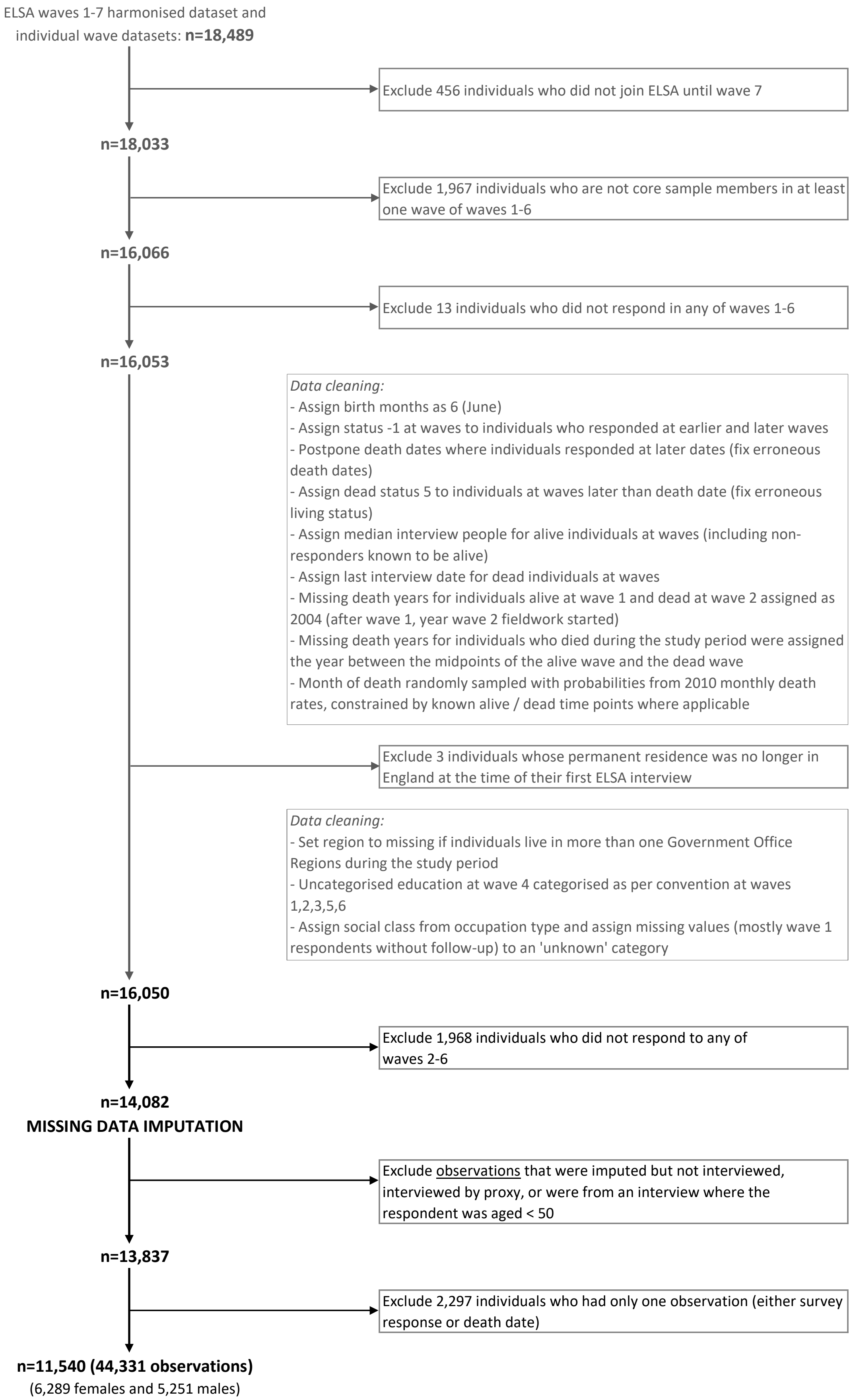

FIGURE 5.4: ELSA sample size for analysis in R 'msm' and 'elect' packages (lighter text shows data preparation for the previous study - see page 103)

TABLE 5.6: Contingency table of HWLE status transitions observed in one imputed dataset for R multi-state analysis of HRRs according to covariate values at the start of the transition

Model	Starting state	Destination state 1	2	3	Total
(Whole study sample)	1	6758	2423	77	9258
	2	964	20972	1597	23533
Sex					
Female	1	3198	1218	24	4440
	2	475	12410	784	13669
Male	1	3560	1205	53	4818
	2	489	8562	813	9864
OA					
Has OA	1	857	477	11	1345
	2	224	7703	574	8501
No OA	1	5901	1946	66	7913
	2	740	13269	1023	15032
Mental health					
Has mental health problem	1	868	407	5	1280
	2	214	5910	662	6786
No mental health problem	1	5890	2016	72	7978
	2	750	15062	935	16747
Obesity					
Obese	1	1876	731	29	2636
	2	340	6719	450	7509
Not obese	1	4882	1692	48	6622
	2	624	14253	1147	16024
Pain interference					
Has pain	1	657	389	9	1055
	2	255	7135	606	7996
No pain	1	6101	2034	68	8203
	2	709	13837	991	15537
Physical inactivity					
Physically inactive	1	1359	557	20	1936
	2	234	8396	1122	9752
Physically active	1	5399	1866	57	7322
	2	730	12576	475	13781
Control at work					
No control at work	1	1264	478	15	1757
	2	507	20012	1568	22087
Has control at work	1	5494	1945	62	7501
	2	457	960	29	1446
Support at work					
No support at work	1	1562	616	17	2195
	2	524	20095	1568	22187
Has support at work	1	5196	1807	60	7063
	2	440	877	29	1346
OA + Sex					
Has OA + Female	1	489	289	4	782
	2	126	5252	350	5728
Has OA + Male	1	368	188	7	563
	2	98	2451	224	2773
No OA + Female	1	2709	929	20	3658

* Continued on next page*

Table 5.6 – continued from previous page

Model	Starting state	Destination state 1	2	3	Total
	2	349	7158	434	7941
No OA + Male	1	3192	1017	46	4255
	2	391	6111	589	7091
OA + Mental health					
Has OA + Has mental health problem	1	134	92	0	226
	2	58	2749	281	3088
Has OA + No mental health problem	1	723	385	11	1119
	2	166	4954	293	5413
No OA + Has mental health problem	1	734	315	5	1054
	2	156	3161	381	3698
No OA + No mental health problem	1	5167	1631	61	6859
	2	584	10108	642	11334
OA + Control at work					
Has OA + No control at work	1	170	98	2	270
	2	85	7335	566	7986
Has OA + Has control at work	1	687	379	9	1075
	2	139	368	8	515
No OA + No control at work	1	1094	380	13	1487
	2	422	12677	1002	14101
No OA + Has control at work	1	4807	1566	53	6426
	2	318	592	21	931
OA + Support at work					
Has OA + No support at work	1	201	107	3	311
	2	93	7341	566	8000
Has OA + Has support at work	1	656	370	8	1034
	2	131	362	8	501
No OA + No support at work	1	1361	509	14	1884
	2	431	12754	1002	14187
No OA + Has support at work	1	4540	1437	52	6029
	2	309	515	21	845
OA + Sex + Control at work					
Has OA + Female + No control at work	1	111	57	1	169
	2	44	5025	349	5418
Has OA + Female + Has control at work	1	378	232	3	613
	2	82	227	1	310
Has OA + Male + No control at work	1	59	41	1	101
	2	41	2310	217	2568
Has OA + Male + Has control at work	1	309	147	6	462
	2	57	141	7	205
No OA + Female + No control at work	1	528	188	2	718
	2	204	6887	426	7517
No OA + Female + Has control at work	1	2181	741	18	2940
	2	145	271	8	424
No OA + Male + No control at work	1	566	192	11	769
	2	218	5790	576	6584
No OA + Male + Has control at work	1	2626	825	35	3486
	2	173	321	13	507
OA + Sex + Support at work					
Has OA + Female + No support at work	1	132	67	2	201
	2	44	5022	349	5415
Has OA + Female + Has support at work	1	357	222	2	581

Continued on next page

* Table 5.6 – continued from previous page *					
Model	Starting state	Destination state 1	2	3	Total
	2	82	230	1	313
Has OA + Male + No support at work	1	69	40	1	110
	2	49	2319	217	2585
Has OA + Male + Has support at work	1	299	148	6	453
	2	49	132	7	188
No OA + Female + No support at work	1	543	201	3	747
	2	212	6906	426	7544
No OA + Female + Has support at work	1	2166	728	17	2911
	2	137	252	8	397
No OA + Male + No support at work	1	818	308	11	1137
	2	219	5848	576	6643
No OA + Male + Has support at work	1	2374	709	35	3118
	2	172	263	13	448

Notes:
States: Healthy and in work (HWLE) [1]; Not healthy and/or not in work (including: healthy and not in work, not healthy and in work, not healthy and not in work)[2]; Dead [3]
Transitions:
1-2 From healthy and working to unhealthy and/or not working
1-3 From healthy and working to dead
2-1 From unhealthy and/or not working to healthy and working
2-3 From unhealthy and/or not working to dead

5.3.2 Associations between OA and health, socio-demographic and lifestyle factors and transitioning out of health and work

The hazard rate ratio (HRR) of healthy and working adults aged 50 years and over becoming unhealthy and/or stopping working was estimated as 1.07 (95% CI [1.06,1.08]) for each year of age when no additional covariates were included in the multi-state model (table 5.7). That is, with each additional year of age, the transition intensity from healthy and working (state 1) to unhealthy and/or not working (state 2) increased by an estimated 7% compared to the age one year younger. As age increased, the risk of dying was also found to increase from the unhealthy and/or not working state 2 (HRR 1.10 [1.10,1.11]) but the estimated hazard rate ratio of 1.06 (0.98,1.15) for increased risk of dying with one additional year of age from being healthy and in work was not found to be statistically significant. With each additional year of age, unhealthy and/or not working adults became less likely to become both healthy and working for pay. Table 5.7 gives age-adjusted HRRs for each biopsychosocial factor included in the HWLE multi-state models.

Compared to men, women had a significantly increased risk of leaving the healthy and working state not due to death (transition out of state 1 into state 2) (HRR 1.18 [1.09,1.29]). Women were also significantly less likely to rejoin the healthy and working state at any age (transition 2-1, HRR 0.64 [0.56,0.73]). Significantly reduced risks of death were found for women from either alive state (transitions 1-3 (0.12 [0.02,0.90]) and 2-3 (0.67 [0.61,0.74])).

The risk of leaving the healthy and working state and becoming not healthy and/or not in work (transition 1-2) was significantly higher among people with OA compared to those without; healthy and working people with OA had a 1.32 (1.19,1.46) times higher risk of becoming unhealthy and/or stopping working compared to healthy and working people without OA of the same age. There was no evidence of an increased risk of death from the healthy and working state for people with OA and the wide confidence interval suggests that the data may contain an insufficient number of observations of this transition (1-3) by OA status to accurately estimate the HRR. Once in the not healthy and/or not working state (state 2), having OA was associated with significantly lower transition rates out of this state (either to join the healthy and working state (1) or the death state (3)). Having OA continued to be associated with increased risk of leaving the healthy and working state and becoming not healthy and/or not in work (transition 1-2) after adjusting for mental health problems, sex, control at work and support at work individually and after adjusting for sex and control at work as well as sex and support at work. Adjusting for sex slightly lowered the HRR point estimate for OA to 1.28 (1.16,1.42), suggesting a possibility that female sex explained some of the association observed between OA and the increased risk of leaving the healthy and working state and becoming not healthy and/or not in work (transition 1-2).

At any age, healthy working people often troubled with pain were found to be at 1.5 times higher risk of becoming unhealthy and/or stop working (HRR 1.50 [1.34,1.68]). Unhealthy and/or not working people (people in state 2) with pain interference had reduced chances compared to those without pain interference of becoming healthy and working (transition 2-1, HRR 0.57 [0.49,0.66]) and had a 25% higher risk of death (HRR 1.25 [1.13,1.39]). There was no significant effect of pain interference on the transition intensity from healthy and working state 1 into the death state (transition 1-3).

Having a mental health problem was associated with increased risk of leaving the healthy and working state not due to death (transition 1-2 HRR 1.36 [1.22,1.52]) and death from being not healthy and/or not in work (transition 2-3 HRR 1.63 [1.47,1.81]). No significant effect was detected for risk of death while in the healthy and working state but a very wide 95% confidence interval may indicate insufficient data for estimating HRRs reliably for this transition. Compared to people without a mental health problem of the same age, people with mental health problem(s) had a significantly reduced risk of rejoining the healthy and working state (transition 2-1 HRR 0.51 [0.43,0.59]).

Being obese was associated with a 12% increased risk of becoming not healthy and/or not in work among healthy and working people (transition 1-2) (HRR 1.12 [1.02,1.23]). No significant HRR was observed for the association between obesity and the transition intensity from unhealthy and/or not working to healthy and working (transition 2-1) or transition intensities to death from either alive state (transition 1-3 from healthy and working to dead; transition 2-3 from unhealthy and/or not working to dead).

Physically inactive healthy and working adults were found to have a 1.12 times higher risk of become unhealthy and/or stopping working than healthy working adults of the same age who exercised with at least moderate intensity (for example going for a walk) at least twice per week (HRR 1.12 [1.02,1.24]). No significant effect of physical inactivity was detected on the transition intensity for dying after being healthy and working (transition 1-3) but unhealthy and/or not working adults who were physically inactive had over twice the risk of dying compared to physically active adults of the same age who were also unhealthy and/or not working (transition 2-3 HRR 2.27 [2.03,2.53]).

Healthy and working people who perceived little control over what happens in situations at work had a 43% increased risk of becoming unhealthy and/or exiting paid work (HRR 1.43 [1.27,1.61]). Similarly, people who reported not having adequate support at work in difficult situations had a 38% higher risk of ceasing to be healthy and in work not due to death (transition 1-2 HRR 1.38 [1.24,1.53]). Not having control at work or support at work continued to be associated with increased risk of becoming unhealthy and/or stopping working after adjusting for OA and sex.

Convergence of the 'msm' model parameters failed on one or more of the 20 imputed datasets for models: age + sex (failed on four datasets); age + OA (failed on two datasets); age + pain interference (failed on one dataset); age + physical inactivity (failed on two datasets); age + OA + sex + control at work (failed on one dataset); age + OA + sex + support at work (failed on two datasets). Different imputed values for small numbers of individual missing data cases affected convergence success (implying an insufficient sample size for estimating more complex models).

TABLE 5.7: Hazard rate ratios for each year of age and binary covariates from models estimated with combinations of covariates for transitions: from healthy and working (HW) to unhealthy and/or not working (nHW); from healthy and working to dead; from unhealthy and/or not working to healthy and working; from unhealthy and/or not working to dead

Model covariates	Transition*	Age (95% CI)	Variable 1 (95% CI)	Variable 2 (95% CI)	Variable 3 (95% CI)
(Age only)		*age*			
	HW-nHW	1.07 (1.06,1.08)			
	HW-dead	1.06 (0.98,1.15)			
	nHW-HW	0.86 (0.85,0.87)			
	nHW-dead	1.10 (1.10,1.11)			
Sex		*age*	*sex female*		
	HW-nHW	1.07 (1.07,1.08)	1.18 (1.09,1.29)		
	HW-dead	1.02 (0.93,1.11)	0.12 (0.02,0.90)		
	nHW-HW	0.86 (0.85,0.87)	0.64 (0.56,0.73)		
	nHW-dead	1.10 (1.10,1.11)	0.67 (0.61,0.74)		
OA		*age*	*has OA*		
	HW-nHW	1.07 (1.06,1.08)	1.32 (1.19,1.46)		
	HW-dead	1.08 (1,1.17)	0.19 (0.00,21.77)		
	nHW-HW	0.86 (0.85,0.87)	0.66 (0.57,0.77)		
	nHW-dead	1.10 (1.10,1.11)	0.89 (0.8,0.98)		
Mental health		*age*	*has mental health problem*		
	HW-nHW	1.07 (1.06,1.08)	1.36 (1.22,1.52)		
	HW-dead	1.06 (0.99,1.14)	0.01 (0,>1000)		
	nHW-HW	0.85 (0.84,0.86)	0.51 (0.43,0.59)		
	nHW-dead	1.10 (1.09,1.11)	1.63 (1.47,1.81)		
Obesity		*age*	*obese*		
	HW-nHW	1.07 (1.06,1.08)	1.12 (1.02,1.23)		
	HW-dead	1.06 (0.97,1.15)	1.59 (0.48,5.27)		
	nHW-HW	0.86 (0.85,0.87)	0.91 (0.79,1.04)		
	nHW-dead	1.10 (1.10,1.11)	1.00 (0.89,1.13)		
Pain interference		*age*	*has pain*		
	HW-nHW	1.07 (1.06,1.08)	1.50 (1.34,1.68)		

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Table 5.7 – continued from previous page

Model covariates	Transition*	Age (95% CI)	Variable 1 (95% CI)	Variable 2 (95% CI)	Variable 3 (95% CI)
	HW-dead	1.07 (0.98,1.16)	1.60 (0.50,5.13)		
	nHW-HW	0.85 (0.84,0.86)	0.57 (0.49,0.66)		
	nHW-dead	1.10 (1.10,1.11)	1.25 (1.13,1.39)		
Physical inactivity		*age*	*physically inactive*		
	HW-nHW	1.07 (1.06,1.08)	1.12 (1.02,1.24)		
	HW-dead	1.07 (0.99,1.15)	0.73 (0.21,2.58)		
	nHW-HW	0.86 (0.85,0.87)	0.55 (0.47,0.64)		
	nHW-dead	1.09 (1.08,1.10)	2.27 (2.03,2.53)		
Control at work		*age*	*no control*		
	HW-nHW	1.07 (1.07,1.08)	1.43 (1.27,1.61)		
	HW-dead	1.06 (0.98,1.15)	1.75 (0.38,8.02)		
	nHW-HW	0.86 (0.85,0.87)	1.00 (fixed)		
	nHW-dead	1.10 (1.10,1.11)	1.00 (fixed)		
Support at work		*age*	*no support*		
	HW-nHW	1.07 (1.07,1.08)	1.38 (1.24,1.53)		
	HW-dead	1.06 (0.98,1.15)	1.81 (0.47,6.97)		
	nHW-HW	0.86 (0.85,0.87)	1.00 (fixed)		
	nHW-dead	1.10 (1.10,1.11)	1.00 (fixed)		
OA + sex		*age*	*has OA*	*sex female*	
	HW-nHW	1.07 (1.06,1.08)	1.28 (1.16,1.42)	1.16 (1.07,1.26)	
	HW-dead	1.02 (0.93,1.13)	0.70 (0.1,4.88)	0.14 (0.02,0.97)	
	nHW-HW	0.86 (0.85,0.87)	0.70 (0.60,0.81)	0.67 (0.58,0.76)	
	nHW-dead	1.10 (1.10,1.11)	0.93 (0.84,1.03)	0.68 (0.61,0.75)	
OA + mental health		*age*	*has OA*	*has mental health problem*	
	HW-nHW	1.07 (1.06,1.08)	1.30 (1.17,1.44)	1.35 (1.21,1.51)	
	HW-dead	1.07 (1.00,1.15)	0.56 (0.10,3.16)	0.01 (0,>1000)	
	nHW-HW	0.85 (0.84,0.86)	0.71 (0.61,0.83)	0.53 (0.45,0.62)	
	nHW-dead	1.10 (1.10,1.11)	0.82 (0.74,0.91)	1.68 (1.51,1.86)	
OA + control at work		*age*	*has OA*	*no control*	
	HW-nHW	1.07 (1.06,1.08)	1.32 (1.19,1.47)	1.44 (1.28,1.62)	

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Table 5.7 – continued from previous page

Model covariates	Transition*	Age (95% CI)	Variable 1 (95% CI)	Variable 2 (95% CI)	Variable 3 (95% CI)
	HW-dead	1.08 (1.00,1.17)	0.22 (0.00,19.59)	1.59 (0.33,7.70)	
	nHW-HW	0.86 (0.85,0.87)	0.67 (0.57,0.78)	1.00 (fixed)	
	nHW-dead	1.10 (1.10,1.11)	0.89 (0.80,0.98)	1.00 (fixed)	
OA + support at work		*age*	*has OA*	*no support*	
	HW-nHW	1.07 (1.06,1.08)	1.33 (1.2,1.47)	1.39 (1.25,1.54)	
	HW-dead	1.08 (1.00,1.17)	0.22 (0.00,18.58)	1.61 (0.42,6.16)	
	nHW-HW	0.86 (0.85,0.87)	0.67 (0.57,0.78)	1.00 (fixed)	
	nHW-dead	1.10 (1.10,1.11)	0.89 (0.80,0.98)	1.00 (fixed)	
OA + sex + control at work		*age*	*has OA*	*sex female*	*no control*
	HW-nHW	1.07 (1.06,1.08)	1.29 (1.16,1.43)	1.16 (1.06,1.26)	1.43 (1.27,1.61)
	HW-dead	1.03 (0.94,1.13)	0.77 (0.12,4.80)	0.13 (0.02,0.96)	1.98 (0.40,9.94)
	nHW-HW	0.86 (0.85,0.87)	0.70 (0.60,0.82)	0.67 (0.59,0.76)	1.00 (fixed)
	nHW-dead	1.10 (1.10,1.11)	0.93 (0.84,1.03)	0.68 (0.62,0.75)	1.00 (fixed)
OA + sex + support at work		*age*	*has OA*	*sex female*	*no support*
	HW-nHW	1.07 (1.06,1.08)	1.29 (1.16,1.43)	1.18 (1.08,1.28)	1.40 (1.26,1.56)
	HW-dead	1.03 (0.93,1.13)	0.75 (0.11,5.01)	0.14 (0.02,0.98)	1.58 (0.48,5.26)
	nHW-HW	0.86 (0.85,0.87)	0.70 (0.60,0.82)	0.67 (0.59,0.77)	1.00 (fixed)
	nHW-dead	1.10 (1.10,1.11)	0.93 (0.84,1.03)	0.68 (0.62,0.75)	1.00 (fixed)

Notes:
States: Healthy and in work (HWLE) [1]; Not healthy and/or not in work (including: healthy and not in work; not healthy and in work; not healthy and not in work) [2]; Dead [3]
*Transitions:
"HW-nHW" From healthy and working to unhealthy and/or not working (transition1-2)
"HW-dead" From healthy and working to dead (transition 1-3)
"nHW-HW" From unhealthy and/or not working to healthy and working (transition 2-1)
"nHW-dead" From unhealthy and/or not working to dead (transition 2-3)

5.3.3 Healthy Working Life Expectancy estimates

HWLE at age 50 for England overall was estimated as 9.03 years (95% CI [8.78,9.29]) by modelling transitions on age without any additional covariates (table 5.8). By including sex in the model, HWLE was found to be higher for men (9.94 [9.58,10.31] years from age 50) and lower for women (8.25 [7.92,8.58] years).

HWLE at age 50 without OA (at age 50 or any subsequent age) was estimated as 9.50 (9.22,9.79) years. HWLE at age 50 for people with OA was lower at 7.29 (6.20,8.39) years.

TABLE 5.8: Remaining years expected to be spent healthy and in work (HWLE) at age 50 and life expectancy (LE) at age 50 from models estimated with combinations of covariates

Model	HWLE (95% CI)	Years not healthy and/or not in work (95% CI)	LE (95% CI)
(Age only)	9.03 (8.78,9.28)	22.59 (22.11,23.07)	31.62 (31.17,32.07)
Sex			
Female	8.25 (7.92,8.58)	25.11 (24.39,25.83)	33.36 (32.64,34.07)
Male	9.94 (9.58,10.31)	19.78 (19.13,20.44)	29.73 (29.06,30.39)
OA			
Has OA	7.29 (6.20,8.39)	25.01 (21.30,28.72)	32.30 (27.64,36.96)
No OA	9.50 (9.22,9.79)	21.80 (21.24,22.35)	31.30 (30.77,31.83)
Mental health			
Has mental health problem	6.87 (1.58,12.15)	22.02 (6.94,37.09)	28.89 (8.56,49.21)
No mental health problem	9.76 (9.48,10.05)	23.24 (22.63,23.86)	33.01 (32.42,33.60)
Obesity			
Obese	8.44 (8.02,8.86)	22.94 (21.98,23.90)	31.38 (30.45,32.31)
Not obese	9.31 (9.01,9.62)	22.42 (21.84,22.99)	31.73 (31.18,32.28)
Pain interference			
Has pain	6.54 (6.07,7.01)	23.33 (22.36,24.30)	29.87 (28.90,30.83)
No pain	9.79 (9.50,10.08)	22.62 (22.04,23.19)	32.41 (31.86,32.96)
Physical inactivity			
Physically inactive	7.67 (7.23,8.12)	20.69 (19.96,21.43)	28.36 (27.66,29.07)
Physically active	9.62 (9.32,9.91)	26.39 (25.46,27.32)	36.01 (35.09,36.92)
Control at work			
No control at work	7.67 (7.22,8.12)	23.54 (22.74,24.34)	31.21 (30.41,32.00)
Has control at work	9.50 (9.20,9.79)	22.26 (21.75,22.77)	31.76 (31.28,32.23)
Support at work			
No support at work	7.86 (7.46,8.27)	23.37 (22.67,24.08)	31.24 (30.55,31.92)
Has support at work	9.52 (9.22,9.82)	22.25 (21.74,22.76)	31.78 (31.30,32.25)
OA + Sex			
Has OA + Female	6.82 (6.33,7.30)	26.70 (25.76,27.65)	33.52 (32.63,34.40)
Has OA + Male	8.20 (7.48,8.93)	21.88 (20.10,23.66)	30.08 (27.94,32.21)
No OA + Female	8.72 (8.36,9.09)	24.44 (23.64,25.24)	33.16 (32.37,33.96)
No OA + Male	10.30 (9.91,10.69)	19.32 (18.62,20.02)	29.62 (28.92,30.33)

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Table 5.8 – continued from previous page

Model	HWLE (95% CI)	Years not healthy and/or not in work (95% CI)	LE (95% CI)
OA + Mental health			
Has OA + Has mental health problem	5.61 (1.08,10.13)	23.90 (7.33,40.48)	29.51 (8.47,50.54)
Has OA + No mental health problem	8.06 (7.52,8.60)	26.10 (24.87,27.34)	34.16 (32.91,35.41)
No OA + Has mental health problem	7.26 (1.32,13.20)	21.01 (5.84,36.17)	28.27 (7.24,49.29)
No OA + No mental health problem	10.17 (9.86,10.48)	22.36 (21.71,23.01)	32.53 (31.90,33.15)
OA + Control at work			
Has OA + No control at work	6.09 (5.02,7.15)	25.97 (21.66,30.29)	32.06 (26.85,37.27)
Has OA + Has control at work	7.71 (6.67,8.76)	24.67 (21.35,27.99)	32.38 (28.19,36.57)
No OA + No control at work	8.08 (7.61,8.55)	22.82 (21.93,23.70)	30.90 (30.01,31.80)
No OA + Has control at work	9.99 (9.66,10.33)	21.44 (20.85,22.04)	31.43 (30.86,32.01)
OA + Support at work			
Has OA + No support at work	6.23 (5.15,7.31)	25.86 (21.57,30.14)	32.08 (26.88,37.29)
Has OA + Has support at work	7.72 (6.68,8.76)	24.67 (21.36,27.97)	32.39 (28.22,36.55)
No OA + No support at work	8.27 (7.85,8.70)	22.66 (21.88,23.44)	30.94 (30.16,31.71)
No OA + Has support at work	10.03 (9.70,10.37)	21.42 (20.82,22.02)	31.46 (30.88,32.03)
OA + Sex + Control at work			
Has OA + Female + No control at work	5.70 (5.17,6.22)	27.62 (26.50,28.73)	33.31 (32.23,34.40)
Has OA + Female + Has control at work	7.22 (6.71,7.73)	26.37 (25.42,27.32)	33.59 (32.71,34.47)
Has OA + Male + No control at work	6.89 (6.01,7.77)	22.63 (19.93,25.34)	29.52 (26.25,32.79)
Has OA + Male + Has control at work	8.63 (7.90,9.35)	21.57 (19.95,23.19)	30.20 (28.26,32.14)
No OA + Female + No control at work	7.42 (6.93,7.91)	25.46 (24.49,26.44)	32.88 (31.92,33.85)
No OA + Female + Has control at work	9.20 (8.79,9.60)	24.08 (23.25,24.90)	33.27 (32.46,34.09)
No OA + Male + No control at work	8.78 (8.18,9.38)	20.08 (18.82,21.35)	28.86 (27.39,30.34)
No OA + Male + Has control at work	10.79 (10.36,11.22)	19.05 (18.32,19.77)	29.84 (29.10,30.59)
OA + Sex + Support at work			
Has OA + Female + No support at work	5.76 (5.26,6.27)	27.57 (26.53,28.61)	33.33 (32.34,34.33)
Has OA + Female + Has support at work	7.21 (6.71,7.72)	26.37 (25.44,27.31)	33.59 (32.72,34.45)
Has OA + Male + No support at work	7.06 (6.27,7.85)	22.63 (20.34,24.93)	29.69 (26.95,32.43)
Has OA + Male + Has support at work	8.70 (7.96,9.45)	21.50 (19.82,23.18)	30.20 (28.20,32.21)
No OA + Female + No support at work	7.51 (7.04,7.97)	25.40 (24.47,26.33)	32.91 (32.01,33.81)
No OA + Female + Has support at work	9.20 (8.80,9.61)	24.06 (23.25,24.87)	33.27 (32.47,34.07)
No OA + Male + No support at work	9.01 (8.49,9.53)	20.11 (19.09,21.12)	29.12 (27.99,30.25)
No OA + Male + Has support at work	10.89 (10.45,11.34)	18.95 (18.21,19.69)	29.84 (29.08,30.61)

HWLE was estimated to be almost two years lower for people without control at work (7.67 [7.22,8.12] years) than people with control at work (9.50 [9.20,9.79] years). A similar effect was observed from not having support at work (HWLE was 7.86 [7.46,8.27] years for people with no support at work compared to 9.52 [9.22,9.82] years for people with support). Absence of these work factors was associated with further reduced HWLE among people with and without OA and among men and women with and without OA. For example, the lowest HWLE estimate from modelling transitions on age, OA status, sex, and support at work was for women with OA and without support at work (HWLE 5.76 [5.26,6.27] years from age 50) while the highest HWLE estimate was for men without OA and with support at work (HWLE 10.89 [10.45,11.34] years from age 50). Both men and women with OA but with support at work (HWLE for men: 8.70 [7.96,9.45] years, women: 7.21 [6.71,7.72] years) or control at work (men: 8.63 [7.90,9.35] years, women: 7.22 [6.71,7.73] years) were estimated to have similar HWLEs to those without OA and without support at work (men: 9.01 [8.49,9.53] years, women: 7.51 [7.04,7.97] years) or control at work (men: 8.78 [8.18,9.38] years, women: 7.42 [6.93,7.91] years).

HWLE at age 50 was 6.87 (1.58,12.15) years for people experiencing mental health problems compared to those not experiencing mental health problems (HWLE 9.76 [9.48,10.05] years). When OA and mental health problems were modelled together, HWLE at age 50 was found to be lowest for people with OA and a mental health problem (HWLE 5.61 [1.08,10.13] years) and highest for people without OA and without mental health problems (HWLE 10.17 [9.86,10.48] years).

The lowest estimate of HWLE found from models of HWLE transitions with age and a single additional covariate was HWLE at age 50 for people with pain interference; HWLE was 6.54 (6.07,7.01) years for people with pain interference compared to 9.79 (9.50,10.08) years for those without pain interference.

HWLE was almost one year lower for obese people than those who were not obese (8.44 [8.02,8.86] years compared to 9.31 [9.01,9.62] years). HWLE was approximately two years lower for physically inactive people than physically active people (7.67 [7.23,8.12] years compared to 9.62 [9.32,9.91] years).

TABLE 5.9: Remaining years expected to be spent healthy and in work (HWLE) at age 50 based on starting state occupied at age 50 with combinations of covariates

Model	Starting state at age 50	HWLE (95% CI)	Years not healthy and/or not in work (95% CI)
(Age only)	Healthy and working	9.73 (9.48,9.98)	21.95 (21.48,22.43)
	Unhealthy and/or not working	6.22 (5.87,6.56)	25.16 (24.63,25.69)
Sex			
Female	Healthy and working	9.00 (8.67,9.34)	24.43 (23.70,25.17)
	Unhealthy and/or not working	5.21 (4.81,5.60)	27.83 (27.11,28.55)
Male	Healthy and working	10.54 (10.17,10.90)	19.22 (18.56,19.88)
	Unhealthy and/or not working	7.55 (7.07,8.03)	22.04 (21.33,22.75)
OA			
Has OA	Healthy and working	8.02 (6.82,9.22)	24.36 (20.32,28.40)
	Unhealthy and/or not working	4.34 (3.60,5.09)	27.61 (25.17,30.04)
No OA	Healthy and working	10.16 (9.88,10.44)	21.20 (20.65,21.76)
	Unhealthy and/or not working	6.85 (6.46,7.24)	24.21 (23.59,24.82)
Mental health			
Has mental health problem	Healthy and working	7.62 (1.75,13.49)	21.39 (4.84,37.95)
	Unhealthy and/or not working	3.81 (0.88,6.74)	24.55 (14.37,34.73)
No mental health problem	Healthy and working	10.34 (10.06,10.61)	22.71 (22.09,23.32)
	Unhealthy and/or not working	7.44 (7.03,7.85)	25.43 (24.76,26.09)
Obesity			
Obese	Healthy and working	9.13 (8.71,9.55)	22.30 (21.32,23.27)
	Unhealthy and/or not working	5.65 (5.16,6.15)	25.53 (24.56,26.51)
Not obese	Healthy and working	10.00 (9.70,10.30)	21.79 (21.22,22.37)
	Unhealthy and/or not working	6.53 (6.11,6.95)	24.94 (24.30,25.58)
Pain interference			
Has pain	Healthy and working	7.21 (6.70,7.71)	22.71 (21.69,23.73)
	Unhealthy and/or not working	3.83 (3.41,4.26)	25.83 (24.98,26.69)
No pain	Healthy and working	10.38 (10.10,10.66)	22.08 (21.51,22.65)

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Table 5.9 – continued from previous page

Model	Starting state at age 50	HWLE (95% CI)	Years not healthy and/or not in work (95% CI)
	Unhealthy and/or not working	7.41 (6.99,7.83)	24.81 (24.17,25.45)
Physical inactivity			
Physically inactive	Healthy and working	8.51 (8.04,8.97)	20.01 (19.27,20.75)
	Unhealthy and/or not working	4.29 (3.81,4.77)	23.45 (22.68,24.22)
Physically active	Healthy and working	10.22 (9.94,10.51)	25.82 (24.89,26.76)
	Unhealthy and/or not working	7.16 (6.75,7.56)	28.68 (27.72,29.65)
Control at work			
No control at work	Healthy and working	8.26 (7.79,8.73)	22.98 (22.14,23.82)
	Unhealthy and/or not working	5.28 (4.89,5.68)	25.79 (25.11,26.47)
Has control at work	Healthy and working	10.20 (9.91,10.50)	21.62 (21.11,22.13)
	Unhealthy and/or not working	6.63 (6.25,7.01)	24.86 (24.31,25.42)
Support at work			
No support at work	Healthy and working	8.47 (8.04,8.89)	22.80 (22.07,23.54)
	Unhealthy and/or not working	5.42 (5.04,5.80)	25.68 (25.05,26.31)
Has support at work	Healthy and working	10.24 (9.93,10.54)	21.61 (21.10,22.12)
	Unhealthy and/or not working	6.64 (6.25,7.03)	24.87 (24.31,25.42)
OA + Sex			
Has OA + Female	Healthy and working	6.69 (5.51,7.86)	25.43 (20.75,30.12)
	Unhealthy and/or not working	3.66 (2.95,4.36)	28.14 (25.29,31.00)
Has OA + Male	Healthy and working	8.46 (7.32,9.60)	24.01 (20.41,27.61)
	Unhealthy and/or not working	4.69 (3.94,5.44)	27.33 (25.08,29.58)
No OA + Female	Healthy and working	8.64 (8.15,9.13)	22.30 (21.38,23.22)
	Unhealthy and/or not working	5.82 (5.39,6.26)	24.93 (24.14,25.72)
No OA + Male	Healthy and working	10.66 (10.32,10.99)	20.84 (20.24,21.44)
	Unhealthy and/or not working	7.29 (6.86,7.72)	23.88 (23.23,24.53)
OA + Control at work			
Has OA + No control at work	Healthy and working	7.57 (7.05,8.08)	26.03 (25.06,27.00)
	Unhealthy and/or not working	3.78 (3.29,4.27)	29.43 (28.49,30.36)

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* **Table 5.9 – continued from previous page** *

Model	Starting state at age 50	HWLE (95% CI)	Years not healthy and/or not in work (95% CI)
Has OA + Has control at work	Healthy and working	8.86 (8.09,9.62)	21.27 (19.37,23.18)
	Unhealthy and/or not working	5.54 (4.85,6.24)	24.32 (22.94,25.70)
No OA + No control at work	Healthy and working	9.44 (9.07,9.81)	23.80 (22.99,24.61)
	Unhealthy and/or not working	5.82 (5.36,6.28)	27.03 (26.21,27.86)
No OA + Has control at work	Healthy and working	10.86 (10.48,11.25)	18.80 (18.10,19.50)
	Unhealthy and/or not working	8.03 (7.52,8.53)	21.46 (20.70,22.22)
OA + Support at work			
Has OA + No support at work	Healthy and working	6.84 (5.65,8.03)	25.31 (20.65,29.97)
	Unhealthy and/or not working	3.74 (3.03,4.45)	28.08 (25.27,30.89)
Has OA + Has support at work	Healthy and working	8.47 (7.34,9.60)	24.01 (20.43,27.58)
	Unhealthy and/or not working	4.69 (3.93,5.44)	27.34 (25.09,29.58)
No OA + No support at work	Healthy and working	8.84 (8.40,9.29)	22.13 (21.33,22.94)
	Unhealthy and/or not working	5.96 (5.54,6.39)	24.81 (24.09,25.54)
No OA + Has support at work	Healthy and working	10.70 (10.37,11.04)	20.82 (20.22,21.42)
	Unhealthy and/or not working	7.32 (6.88,7.75)	23.87 (23.22,24.52)
OA + Mental health			
Has OA + Has mental health problem	Healthy and working	6.31 (1.22,11.41)	23.30 (4.56,42.05)
	Unhealthy and/or not working	2.74 (0.52,4.96)	26.33 (13.23,39.42)
Has OA + No mental health problem	Healthy and working	8.68 (8.14,9.23)	25.52 (24.25,26.80)
	Unhealthy and/or not working	5.53 (4.91,6.15)	28.44 (27.29,29.59)
No OA + Has mental health problem	Healthy and working	7.99 (1.45,14.54)	20.40 (3.66,37.15)
	Unhealthy and/or not working	4.30 (0.78,7.81)	23.44 (8.98,37.91)
No OA + No mental health problem	Healthy and working	10.72 (10.41,11.02)	21.84 (21.20,22.49)
	Unhealthy and/or not working	7.96 (7.51,8.40)	24.42 (23.71,25.14)
OA + Sex + Control at work			
Has OA + Female + No control at work	Healthy and working	6.31 (5.75,6.88)	27.05 (25.88,28.22)
	Unhealthy and/or not working	3.19 (2.76,3.63)	29.90 (28.92,30.87)
Has OA + Female + Has control at work	Healthy and working	7.99 (7.45,8.54)	25.68 (24.71,26.65)

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Table 5.9 – continued from previous page

Model	Starting state at age 50	HWLE (95% CI)	Years not healthy and/or not in work (95% CI)
	Unhealthy and/or not working	4.10 (3.58,4.61)	29.17 (28.24,30.11)
Has OA + Male + No control at work	Healthy and working	7.43 (6.48,8.39)	22.09 (19.18,25.01)
	Unhealthy and/or not working	4.68 (3.98,5.38)	24.81 (22.89,26.73)
Has OA + Male + Has control at work	Healthy and working	9.29 (8.53,10.06)	20.96 (19.24,22.68)
	Unhealthy and/or not working	5.93 (5.20,6.66)	24.05 (22.73,25.36)
No OA + Female + No control at work	Healthy and working	8.02 (7.51,8.54)	24.91 (23.91,25.92)
	Unhealthy and/or not working	4.96 (4.50,5.42)	27.70 (26.81,28.59)
No OA + Female + Has control at work	Healthy and working	9.93 (9.52,10.34)	23.43 (22.59,24.26)
	Unhealthy and/or not working	6.23 (5.73,6.73)	26.72 (25.87,27.57)
No OA + Male + No control at work	Healthy and working	9.26 (8.64,9.88)	19.60 (18.28,20.91)
	Unhealthy and/or not working	6.83 (6.26,7.40)	22.05 (20.95,23.16)
No OA + Male + Has control at work	Healthy and working	11.36 (10.94,11.79)	18.52 (17.79,19.25)
	Unhealthy and/or not working	8.49 (7.95,9.04)	21.18 (20.40,21.96)
OA + Sex + Support at work			
Has OA + Female + No support at work	Healthy and working	6.39 (5.84,6.93)	27.01 (25.92,28.09)
	Unhealthy and/or not working	3.23 (2.79,3.66)	29.87 (28.93,30.82)
Has OA + Female + Has support at work	Healthy and working	7.99 (7.45,8.52)	25.68 (24.72,26.64)
	Unhealthy and/or not working	4.09 (3.58,4.60)	29.18 (28.24,30.11)
Has OA + Male + No support at work	Healthy and working	7.62 (6.77,8.46)	22.10 (19.62,24.57)
	Unhealthy and/or not working	4.79 (4.12,5.46)	24.81 (23.15,26.47)
Has OA + Male + Has support at work	Healthy and working	9.38 (8.6,10.16)	20.88 (19.10,22.67)
	Unhealthy and/or not working	5.97 (5.23,6.72)	24.00 (22.65,25.35)
No OA + Female + No support at work	Healthy and working	8.12 (7.64,8.61)	24.84 (23.89,25.80)
	Unhealthy and/or not working	5.02 (4.57,5.48)	27.65 (26.77,28.53)
No OA + Female + Has support at work	Healthy and working	9.94 (9.53,10.34)	23.41 (22.58,24.23)
	Unhealthy and/or not working	6.23 (5.74,6.73)	26.71 (25.88,27.54)
No OA + Male + No support at work	Healthy and working	9.50 (8.97,10.04)	19.62 (18.58,20.67)
	Unhealthy and/or not working	7.01 (6.48,7.55)	22.07 (21.14,23.00)

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* **Table 5.9 – continued from previous page** *

Model	Starting state at age 50	HWLE (95% CI)	Years not healthy and/or not in work (95% CI)
No OA + Male + Has support at work	Healthy and working	11.47 (11.02,11.91)	18.42 (17.68,19.16)
	Unhealthy and/or not working	8.57 (8.01,9.13)	21.11 (20.32,21.89)

Overall population HWLE estimates were weighted averages of starting-state specific health expectancies, which are shown in table 5.9.

5.3.4 Sensitivity analyses

Sensitivity of results to use of simplified 3-state HWLE model

The 5-state model hazard rate ratio estimates led to HWLE estimated as 8.75 years, slightly lower than the 3-state model point estimate estimate of 9.03 years with 95% CI [8.78,9.29] (tables 5.8 and 5.12). Confidence intervals could not be obtained for health expectancy estimates from the 5-state model as the confidence intervals for transition 4-1 (from unhealthy and not working to healthy and working) or 1-4 (from healthy and working to unhealthy and not working) were uncertain but the closeness of the point estimate to the confidence interval lower bound from the 3-state model implies there is likely to be no significant difference (table 5.10). Estimates of life expectancy from age 50 were similar. HWLE estimates from starting in the healthy and working state were consistent between the models: 9.73 (9.48,9.98) years (3-state model); 9.70 years (5-state model).

The HRR with each additional year of age for transition 1-2 in the 3-state model (from healthy and working to unhealthy and/or not working) was within the range of HRRs 1-2 (from healthy and working to healthy and not working), 1-3 (from healthy and working to unhealthy and working), and 1-4 (from healthy and working to unhealthy and not working) in the 5-state models. Total life expectancy from age 50 was estimated as 31.69 years in the 5-state model compared to 31.62 years (31.17,32.07) in the 3-state model. These similarities indicate a lack of theoretical sensitivity of HWLE estimates to the complexity of the underlying model (3-state or 5-state model) and differences in HWLE estimates between the 3-state model and 5-state model may therefore indicate insufficient sample size from which to estimate four health expectancies from four starting states (table 5.11).

Sensitivity of results to operationalisation of health using limiting long-standing illness

Transition HRRs were similar using alternative health definitions SAH and difficulties with ADLs, with the HRR with each additional year of age for transition 1-2 (from healthy and working to unhealthy and/or not working) slightly higher using the ADL-based health definition (1.09 [1.08,1.10]) compared to SAH (1.07 [1.07,1.08]) or the main operationalisation using limiting long-standing illness (1.07 [1.06,1.08]) (table 5.10). Despite this, ADL-based HWLE (10.12 [9.85,10.38] years from age 50) was higher than HWLE estimated using SAH (9.38 [9.12,9.64]) or limiting long-standing illness (9.03 [8.78,9.28]) health operationalisations (tables 5.11 and 5.12).

Life expectancy estimates from age 50 were similar in the main and health definition sensitivity analyses (table 5.12).

TABLE 5.10: Sensitivity analyses of hazard rate ratios to health definition and number of model states (3 or 5-state model)

Sensitivity analysis	Health Definition	Number of model states	Transition*	Age (95% CI)
(Main analysis)	Limiting long-standing illness	3		*age*
			1-2 (HW-nHW)	1.07 (1.06,1.08)
			1-3 (HW-dead)	1.06 (0.98,1.15)
			2-1 (nHW-HW)	0.86 (0.85,0.87)
			2-3 (nHW-dead)	1.10 (1.10,1.11)
Health definition	**ADLs**	3		*age*
			1-2 (HW-nHW)	1.09 (1.08,1.10)
			1-3 (HW-dead)	1.05 (0.98,1.13)
			2-1 (nHW-HW)	0.87 (0.86,0.88)
			2-3 (nHW-dead)	1.10 (1.10,1.11)
Health definition	**SAH**	3		*age*
			1-2 (HW-nHW)	1.07 (1.07,1.08)
			1-3 (HW-dead)	1.04 (0.94,1.14)
			2-1 (nHW-HW)	0.86 (0.85,0.87)
			2-3 (nHW-dead)	1.10 (1.10,1.11)
Number of model states	Limiting long-standing illness	**5**		*age*
			1-2	1.09 (1.08,1.10)
			1-3	1.03 (1.02,1.05)
			1-4	0.00 (0.00,19.29)
			1-5	1.09 (1.03,1.16)
			2-1	0.86 (0.85,0.88)
			2-3	0.74 (0.64,0.85)
			2-4	1.03 (1.03,1.04)
			2-5	1.16 (1.14,1.19)
			3-1	0.99 (0.97,1.01)
			3-2	1.09 (1.06,1.13)
			3-4	1.07 (1.06,1.09)
			3-5	1.09 (0.97,1.23)
			4-1	0.11 (0.00,>1000)
			4-2	1.01 (1.01,1.02)
			4-3	0.91 (0.89,0.94)
			4-5	1.08 (1.07,1.09)

Notes:
Results are given in years
Confidence intervals are shown in parentheses
Differences between sensitivity and main analyses are indicated in bold type
*States in the 3-state model: Healthy and in work (HWLE) [1]; Not healthy and/or not in work (including: healthy and not in work, not healthy and in work, not healthy and not in work)[2]; Dead [3]
*Transitions in the 3-state model:
1-2 From healthy and working to unhealthy and/or not working ("HW-nHW")
1-3 From healthy and working to dead ("HW-dead")
2-1 From unhealthy and/or not working to healthy and working ("nHW-HW")
2-3 From unhealthy and/or not working to dead ("nHW-dead")
*States in the 5-state model: Healthy and in work (HWLE) [1]; Healthy and not in work [2]; Not healthy and in work [3]; Not healthy and not in work [4]; Dead [5]

TABLE 5.11: Sensitivity analyses of starting-state health expectancies to health definition and number of model states

Sensitivity analysis	Health Definition	Number of model states	Starting state	HWLE (95% CI)	Years unhealthy and/or not working (95% CI)		
(Main analysis)	Limiting long-standing illness	3	Healthy and working	9.73 (9.48,9.98)	21.95 (21.48,22.43)		
			Unhealthy and/or not working	6.22 (5.87,6.56)	25.16 (24.63,25.69)		
Health definition	**ADL**	3	Healthy and working	10.72 (10.46,10.98)	20.97 (20.49,21.45)		
			Unhealthy and/or not working	6.09 (5.65,6.52)	25.19 (24.61,25.78)		
Health definition	**SAH**	3	Healthy and working	10.06 (9.80,10.32)	21.65 (21.16,22.13)		
			Unhealthy and/or not working	6.34 (5.99,6.69)	25.01 (24.47,25.55)		
				HWLE*	Years healthy and not working*	Years unhealthy but working*	Years unhealthy and not working*
Number of states	Limiting long-standing illness	**5**	Healthy and working	9.70	11.72	1.57	8.88
			Healthy and not working	5.64	14.75	1.29	9.90
			Unhealthy and working	7.07	11.41	3.37	9.60

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Sensitivity analysis	Health Definition	Number of model states	Starting state	HWLE*	Years healthy and not working*	Years unhealthy but working*	Years unhealthy and not working*
			Unhealthy and not working	2.72	11.79	0.95	14.31

Notes:
Results are given in years
Confidence intervals are shown in parentheses
*Confidence intervals could not be estimated from 5-state model hazard rate ratio results
Main results are given in the first row and results sensitivity analyses are shown in subsequent rows
Differences between sensitivity and main analyses are indicated in bold type

TABLE 5.12: Sensitivity analyses of HWLE and life expectancy to health definition and number of model states

Sensitivity analysis	Health Definition	Number of model states	HWLE (95% CI)	LE (95% CI)
(Main analysis)	Limiting long-standing illness	3	9.03 (8.78,9.28)	31.62 (31.17,32.07)
Health definition	**ADL**	3	10.12 (9.85,10.38)	31.64 (31.18,32.09)
Health definition	**SAH**	3	9.38 (9.12,9.64)	31.64 (31.18,32.10)
Number of states	Limiting long-standing illness	**5**	8.75*	31.69*

Notes:
Results are given in years
Confidence intervals are shown in parentheses
*Confidence intervals could not be estimated from 5-state model hazard rate ratio results
Main results are given in the first row and results sensitivity analyses are shown in subsequent rows
Differences between sensitivity and main analyses are indicated in bold type

5.4 Discussion

Using continuous-time multi-state models, this study has demonstrated that health, socio-demographic and workplace factors were associated with higher or lower rates with which healthy working adults aged 50 and over become unhealthy and/or stop working, and therefore reduced HWLE. The study presented in this chapter used a different approach to estimating HWLE than the IMaCh approach used in previous chapter in order to estimate hazard rate ratios of healthy and working adults becoming unhealthy and/or stopping working associated with osteoarthritis and health, socio-demographic and workplace factors. This R 'msm' and 'elect' approach also allowed for analysis of work factors, which was not possible in IMaCh as these did not apply to all people at all time points or to certain transitions (from a not working state). There were also key study differences that may (at least partly) explain why some of the results in this chapter differ from related findings in previous chapters that also used ELSA study data. Firstly, the R 'msm' approach had more intensive data requirements (for the transition data but not for the covariate data as this could be handled with multiple imputation) and only ELSA waves 2-6 were analysed (wave 1 could not be used as work factors were not measured until wave 1). This meant that 32,791 transitions were anlysed from a sample size of 11,540 adults, compared to 42,978 transitions in chapter 2 (of which 2476 had information loss with unknown destination states but were still able to be included in the analysis) from a sample size of 15,284 adults. Secondly, in calculating the health expectancies the 'elect' package assumes that covariate values remain fixed throughout the lifecourse (from age 50 when HWLE is calculated) whereas IMaCh averages the health expectancies according to possible future covariate values. The less restricted study sample analysed using IMaCh in previous chapters, as well as the software's scope to incorprate time-varying variables, are both advantages of the IMaCh approach over the R 'msm' and 'elect' approach that imply, when resulting HWLE estimates are different, that IMaCh HWLE estimates are likely to more closely reflect the true length of healthy working life from age 50 in the national population. However, as it is difficult to interpret more than one HRR due to the complexity of people transitioning between states over time, the ‘elect’ results make an important contribution in this chapter as they serve to demonstrate (using all the HRRs for a model) the direction in which HWLE is affected (in particular, HWLE reductions) in the presence of osteoarthritis and health, socio-demographic and workplace factors. This was the reason for using ‘elect’ in this study. An alternative approach to estimating HWLE using ‘elect’ that would avoid this issue would be (if practicable) to incorporate the factors of interest individually into the states within the multi-state model (thereby increasing the number of model states in order to include each health and work state with/without the presence of the factors). (This approach was considerd for a sensitivity analysis of HWLE for people with and without OA at age 50 but the multi-state models failed to converge.) However, the aim of this study was to investigate the associations with rates of becoming unhealthy and/or stopping working (that is, age-adjusted HRRs), which was done by adding the factors as covariates in ‘msm’ models. IMaCh also implements a discrete-time approach instead of the continuous-time approach of R ‘msm’ and ‘elect, but the effect of this difference on estimates is unclear.

At any age, healthy and working women were more likely to become unhealthy and/or stop working than men, corresponding to a reduced HWLE by over 1.5 years. Similar findings that HWLE is lower for women were observed (to a greater extent) in previous chapters. This likely reflects the historically lower State Pension age and employment rates for women as well as health differences within the context of work. Sickness absence rates are higher for women than men in the UK and in many European countries (ONS, 2019m; Laaksonen et al., 2010), which may reflect higher levels of work-related or non-work-related health problems among women (for example (non-)work-related musculoskeletal disorders) and differences in working conditions between male dominated and female dominated occupations (Laaksonen et al., 2010; Karasek and Theorell, 1990).

Having osteoarthritis was associated with an increased risk to healthy working adults aged over 50 of becoming unhealthy and/or stopping working by 32% (HRR 1.32 [1.19,1.46]) and was associated with a reduced HWLE from age 50 by over two years. Having OA was more strongly linked to reduced HWLE than lifestyle factors obesity and inactivity, but not as strongly as work factors. Not having support at work and control at work were each identified as strongly related to ceasing to be both healthy and in work. Having control at work can be common in more senior roles with decision-making power associated with having a higher education level (HWLE was found in previous chapters to be higher among those with higher education levels), although sharing decision making more equally between those in more and less senior roles (or employers and employees) may be beneficial for both groups (Saridakis et al., 2017; Karasek and Theorell, 1990). Through modelling HWLE transitions on OA and control at work, HWLE estimates were low for people without control (lowest for those with OA) and higher for people with control (highest for those without OA). The similarity of estimates for people with OA and with control at work and people without OA and without control at work highlight the importance of work factors for staying healthy and in work and suggest that, with adequate workplace accommodations and dialogue with employers, people with OA can achieve healthy working lives approaching in length to that of people without OA. Findings were similar for support at work. Among those in work, the majority reported having both control and support at work (or having neither). Around a fifth of people in work reported having either support or control at work but not both. The higher HWLE for people with OA with positive work environments is likely due to implementation of workplace accommodations to help manage their condition. Even without practical workplace accommodations, improvements in HWLE may also be contributed to by positive communication with employers leading to or reinforcing perceptions of being valued as an employee (Wainwright et al., 2013; Gignac and Cao, 2009).

Having a mental health problem was also identified as being associated with an increased risk of transitions out of the healthy and working state (possibly to a greater extent than having osteoarthritis). Mental health issues present a major reason for sickness absence as well as being associated with significantly increased risk of becoming unemployed or leaving work for health reasons (ONS, 2019m; Rijn et al., 2014). Findings from this study suggest that HWLE for people experiencing poor mental health is reduced by almost three years (HWLE of 6.87 years from age 50 compared to 9.76 years for people without any mental health problem).

Obesity is associated with increased health risks including cardiovascular disease, type 2 diabetes, and nonalcoholic fatty liver disease, and is associated with excess mortality (especially due to cardiovascular disease) (Ogden et al., 2007). There are also higher risks of work absenteeism, presenteeism, and premature work loss due to health problems (Goettler et al., 2017). While not being obese was associated with having a higher HWLE by almost one year compared to HWLE for people with an obese BMI, people who were physically active were expected to spend two more years healthy and working from age 50 than those who were physically inactive. This is in line with evidence of sizeable health benefits from being active regardless of body weight (Do et al., 2018). Classification as obese or not obese meant underweight adults were included in the not obese category, which could reduce the difference in transition intensities associated with obesity as underweight is also associated with increased mortality risks (Roh et al., 2014). However, at each of the waves where BMI was measured (waves 2, 4 and 6), fewer than 1% of the people who had measurements taken had an underweight BMI.

The highest HRR point estimate for transitions out of the healthy and working state (not due to death) was that associated pain interference. Pain is common among adults; two in three adults aged 50 and over report recently experiencing pain that lasted over a day, but around half of these do not perceive their pain to disrupt daily activities, relationships, roles, or employment (Jordan et al., 2019; Barry et al., 2017; Thomas et al., 2004b). That the HRR associated with pain interference for transitions from healthy and working to unhealthy and/or not working is similar to or possibly higher than that associated with having OA is consistent with previous findings that pain is a primary driver of premature work loss among people with OA (Wilkie et al., 2014b) and, more generally, is associated with poorer health, quality of life, and productivity in work and non-work tasks (Sadosky et al., 2015; McDonald et al., 2011; Vassend et al., 2011; Langley et al., 2010).

5.4.1 Study strengths and limitations

There were various strengths and limitations affecting this study. All measures except for obesity were self-reported, which could affect the accuracy of the results (see pages 57 and 183 for more on self-reported health measurements). Individuals were considered to be physically active if they reported carrying out moderate or vigorous activity at least two times per week, however the guidance as to what constituted each level of activity was modest compared to exercise guidelines by the National Health Service, and there is evidence that people tend to overreport the amount of exercise they do (Yuen et al., 2013). Misclassification of some physically inactive people as physically active may explain why this variable was not found to be associated with increased risk of death among healthy working adults. Despite this possible bias underestimating its effect, physical inactivity was identified as an important factor associated reduced HWLE implying that even gentle regular exercise can be beneficial to length of healthy working life. However, other lifestyle choices such as diet are likely to be correlated with physical activity; a study limitation was that it was not possible to address confounding, and the extent to which the association with reduced HWLE is attributable to physical inactivity is therefore unclear. The lack of adjustment for this and other analyses is a limitation of this study; further research is needed to identify drivers of HWLE for the purpose of identifying targeted interventions. Associations between factors and reduced HWLE could be explained by correlated variables.

As discussed in previous chapters, OA status from ELSA data is likely to be affected by misclassification as respondents did not always respond consistently at each wave. Having a physical health problem is associated with increased prevalence of mental health problems (Baek et al., 2015) and confounding may widen the HWLE gap observed associated with mental health. An apparent protective effect of OA against transition 2-3 (dying after being unhealthy and/or not in work) may be due to people without OA in this state having other health problems that are stronger determinants of mortality, or could be related to the distribution of health statuses and work statuses of people with and without OA in state 2 (unhealthy and/or not in work); this collapsed state (compared to the 5-state HWLE model used in previous chapters) contains not only unhealthy people but also healthy people who were not in paid employment.

Most people with OA have one or more comorbidities and people with OA are more likely to have high levels of comorbidity than people without OA (Marshall et al., 2019; Kadam et al., 2004). It may be that healthy and working people with OA have improved management of comorbidities, which (in addition to few observations of the transition from healthy and working to death among participants with OA) could also be a reason for no association found between OA and increased risk of death (from either alive state). Another limitation that may affect HRRs for OA is that the use of covariate values reported at the start of the transition may misclassify some transitions in which OA was present as non-OA (thereby lowering HWLE for the non-OA group) as doctor diagnosed OA at one time point implies that OA is likely to have been present to some extent in preceding years (Mastbergen and Lafeber, 2011).

Region was identified as identified in the ELSA technical reports as predictive of non-response but was problematic when included as an auxilliary variable in multiple imputation of missing data. Because it introduced perfect prediction, the categorical variable with nine levels was excluded. It was a study limitation that region and urban/rural (due to unavailability) were not included as auxilliary variables as this could compromise the MAR assumption for missing values.

Collapsing the original 5-state HWLE model has strengths in that these analyses resulted in a higher success rate of convergence of model parameter estimates with improved ease of interpretation of transitions where movement into and away from the healthy and working state was of particular interest. However, a 5-state model would have allowed for work factors to be modelled for people who were unhealthy and in work as well (as those who were both healthy and in work) thereby more closely reflecting the complexity of the real world.

The similarity of HWLE estimates for the England population overall derived from the 5-state model and the main 3-state model suggests that HWLE is not over or underestimated as a result of simplifying the model. HWLE estimates for England overall and for females were also similar to estimates identified using IMaCh software in chapter 2. The HWLE estimated for males in this study was one year lower than that identified in the study of ELSA data using IMaCh software (chapter 2), which could suggest that the men excluded for this study were not representative of the overall sample or which could reflect methodological differences (including that the discrete-time IMaCh approach incorporates transitions from a known state into an unknown alive state thereby utilising more of the study data). HWLE for people with OA was also higher in this study than in the previous study in chapter 4; as well as possible 'dilution' of the effect of OA where pre-diagnosis years are counted as not having OA, this may be contributed to by the reduced size of study sample as confidence intervals were wide for HRRs associated with each of the factors studied. The methodological approach taken in this study was advantageous for feasability but smaller differences between subpopulations were observed than identified previously using the IMaCh approach (chapters 2 and 4), which was not suitable for use in this study due to restrictive data requirements but is generally accepted to be sound methodologically (Yong and Saito, 2012; Guillot and Yu, 2009). It is therefore possible that HWLE inequalities identified in this study have been underestimated. The higher HWLE estimates resulting from alternative ADL-based health operationalisation despite higher age HRR for transition the from healthy and working to unhealthy and/or not working (transition 1-2) and similar age HRRs for other transitions is likely to reflect different proportions of the population classed as a healthy at age 50.

HRR confidence intervals for transitions to death for factors OA and mental health particularly from the healthy working state were very wide, which is likely to reflect low numbers of deaths among healthy and working study sample members with these conditions; individuals may more commonly transition to the unhealthy and/or not working state before the end of their life and not directly to death.

5.4.2 Implications for policy and practice

There are important implications of these findings for policy, research, and employers. These findings are a starting point for understanding the extent of the effect of different factors on length of healthy working life, and more work is needed to understand mechanisms of action. Acknowledging the potential role of single biopsychosocial factors and how they combine to impact on HWLE highlights the scope to reduce inequalities through targeted initiatives, and more work is needed to understand the impact of potential interventions as these will likely vary in effectiveness across individuals and different subgroups of the population. The results of the analyses presented in this chapter including multiple variables (as well as the interplay of numerous factors in various domains in biopsychosocial models of work) suggest that a single-variable approach to improve HWLE is less likely to be effective without consideration of other factors. There is a need to better understand the relationship between HWLE and combinations of factors especially as some will be more and less amenable to intervention.

The increased risk of ceasing to be healthy and in work among those with OA is evidence that this disease is linked to reduced HWLE and must be considered in policies to extend working life as the prevalence of this common disease increases in the workforce. Interventions such as available treatments focussed on maintaining function (including self-management approaches), initiatives to identify OA early in its development, guidance for employers on ways to improve communication with employees, and individual and group educational activities (therepeutic OA patient education) to equip people with diagnosed OA with the knowledge and confidence to proactively and effectively manage the condition may improve health-related quality of life and mitigate against work loss among people with OA (Wilkie et al., 2014b; Borkhoff et al., 2011; Nuñez et al., 2006). However, the effectiveness of intervention may be limited once this long-term health condition is established. HWLE results from models including OA and work factors as additional covariates point to the role of other personal or external factors included in biopsychosocial work models. The results of this study highlight the potential for HWLE drivers to be identified that are amenable to intervention to improve HWLE outcomes among people with OA.

As State Pension age is equal and rising for both men and women, women may benefit from interventions to promote healthy working lives as being female was identified as associated with reduced HWLE. The mechanism to reduced HWLE may also be different in men than women; for example, women are at a higher risk of OA, which has been shown to be associated with reduced HWLE. Importantly, the factors associated with the furthest reduced HWLE identified in this study were pain interference and work factors. Supportive workplaces are understood to improve work outcomes in those experiencing musculoskeletal or mental health problems (Wilkie et al., 2014b; Nieuwenhuijsen et al., 2004) and this study has revealed that work factors may be key drivers of reduced HWLE among people with osteoarthritis as well as the general population. Evidence-based policy is needed to guide employers to support older workers (especially those with long-term health problems such as OA) effectively at work to reduce HWLE inequalities and promote healthy working lives. This could be offered through information resources, free training opportunities, incentives to retain workers, and new legislation and policies.

5.5 Conclusion

This study identifies demographic, health, lifestyle and workplace factors that are associated with lower HWLE and that can be used to support identification of target groups and risk factors for interventions. The potential to mitigate against premature work exit should be encouraging to policy-makers seeking to extend working life as well as people with osteoarthritis and their employers. However, the HWLE gaps observed associated with OA and other factors suggests that interventions are needed to promote the health, wellbeing and work outcomes of subpopulations with long-term health conditions. As State Pension age is deferred, improving health, lifestyle and workplace conditions will be important for people with long-term health conditions but will also be of benefit to the population in general.

Chapter 6

Summary and discussion

The overall aim of this thesis was to better understand whether the English population is well placed to extend working lives in response to the rising State Pension age. Population and workforce ageing contribute to the need to prepare for the increasing number of older workers (one third of UK workers are now aged 50 and over), who are more likely to be affected by long term health problems that increase in prevalence with age. Health and work outcomes are closely related; extending working lives requires a significant proportion of the population to be able and willing to work for longer and for whom suitable jobs are available and accessible. One of the findings of a systematic search was the identification of Healthy Working Life Expectancy (HWLE) as a population health indicator to measure the capacity for a population to extend working life. HWLE was applied in the studies described in this thesis to examine whether the population of England is 'able' to work for longer and investigate future trends and drivers of HWLE because of the importance of maintaining a healthy workforce (especially in later working life).

6.1 Key findings

There are five key and novel findings from this thesis (table 6.1).

TABLE 6.1: Key findings from this thesis

• HWLE can be operationalised and used as a population indicator for work • HWLE in England is 9.42 years, which is over six years less than the number of years to State Pension age • There are inequalities in HWLE between population subgroups according to sex, region, occupation type, education level, and deprivation • HWLE is unlikely to rise with the State Pension age without interventions to reduce inequalities and improve population health and wellbeing • Having osteoarthritis reduces remaining length of healthy working life by over one third • Health, lifestyle and workplace factors are associated with reduced length of healthy working life

6.1.1 HWLE can be operationalised and used as a population indicator for work

The work presented in this thesis has demonstrated that HWLE can be operationalised and has the potential to be used as a population indicator for work in England. HWLE was applied using longitudinal data with and without linked medical records (national survey data as well as local data with linked electronic health record data), as well as using cross-sectional survey data and official mortality rate statistics. HWLE was operationalised using individuals' health status and work status at data collection time points. Health for HWLE was based on functional loss and was defined as the absence of a limiting long-standing illness. Work for HWLE was defined as participating in employment or self-employment (for any number of hours) in the preceding week or month (depending on data source). Methodological complexity and high data requirements meant that it was necessary to use different techniques throughout this thesis to calculate the extent of HWLE, estimate HWLE projections, and look at factors associated with HWLE to lead to potential interventions. HWLE has potential to be an instrument for surveillance of health and work as policy makers seek to extend working life; the combination of health and work statuses offers an approach for monitoring overall population wellbeing with respect to health, work participation, and the quality and availability of job opportunities in later working-age life. The scope for electronic health records to be used to estimate HWLE in relation to doctor diagnosed health conditions that may not be included in surveys provides an opportunity to further investigate HWLE inequalities in order to identify subpopulations that may benefit from initiatives to improve health and wellbeing and for surveillance of how this may change over time as the State Pension age rises.

6.1.2 HWLE in England is 9.42 years, which is over six years less than the number of years to State Pension age

That the number of years from age 50 to State Pension age exceeds HWLE was a consistent finding throughout the various analyses of differing methods and using different data sources. The main objective of the study presented in chapter 2 was to estimate HWLE in England overall and for subpopulations by sex, education level, occupation type, region, and area level deprivation quintile. Using interpolated Markov chain multistate modelling (IMaCh) methodology and data from the English Longitudinal Study of Ageing (ELSA), the primary estimate of HWLE was found to be 9.42 years from age 50 on average (10.94 years for men and 8.25 years for women) (chapter 2). In addition, men can expect to spend 9.58 years healthy and not in work, 2 years not healthy but in work, and 7.52 years not healthy and not in work. Women can expect to spend 12.57 years healthy and not in work, 1.7 years not healthy but in work, and 10.97 years not healthy and not in work. For all subpopulations, HWLE from age 50 was less than the number of years to State Pension age (66 in late 2020). HWLE estimates and inequalities suggested that many people will find working for longer challenging and questioned whether HWLE will increase with the State Pension age. In addressing further research objectives requiring alternative methods and/or data, each of chapters 3, 4 and 5 also identified HWLE estimates for England that were similar to or lower than the primary estimates.

These estimates of HWLE are the first published for England. The systematic review of published estimates and indicators of length of healthy working life (chapter 1) identified

1995-1996 estimates of HWLE for the United Kingdom (Lièvre et al., 2007), which were limited by insufficient data and are now over 20 years out of date. Lièvre et al. (2007) estimates of HWLE in the UK were 8.8 years for men and 5.8 years for women. HWLE increases since then (2002/3-2012/13, chapter 2) are likely to be partly attributable to several changes since 1996. Firstly, life expectancy from age 50 has increased (an indication of improvements to population health and wellbeing) from 27.10 years for men and 31.32 years for women in 1996 (the end of the study period for Lièvre et al. (2007)) to 31.28 years for men and 34.33 years for women in 2013 (the end of the study period analysed in chapter 2), and 31.63 years for men and 34.58 years for women in 2018 (the most recent year for which single year life tables are available at the time of writing) (ONS, 2019n). Secondly, employment rates (especially of women) aged 50 and over have increased (ONS, 2020c). In 1996, 49.4% of women and 66% of men aged 50-64 were doing paid work, as well as 3% of women and 7.3% of men aged 65 and over. In 2013, 62% of women and 73.3% of men aged 50-64 were employed as well as 6.9% of women and 12.9% of men aged 65 and over. Finally, pension legislation (then, the Pensions Act 1995) foretold an expectation for women to work for as long as men by withholding the State Pension until age 65, which would have affected many of the (younger) women in the study sample. Those women aged 56 and 57 in 2011 during the study period were also affected by the acceleration of this timetable in the Pensions Act 2011.

6.1.3 There are inequalities in HWLE between population subgroups according to sex, region, occupation type, education level, and deprivation

In England, HWLE is highest for people in self-employed (or non-manual) occupations (HWLE is 11.76 years and 10.32 years from age 50 respectively), those with tertiary educations (11.27 years), and those living in southern regions (10.73 years in the South East and 10.51 years in the South West) and the least deprived areas (10.53 years). HWLE is also higher for men (10.94 years) than for women (8.25 years) (chapter 2). Those with the shortest healthy working lives on average have less than secondary education (HWLE is 7.68 years from age 50), work in manual occupations (8.72 years), live in northern regions (7.34 years in the North East) and the most deprived areas (6.8 years) (chapter 2). In addition to the novelty of identifying these HWLE inequalities in England, these studies also serve as the first demonstrations of HWLE estimation by population subgroups (in any population). Those subpopulations in England that, on average, are more and less likely to be able to work for longer reflect similar trends to inequalities in life expectancy, healthy life expectancy, and working life expectancy, indicating that the same factors that influence those attributes may also impact HWLE.

Population health is a reflection of the extent of social and economic inequity, and the conditions people live in throughout the lifecourse in childhood, adulthood, at work, and in ageing (Marmot, 2020). The social determinants of health are interrelated; society and health flourish (or do not flourish) together (Marmot, 2020). Since the financial crisis of 2008 and the period of austerity that followed from 2010, England has seen the equity of social determinants of health worsening with increasing preventable illness, stalling life expectancy, and an increasing percentage of life lived in poor health (Marmot et al., 2020; Leon et al., 2019). Systematic health inequalities are widening (Marmot et al., 2020; Barr et al., 2015). There are increasing rates of child poverty, increasing numbers of working adults in poverty, and an increasing share of national wealth held by the richest 1% (Marmot et al., 2020; Bourquin et al., 2019; Taylor-Robinson et al., 2019). The social gradient in household wealth is steepening with tax and benefits policies that redistribute household wealth away from those with the lowest incomes and systematically disadvantage working-aged adults (especially those with children) in the lowest income deciles (De Agostini et al., 2014). Social mobility is stalling and, for many, wages have stagnated despite rising living costs especially for housing (ONS, 2020b; Blundell et al., 2018; Tucker, 2017). More and more people have insufficient money to live a healthy lifestyle, with food insecurity and food bank use increasing (Marmot et al., 2020; Loopstra et al., 2019; Loopstra, 2018). Since 2010 there has also been at least a three-fold increase in the number of people experiencing homelessness (Marmot et al., 2020; O'Leary et al., 2018; NAO, 2017).

Regional inequalities in life expectancy persist in England and are widening, with some groups experiencing life expectancy declines (ONS, 2019f). The social gradient in healthy life expectancy is steeper than that of life expectancy and is steeper still within less affluent regions especially the North East and North West (Marmot, 2010). Healthy years from birth for men has slightly decreased since 2009-2011, with both sexes experiencing reductions in Disability Free Life Expectancy and additional years spent in poor health (Marmot et al., 2020). This emphasizes the need to monitor HWLE as the State Pension age increases as any working years gained will be disproportionately unhealthy if health and life expectancy do not improve in line with State Pension age increases.

6.1.4 HWLE is unlikely to rise with the State Pension age without interventions to reduce inequalities and improve population health and wellbeing

HWLE has increased in recent decades but the rate of these increases may be slowing. A novel study of HWLE projections, presented in chapter 3, suggested that HWLE gains from 2015 to 2035 (men: 0.38 years; women: 1.08 years) will be much lower than expected life expectancy gains (men: 3.37 years; women: 2.46 years) and the number deferred years until State Pension eligibility. State Pension age was 65 for men and lower for women in 2015 and will have increased to 67 in 2035 for both men and women with imminent increases to 68 anticipated.

The Lee Carter forecasting approach was used to estimate HWLE projections and expected trends in length of healthy working life from age 50 in the coming years (2015-2035) in conjunction with the intercensal approach to estimate HWLE, which has more flexible data requirements for estimation of health expectancies. Health and work status prevalence data for the study were obtained from the Health Survey for England and were used with national mortality rate statistics. Comparisons to HWLE estimates previously obtained using the IMaCh approach, sensitivity analyses, and relevant literature suggested that observed and projected HWLE values were underestimated in this study but that time trends may provide useful insight into future HWLE. HWLE was estimated to be 8.85 years for men and 7.74 years for women in 2020 using projected health and work data, and 9.05 years and 8.57 years respectively in 2035. The projections suggest that HWLE is likely to increase but at a slower rate than has been observed since 1996 (the first year for which HWLE was estimated in the study presented in chapter 3). HWLE gains are also expected to be achieved at a slower rate for men than women. The projected slowing of HWLE gains and widening of the gap between HWLE and State

Pension age evidenced a need to better understand barriers to extending healthy working life and the impact on HWLE of common age-associated health problems. The HWLE projections were estimated based on conditions throughout the study period remaining the same or maintaining the same trends of change. Potential HWLE gains in recent years in England may have been limited by the diminishing improvements to population health, and the trajectory of HWLE changes in the future will likely be influenced by factors such as increasing obesity and inactivity levels (which can reduce length of healthy working life) and changes to the nature of work and job availability (Kohl et al., 2012; Wang et al., 2011). More work is needed to examine the biopsychosocial drivers of HWLE that may require targeted intervention to enable people in the population to meet policy goals by working for longer. A wide range of interventions that invest in society through long-term planning and consideration of health equity in all policies have been shown to be cost-effective strategies to support good health, avoid harming health, and avoid disempowering individuals to make healthy choices (Marmot et al., 2020; Marmot, 2020; PHE, 2019b). Policy changes and interventions to reduce inequalities, reduce inequities in power and resources, improve population health and wellbeing, and help society to prosper may be key to achieving longer healthy working lives (Marmot et al., 2020; Marmot, 2020).

6.1.5 Having osteoarthritis reduces remaining length of healthy working life by over one third

The association with HWLE of osteoarthritis (OA) was investigated using this long-term condition as an example of a prevalent musculoskeletal disorder. Characterised by pain and functional limitation, OA is the most common form of arthritis (Hunter and Bierma-Zeinstra, 2019). Over a quarter of the UK population aged 50-65 have consulted their general practice for OA treatment (Versus Arthritis, 2013). Musculoskeletal disorders are a major driver of sickness absence from work, reduced productivity at work, and early retirement, and are the most common reason for work days lost to sickness absence in the UK. The studies presented in chapters 4 and 5 found that HWLE is reduced by over a third for people with OA.

In chapter 4, the association of OA with HWLE was examined by IMaCh analyses of two longitudinal datasets. Using ELSA data, OA was modelled as a time-varying covariate to estimate HWLE from age 50 as ten years for people without OA (at age 50) and 5.68 years for people with OA (at age 50 and irreversible). Both estimates were higher for men and lower for women. The analyses were repeated using data from the North Staffordshire OA Project, which collected medical record data and allowed the population to be stratified according to doctor diagnosis of OA. In this regional dataset, HWLE estimates were 6.58 years for the population on average, 6.90 years for people who did not have OA (throughout the study period), and 4.31 years for people who had OA. Analyses of both datasets indicated that expected length of healthy working life reduces by around 40% on average for people with OA.

No known estimates of HWLE for people with OA have existed prior to the study presented in chapter 4. The relative gap in HWLE may be larger where general population estimates are higher (as in England compared to North Staffordshire); where other people may be working for longer for various reasons, people with OA often experience premature work loss especially where pain interferes with work activities and individuals do not feel supported in the workplace (Wilkie et al., 2014b). Various studies have shown reductions in working life expectancy for adults with OA (Kontio et al., 2019; Laires et al., 2018; Lacaille and Hogg, 2001). Kontio et al. (2019) found that 50-year-olds in Finland who had experienced long-term sickness absence due to OA were expected to spend 5.4 years in work on average in the 13 potential working years until the relevant retirement age (63 years), approximately two years less than the general population estimate of working life expectancy. The HWLE gap associated with having OA observed in chapter 4 reflects similar work behaviour; the wider gap likely reflects the reduction in healthy years for people with OA (compared to measuring only working life expectancy), the higher HWLE generally due to more recent measurement, and the more inclusive measurement of OA that does not require those affected to have experienced long term sickness absence from work. As the number of people with osteoarthritis both in the general population and in the workforce is growing with life expectancy increases, rising obesity, and an expectation to work for longer, these findings indicate a need for interventions to reduce inequalities and improve factors driving reduced HWLE for people with this common long-term condition.

6.1.6 Health, lifestyle and workplace factors are associated with reduced length of healthy working life

In line with models of work disability (outlined in chapter 1), the role of a number of biopsychosical factors (sex, osteoarthritis, health, lifestyle and workplace factors) on HWLE were investigated. The study (presented in chapter 5) found these factors to be associated with higher rates of healthy working adults aged 50 and over becoming unhealthy and/or stopping working. Women and people with osteoarthritis, pain interference, mental health problems, obesity, physical inactivity, no control at work (for workers), and no support at work (for workers) had lower HWLE.

Using continuous-time multistate modelling in R software (for feasibility instead of IMaCh), models with age and biopsychosocial factors as covariates were estimated using a more restricted ELSA sample (compared to the analyses using the same data source presented in chapters 2 and 4). Of those that were tested, the factors that were associated with the largest effect on HWLE (after adjusting for age) were: pain interference, mental health problems, having no control at work, having no support at work, and osteoarthritis. The presence of any of these characteristics individually (without accounting for other factors) was estimated to be associated with an approximately 30% increased risk to healthy working people of becoming unhealthy and/or stop working, leading to HWLE reductions of around two years. Corresponding HWLE estimates were found using a recently developed health expectancy approach (van den Hout and Sum Chan, 2019; van den Hout and Matthews, 2019) which required certain assumptions to be made about the study sample analysed, but which was useful in order to demonstrate the direction of effect of transition intensities on HWLE (that is, to show that the higher rates of transitions out of the healthy working state links with reduced HWLE).

The results presented in chapter 5 suggest that there are modifiable factors that could increase HWLE and provide a starting point for future work identifying interventions to promote healthy ageing, healthy work, and extended HWLE. Physical inactivity, obesity, and prevalence of mental health problems vary in prevalence in English regions and subpopulations as do workplaces and job opportunities, which all contribute to societal health and wellbeing and have now been shown to be linked to length of healthy working life (Marmot, 2010; Marmot et al., 2020; McManus et al., 2016). The prevalence of health problems (some of which are preventable) and the extent of their effects is influenced by a range of local factors from infrastructure that promotes exercise such as cycling lanes, safe walking options, and green spaces, to whether transport options are accessible and affordable to help avoid feelings of isolation (Marmot et al., 2020). Employers are also important stakeholders in the health and work life of their workers and collaboration between employer and employee helps to maintain work participation in those with health problems such as osteoarthritis and may also promote maintenance of health and work participation in employees more generally (Wilkie et al., 2020). Models including both osteoarthritis and individual work factors as covariates implied that having supportive work environments and a sense of control over what happens at work can mitigate against reductions in healthy working life associated with long term health problems such as osteoarthritis.

6.2 Discussion

A key challenge for this thesis was the question of whether HWLE can be calculated using existing data and methods. This was addressed in chapter 2 using interpolated Markov chain multi-state modelling (IMaCh approach) applied to ELSA data. Subsequent research objectives required alternative approaches that inevitably produced additional HWLE estimates to those initially identified, which differed (sometimes by several years) from the initial estimates presented in chapter 2 (HWLE estimates depended on the methodological approach). Markov chain methods (including the IMaCh approach) allow for estimation of more than two alive health expectancies (for multi-state models with more than two alive states), and IMaCh uses a theoretical and methodological approach that was specifically designed for health expectancies. The simulation of a synthetic cohort through the health statuses based on the flow of individuals observed in longitudinal data is ideal for construction of multi-state life tables (Cambois et al., 1999). The IMaCh results from chapter 2 achieved health expectancies for each of the four alive health and work states in the full 5-state HWLE model. However, the methodological complexity and high data requirements meant that the study of factors driving HWLE could - at present - only be feasibly analysed with R package ‘msm’, which was also able to incorporate work factors that by nature only apply to transitions affecting working people and enabled a hazard rate approach to understanding drivers of transitions. However, ‘msm’ models reflecting an ageing process must be defined on age as well as any other covariates, and functionality to estimate total lengths of stay in each state is restricted in this package to models without age. The recently developed add-on R package ‘elect’ for estimation of state-specific and marginal life expectancies using multi-state models fitted in ‘msm’ was therefore used to estimate HWLE. This set of functions enabled estimates of HWLE for the variety of biopsychsocial factors investigated, many of which could not have otherwise been attained due to a combination of insufficient data and the implementation of complex, restrictive methodology. For example: missing data in covariates causes IMaCh to ignore all data from the participant, IMaCh requires that all covariates apply to all individuals at all time points, and successful estimation in IMaCh is unlikely for models with more than one additional covariate (using this data source and time-varying variables). There is little discussion of limitations of the R ‘msm’ and ‘elect’ approach in the literature. HWLE gaps associated with the presence and absence of each covariate could be underestimated, implied by the markedly higher estimates of HWLE for people with OA produced using the ‘msm’ and ‘elect’ functions compared to the larger HWLE gaps identified in chapter 4 using IMaCh. This could be an effect of ‘elect’ functions assuming that covariate values do not change over time (and being intended for use with time independent variables). The lower estimate of male HWLE by one year using this approach compared to IMaCh despite consistent estimates for females also implies bias introduced by restricting the study sample; IMaCh was able to utilise data from almost four thousand more ELSA participants than ‘msm’. ELSA data could not be used for estimating HWLE projections and a further methodological approach to estimating health expectancies (the intercensal method) was implemented, for which limitations and biases are also not well researched. Similar time trends were found between this approach and sensitivity analyses using the Sullivan method (based on the earlier method presented by Wolfbein (1949)), which has been subjected to well-known criticism for assuming that transitions occur in only one direction, that maximum prevalence of the measured health or activity characteristic occurs at the earliest age analysed in the life table, and that mortality rates are the same across groups with or without the measured health or activity characteristic (Cambois et al., 1999). The key advantage of prevalence-based approaches (the Sullivan method and the intercensal approach) is that routine estimation of health expectancies becomes possible using smaller cross-sectional surveys (mortality-linked longitudinal data for IMaCh is not always available) from which time trends can be investigated and monitored (Cambois et al., 1999).

6.2.1 Recently published studies of population ableness to work for longer

The most recent study identified in the systematic review (chapter 1) was published in 2007 - 13 years prior to the time of writing this thesis. Various studies relating to healthy and working life expectancies in the context of rising state pension ages internationally have been published since undertaking the systematic review (Brønnum-Hansen et al., 2020; Pedersen et al., 2020; Robroek et al., 2020; Murray et al., 2019; van der Noordt M. et al., 2019; Wind et al., 2018).

Brønnum-Hansen et al. (2020) used the Sullivan approach to estimate healthy life expectancy (operationalised as expected lifetime without activity limitations and, separately, without long-term illness) from age 50 for Danish subpopulations defined by current or most recent occupation type. Using linked national register and Survey of Health, Ageing and Retirement in Europe (SHARE) data, the authors suggest that healthy life expectancy from age 50 implies potential working years, and that the corresponding socioeconomic gradient will increase inequalities if pension age rises uniformly without efforts to improve healthy life expectancy in subpopulations with lower estimates. Robroek et al. (2020) estimated working life expectancy and working years lost from age 30 based on employment status for subpopulations of The Netherlands defined by education level. Using the 'mstate' R package to analyse monthly Statistics Netherlands data for the whole population, education level was found to be associated with both working life expectancy and working years lost from age 30. Pedersen et al. (2020) investigated the effect of high physical workload exposure on working life expectancy in Denmark using a multi-state Cox-regression method introduced in 2017 (Pedersen and Bjorner, 2017). Using national register data of employment status, transition intensity matrices were estimated for 100 time points each year (of age) from which transition probability matrices were estimated; the area under the transition probability curves were used as the expected stay-time in each state. The study demonstrated an association between physically demanding work and reduced healthy (not away from work for health reasons) working life (defined as employment without receipt of social benefits such as for sickness absence or maternity leave), with working life expectancy for women negatively affected to a greater extent by physically demanding work than men. The limitation of these studies within the contexts of the aim of this thesis is that they do not estimate time spent both healthy and in work. However, the ongoing interest in this topic highlights the relevance of measuring length of healthy working life in various national contexts and demonstrates a need for and interest in developing the methodological toolkit for HWLE applications.

Taking a different approach, Murray et al. (2019) estimated the number of years from stopping paid work until death in the UK. Analysis of data from the ONS Longitudinal Study 2001-2011 found that people in lower occupational social classes were more likely to exit work earlier than others due to poor health, and then spend a larger number of years not working before death compared to people in higher occupational social classes. The authors suggest that individuals - especially those with poor health or of lower occupational class - are more likely to find themselves pushed out of work than to choose to leave, and that people in manual work may be unable to continue in their jobs despite a financial need for income from paid work. The study concluded that, even with policy interventions (for example to promote work engagement), raising the State Pension age uniformly will increase inequalities as those individuals who are unable to work for longer due to individual health and/or work circumstances are also those without the financial means to retire early. The different approach taken by Murray et al. (2019) to indirectly investigate work-related health expectancies compared to this thesis and other related studies could be due to insufficient data for using health expectancy methods. This points to the extent of the knowledge gap around health, work, retirement and socio-demographic factors and the need for improved resources with which to investigate health expectancies as State Pension age rises.

The systematic review in chapter 1 identified two studies that, while ineligible for the review (due to not estimating time spent healthy and in work for the general population including adults aged 50-59), were related in theme and may be of interest to the reader. These were studies of the Longitudinal Aging Study Amsterdam (LASA) by Wind et al. (2018) and van der Noordt M. et al. (2019) that investigated working life expectancy using R packages 'msm' and 'elect'. By modelling transitions in a 3-state model (working with good self-rated health, working with poor self-rated health, and exit from work), Wind et al. (2018) found that 55-year-old workers with chronic health problems had longer healthy working life expectancies and longer unhealthy working life expectancies in 2016 compared to 1992. van der Noordt M. et al. (2019) used self-reported dates of work exit and health defined as no limiting long-standing illness to specify a 3-state model: in the workforce without disability; in the workforce with disability; out of the workforce. The study found that, among those who were in paid work at age 55, working life expectancy (overall as well as working years both with and without disability) from age 58 has increased in recent years (van der Noordt M. et al., 2019).

The presence and directions of inequalities in health and work in later working life is generally in concordance between studies of varying study contexts. Education is a key driver of improving (absolute and relative) mortality internationally (Jasilionis and Shkolnikov, 2016) and its associations with improved health and job prospects are widely discussed (Marmot et al., 2020), but it is not clear whether the link between education and healthy and/or working life expectancy is straightforward and internationally generalisable. Differences in improvements and international rankings of (healthy/working) life expectancy for men and women in different countries (Robroek et al., 2020; Leon et al., 2019; Loichinger and Weber, 2016; Jagger, 2015) suggest caution around assuming generalisability of results over time and between countries, and point to the importance of using a combined health and work indicator for surveillance of whether there are potential working years to be gained (Loichinger and Weber, 2020).

6.2.2 The changing nature of work

In addition to policies to defer retirement having potential to affect the course of HWLE changes in the near future, so too does the continually evolving nature of work, workers, and the increasingly diverse workforce. Types of jobs available are changing; new jobs such as on social media have emerged while others have become less common or entirely disappeared (FPFIS team, 2019; Hoffman et al., 2020; Webster and Ivanov, 2020). Many workers find themselves in roles that are mismatched to their experience and qualifications - either vertically (the job does not require such a high level of education) or horizontally (the job content does not correspond to the studied subject area) - contributing to emerging behaviour of workers to change job regularly through choice or necessity (Hoffman et al., 2020; Jackson, 2020). Full-time permanent ('traditional') employment is giving way to temporary, flexible, fragmented task-based, on-demand, gig-economy work with nonpermanent employer relationships now the expected norm, often disassociating individuals from self-identifying with their work as well as those social and legal protections (such as having medical insurance, pension schemes, and contributing taxes) for which legal infrastructure and implemented processes may now be outdated (Webster and Ivanov, 2020).

Manual job opportunities are declining and, as humans play a decreasing role in manufacture work with similar changes expected in the years to come the service industry, workers may find themselves competing for roles that supervise or assist robots, artificial intelligence and automated technologies (for example in those tasks that are straightforward for a person to carry out but which robots cannot (yet) perform with ease) (Webster and Ivanov, 2020; Pantea, 2019). Salaries have stagnated for people whose work is no longer highly valued for example due to the potential to automate tasks (Webster and Ivanov, 2020; Rani and Grimshaw, 2019). Commonly outsourced production work is returning to countries with high labour costs to avoid transportation costs as automation reduces the need for human labour (Webster and Ivanov, 2020). Future years may present an oversupply of manual workers competing for deskilled jobs (Pantea, 2019). In this case, a lack of job opportunities (and the possibility of poor work quality where jobs are availlable) could lead to HWLE reductions for people with manual occupation types

- a group that is already disadvantaged in length of healthy working life.

Meanwhile, historically highly-valued ‘knowledge-based’ (highly educated) work can increasingly be carried out by technology and artificial intelligence processes (Webster and Ivanov, 2020). Instead, those skills to enable people to compete in the job market are becoming those of complex problem solving, emotional intelligence, creativity, and communication (Ackerman and Kanfer, 2020; Webster and Ivanov, 2020). More and more, workers value opportunities for professional development, continual and self-directed learning, career advancement, and autonomous and flexible working (in 2019 approximately a quarter of US workers regularly worked at least some of their hours from home (US Bureau of Labour Statistics, 2020)) while changeable work tasks demand an ability to adapt at pace (Hoffman et al., 2020). Both education providers and employers will need to consider an approach to training that prepares people to readily learn and adapt to new work tasks, software, and processes (Ackerman and Kanfer, 2020; Hoffman et al., 2020). The effect of these changes on HWLE will depend on the number of jobs created to replace (or adapted from) destroyed knowledge-based jobs. Fewer (attainable) jobs and precarious employment could both slow HWLE increases.

For older workers, low physical demands and fewer repetitive tasks at work is likely to be advantageous, but competing for (possibly fewer, and shorter-term) ‘good’ jobs may be challenging (Ackerman and Kanfer, 2020; Webster and Ivanov, 2020). While advances in robotics, artificial intelligence and automation technologies take away jobs that can be automated, new jobs are also appearing - but it is hard to predict where and of what type (Hoffman et al., 2020; Webster and Ivanov, 2020; FPFIS team, 2019). There are likely to be “winners and losers” with inequalities increasing as some people find their skills do not match those required to compete for well-paid jobs (Webster and Ivanov, 2020, p.132) (Hoffman et al., 2020; Rani and Grimshaw, 2019; Lemieux, 2008). The overall effect of these anticipated changes to the nature of work may therefore enable HWLE gains for some and HWLE stagnation or losses for others, the overall effect of which is not yet clear.

6.2.3 Implications for policy and practice

This research on HWLE and the broader (inter)national efforts to extend working lives carry implications for policy makers, healthcare professionals, employers, and individuals. Various stakeholders have begun taking steps to prepare for and encourage extended working lives.

Government efforts in the UK have included the abolishment of the default retirement age, which formerly allowed employers to require employees to retire at age 65, in addition to raising the State Pension age (DWP, 2017a). The Department for Work and Pensions (DWP) has also sought to work with businesses, researchers, and other areas of government to better enable older workers to stay in the workplace and improve options for reentry (DWP, 2017a). Initiatives include policy changes to allow all employees who have held their post for six months to request flexible working regardless of age, initiatives to improve the accessibility of the Jobcentre Plus offering to older workers, and collaboration with businesses, academics and research organisations to develop an evidence base to support actions to extend working lives (DWP, 2017a). DWP has also identified as priorities the need to promote among employers the benefits of a diverse workforce (age-diverse and inclusive of women, carers, people from Black, Asian and minority ethnic groups, and people with long-term health problems) and the need to ensure learning opportunities (including but not limited to apprenticeships) are accessible to people of all ages (DWP, 2017a).

Among businesses, prioritising adapting for older workers and an ageing workforce is largely limited to larger employers who have trialled or implemented new (additional or alternative) schemes geared towards older workers and an age-diverse workforce such as offering mid-career reviews, reverse mentoring, wellbeing programmes, financial planning provision, and flexible working for most roles (DWP, 2017a). Employer initiatives have also included opening up work opportunities and apprenticeships that may be stereotypically age-associated to people of any age, and reviewing age-inclusive hiring practices where those qualities valued in older workers are not the characteristics assessed in interviews (DWP, 2017a). Some employers have introduced training for all managers to be better equipped to understand and respond to the needs of an age-diverse team including older workers after identifying that line managers' uncertainty over what constituted reasonable adjustments and setting precedents impeded implementation of adjustments to enable older workers to function well at work (DWP, 2017a; DWP, 2014a).

To support healthcare professionals and employers in retaining older workers and promoting health ageing, Public Health England (PHE) has taken a joined up approach with businesses, clinicians, and government departments to research and disseminate evidence on health and work in adults in their later working life (PHE, 2020; DWP and DoH, 2016; DWP, 2014a). 'Fingertips' is an online collection of resources on employment and productive healthy ageing intended to guide improvements to work opportunities for older workers (PHE, 2020) and PHE has sought to develop a suite of work and health indicators to enable monitoring and sharing of 'what works' in recruiting and retaining older workers (DWP and DoH, 2016). In 2017, PHE released an interactive economic tool commissioned to support local government decision-makers by quantifying the financial and health effects of securing sustainable employment for unemployed individuals (PHE, 2017b; DWP and DoH, 2016). PHE has acknowledged the importance of providing healthcare professionals with training to implement evidence-based strategies to support older people to stay in work and increase healthy years lived after age 50; PHE has been involved in a pilot trial of training Health and Work Champions to boost the knowledge and confidence of healthcare professionals to support people in the context of employment through appropriate advice and referrals as well as actively raising the subject of work with adults in later working life. (DWP and DoH, 2016; DWP, 2014a).

The findings presented in this thesis indicate that still more must be done to support people aged 50 and over to be able to engage positively with the strategy to extend working lives. More businesses will need to plan for ageing workforces by training line managers to manage older workers and age-diverse teams, and should consider policies that promote healthy ageing (for example allowing flexible working, extended paid or unpaid breaks from work, and compassionate leave in the event of a family crisis) (Altmann, 2015). Smaller employers in particular may require government support and guidance for this. Various push and pull factors encourage early work exit or discourage return to work, some of which will be more amenable to intervention than others and are likely to affect subpopulations differently (Weyman et al., 2012; Phillipson and Smith, 2005).

In her report to the government, Altmann (2015) suggested imposing penalties for age discrimination in workplaces and introducing financial incentives for recruiting and retaining older workers (such as relief for employer National Insurance contributions and government support for apprenticeships for older workers). While some adults in later working life experience a high level of control over their life circumstances, others have little; improving policy and workplace structures to promote the opportunity to make meaningful choices (especially for those of lower socioeconomic status) is likely to benefit individuals, employers and government alike (Holley-Moore et al., 2017; Phillipson and Smith, 2005). Changing the landscape of contributing to and accessing pensions to promote extended working lives and make working for longer financially advantageous is likely to be more effective in changing the retirement behaviour of older workers than focusing on shifting attitudes (Weyman et al., 2012). Partnerships between government and medium and large employers may also be advantageous to identify positive human resources practices and develop positive choice architecture that enables and motivates older workers to continue in paid work (Weyman et al., 2012). There is also scope for training opportunities to promote work engagement for individuals both in work (for example, to prepare manual workers to take on new roles) and out of work (for example, making IT and social media training widely available), which may be best placed as continual lifelong learning to avoid loss of confidence and motivation among workers (Altmann, 2015; Phillipson and Smith, 2005).

In all policy strategies to bring extended working lives into fruition, the major role of health in driving workers' decisions (particularly in the 50-55 year age range) and health equity should be considered (Marmot et al., 2020; Holley-Moore et al., 2017; Phillipson and Smith, 2005). For example, the need to prioritize policies to mitigate against work loss in people with osteoathritis has already been raised in the literature (Laires et al., 2018) and the studies in this thesis further emphasize this point; interventions well-evidenced to support people with musculoskeletal conditions to stay in work may be necessary to avoid such individuals being 'left behind' as State Pension eligibility becomes more distant to those in their 50s. The question of whether working life can be extended is critical to policy makers today and in the coming years; individuals, employers, health care providers, and policy makers stand to benefit from the answer to this question being constantly checked - for example, through population surveillance of HWLE.

6.2.4 Challenges and further research

The main challenge for further research and continued use of the HWLE indicator is that of how (and whether) HWLE can be calculated in the future. There is also a need to identify or develop data and methods that can be used to investigate targeted interventions to improve HWLE and estimate more complex models to identify factors that are key drivers of HWLE.

Identification of data source(s) for long-term HWLE surveillance

ELSA data were used in chapters 2, 4 and 5 but recent ELSA survey waves are not linked to mortality data. Additionally, recent survey waves of the Health Survey for England (a national EU health examination survey) (chapter 3) do not provide individual year of age data. Understanding Society is an ongoing longitudinal study that contains a wealth of population data and benefits from boost samples to represent minority ethnic groups in the UK, but could not be analysed in this thesis due to no mortality data linkage. With suitable survey data becoming more difficult to obtain, future research is needed to identify multiple (partial) sources of health, employment, and mortality data and investigate the scope for longitudinal survey data (that measure health status and work status) to be used in conjunction with data from these other sources, such as mortality statistics and databases of routinely collected primary care medical records such as Clinical Practice Research Datalink (CPRD).

Methodological challenges for long-term HWLE surveillance

The various approaches to estimating HWLE in this thesis demonstrate the dependency of HWLE estimates on methodology and definitions. A sustainable approach to estimating HWLE therefore requires consistency and is likely to include methodological development alongside addressing data challenges. One avenue of further research for this purpose is to include information from different data sources within a dynamic microsimulation approach (where CPRD, for example, provides means of determining probabilities of certain outcomes associated with certain factors), which then simulates data for analysis and facilitates investigation of HWLE under different scenarios and interventions.

Developing new methods

A simulation approach would also be advantageous for producing local HWLE estimates, which is challenging using survey data alone due to the need for large sample sizes and (if using a Markov chain approach) the limited possibility to incorporate survey weighting.

To estimate HWLE using a dynamic microsimulation approach, a base population would be required which could include data from:

- ELSA (as this ongoing survey includes the necessary health and work questions and has been demonstrated in this thesis to be suitable for estimation of HWLE)
- Understanding Society (advantageous in its boost samples of minority ethnic groups)
- UK Biobank sample (a source of medical record data linked to socio-demographic data with some self-reported health data)

A CPRD sample (advantageous as this data source will continue to be available and allows objective identification of health conditions such as osteoarthritis and cardiovascular disease) would also be used for estimation of probabilities of death and objectively recorded health events occurring. ELSA and Understanding Society data (and, where possible, UK Biobank data) would be used for estimation of probabilities of changes in health (limiting long-standing illness) and work statuses, and self-reported health, lifestyle, socio-demographic and workplace factors. Probabilities would be estimated over a two year period to correspond to the ELSA and Understanding Society data collection timetable; the most recent two survey waves would be used for this with the earlier wave included in the base population. Missing values and variables that were not collected in each data source would be imputed using multiple imputation by chained equations (with additional auxilliary variables available across data sources including socio-demographic variables, self-reported specific health conditions, and number of co-morbidities) before scaling the base population up to the size of the national population using (survey) weights. A random sample would then be taken for which future values of variables are simulated (using the two-year probabilities of events estimated and in a designated order). The proposed approach to estimating HWLE is to simulate three 'waves' of data two years apart (as in survey data) and estimate health expectancies using IMaCh, as this methodology was specifically designed for the estimation of health expectancies. Other approaches would also be considered, for example estimating the monthly probabilities of each event and simulating a larger number of years into the future (allowing direct calculation of the average number of healthy working years). Newer approaches such as the theory of Markov chains with rewards (health and working status) would also be considered (Caswell and Zarulli, 2018). The ability to specify and simulate a large sample size would allow for more complex models to be estimated (for example to identify drivers of reduced HWLE among people with OA) using the IMaCh and R methods used in chapters 2, 4 and 5.

6.3 Final conclusions

Taken as an indicator of population ableness to work for longer, the studies of Healthy Working Life Expectancy presented in this thesis indicate that deferred eligibility for the State Pension and an expectation to work for longer will present difficulties for many people in England. Promoting healthy lifestyles, reducing inequalities, and improving access to good work opportunities in later working life may enable longer healthy working lives. However, more work is needed to identify, understand the potential effect of, and support the implementation of evidence-based interventions. As a population indicator, HWLE will be most useful to policy makers when used for surveillance and population monitoring. Population health, wellbeing, demographics, opportunities, and preferences are constantly changeable; as the question of whether people can work until they are older will remain important, so too will the need to find a sustainable approach to regularly update HWLE estimates.

Bibliography

Abuladze, Liili et al. (2017). “Associations between self-rated health and health behaviour among older adults in Estonia: a cross-sectional analysis”. *BMJ Open* 7.6, e013257.

Ackerman, Phillip L and Ruth Kanfer (2020). “Work in the 21st century: New directions for aging and adult development”. *Am. Psychol.* 75.4, pp. 486–498.

Ahola, Kirsi and Jari Hakanen (2007). “Job strain, burnout, and depressive symptoms: a prospective study among dentists”. *J. Affect. Disord.* 104.1-3, pp. 103–110.

Allen, Jessica and Sorcha Daly (2016). *Older people and the social determinants of health*. Tech. rep. UCL Institute of Health Equity.

Altmann, Ros (2015). *A new vision for older workers: retain, retrain, recruit*. Tech. rep.

Andersen, Per Kragh and Niels Keiding (2002). “Multi-state models for event history analysis”. *Stat. Methods Med. Res.* 11.2, pp. 91–115.

Au, Nicole and David W Johnston (2014). “Self-assessed health: what does it mean and what does it hide?” *Soc. Sci. Med.* 121, pp. 21–28.

Bachtler, John (2004). “Regional disparities in the United Kingdom”. *Employment and regional development policy: Market efficiency versus policy intervention*. Hannover: Verlag der ARL-Akademie für Raumforschung und Landesplanung, pp. 36–49.

Baek, Ji Hye, Young Sun Kim, and Kwan Hyung Yi (2015). “Relationship between Comorbid Health Problems and Musculoskeletal Disorders Resulting in Musculoskeletal Complaints and Musculoskeletal Sickness Absence among Employees in Korea”. *Saf. Health Work* 6.2, pp. 128–133.

Bagavos, Christos (2013). “Gender and regional differentials in health expectancy in Greece”. *J. Public Health Res.* 2.2, e12.

Baidwan, Navneet K et al. (2019). “A longitudinal study of work-related psychosocial factors and injuries: Implications for the aging United States workforce”. *Am. J. Ind. Med.* 62.3, pp. 212–221.

Baker, Michael, Mark Stabile, and Catherine Deri (2004). "What Do Self-Reported, Objective, Measures of Health Measure?" *J. Hum. Resour.* 39.4, pp. 1067–1093.

Banerjee, Pallavi Amitava (2016). "A systematic review of factors linked to poor academic performance of disadvantaged students in science and maths in schools". *Cogent Education* 3.1, p. 1178441.

Banks, J et al. (2003). *Health, Wealth and lifestyles of the older population in England: The 2002 English Longitudinal Study of Ageing*. Tech. rep. London.

Banks, James et al. (2010). *Financial circumstances, health and well-being of the older population in England*. Tech. rep. ELSA.

Banks, James, James Nazroo, and Andrew Steptoe (2012). *The dynamics of ageing: evidence from the English longitudinal study of ageing 2002-10 (wave 5)*. Tech. rep. ELSA.

— (2014). *The dynamics of ageing: Evidence from the English Longitudinal Study of ageing 2002-12 (Wave 6)*. Tech. rep. ELSA.

Banks, James et al. (2016). *The dynamics of ageing: evidence from the English Longitudinal Study of Ageing 2002-15 (Wave 7)*. Tech. rep.

Barley, Stephen R, Beth A Bechky, and Frances J Milliken (2017). "The Changing Nature of Work: Careers, Identities, and Work Lives in the 21st Century". *AMD* 3.2, pp. 111–115.

Barr, Ben et al. (2012). "Suicides associated with the 2008-10 economic recession in England: time trend analysis". *BMJ* 345, e5142.

Barr, Ben, Peter Kinderman, and Margaret Whitehead (2015). "Trends in mental health inequalities in England during a period of recession, austerity and welfare reform 2004 to 2013". *Soc. Sci. Med.* 147, pp. 324–331.

Barry, Declan T et al. (2017). "Pain Interference and Incident Medical Disorders in the General Population". *Pain Med.* 18.7, pp. 1209–1217.

Bartley, M and C Owen (1996). "Relation between socioeconomic status, employment, and health during economic change, 1973-93". *BMJ* 313.7055, pp. 445–449.

Baumberg, Ben (2012). "Re-evaluating trends in the employment of disabled people in Britain". *Work, health and wellbeing; The challenges of managing health at work*. Ed. by Sarah Vickerstaff, Chris Phillipson, and Ross Wilkie. Bristol: Policy Press, pp. 79–94.

Behr, Andreas, Egon Bellgardt, and Ulrich Rendtel (2005). "Extent and Determinants of Panel Attrition in the European Community Household Panel". *Eur. Sociol. Rev.* 21.5, pp. 489–512.

Beltrán-Sánchez, Hiram, Fahad Razak, and S V Subramanian (2014). "Going beyond the disability-based morbidity definition in the compression of morbidity framework". *Glob. Health Action* 7.1, p. 24766.

Beltrán-Sánchez, Hiram, Samir Soneji, and Eileen M Crimmins (2015). "Past, Present, and Future of Healthy Life Expectancy". *Cold Spring Harb. Perspect. Med.* 5.11.

Benítez-Silva, Hugo et al. (2004). "How Large Is the Bias in Self-Reported Disability?" *J. Appl. Econometrics* 19.6, pp. 649–670.

Black, Carol (2008). *Working for a healthier tomorrow: Dame Carol Black's Review of the health of Britain's working age population*. The Stationery Office.

Black, Nicole et al. (2017). "Who provides inconsistent reports of their health status? The importance of age, cognitive ability and socioeconomic status". *Soc. Sci. Med.* 191, pp. 9–18.

Blundell, Richard et al. (2018). "Income inequality and the labour market in Britain and the US". *J. Public Econ.* 162, pp. 48–62.

Bongers, P M et al. (2006). "Epidemiology of work related neck and upper limb problems: psychosocial and personal risk factors (part I) and effective interventions from a bio behavioural perspective (part II)". *J. Occup. Rehabil.* 16.3, pp. 279–302.

Bonsaksen, Tore et al. (2019). "Who reported having a high-strain job, low-strain job, active job and passive job? The WIRUS Screening study". *PLoS One* 14.12, e0227336.

Booth, H and R Hyndman (2019). *demography: Forecasting Mortality, Fertility, Migration and Population Data*.

Borkhoff, Cornelia M et al. (2011). "Reaching those most in need: a scoping review of interventions to improve health care quality for disadvantaged populations with osteoarthritis". *Arthritis Care Res.* 63.1, pp. 39–52.

Bound, John (1991). "Self-Reported Versus Objective Measures of Health in Retirement Models". *J. Hum. Resour.* 26.1, pp. 106–138.

Bourquin, Pascale et al. (2019). *Why has in-work poverty risen in Britain?* Tech. rep. IFS.

Bowling, Ann (2005). "Just one question: If one question works, why ask several?" *J. Epidemiol. Community Health* 59.5, pp. 342–345.

Bowling, Ann (2014). *Research Methods In Health: Investigating Health And Health Services*. McGraw-Hill Education (UK).

Bridges, S et al. (2015a). *Health Survey for England 2014 Methods and documentation*. Tech. rep. NatCen.

Bridges, Sally, David Hussey, and Margaret Blake (2015b). *The Dynamics of Ageing: The 2012 English Longitudinal Study of Ageing (Wave 6) Technical Report*. Tech. rep.

Brønnum-Hansen, Henrik, Else Foverskov, and Ingelise Andersen (2020). "Occupational inequality in health expectancy in Denmark". *Scand. J. Public Health* 48.3, pp. 338–345.

Brooker, Ann-Sylvia and Joan M Eakin (2001). "Gender, class, work-related stress and health: toward a power-centred approach". *J. Community Appl. Soc. Psychol.* 11.2, pp. 97–109.

Burgard, Sarah A and Katherine Y Lin (2013). "Bad Jobs, Bad Health? How Work and Working Conditions Contribute to Health Disparities". *Am. Behav. Sci.* 57.8.

Burgard, Sarah A, Lucie Kalousova, and Kristin S Seefeldt (2012). "Perceived job insecurity and health: the Michigan Recession and Recovery Study". *J. Occup. Environ. Med.* 54.9, pp. 1101–1106.

Bussolo, Maurizio, Johannes Koettl, and Emily Sinnott (2015). *Golden Aging: Prospects for Healthy, Active, and Prosperous Aging in Europe and Central Asia*. Ed. by World Bank Group. International Bank for Reconstruction and Development / The World Bank.

Buuren, S van and Karin Groothuis-Oudshoorn (2010). "mice: Multivariate imputation by chained equations in R". *J. Stat. Softw.* Pp. 1–68.

Buuren, Stef van and Karin Groothuis-Oudshoorn (2011). *mice: Multivariate Imputation by Chained Equations in R*.

Cai, Lixin (2010). "The relationship between health and labour force participation: Evidence from a panel data simultaneous equation model". *Labour Econ.* 17.1, pp. 77–90.

Cai, Lixin and Guyonne Kalb (2006). "Health status and labour force participation: evidence from Australia". *Health Econ.* 15.3, pp. 241–261.

Cambois, Emmanuelle, Jean-Marie Robine, and Nicolas Brouard (1999). "Life Expectancies Applied to Specific Statuses: a History of the Indicators and the Methods of Calculation". *Population* 11.1, pp. 7–34.

Cao, Bochen (2016). "Future healthy life expectancy among older adults in the US: a forecast based on cohort smoking and obesity history". *Popul. Health Metr.* 14, p. 23.

Carr, Ewan et al. (2016). "Working conditions as predictors of retirement intentions and exit from paid employment: a 10-year follow-up of the English Longitudinal Study of Ageing". *Eur. J. Ageing* 13, pp. 39–48.

Cassarly, Christy et al. (2017). "Assessing type I error and power of multistate Markov models for panel data-A simulation study". *Commun. Stat. Simul. Comput.* 46.9, pp. 7040–7061.

Caswell, Hal and Virginia Zarulli (2018). "Matrix methods in health demography: a new approach to the stochastic analysis of healthy longevity and DALYs". *Popul. Health Metr.* 16.1, p. 8.

Cessie, Saskia le et al. (2012). "Quantification of bias in direct effects estimates due to different types of measurement error in the mediator". *Epidemiology* 23.4, pp. 551–560.

Chen, A et al. (2012). "The Global Economic Cost of Osteoarthritis: How the UK Compares". *Arthritis* 2012, p. 698709.

Chen, Joseph J (2007). "Functional capacity evaluation & disability". *Iowa Orthop. J.* 27, pp. 121–127.

Collett, David (2015). *Modelling Survival Data in Medical Research*. CRC Press.

Costa, Bruno R da and Edgar Ramos Vieira (2010). "Risk factors for work-related musculoskeletal disorders: a systematic review of recent longitudinal studies". *Am. J. Ind. Med.* 53.3, pp. 285–323.

Costa-Black, Katia M, Michael Feuerstein, and Patrick Loisel (2013). "Work disability models: Past and present". *Handbook of work disability: Prevention and management , (pp*. Ed. by Patrick Loisel. Vol. 513. New York, NY, US: Springer Science + Business Media, xxiii, pp. 71–93.

Cridland, John (2016). *Independent review of the State Pension age: interim report*. Tech. rep. Department for Work and Pensions.

— (2017). *Independent Review of the State Pension Age: Smoothing the Transition Final Report*. Tech. rep. Department for Work and Pensions.

Crimmins, E (2002). “Health expectancies: what can we expect from summary indicators of population health”. *Summary measures of population health: concepts, ethics, measurement and application.* Geneva: World Health Organization, pp. 213–221.

Crossley, Thomas F and Steven Kennedy (2002). “The reliability of self-assessed health status”. *J. Health Econ.* 21.4, pp. 643–658.

Cutler, David M and Adriana Lleras-Muney (2006). “Education and Health: Evaluating Theories and Evidence”.

De Agostini, Paola et al. (2014). *Were we really all in it together? The distributional effects of the UK Coalition government’s tax-benefit policy changes*. Tech. rep.

De Silva, Anurika Priyanjali et al. (2019). “Multiple imputation methods for handling missing values in a longitudinal categorical variable with restrictions on transitions over time: a simulation study”. *BMC Med. Res. Methodol.* 19.1, p. 14.

Dhillon, Preeti and Laishram Ladusingh (2013). “Working life gain from gain in old age life expectancy in India”. *Demogr. Res.* 28, pp. 733–762.

Do, Kathy et al. (2018). “Association between cardiorespiratory fitness and metabolic risk factors in a population with mild to severe obesity”. *BMC Obes* 5, p. 5.

Dueñas, María et al. (2016). “A review of chronic pain impact on patients, their social environment and the health care system”. *J. Pain Res.* 9, pp. 457–467.

Dür, Mona et al. (2016). “Initial evidence for the link between activities and health: Associations between a balance of activities, functioning and serum levels of cytokines and C-reactive protein”. *Psychoneuroendocrinology* 65, pp. 138–148.

DWP (2010). *A sustainable State Pension: when the State Pension age will increase to 66*. Tech. rep.

— (2014a). *Fuller Working Lives – A Framework for Action*. Tech. rep.

— (2014b). *State Pension age timetable*. Tech. rep.

— (2017a). *Fuller working lives: a partnership approach*. Tech. rep.

— (2017b). *State Pension age review*. Tech. rep.

— (2017c). *Work, health and disability: improving lives*. Tech. rep.

— (2018). *Economic labour market status of individuals aged 50 and over, trends over time: September 2018 (experimental)*. Title of the publication associated with this dataset: Economic labour market status of individuals aged 50 and over, trends over time: October 2018.

DWP and DoH (2016). *Improving Lives: The Work, Health and Disability Green Paper*. Tech. rep.

Edemekong, Peter F et al. (2020). "Activities of Daily Living (ADLs)". *StatPearls*. Treasure Island (FL): StatPearls Publishing.

Eggleston, Karen N and Victor R Fuchs (2012). "The New Demographic Transition: Most Gains in Life Expectancy Now Realized Late in Life". *J. Econ. Perspect.* 26.3, pp. 137–156.

Eime, Rochelle M et al. (2015). "Participation in sport and physical activity: associations with socio-economic status and geographical remoteness". *BMC Public Health* 15, p. 434.

Equality Act (2010). *c. 15*.

Eriksen, Mette Lindholm, Sonja Vestergaard, and Karen Andersen-Ranberg (2013). "13 Health among Europeans–a cross-sectional comparison of 16 SHARE countries". *Active ageing and solidarity between generations in Europe: First results from SHARE after the economic crisis*, p. 149.

Eskelinen, L et al. (1991). "Relationship between the self-assessment and clinical assessment of health status and work ability". *Scand. J. Work Environ. Health* 17 Suppl 1, pp. 40–47.

Fabbri, Elisa et al. (2015). "Aging and Multimorbidity: New Tasks, Priorities, and Frontiers for Integrated Gerontological and Clinical Research". *J. Am. Med. Dir. Assoc.* 16.8, pp. 640–647.

Farr Ii, Jack, Larry E Miller, and Jon E Block (2013). "Quality of life in patients with knee osteoarthritis: a commentary on nonsurgical and surgical treatments". *Open Orthop. J.* 7, pp. 619–623.

Fila, Marcus J, Justin Purl, and Rodger W Griffeth (2017). "Job demands, control and support: Meta-analyzing moderator effects of gender, nationality, and occupation". *Human Resource Management Review* 27.1, pp. 39–60.

FPFIS team (2019). *The changing nature of work and skills in the digital age*. Tech. rep. EU Science Hub - European Commission.

Fransson, Eleonor I et al. (2012). "Job strain as a risk factor for leisure-time physical inactivity: an individual-participant meta-analysis of up to 170,000 men and women: the IPD-Work Consortium". *Am. J. Epidemiol.* 176.12, pp. 1078–1089.

Fries, James F (1980). "Aging, natural death, and the compression of morbidity". *Bull. World Health Organ.* 303.3, pp. 130–135.

Gary-Webb, Tiffany L et al. (2011). "Neighborhood socioeconomic status, depression, and health status in the Look AHEAD (Action for Health in Diabetes) study". *BMC Public Health* 11, p. 349.

Gelbard, A, C Haub, and M M Kent (1999). "World population beyond six billion". *Popul. Bull.* 54.1, pp. 1–44.

Gignac, Monique A M and Xingshan Cao (2009). ""Should I tell my employer and coworkers I have arthritis?" A longitudinal examination of self-disclosure in the work place". *Arthritis Rheum.* 61.12, pp. 1753–1761.

Gignac, Monique A M, Deborah Sutton, and Elizabeth M Badley (2007). "Arthritis symptoms, the work environment, and the future: measuring perceived job strain among employed persons with arthritis". *Arthritis Rheum.* 57.5, pp. 738–747.

Gignac, Monique A M et al. (2012). "Tension at the borders: perceptions of role overload, conflict, strain and facilitation in work, family and health roles among employed individuals with arthritis". *Rheumatology* 51.2, pp. 324–332.

Gillam, Marianne H et al. (2010). "Competing risks survival analysis applied to data from the Australian Orthopaedic Association National Joint Replacement Registry". *Acta Orthop.* 81.5, pp. 548–555.

Gisev, Natasa, J Simon Bell, and Timothy F Chen (2013). "Interrater agreement and interrater reliability: key concepts, approaches, and applications". *Res. Social Adm. Pharm.* 9.3, pp. 330–338.

Godwin, Marshall et al. (2003). "Pragmatic controlled clinical trials in primary care: the struggle between external and internal validity". *BMC Med. Res. Methodol.* 3, p. 28.

Goettler, Andrea, Anna Grosse, and Diana Sonntag (2017). "Productivity loss due to overweight and obesity: a systematic review of indirect costs". *BMJ Open* 7.10, e014632.

González, Karimé, Jorge Fuentes, and José Luis Márquez (2017). "Physical Inactivity, Sedentary Behavior and Chronic Diseases". *Korean J. Fam. Med.* 38.3, pp. 111–115.

Graham, J W, A E Olchowski, and T D Gilreath (2007). "How many imputations are really needed? Some practical clarifications of multiple imputation theory". *Prev. Sci.*

Gray, Linsay (2016). “The importance of post hoc approaches for overcoming non-response and attrition bias in population-sampled studies”. *Soc. Psychiatry Psychiatr. Epidemiol.* 51.1, pp. 155–157.

Greene, William H, Mark N Harris, and Bruce Hollingsworth (2015). “Inflated Responses in Measures of Self-Assessed Health”. *American Journal of Health Economics* 1.4, pp. 461–493.

Griffin, Mark A and Sharon Clarke (2011). “Stress and well-being at work”. *APA Handbook of Industrial/Organizational Psychology. Volume 3: Maintaining, Expanding, and Contracting the Organization*. Ed. by Sheldon Zedeck. American Psychological Association, pp. 359–398.

Gronlund, Carina J (2014). “Racial and socioeconomic disparities in heat-related health effects and their mechanisms: a review”. *Curr Epidemiol Rep* 1.3, pp. 165–173.

Groot, W (2000). “Adaptation and scale of reference bias in self-assessments of quality of life”. *J. Health Econ.* 19.3, pp. 403–420.

Grzywacz, Joseph G and Brenda L Bass (2003). “Work, Family, and Mental Health: Testing Different Models of Work-Family Fit”. *J Marriage and Family* 65.1, pp. 248–261.

Guillot, Michel and Yan Yu (2009). “Estimating health expectancies from two cross-sectional surveys: The intercensal method”. *Demogr. Res.* 21, pp. 503–534.

Haan, Peter and Michal Myck (2009). “Dynamics of health and labor market risks”. *J. Health Econ.* 28.6, pp. 1116–1125.

Hacking, John M, Sara Muller, and Iain E Buchan (2011). “Trends in mortality from 1965 to 2008 across the English north-south divide: comparative observational study”. *BMJ* 342, p. d508.

Hallqvist, J et al. (1998). “Is the effect of job strain on myocardial infarction risk due to interaction between high psychological demands and low decision latitude? Results from Stockholm Heart Epidemiology Program (SHEEP)”. *Soc. Sci. Med.* 46.11, pp. 1405–1415.

Hammer, Gaël P, Jean-Baptist du Prel, and Maria Blettner (2009). “Avoiding bias in observational studies: part 8 in a series of articles on evaluation of scientific publications”. *Dtsch. Arztebl. Int.* 106.41, pp. 664–668.

Harezlak, Jaroslaw, Sujuan Gao, and Siu L Hui (2003). “An illness-death stochastic model in the analysis of longitudinal dementia data”. *Stat. Med.* 22.9, pp. 1465–1475.

Haseen, Fariha, Ramesh Adhikari, and Kusol Soonthorndhada (2010). "Self-assessed health among Thai elderly". *BMC Geriatr.* 10, p. 30.

Häusser, Jan Alexander et al. (2010). "Ten years on: A review of recent research on the Job Demand–Control (-Support) model and psychological well-being". *Work & Stress* 24.1, pp. 1–35.

Hayden, Jill A et al. (2013). "Assessing bias in studies of prognostic factors". *Ann. Intern. Med.* 158.4, pp. 280–286.

Healey, Emma Louise et al. (2018). "Uptake of the NICE osteoarthritis guidelines in primary care: a survey of older adults with joint pain". *BMC Musculoskelet. Disord.* 19.1, p. 295.

Heerkens, Yvonne et al. (2004). "The use of the ICF to describe work related factors influencing the health of employees". *Disabil. Rehabil.* 26.17, pp. 1060–1066.

Herr, Raphael M et al. (2015). "Three job stress models and their relationship with musculoskeletal pain in blue- and white-collar workers". *J. Psychosom. Res.* 79.5, pp. 340–347.

Ho, Jessica Y and Arun S Hendi (2018). "Recent trends in life expectancy across high income countries: retrospective observational study". *BMJ* 362, k2562.

Hofäcker, Dirk et al. (2016). "Trends and Determinants of Work-Retirement Transitions under Changing Institutional Conditions: Germany, England and Japan compared". *J. Soc. Policy* 45.1, pp. 39–64.

Hoffman, Brian J, Mindy K Shoss, and Lauren A Wegman (2020). *The Cambridge Handbook of the Changing Nature of Work*. Cambridge University Press.

Holley-Moore, G, D Hochlaf, and A Riaz (2017). *Working for everyone: Addressing barriers and inequalities in the extended working lives agenda*. Tech. rep. ILC-UK.

Hougaard, P (1999). "Multi-state models: a review". *Lifetime Data Anal.* 5.3, pp. 239–264.

House of Commons Health Committee (2009). "Health inequalities: Third report of session 2008–09". *London: The Stationery Office*.

Hsiao, Ru-Ling et al. (2019). "Validation of the global activity limitation indicator in Taiwan". *BMC Med. Res. Methodol.* 19.1, p. 52.

Huggins, Robert, Piers Thompson, and Daniel Prokop (2019). *UK Competitiveness Index 2019*. Tech. rep.

Hunter, David J and Sita Bierma-Zeinstra (2019). "Osteoarthritis". *Lancet* 393.10182, pp. 1745–1759.

Hunter, David J and Felix Eckstein (2009). "Exercise and osteoarthritis". *J. Anat.* 214.2, pp. 197–207.

Hurtado, D A et al. (2012). "Racial disparities in job strain among American and immigrant long-term care workers". *Int. Nurs. Rev.* 59.2, pp. 237–244.

Hutchinson, Rebecca A et al. (2015). "Penalized likelihood methods improve parameter estimates in occupancy models". *Methods Ecol. Evol.* 6.8. Ed. by Robert Freckleton, pp. 949–959.

Hyndman, Rob et al. (2020). *forecast: Forecasting functions for time series and linear models*.

Hyndman, Rob J and Yeasmin Khandakar (2008). *Automatic time series forecasting: the forecast package for R*.

Jackson, Christopher H (2011). "Multi-State Models for Panel Data: The msm Package for R". *Journal of Statistical Software, Articles* 38.8, pp. 1–29.

Jackson, Christopher H et al. (2003). "Multistate Markov models for disease progression with classification error". *Journal of the Royal Statistical Society: Series D (The Statistician)* 52.2, pp. 193–209.

Jackson, Denise (2020). "The changing nature of graduate roles and the value of the degree". *Journal of Higher Education Policy and Management*, pp. 1–16.

Jagger, Carol (2015). *Trends in life expectancy and healthy life expectancy*. Tech. rep. Government Office for Science, p. 29.

Jagger, Carol and Jean-Marie Robine (2011). "Healthy Life Expectancy". *International Handbook of Adult Mortality*. International Handbooks of Population. Springer, Dordrecht, pp. 551–568.

Jagger, Carol et al. (2007). "The burden of diseases on disability-free life expectancy in later life". *J. Gerontol. A Biol. Sci. Med. Sci.* 62A.4, pp. 408–414.

Jagger, Carol et al. (2008). "Inequalities in healthy life years in the 25 countries of the European Union in 2005: a cross-national meta-regression analysis". *Lancet* 372.9656, pp. 2124–2131.

Jagger, Carol et al. (2010). "The Global Activity Limitation Index measured function and disability similarly across European countries". *J. Clin. Epidemiol.* 63.8, pp. 892–899.

Jagger, Carol, Herman Van Oyen, and Jean-Marie Robine (2014). "Health expectancy calculation by the Sullivan method: a practical guide". *Nihon University Population Research Institute (NUPRI) Research Paper Series* 68.

Jalali, Arash et al. (2014). "The EBMT Risk Score in the Presence of Graft Versus Host Disease in Allogeneic Stem Cell Transplantation in Adult Acute Myelogenous Leukemia: A Multistate Model for Competing Risks". *Int J Hematol Oncol Stem Cell Res* 8.3, pp. 1–11.

Jasilionis, Domantas and Vladimir M Shkolnikov (2016). "Longevity and Education: A Demographic Perspective". *Gerontology* 62.3, pp. 253–262.

Johnston, David W, Carol Propper, and Michael A Shields (2009). "Comparing subjective and objective measures of health: Evidence from hypertension for the income/health gradient". *J. Health Econ.* 28.3, pp. 540–552.

Johri, Roopali (2005). "Work values and the quality of employment: A literature review". *New Zealand: Department of Labour*.

Jordan, Kelvin P et al. (2019). "Pain that does not interfere with daily life-a new focus for population epidemiology and public health?" *Pain* 160.2, pp. 281–285.

Jylhä, Marja (2009). "What is self-rated health and why does it predict mortality? Towards a unified conceptual model". *Soc. Sci. Med.* 69.3, pp. 307–316.

Kadam, U T, K Jordan, and P R Croft (2004). "Clinical comorbidity in patients with osteoarthritis: a case-control study of general practice consulters in England and Wales". *Ann. Rheum. Dis.* 63.4, pp. 408–414.

Kain, Jason and Steve Jex (2010). "Karasek's (1979) job demands-control model: A summary of current issues and recommendations for future research". *New Developments in Theoretical and Conceptual Approaches to Job Stress*. Ed. by L Perrewé Pamela and C Ganster Daniel. Vol. 8. Research in Occupational Stress and Well Being. Emerald Group Publishing Limited, pp. 237–268.

Kaprio, J et al. (1996). "Total and occupationally active life expectancies in relation to social class and marital status in men classified as healthy at 20 in Finland". *Journal of Epidemiology & Community Health* 50.6, pp. 653–660.

Karasek, R and T Theorell (1990). *Healthy Work: Stress, Productivity, and the Reconstruction of Working Life*. Basic Books.

Karasek, Robert A (1979). "Job Demands, Job Decision Latitude, and Mental Strain: Implications for Job Redesign". *Adm. Sci. Q.* 24.2, pp. 285–308.

Katikireddi, Srinivasa Vittal et al. (2017). "Devolution of power, revolution in public health?" *J. Public Health* 39.2, pp. 241–247.

Kingston, Andrew et al. (2018). "Forecasting the care needs of the older population in England over the next 20 years: estimates from the Population Ageing and Care Simulation (PACSim) modelling study". *Lancet Public Health* 3.9, e447–e455.

Kohl, Harold W et al. (2012). "The pandemic of physical inactivity: global action for public health". *Lancet* 380.9838, pp. 294–305.

Kontio, Tea, Eira Viikari-Juntura, and Svetlana Solovieva (2019). "Effect of Osteoarthritis on Work Participation and Loss of Working Life-years". *J. Rheumatol.*

Kozlov, Elissa et al. (2020). "The Epidemiology of Depressive Symptoms in the Last Year of Life". *J. Am. Geriatr. Soc.* 68.2, pp. 321–328.

Laaksonen, Mikko et al. (2010). "Gender differences in sickness absence–the contribution of occupation and workplace". *Scand. J. Work Environ. Health* 36.5, pp. 394–403.

Lacaille, D and R S Hogg (2001). "The effect of arthritis on working life expectancy". *J. Rheumatol.* 28.10, pp. 2315–2319.

Lacey, R J et al. (2015). "Clustering of pain and its associations with health in people aged 50 years and older: cross-sectional results from the North Staffordshire Osteoarthritis Project". *BMJ Open* 5.11, e008389.

Laditka, Sarah B and Douglas A Wolf (1995). "Active Life Expectancy and the Use of Home and Community-Based Long-Term Care Services: A Microsimulation Approach". *Center for Policy Research, Syracuse University. Paper presented at the 48th Annual Scientific Meeting of the Gerontological Society of America, Los Angeles, CA*.

— (1998). "New methods for analyzing active life expectancy". *J. Aging Health* 10.2, pp. 214–241.

Laires, Pedro A et al. (2018). "The impact of osteoarthritis on early exit from work: results from a population-based study". *BMC Public Health* 18.1, p. 472.

Landis, J R and G G Koch (1977). "The measurement of observer agreement for categorical data". *Biometrics* 33.1, pp. 159–174.

Langley, Paul et al. (2010). “The societal impact of pain in the European Union: health-related quality of life and healthcare resource utilization”. *J. Med. Econ.* 13.3, pp. 571–581.

Lavrusheva, Olga (2020). “The concept of vitality. Review of the vitality-related research domain”. *New Ideas Psychol.* 56, p. 100752.

Lee, Aeyoung et al. (2017). “Night Shift Work and Risk of Depression: Meta-analysis of Observational Studies”. *J. Korean Med. Sci.* 32.7, pp. 1091–1096.

Lee, Ronald D and Lawrence R Carter (1992). “Modeling and Forecasting U.S. Mortality”. *J. Am. Stat. Assoc.* 87.419, pp. 659–671.

Lemieux, Thomas (2008). “The changing nature of wage inequality”. *J. Popul. Econ.* 21.1, pp. 21–48.

Lenderink, Annet F et al. (2012). “Review on the validity of self-report to assess work-related diseases”. *Int. Arch. Occup. Environ. Health* 85.3, pp. 229–251.

Leon, David A, Dmitry A Jdanov, and Vladimir M Shkolnikov (2019). “Trends in life expectancy and age-specific mortality in England and Wales, 1970-2016, in comparison with a set of 22 high-income countries: an analysis of vital statistics data”. *Lancet Public Health* 4.11, e575–e582.

Lièvre, A et al. (2007). “Healthy working life expectancies at age 50 in Europe: a new indicator”. *J. Nutr. Health Aging* 11.6, pp. 508–514.

Lièvre, Agnès, Nicolas Brouard, and Christopher Heathcote (2003). “THE ESTIMATION OF HEALTH EXPECTANCIES FROM CROSS-LONGITUDINAL SURVEYS”. *Math. Popul. Stud.* 10.4, pp. 211–248.

Loeser, Richard F (2013). “Aging processes and the development of osteoarthritis”. *Curr. Opin. Rheumatol.* 25.1, pp. 108–113.

Loeser, Richard F et al. (2012). “Osteoarthritis: A disease of the joint as an organ”. *Arthritis & Rheumatism* 64.6, pp. 1697–1707.

Loichinger, Elke and Daniela Weber (2016). “Trends in Working Life Expectancy in Europe”. *J. Aging Health* 28.7, pp. 1194–1213.

— (2020). “Combining Working Life and Health Expectancies”. *International Handbook of Health Expectancies*. Ed. by Carol Jagger et al. Cham: Springer International Publishing, pp. 249–261.

Loisel, P et al. (1997). "A population-based, randomized clinical trial on back pain management". *Spine* 22.24, pp. 2911–2918.

Loisel, Patrick et al. (2005). "Prevention of work disability due to musculoskeletal disorders: the challenge of implementing evidence". *J. Occup. Rehabil.* 15.4, pp. 507–524.

Loopstra, R (2018). "Rising food bank use in the UK: Sign of a new public health emergency?" *Nutr. Bull.* 43.1, pp. 53–60.

Loopstra, Rachel, Aaron Reeves, and Valerie Tarasuk (2019). "The rise of hunger among low-income households: an analysis of the risks of food insecurity between 2004 and 2016 in a population-based study of UK adults". *J. Epidemiol. Community Health* 73.7, pp. 668–673.

Loretto, Wendy and Sarah Vickerstaff (2015). "Gender, age and flexible working in later life". *Work Employ. Soc.* 29.2, pp. 233–249.

Lourenço, Sara et al. (2015). "Psychosocial Work Environment and Musculoskeletal Symptoms among 21-Year-Old Workers: A Population-Based Investigation (2011-2013)". *PLoS One* 10.6, e0130010.

Luchman, Joseph N and M Gloria González-Morales (2013). "Demands, control, and support: a meta-analytic review of work characteristics interrelationships". *J. Occup. Health Psychol.* 18.1, pp. 37–52.

Majer, Istvan M et al. (2013). "Modeling and forecasting health expectancy: theoretical framework and application". *Demography* 50.2, pp. 673–697.

Makin, Anne-marie and Chris Winder (2009). "Managing hazards in the workplace using organisational safety management systems: a safe place, safe person, safe systems approach". *J. Risk Res.* 12.3-4, pp. 329–343.

Mallen, Christian et al. (2005). "Severely disabling chronic pain in young adults: prevalence from a population-based postal survey in North Staffordshire". *BMC Musculoskelet. Disord.* 6, p. 42.

Maltby, Tony (2012). "'Work Ability': a practical model for improving the quality of work, health and wellbeing across the life-course?" *Work, Health and Wellbeing*. Ed. by Sarah Vickerstaff, Chris Phillipson, and Ross Wilkie. Policy Press, pp. 187–208.

Manton, K G (1982). "Changing concepts of morbidity and mortality in the elderly population". *Milbank Mem. Fund Q. Health Soc.* 60.2, pp. 183–244.

Marmot (2010). *Marmot Review: Fair Society, Healthy Lives*. Tech. rep.

Marmot, M et al. (2020). *Health equity in England: the Marmot Review 10 years on*. Tech. rep. Institute of Health Equity.

Marmot, Michael (2020). "Health equity in England: the Marmot review 10 years on". *BMJ* 368, p. m693.

Marshall, Andrea et al. (2009). "Combining estimates of interest in prognostic modelling studies after multiple imputation: current practice and guidelines". *BMC Med. Res. Methodol.* 9, p. 57.

Marshall, Deborah A et al. (2019). "Existing comorbidities in people with osteoarthritis: a retrospective analysis of a population-based cohort in Alberta, Canada". *BMJ Open* 9.11, e033334.

Mastbergen, S C and F P J G Lafeber (2011). "Changes in subchondral bone early in the development of osteoarthritis". *Arthritis Rheum.* 63.9, pp. 2561–2563.

Matsena Zingoni, Zvifadzo et al. (2019). "HIV Disease Progression Among Antiretroviral Therapy Patients in Zimbabwe: A Multistate Markov Model". *Front Public Health* 7, p. 326.

McDonald, Margaret, Marco Dacosta DiBonaventura, and Stacey Ullman (2011). "Musculoskeletal pain in the workforce: the effects of back, arthritis, and fibromyalgia pain on quality of life and work productivity". *J. Occup. Environ. Med.* 53.7, pp. 765–770.

McHorney, C A, J E Ware Jr, and A E Raczek (1993). "The MOS 36-Item Short-Form Health Survey (SF-36): II. Psychometric and clinical tests of validity in measuring physical and mental health constructs". *Med. Care* 31.3, pp. 247–263.

McHugh, Mary L (2012). "Interrater reliability: the kappa statistic". *Biochem. Med.* 22.3, pp. 276–282.

McManus, Sally et al. (2016). *Adult psychiatric morbidity survey: survey of mental health and wellbeing, England, 2014*. Tech. rep.

Mears, Meghann et al. (2019). "Understanding the socioeconomic equity of publicly accessible greenspace distribution: The example of Sheffield, UK". *Geoforum* 103, pp. 126–137.

Mein, G et al. (2000). "Predictors of early retirement in British civil servants". *Age Ageing* 29.6, pp. 529–536.

Meltzer, Howard (2003). *General Measures of Health for use in Health Interview Surveys and Censuses: the UK experience*. Tech. rep. ONS.

Mirowsky, John and Catherine E Ross (2007). "Creative work and health". *J. Health Soc. Behav.* 48.4, pp. 385–403.

Mobasheri, Ali and Mark Batt (2016). "An update on the pathophysiology of osteoarthritis". *Ann. Phys. Rehabil. Med.* 59.5-6, pp. 333–339.

Moher, David et al. (2009). "Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement". *PLoS Med.* 6.7, e1000097.

Moler, Cleve and Charles Van Loan (2003). "Nineteen Dubious Ways to Compute the Exponential of a Matrix, Twenty-Five Years Later". *SIAM Rev.* 45.1, pp. 3–49.

Monden, Christiaan W S, Frank J van Lenthe, and Johan P Mackenbach (2006). "A simultaneous analysis of neighbourhood and childhood socio-economic environment with self-assessed health and health-related behaviours". *Health Place* 12.4, pp. 394–403.

Moon, Ju Ryoung et al. (2017). "The Center for Epidemiologic Studies Depression Scale is an adequate screening instrument for depression and anxiety disorder in adults with congential heart disease". *Health Qual. Life Outcomes* 15.1, p. 176.

Morris, Tim P, Ian R White, and Patrick Royston (2014). "Tuning multiple imputation by predictive mean matching and local residual draws". *BMC Med. Res. Methodol.* 14, p. 75.

Murray, C J and A D Lopez (2000). "Progress and directions in refining the global burden of disease approach: a response to Williams". *Health Econ.* 9.1, pp. 69–82.

Murray, Christopher J L et al. (2012). "Disability-adjusted life years (DALYs) for 291 diseases and injuries in 21 regions, 1990-2010: a systematic analysis for the Global Burden of Disease Study 2010". *Lancet* 380.9859, pp. 2197–2223.

Murray, Emily T et al. (2019). "Inequalities in time from stopping paid work to death: findings from the ONS Longitudinal Study, 2001-2011". *J. Epidemiol. Community Health* 73.12, pp. 1101–1107.

Muszyńska, Magdalena M and Roland Rau (2012). "The Old-Age Healthy Dependency Ratio in Europe". *J. Popul. Ageing* 5.3, pp. 151–162.

Mutafova, M et al. (1996). "Occupational handicap-free life expectancy in Bulgaria 1976-1992 based on the data of the medical expert commissions". *Soc. Sci. Med.* 43.4, pp. 537–542.

NAO (2017). *Homelessness*. Tech. rep. Department for Communities and Local Government.

NatCen Social Research (2018). *User Guide to the Nurse Visit Datasets (Waves 2, 4, 6, 8)*. Tech. rep.

NCCMH (2011). “Common Mental Health Disorders”. *Common Mental Health Disorders: Identification and Pathways to Care*. The British Psychological Society and The Royal College of Psychiatrists.

Nesson, Erik T and Joshua J Robinson (2019). “On the measurement of health and its effect on the measurement of health inequality”. *Econ. Hum. Biol.* 35, pp. 207–221.

NICE (2014). *Obesity: identification, assessment and management. Clinical guideline [CG189]*.

Nieuwenhuijsen, K et al. (2004). “Supervisory behaviour as a predictor of return to work in employees absent from work due to mental health problems”. *Occup. Environ. Med.* 61.10, pp. 817–823.

Noble, S et al. (2019). *The English indices of deprivation 2019: research report 2019*. Tech. rep. MHCLG.

Nuñez, M et al. (2006). “The effect of an educational program to improve health-related quality of life in patients with osteoarthritis on waiting list for total knee replacement: a randomized study”. *Osteoarthritis Cartilage* 14.3, pp. 279–285.

Nurminen, M (2013). “Measuring Working-Life Expectancies: Multistate Vector Regression Approach vs. Prevalence-Based Life Table”. *The Internet Journal of Epidemiology* 12.1.

Nurminen, Markku (2004). “Working population health metrics”. *Scand. J. Work Environ. Health* 30.5, pp. 339–349.

Nurminen, Markku M, Christopher R Heathcote, and Brett A Davis (2004). “Estimating Marginal Cohort Working Life Expectancies from Sequential Cross-sectional Survey Data”. *J. Off. Stat.* 20.3, pp. 495–517.

Nyberg, Solja T et al. (2013). “Job strain and cardiovascular disease risk factors: meta-analysis of individual-participant data from 47,000 men and women”. *PLoS One* 8.6, e67323.

OBR (2017). *Fiscal sustainability report*. Tech. rep. Office for Budget Responsibility.

OECD (1999). *Classifying educational programmes: Manual for ISCED-97 implementation in OECD countries*. OECD Paris.

Oeppen, Jim and James W Vaupel (2002). “Broken limits to life expectancy”. *Science* 296.5570, pp. 1029–1031.

Ogden, Cynthia L et al. (2007). "The epidemiology of obesity". *Gastroenterology* 132.6, pp. 2087–2102.

O'Leary, Chris, Susan O'Shea, and K Albertson (2018). *Homelessness and the Private Rented Sector*. Tech. rep.

Olesen, Sarah C, Peter Butterworth, and Bryan Rodgers (2012). "Is poor mental health a risk factor for retirement? Findings from a longitudinal population survey". *Soc. Psychiatry Psychiatr. Epidemiol.* 47.5, pp. 735–744.

Olshansky, S Jay et al. (1991). "Trading Off Longer Life for Worsening Health: The Expansion of Morbidity Hypothesis". *J. Aging Health* 3.2, pp. 194–216.

ONS (2011). *Monthly figures on deaths registered by area of usual residence, 2010*. Title of the publication associated with this dataset: Deaths registered monthly in England and Wales.

— (2017). *Age distribution of the UK population, 1976 to 2046 (projected)*.

— (2018). *Health state life expectancies, UK QMI*. `https://www.ons.gov.uk/peoplepopulationandc healthandsocialcare/healthandlifeexpectancies/methodologies/healthstatelifeexpec` Accessed: 2020-9-8.

— (2019a). *Expectation of life, high life expectancy variant, England*.

— (2019b). *Expectation of life, low life expectancy variant, England*.

— (2019c). *Expectation of life, principal projection, UK*.

— (2019d). *Health state life expectancies, UK: 2016 to 2018*. `https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/healthandlifeexpectancies/bulletins/healthstatelifeexpectanciesuk/2016to2018`. Accessed: 2020-5-13.

— (2019e). *Health state life expectancy, all ages, UK*.

— (2019f). *Life expectancy at birth and at age 65 years by local areas, UK*.

— (2019g). *National population projections, mortality assumptions: 2018-based*. `https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationproject methodologies/nationalpopulationprojectionsmortalityassumptions2018based`. Accessed: 2020-9-16.

— (2019h). *Past and projected period and cohort life tables, 2018-based, UK*. Tech. rep.

— (2019i). *Past and projected period and cohort life tables, 2018-based, UK: 1981 to 2068*. Tech. rep.

ONS (2019j). *Period and cohort life expectancy explained: December 2019*. https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/lifeexpectancies/methodologies/periodandcohortlifeexpectancyexplained. Accessed: 2020-5-10.

— (2019k). *Principal projection - UK summary*.

— (2019l). *Regional labour market statistics in the UK*. Tech. rep.

— (2019m). *Sickness absence in the UK labour market: 2018*. Tech. rep.

— (2019n). *Single-year life tables, UK: 1980 to 2018*.

— (2020a). *Employment in the UK - Office for National Statistics*. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/employmentintheuk/may2020. Accessed: 2020-5-20.

— (2020b). *Index of Private Housing Rental Prices, UK*. Tech. rep.

— (2020c). *Labour market statistics time series*.

Oxford Economics (2010). *The economic costs of arthritis for the UK economy*. Tech. rep.

Padkapayeva, Kathy et al. (2018). "Gender/Sex Differences in the Relationship between Psychosocial Work Exposures and Work and Life Stress". *Ann Work Expo Health* 62.4, pp. 416–425.

Palace, Jacqueline et al. (2014). "UK multiple sclerosis risk-sharing scheme: a new natural history dataset and an improved Markov model". *BMJ Open* 4.1, e004073.

Pannucci, Christopher J and Edwin G Wilkins (2010). "Identifying and avoiding bias in research". *Plast. Reconstr. Surg.* 126.2, pp. 619–625.

Pantea, Maria-Carmen (2019). "The Changing Nature and Meanings of Manual Work". *Precarity and Vocational Education and Training: Craftsmanship and Employability in Romania*. Ed. by Maria-Carmen Pantea. Cham: Springer International Publishing, pp. 19–34.

Pedersen, Jacob and Jakob Bue Bjorner (2017). "Worklife expectancy in a cohort of Danish employees aged 55-65 years - comparing a multi-state Cox proportional hazard approach with conventional multi-state life tables". *BMC Public Health* 17, pp. 1–11.

Pedersen, Jacob et al. (2020). "High physical work demands and working life expectancy in Denmark". *Occup. Environ. Med.* 77.8, pp. 576–582.

Pfarr, Christian et al. (2010). "I Feel Good! Gender Differences and Reporting Heterogeneity in Self-Assessed Health".

PHE (2017a). *Chapter 1: life expectancy and healthy life expectancy - GOV.UK*. https://www.gov.uk/government/publications/health-profile-for-england/chapter-1-life-expectancy-and-healthy-life-expectancy. Accessed: 2017-10-18.

— (2017b). *Movement Into Employment: Return on Investment Tool*. Tech. rep.

— (2018). *Health profile for England: 2018*. Tech. rep.

— (2019a). *Health profile for England: 2019 Chapter 1: population, deaths, life expectancy and healthy life expectancy (data tables)*.

— (2019b). *PHE Strategy 2020 to 2025*. Tech. rep.

— (2020). *Productive Healthy Ageing Profile*. https://fingertips.phe.org.uk/profile/healthy-ageing/supporting-information/employment. Accessed: 2020-7-30.

Phillipson, Chris and Allison Smith (2005). *Extending working life: A review of the research literature*. Tech. rep. DWP.

Polvinen, Anu et al. (2014). "The contribution of major diagnostic causes to socioeconomic differences in disability retirement". *Scand. J. Work Environ. Health* 40.4, pp. 353–360.

Poole, Lydia and Marta Jackowska (2018). "The Epidemiology of Depressive Symptoms and Poor Sleep: Findings from the English Longitudinal Study of Ageing (ELSA)". *Int. J. Behav. Med.* 25.2, pp. 151–161.

Popay, Jennie et al. (2006). *Guidance on the conduct of narrative synthesis in systematic reviews: A product from the ESRC Methods Programme*.

Price, Richard H, Jin Nam Choi, and Amiram D Vinokur (2002). "Links in the chain of adversity following job loss: how financial strain and loss of personal control lead to depression, impaired functioning, and poor health". *J. Occup. Health Psychol.* 7.4, pp. 302–312.

Pugalis, Lee (2011). "Sub-national economic development: Where do we go from here?" *Journal of Urban Regeneration & Renewal* 4.3, pp. 255–268.

Rani, Uma and Damian Grimshaw (2019). "Introduction: What does the future promise for work, employment and society?" *Int. Labour Rev.* 158.4, pp. 577–592.

Raykov, Tenko and George A Marcoulides (2004). "Using the Delta Method for Approximate Interval Estimation of Parameter Functions in SEM". *Struct. Equ. Modeling* 11.4, pp. 621–637.

Reeuwijk, Kerstin G et al. (2017). "The influence of poor health on competing exit routes from paid employment among older workers in 11 European countries". *Scand. J. Work Environ. Health* 43.1, pp. 24–33.

Reeves, Aaron et al. (2013). "Austere or not? UK coalition government budgets and health inequalities". *J. R. Soc. Med.* 106.11, pp. 432–436.

Rijn, Rogier M van et al. (2014). "Influence of poor health on exit from paid employment: a systematic review". *Occup. Environ. Med.* 71.4, pp. 295–301.

Ringen, Stein (1995). "Well-being, Measurement, and Preferences". *Acta Sociol.* 38.1, pp. 3–15.

Robine, Jean-Marie, Carol Jagger, and Euro-REVES Group (2003a). "Creating a coherent set of indicators to monitor health across Europe: the Euro-REVES 2 project". *Eur. J. Public Health* 13.3 Suppl, pp. 6–14.

Robine, Jean-Marie et al. (2003b). *Determining Health Expectancies*. John Wiley & Sons.

Robroek, Suzan J W et al. (2013). "Poor health, unhealthy behaviors, and unfavorable work characteristics influence pathways of exit from paid employment among older workers in Europe: a four year follow-up study". *Scand. J. Work Environ. Health* 39.2, pp. 125–133.

Robroek, Suzan Jw et al. (2020). "Educational differences in duration of working life and loss of paid employment: working life expectancy in The Netherlands". *Scand. J. Work Environ. Health* 46.1, pp. 77–84.

Rodríguez, Germán (2017). *Statistics and Population*. `https://data.princeton.edu/eco572/leecarter`. Accessed: 2020-6-30.

Roh, Lucienne et al. (2014). "Mortality risk associated with underweight: a census-linked cohort of 31,578 individuals with up to 32 years of follow-up". *BMC Public Health* 14, p. 371.

Roser, Max, Esteban Ortiz-Ospina, and Hannah Ritchie (2020). *Life Expectancy*. `https://ourworldindata.org/life-expectancy`.

Rugulies, Reiner (2019). "What is a psychosocial work environment?" *Scand. J. Work Environ. Health* 45.1.

Ryan, Richard M et al. (2010). "Vitalizing effects of being outdoors and in nature". *J. Environ. Psychol.* 30.2, pp. 159–168.

Sabariego, Carla et al. (2018). "Effectiveness of Integration and Re-Integration into Work Strategies for Persons with Chronic Conditions: A Systematic Review of European Strategies". *Int. J. Environ. Res. Public Health* 15.3.

Sadosky, Alesia B et al. (2015). "The association between lower back pain and health status, work productivity, and health care resource use in Japan". *J. Pain Res.* 8, pp. 119–130.

Salomon, Joshua A et al. (2012). "Healthy life expectancy for 187 countries, 1990-2010: a systematic analysis for the Global Burden Disease Study 2010". *Lancet* 380.9859, pp. 2144–2162.

Saridakis, George, Yanqing Lai, and Stewart Johnstone (2017). "Does workplace partnership deliver mutual gains at work?" *Economic and Industrial Democracy*, p. 0143831X17740431.

Sassi, Franco (2006). "Calculating QALYs, comparing QALY and DALY calculations". *Health Policy Plan.* 21.5, pp. 402–408.

Schaufeli, Wilmar B and Toon W Taris (2014). "A critical review of the job demands-resources model: Implications for improving work and health". *Bridging occupational, organizational and public health: A transdisciplinary approach , (pp*. Ed. by Georg F Bauer. Vol. 249. New York, NY, US: Springer Science + Business Media, viii, pp. 43–68.

Scholes, S et al. (2006). *Living in the 21st century: older people in England*. Tech. rep. ELSA.

Scholes, S et al. (2008). *Technical report (ELSA wave 2): retirement, health and relationships of the older population in England*. Tech. rep. ELSA.

Schuring, Merel et al. (2007). "The effects of ill health on entering and maintaining paid employment: evidence in European countries". *J. Epidemiol. Community Health* 61.7, pp. 597–604.

Schuring, Merel et al. (2013). "The effect of ill health and socioeconomic status on labor force exit and re-employment: a prospective study with ten years follow-up in the Netherlands". *Scand. J. Work Environ. Health* 39.2, pp. 134–143.

Sen, D (2015). "Working with asbestos and the possible health risks". *Occup. Med.* 65.1, pp. 6–14.

Shane Anderson, A and Richard F Loeser (2010). "Why is osteoarthritis an age-related disease?" *Best Pract. Res. Clin. Rheumatol.* 24.1, pp. 15–26.

Siegrist, J, D Klein, and K H Voigt (1997). "Linking sociological with physiological data: the model of effort-reward imbalance at work". *Acta Physiol. Scand. Suppl.* 640, pp. 112–116.

Siegrist, Johannes et al. (2004). "The measurement of effort-reward imbalance at work: European comparisons". *Soc. Sci. Med.* 58.8, pp. 1483–1499.

Siegrist, Johannes et al. (2007). "Quality of work, well-being, and intended early retirement of older employees: baseline results from the SHARE Study". *Eur. J. Public Health* 17.1, pp. 62–68.

Sim, Ida (2016). "Two Ways of Knowing: Big Data and Evidence-Based Medicine". *Ann. Intern. Med.* 164.8, pp. 562–563.

Simundić, Ana-Maria (2013). "Bias in research". *Biochem. Med.* 23.1, pp. 12–15.

Skelly, Andrea C, Joseph R Dettori, and Erika D Brodt (2012). "Assessing bias: the importance of considering confounding". *Evid. Based Spine Care J.* 3.1, pp. 9–12.

Smith, Diane et al. (2018). "Pain and Mortality in Older Adults: The Influence of Pain Phenotype". *Arthritis Care Res.* 70.2, pp. 236–243.

Smith, Kimberly V and Noreen Goldman (2011). "Measuring health status: self-, interviewer, and physician reports of overall health". *J. Aging Health* 23.2, pp. 242–266.

Solinge, Hanna van and Kène Henkens (2010). "Living longer, working longer? The impact of subjective life expectancy on retirement intentions and behaviour". *Eur. J. Public Health* 20.1, pp. 47–51.

Sonnega, Amanda et al. (2014). "Cohort Profile: the Health and Retirement Study (HRS)". *Int. J. Epidemiol.* 43.2, pp. 576–585.

Spijker, Jeroen and John MacInnes (2013). "Population ageing: the timebomb that isn't?" *BMJ* 347, f6598.

Steenbergen, E van et al. (2016). "Insights into the concept of vitality: associations with participation and societal costs". *Eur. J. Public Health* 26.2, pp. 354–359.

Steptoe, Andrew et al. (2013). "Cohort profile: the English longitudinal study of ageing". *Int. J. Epidemiol.* 42.6, pp. 1640–1648.

Stern, Steven (1989). "Measuring The Effect Of Disability On Labor Force Participation". *The Journal of Human Resources; Madison* 24.3, pp. 361–396.

Suri, Pradeep, David C Morgenroth, and David J Hunter (2012). "Epidemiology of osteoarthritis and associated comorbidities". *PM R* 4.5 Suppl, S10–9.

Sverke, Magnus, Johnny Hellgren, and Katharina Näswall (2002). “No security: A meta-analysis and review of job insecurity and its consequences”. *J. Occup. Health Psychol.* 7.3, pp. 242–264.

Swain, Subhashisa et al. (2019). “Comorbidities in Osteoarthritis: A Systematic Review and Meta-Analysis of Observational Studies”. *Arthritis Care Res.*

Szklo, M and F J Nieto (2014). “Chapter 5: Identifying Noncausal Associations: Confounding”. *Epidemiology: beyond the basics, third edition*. Jones & Bartlett Learning, pp. 153–184.

Taruc-Uy, Rafaelani L and Scott A Lynch (2013). “Diagnosis and treatment of osteoarthritis”. *Prim. Care* 40.4, pp. 821–36, vii.

Taylor, Nick (2017). “A Job, Any Job : The UK Benefits System and Employment Services in an Age of Austerity”. *Observatoire de la société britannique* 19, pp. 267–285.

Taylor, R et al. (2007). *Health, wealth and lifestyles of the older population in England: The 2002 English Longitudinal Study of Ageing Technical Report*. Tech. rep.

Taylor-Robinson, David et al. (2019). “Assessing the impact of rising child poverty on the unprecedented rise in infant mortality in England, 2000-2017: time trend analysis”. *BMJ Open* 9.10, e029424.

Team, R Core and Others (2013). *R: A language and environment for statistical computing*.

The World Bank (2019). *Age dependency ratio, old (% of working-age population)*. `https://data.worldbank.org/indicator/SP.POP.DPND.OL?locations=JP&most_recent_value_desc=true`. Accessed: 2025-11-19.

— (2020). *Life expectancy at birth, total (years)*.

Thijssen, Eva, Arjan van Caam, and Peter M van der Kraan (2015). “Obesity and osteoarthritis, more than just wear and tear: pivotal roles for inflamed adipose tissue and dyslipidaemia in obesity-induced osteoarthritis”. *Rheumatology* 54.4, pp. 588–600.

Thomas, Elaine et al. (2004a). “The North Staffordshire Osteoarthritis Project - NorStOP: prospective, 3-year study of the epidemiology and management of clinical osteoarthritis in a general population of older adults”. *BMC Musculoskelet. Disord.* 5, p. 2.

Thomas, Elaine et al. (2004b). “The prevalence of pain and pain interference in a general population of older adults: cross-sectional findings from the North Staffordshire Osteoarthritis Project (NorStOP)”. *Pain* 110.1-2, pp. 361–368.

Thomas, Elaine et al. (2007). "The effect of age on the onset of pain interference in a general population of older adults: prospective findings from the North Staffordshire Osteoarthritis Project (NorStOP)". *Pain* 129.1-2, pp. 21–27.

Touraine, Célia, Catherine Helmer, and Pierre Joly (2016). "Predictions in an illness-death model". *Stat. Methods Med. Res.* 25.4, pp. 1452–1470.

Tucker, J (2017). *The Austerity Generation: the impact of a decade of cuts on family incomes and child poverty*. Tech. rep. CPAG.

Tuomi, K et al. (2001). "Promotion of work ability, the quality of work and retirement". *Occup. Med.* 51.5, pp. 318–324.

UN (2019). *World Population Prospects 2019, Online Edition*.

UN DESA (2015). *World Population Ageing*. Tech. rep. United Nations.

University College London, Department of Epidemiology and Public Health, National Centre for Social Research (NatCen). (2017). *Health Survey for England*. Ed. by UK Data Service. Title of the publication associated with this dataset: SN: 8488.

US Bureau of Labour Statistics (2020). *Table 6. Employed persons working at home, workplace, and time spent working at each location by full- and part-time status and sex, jobholding status, and educational attainment, 2019 annual averages*.

Van Aerden, Karen et al. (2016). "How does employment quality relate to health and job satisfaction in Europe? A typological approach". *Soc. Sci. Med.* 158, pp. 132–140.

van den Hout, Ardo and Fiona Matthews (2019). "Estimation of life expectancies using continuous-time multi-state models". *Comput. Methods Programs Biomed.* 178, pp. 11–18.

van den Hout, Ardo and Mei Sum Chan (2019). *elect: Estimation of Life Expectancies Using Multi-State Models*.

van der Noordt M. et al. (2019). "Changes in working life expectancy with disability in the Netherlands, 1992-2016". *Scand. J. Work Environ. Health* 45.1, pp. 73–81.

Vassend, O et al. (2011). "Predicting the long-term impact of acquired severe injuries on functional health status: the role of optimism, emotional distress and pain". *Spinal Cord* 49.12, pp. 1193–1197.

Versus Arthritis (2013). *Osteoarthritis in general practice: data and perspectives*. Tech. rep.

Vickerstaff, Sarah, Chris Phillipson, and Ross Wilkie (2012). "Work, health and wellbeing: an introduction". *Work, Health and Wellbeing: The Challenges of Managing Health at Work*. Ed. by Sarah Vickerstaff, Chris Phillipson, and Ross Wilkie. Policy Press, pp. 1–20.

Vyas, Manav V et al. (2012). "Shift work and vascular events: systematic review and meta-analysis". *BMJ* 345, e4800.

Waddell, Gordon and A Kim Burton (2006). *Is Work Good for Your Health and Well-being?* Tech. rep.

Wade, Derick T and Peter W Halligan (2017). "The biopsychosocial model of illness: a model whose time has come". *Clin. Rehabil.* 31.8, pp. 995–1004.

Wagenaar, Alexander C, Amy L Tobler, and Kelli A Komro (2010). "Effects of alcohol tax and price policies on morbidity and mortality: a systematic review". *Am. J. Public Health* 100.11, pp. 2270–2278.

Wagenaar, Alfred F et al. (2012). "Employment contracts and health selection: unhealthy employees out and healthy employees in?" *J. Occup. Environ. Med.* 54.10, pp. 1192–1200.

Wainwright, E et al. (2013). "Return to work with chronic pain: employers' and employees' views". *Occup. Med.* 63.7, pp. 501–506.

Walker, A (2000). "Public policy and the construction of old age in Europe". *Gerontologist* 40.3, pp. 304–308.

Walker, Alan (2002). "A strategy for active ageing". *Int. Soc. Secur. Rev.* 55.1, pp. 121–139.

Wang, Y Claire et al. (2011). "Health and economic burden of the projected obesity trends in the USA and the UK". *Lancet* 378.9793, pp. 815–825.

Wang, Zengmeng et al. (2019). "Five-year native liver survival analysis in biliary atresia from a single large Chinese center: The death/liver transplantation hazard change and the importance of rapid early clearance of jaundice". *J. Pediatr. Surg.* 54.8, pp. 1680–1685.

Webster, Craig and Stanislav Ivanov (2020). "Robotics, Artificial Intelligence, and the Evolving Nature of Work". *Digital Transformation in Business and Society: Theory and Cases*. Ed. by Babu George and Justin Paul. Cham: Springer International Publishing, pp. 127–143.

Weyman, Andrew et al. (2012). "Extending working life: Behaviour change interventions". *London, Department for Work and Pensions*.

White, Ian R, Patrick Royston, and Angela M Wood (2011). "Multiple imputation using chained equations: Issues and guidance for practice". *Stat. Med.* 30.4, pp. 377–399.

White, James et al. (2016). "Duration of depressive symptoms and mortality risk: the English Longitudinal Study of Ageing (ELSA)". *Br. J. Psychiatry* 208.4, pp. 337–342.

WHO (2015). *World Report on Ageing and Health*. Tech. rep.

Wilkie, Ross (2012). "Musculoskeletal disorders: challenges and opportunities". *Work, Health and Wellbeing: The Challenges of Managing Health at Work*. Ed. by Sarah Vickerstaff, Chris Phillipson, and Ross Wilkie. Policy Press, pp. 21–38.

Wilkie, Ross, Manuel Cifuentes, and Glenn Pransky (2011). "Exploring extensions to working life: job lock and predictors of decreasing work function in older workers". *Disabil. Rehabil.* 33.19-20, pp. 1719–1727.

Wilkie, Ross et al. (2014a). "Anticipated significant work limitation in primary care consulters with osteoarthritis: a prospective cohort study". *BMJ Open* 4.9, e005221.

Wilkie, Ross et al. (2014b). "Frequency and predictors of premature work loss in primary care consulters for osteoarthritis: prospective cohort study". *Rheumatology* 53.3, pp. 459–464.

Wilkie, Ross et al. (2019). "Reasons why osteoarthritis predicts mortality: path analysis within a Cox proportional hazards model". *RMD Open* 5.2, e001048.

Wilkie, Ross et al. (2020). "Managing work participation for people with rheumatic and musculoskeletal diseases". *Best Pract. Res. Clin. Rheumatol.* P. 101517.

Wind, Astrid de et al. (2018). "Working life expectancy in good and poor self-perceived health among Dutch workers aged 55-65 years with a chronic disease over the period 1992-2016". *Occup. Environ. Med.* 75.11, pp. 792–797.

Winkler, Megan R et al. (2018). "Does non-standard work mean non-standard health? Exploring links between non-standard work schedules, health behavior, and well-being". *SSM Popul Health* 4, pp. 135–143.

Wolfbein, Seymour L (1949). "The length of working life". *Population Studies* 3.3, pp. 286–294.

Wong, Kapo, Alan H S Chan, and S C Ngan (2019). "The Effect of Long Working Hours and Overtime on Occupational Health: A Meta-Analysis of Evidence from 1998 to 2018". *Int. J. Environ. Res. Public Health* 16.12.

Wynne-Jones, Gwenllian et al. (2018). "Secular trends in work disability and its relationship to musculoskeletal pain and mental health: a time-trend analysis using five cross-sectional surveys (2002-2010) in the general population". *Occup. Environ. Med.* 75.12, pp. 877–883.

Xue, Haihong et al. (2017). "Risk factors of transition from mild cognitive impairment to Alzheimer's disease and death: A cohort study". *Compr. Psychiatry* 78, pp. 91–97.

Yong, Vanessa and Yasuhiko Saito (2012). "Are There Education Differentials in Disability and Mortality Transitions and Active Life Expectancy Among Japanese Older Adults? Findings From a 10-Year Prospective Cohort Study". *The journals of gerontology.Series B, Psychological sciences and social sciences* 67B.3, pp. 343–353.

Yuen, Hon K et al. (2013). "Self-reported versus objectively assessed exercise adherence". *Am. J. Occup. Ther.* 67.4, pp. 484–489.

Zajacova, Anna and Jennifer Beam Dowd (2011). "Reliability of self-rated health in US adults". *Am. J. Epidemiol.* 174.8, pp. 977–983.

Zarini, Gustavo G et al. (2014). "Lifestyle behaviors and self-rated health: the living for health program". *J. Environ. Public Health* 2014, p. 315042.

Zhang, Wei et al. (2010). "Validity of the work productivity and activity impairment questionnaire–general health version in patients with rheumatoid arthritis". *Arthritis Res. Ther.* 12.5, R177.

Zhang, Yuqing and Joanne M Jordan (2010). "Epidemiology of osteoarthritis". *Clin. Geriatr. Med.* 26.3, pp. 355–369.

Zheltoukhova, Ksenia, Lisa O'Dea, and Stephen Bevan (2012). "Taking the strain: the impact of musculoskeletal disorders on work and home life". *London: The Work Foundation*.

Appendix A

Systematic Review Medline Search Strategy (OVID)

TABLE A.1: Systematic review Medline search strategy (using OVID)

	Search	Results
1	occupation.mp. or Occupations/	44932
2	employed.mp.	284862
3	employment/ or employment, supported/ or return to work/ or unemployment/ or workplace/	66609
4	employment.mp.	79103
5	unemployed.mp.	7290
6	unemployment.mp.	12359
7	retirement/ or exp work/	65249
8	retire*.mp.	21663
9	pension.mp. or Pensions/	6001
10	absenteeism/ or presenteeism/	8446
11	absenteeism.mp.	10984
12	presenteeism.mp.	862
13	Workers' Compensation/	7220
14	incapacity benefit.mp.	39
15	"employment and support allowance".mp.	6
	Continued on next page	

Table A.1 – continued from previous page

	Search	Results
16	workers compensation.mp.	8651
17	(long term adj3 sick).mp.	459
18	(longterm adj3 sick).mp.	1
19	Sick Leave/	5090
20	sick leave.mp.	7543
21	(sickness adj3 absence).mp.	2225
22	(attendance adj3 work*).mp.	341
23	productivity.mp.	46966
24	(work* adj3 capacity).mp.	14589
25	(work* adj3 participat*).mp.	4472
26	workplace.mp.	41231
27	1 or 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9 or 10 or 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24 or 25 or 26	580630
28	active life expectanc*.mp.	139
29	disability free life expectanc*.mp.	132
30	disease free life expectanc*.mp.	23
31	health* life year*.mp.	128
32	health adjusted life expectanc*.mp.	51
33	health adjusted life year*.mp.	30
34	disability adjusted life expectanc*.mp.	17
35	disability adjusted life year*.mp.	2412
36	dependent life expectanc*.mp.	6
37	dependent life year*.mp.	0
38	(life expectancy adj3 disabilit*).mp.	263
39	health* expectanc*.mp.	189

Continued on next page

Table A.1 – continued from previous page

	Search	Results
40	work* life expectanc*.mp.	25
41	population indicator*.mp.	49
42	health* life expectanc*.mp.	321
43	28 or 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 41 or 42	3401
44	27 and 43	263

Notes:

1. '.mp' is used to search: title, abstract, original title, name of substance word, subject heading word, keyword heading word, protocol supplementary concept word, rare disease supplementary concept word, unique identifier, synonyms
2. Medical Search Headings (indicated by '/') are used to search content themes
3. Asterisk ('*') used to for truncation. For example, retire* would identify retire, retired, retiree, retirement
4. Using quotation marks restricts the search to the exact term in full as a text string
5. 'adj3' permits up to three words appearing between search terms (which can appear in either order)
6. Boolean operators ('and', 'or') are used to combine and restrict the search using mathematical logic

Appendix B

QUIPS Template

The following questions form the QUIPS template used to assess the quality of research identified in the systematic review.

Bias related to Study Participation

1. The source population or population of interest is adequately described for key characteristics.
2. The sampling frame and recruitment are adequately described, possibly including: methods to identify the sample (number and type used, e.g. referral patterns in healthcare settings); time period of recruitment; place of recruitment (setting and geographic location)
3. Inclusion and exclusion criteria are adequately described, including explicit diagnostic criteria or ′zero time′ description.
4. There is adequate participation in the study by eligible individuals.
5. The baseline study sample (i.e. individuals entering into the study) is adequately described for key characteristics.
6. Study Participation Summary:
   Is the following statement satisfied based on responses to the above questions, "The

study sample represents the population of interest on key characteristics, sufficient to limit potential bias to the results?” (Yes/ Partly/ No/ Unclear/ Not relevant)

Bias related to Study Attrition

7. Response rate (i.e. proportion of study sample completing the study and providing outcome data) is adequate.
8. Attempts to collect information on drop-outs are described.
9. Reasons for ’loss to follow-up’ are provided.
10. Subjects lost to follow-up are adequately described for key characteristics.
11. There are no important differences between completers and non-completers on key characteristics and outcomes.
12. Study Attrition Summary:
    The following statement is satisfied based on responses to the above questions, “Loss to follow-up (from sample to study population) is not associated with key characteristics (i.e. the study data adequately represents the sample), sufficient to limit potential bias?” (Yes/ Partly/ No/ Unclear/ Not relevant)

Bias related to factors associated with the outcome measurement

13. A clear definition or description of the associated factor measured is provided.
14. Continuous variables are reported or appropriate (i.e. not data dependent) cut-points are used.
15. The prognostic factor measure and method used is adequately valid and reliable to limit misclassification bias (e.g. may include relevant outside sources of information on measurement properties, also characteristics such as blind measurement, limited reliance on recall).

16. Adequate proportion of sample has complete data for all relevant outcome periods.

17. The method and setting of measurement is the same for all study participants.

18. Appropriate methods are used if imputation is used for missing prognostic factor data.

19. Prognostic Factor Measurement Summary:
    The following statement is satisfied based on responses to the above questions, "The prognostic factor of interest is adequately measured in study participants to sufficiently limit potential bias?" (Yes/ Partly/ No/ Unclear/ Not relevant)

Bias related to Outcome Measurement

20. A clear definition of the outcome of interest is provided including duration of follow-up, the level and extent of the outcome construct.

21. The outcome measure and method used is adequately valid and reliable to limit misclassification bias (e.g. may include relevant outside sources of information on measurement properties, also characteristics such as blind measurement, confirmation of outcome with valid and reliable test).

22. The method and setting of measurement is the same for all study participants.

23. Outcome Measurement Summary:
    The following statement is satisfied based on responses to the above questions, "The outcome of interest is adequately measured in study participants to sufficiently limit potential bias?" (Yes/ Partly/ No/ Unclear/ Not relevant)

Bias related to Confounding Measurement and Account

24. All important confounders, including treatments (key variables in conceptual model) are measured.

25. Clear definitions of the important confounders measured are provided (e.g. including dose, level, and duration of exposures).

26. Measurement of all important confounders is adequately valid and reliable (e.g. may include relevant outside sources of information on measurement properties, also characteristics such as blind measurement, limited reliance on recall).

27. The method and setting of confounding measurement is the same for all study participants.

28. Appropriate methods are used if imputation is used for missing confounder data.

29. Important potential confounders are accounted for in the study design (i.e. matching for key variables, stratification, or initial assembly of comparable groups).

30. Important potential confounders are accounted for in the analysis (i.e. appropriate adjustment).

31. Confounding Measurement and Account Summary:
    The following statement is satisfied based on responses to the above questions, "Important potential confounders are appropriately accounted for, limiting potential bias with respect to the prognostic factor of interest?" (Yes/ Partly/ No/ Unclear/ Not relevant)

Bias related to Analysis

32. There is sufficient presentation of data to assess the adequacy of the analysis.

33. The strategy for model building (i.e. inclusion of variables) is appropriate and based on a conceptual framework or model.

34. The selected model is adequate for the design of the study.

35. There is no selective reporting of results.

36. Analysis Summary:
    The following statement is satisfied based on the responses to the above questions,

"The statistical analysis is appropriate for the design of the study, limiting potential for presentation of invalid results?" (Yes/ Partly/ No/ Unclear/ Not relevant)

Appendix C

IMaCh parameter file for estimating HWLE in England

Dataset details and instructions for analysis must be saved in a parameter file to be read by IMaCh. The opening lines call the dataset and specify which columns are present in the dataset text file, in order that data are read correctly.

```
title=England datafile=imachEngland.txt lastobs=15284 firstpass=1 lastpass=6
ftol=1.e-24 stepm=1 ncovcol=1 nqv=3 ntv=0 nqtv=0 nlstate=4 ndeath=1 maxwav=6
    mle=1 weight=0
model=1+age+.
```

Continuation of a preceding line is shown here with indentation. The first (uncommented) line is where user specifies a title for the IMaCh run (here 'England'), the name of the dataset to be used ('imachEngland.txt'), the number of observations in the dataset to use (here, all 15,284 observations), and which of the survey waves in the dataset to include in the analysis (here, this is all six waves included in the dataset, which are ELSA waves 1-6). The parameter file can include comments, which are initiated by starting the line with the hash symbol #. The title choice 'England' indicates that the dataset includes all respondents with data and does not stratify by sex or any other factor of interest.

`firstpass` and `lastpass` at the end of the first line allow the user to select a subset of the interviews in the dataset to be analysed by IMaCh.

The second line requires a tolerance value for convergence `ftol`, which can usually be larger (1.e-8 = 0.00000001) for interpolation units of 24 months, but will generally require a smaller value (such as 1.e-14 or smaller) for IMaCh runs with smaller interpolation steps. The length of the interpolation step is specified by `stepm` (**step** size in **m**onths). The number of covariates contained in the dataset (regardless of whether they are included in the model) are declared in `ncovcol`, `nqv`, `ntv` and `nqtv`. The user must then enter the number of living states, number of death states, number of interview waves included in the data, maximum likelihood estimation preferences, and whether or not to use survey weighting. `mle` (maximum likelihood estimation preferences) can be set to 0 to estimate health expectancies using parameters estimated on a previous run.

Line three is where the model is specified. The specified model is estimated for every possible transition, and more models will be estimated for multi-state models with more states. In the estimation of HWLE, there are 16 permitted transitions and therefore 16 models are estimated. `model=1+age+.` is the simplest model with no added covariates. In this case, transition probability models are estimated with only an intercept term and a coefficient for age ($\alpha_{ij} + \beta_{ij}x$ for transitions from state i to state j). Initial guessed estimates for the parameters (here, α_{ij} and β_{ij}) must be entered in the parameter file with states i and j declared at the start of the line.

```
# Parameters
12 0. 0.
13 0. 0.
14 0. 0.
15 0. 0.
21 0. 0.
23 0. 0.
24 0. 0.
25 0. 0.
31 0. 0.
32 0. 0.
34 0. 0.
35 0. 0.
41 0. 0.
```

```
42 0. 0.
43 0. 0.
45 0. 0.
```

At larger values of `stepm` such as 12 or 24 months, the maximum likelihood estimator will usually converge with guessed starting values of zero. For smaller values of `stepm`, starting values can be approximated from parameters estimated in an earlier run with larger interpolation units. There may be occasions where the maximum likelihood estimator will converge from zero starting values at smaller interpolation units (such as `stemp` = 1, 3 or 6 months), but well-chosen starting values at smaller interpolation units can be necessary for convergence even with 12 month steps. In the IMaCh documentation the software authors recommend an approximation found by adoption of intercept term estimates and coefficient(s) from a previous run, with $log(n)$ subtracted from the intercept term where $newstemp = n * oldstepm$. Thus, estimation of HWLE using monthly interpolation steps may first require, for example, the estimation of HWLE at 24, 12, six and three month interpolation units (with $n = 2$ each time the approximation is computed) and a final approximation with $n = 3$ to generate starting values for the run with monthly interpolation steps.

Starting values must also be given for the scales (required for the hessian matrix) and covariance matrix. These values can be guessed as zero.

```
# Scales
12 0. 0.
13 0. 0.
14 0. 0.
15 0. 0.
21 0. 0.
23 0. 0.
24 0. 0.
25 0. 0.
31 0. 0.
32 0. 0.
```

```
34 0. 0.
35 0. 0.
41 0. 0.
42 0. 0.
43 0. 0.
45 0. 0.
# Covariance matrix
121 0.
122 0. 0.
131 0. 0. 0.
132 0. 0. 0. 0.
141 0. 0. 0. 0. 0.
142 0. 0. 0. 0. 0. 0.
151 0. 0. 0. 0. 0. 0. 0.
152 0. 0. 0. 0. 0. 0. 0. 0.
211 0. 0. 0. 0. 0. 0. 0. 0. 0.
212 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
231 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
232 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
241 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
242 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
251 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
252 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
311 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
312 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
321 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
322 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
341 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
342 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
351 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
352 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
411 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
```

```
    0.
412 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
    0. 0.
421 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
    0. 0. 0.
422 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
    0. 0. 0. 0.
431 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
    0. 0. 0. 0. 0.
432 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
    0. 0. 0. 0. 0. 0.
451 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
    0. 0. 0. 0. 0. 0. 0.
452 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
    0. 0. 0. 0. 0. 0. 0. 0.
```

The final lines of the parameter file allow the user to specify an age range and an interview date range from which observed prevalences of state occupations will be taken. Selecting `pop_based=1` means health expectancies will be computed from observed prevalences of state occupancy in the study population. With this setting, health expectancy results using stable prevalences will also be printed in the results file, whereas selecting stable prevalences produces only the stable prevalences set of results.

```
# agemin agemax for life expectancy, bage fage (if mle==0 ie no data nor Max likeli
agemin=50 agemax=75 bage=50 fage=75 estepm=1 ftolpl=6e-4
# Observed prevalence period
begin-prev-date=1/3/2002 end-prev-date=1/5/2013 mov_average=0
# Health expectancies computed from stable (period) prevalence (pop_based=0) or
    population based (1)
pop_based=1
# Prevalence forecasting
prevforecast=1 yearsfproj=10.0 mobil_average=1
prevbackcast=1 yearsbproj=10.0 mobil_average=1
```

```
# Results model=1+age.
result:.
```

`estepm` should match `stepm` (the interpolation units) for the most precise results. The value of `estepm` gives the spacing for trapezoids used to estimate life expectancy, so that models can be compared by choosing values of `estepm` that are larger than `stepm`. `ftolpl` is a tolerance value for prevalence convergence. Other settings at the end of the parameter file relate to forecasting and projection.

The final line of the parameter file specifies the results that should be written to the results files. With the simplest model (`model=1+age+.`) this line can be specified as `result:.` to print all available results, but covariate values are required for more complex models as problems can arise from IMaCh not knowing which covariate combinations are impossible.

For example, with a model including respectively binary and continuous covariates V0 and V1, the user may be interested in two combinations:

```
result: V0=0 V1=3.5
result: V0=1 V1=3.5
```

Appendix D

Stata '.do' file for preparing ELSA data for IMaCh analysis (shortened)

```
********************************
* ELSA waves 1-6
* Marty Parker
********************************


***************************
*LOAD AND MERGE DATA
***************************

* In RI
cd "<filepath>"

*-------------------------------------------------
*Merge variables extracted from ELSA harmonised dataset with
* those extracted from individual waves (2-7)


* Step 1: load "master" dataset
use ELSAh_dm, clear

* Step 2: merge in the "using" datasets
```

```
forvalues i = 1/7 {
        merge 1:1 idauniq using ELSAw`i'_dm, gen(W`i'merge)
}


*-------------------------------------------------
*Make wave specific variables end in _# (wave number)


forvalues i = 1/7 {
        rename r`i'* =_`i'
        renpfix r`i'
}


forvalues i = 2/7 {
        rename h`i'* =_`i'
        renpfix h`i'
}


forvalues i = 2/7 {
        rename hh`i'* =_`i'
        renpfix hh`i'
}



*-----------------------------------------------




...
[DEFINE LABELS FOR STATA]
...




**************************
*DERIVE HEALTH / WORK STATUSES
**************************
```

```
*HEALTH

* heill* (self-reported long standing illness)
forvalues i = 1/7 {
        recode heill_`i' 2=0
        recode heill_`i' -8=.d
        recode heill_`i' -9=.r
}
label values heill* missingnessLab



* helim* has a self-reported limiting illness
forvalues i = 1/7 {
        recode helim_`i' 2=0
        recode helim_`i' -8=.d
        recode helim_`i' -9=.r
        *recode helim_`i' -1=0 if heill_`i'==0
        replace helim_`i' =heill_`i' if helim_`i'==-1

        lab var helim_`i' "Whether has long-standing illness AND it is limiting"

}
label values helim* missingnessLab


forvalues i = 1/7 {
        gen health_`i' = helim_`i'
        recode health_`i' (1=0) (0=1)
        replace health_`i'=. if health_`i'>.

        lab var health_`i' "Health status for HWLE(good/poor)"
        label values health_`i' healthLab
}

*WORK
rename work_* workforpay_*
```

```
rename work2_* work2jobs_*

lab define workLab .r ".r:Refuse" .d ".d:DK" .m ".m:Missing" .o ".o:Other" 0 "0.no" 1 "1.yes"

gen workforpay_1 = 0
replace workforpay_1=.r if wpact1_1==-9
replace workforpay_1=.d if wpact1_1==-8
replace workforpay_1=. if wpact1_1==.
replace workforpay_1=1 if (wpact1_1==1 | wpact1_1==2 |wpact2_1==1 | wpact2_1==2 |wpact3_1==1 |
                wpact3_1==2 |wpact4_1==1 | wpact4_1==2 |wpact5_1==1 | wpact5_1==2 |wpact6_1==1 |
                wpact6_1==2 )
label values workforpay_1 workLab

forvalues i = 1/7 {
        gen work_`i'=0
        replace work_`i'=1 if workforpay_`i'==1
        replace work_`i'=. if workforpay_`i'>=.

        lab var work_`i' "Work participation (for HWLE)"
        label values work_`i' workLab
}


*HWLE STATUS

*HWLE states variable

forvalues i = 1/7 {
        gen HWLEstates_`i' = -1
        replace HWLEstates_`i'=1 if (health_`i'==1&work_`i'==1)
        replace HWLEstates_`i'=2 if (health_`i'==1&work_`i'==0)
        replace HWLEstates_`i'=3 if (health_`i'==0&work_`i'==1)
        replace HWLEstates_`i'=4 if (health_`i'==0&work_`i'==0)
        replace HWLEstates_`i'=-1 if (health_`i'==.|work_`i'==.)

        lab var HWLEstates_`i' "HWLE states"
```

```
        label values HWLEstates_`i' hwlestatesLab
}


forvalues i = 1/7 {
        gen status_`i' = .
        replace status_`i' = -2 if (iwstat_`i'==0 | iwstat_`i'==7 | iwstat_`i'==9)
        replace status_`i' = -1 if ((iwstat_`i'==1 | iwstat_`i'==4) & HWLEstates_`i'==-1)
        replace status_`i' = HWLEstates_`i' if (HWLEstates_`i'>=1 & HWLEstates_`i'<=4)
        replace status_`i' = 5 if (iwstat_`i'==5 | iwstat_`i'==6)

        lab var status_`i' "HWLE status"
        label values status_`i' statusLab
}



***************************
*IDENTIFY STUDY SAMPLE
***************************

* identify participating core sample members

*drop people who are never core sample members
keep if inlist(cohort_e_1,1) | inlist(cohort_e_2,1) | inlist(cohort_e_3,1,4) |
                inlist(cohort_e_4,1,4,8) | inlist(cohort_e_5,1,4,8) |
                inlist(cohort_e_6,1,4,8,12)

*People who never participate in any of these waves need to be dropped
*drop if (status_2==-2 & status_3==-2 & status_4==-2 & status_5==-2 &
                status_6==-2) //(all incl in next line)
drop if (iwstat_1!=1 & iwstat_2!=1 & iwstat_3!=1 & iwstat_4!=1 & iwstat_5!=1 &
                iwstat_6!=1)


* interview date
```

```
tostring iwind*, replace

forvalues i = 1/7 {
        gen interviewdate_‘i’ = "99/9999"
        replace interviewdate_‘i’ = iwindm_‘i’ + "/" + iwindy_‘i’ if(iwindm_‘i’!="."&iwindy_‘i’!=".")
}

lab var interviewdate_1 "Interview date w1"
lab var interviewdate_2 "Interview date w2"
lab var interviewdate_3 "Interview date w3"
lab var interviewdate_4 "Interview date w4"
lab var interviewdate_5 "Interview date w5"
lab var interviewdate_6 "Interview date w6"
lab var interviewdate_7 "Interview date w7"

drop iwindm* iwindy*

* date of birth
*months are missing - insert 6 as the month for all
*make missing values 99/9999

tostring rabyear, replace
gen birth = "99/9999"
replace birth = "6/" + rabyear if rabyear!=".d"
lab var birth "date of birth"

* date of death
*months are missing - insert 6 as the month for all
*make missing values 99/9999

tostring radyear, replace
gen death6 = "99/9999"
replace death6 = "12/" + radyear if radyear!=".x"
lab var death6 "date of death"
```

```
...
[DATA CLEANING]
...



**************************
*IMPUTE DEATH MONTHS
**************************
save hwlestudytempfiles/ELSAhwlestudy_sendtoRforONSdeath, replace

*GO TO R and run deathmonthsfromONSfunction
/*#The distribution of ONS recorded death rates by month was similar throughout the study
# (2004 and 2005 ONS death record data not available).
#Months of death throughout the study period were imputed from the 2010 ONS death rate by
#2010 was chosen as this was a census year that occured within the study period
*/

cd "S:\Marty\PhD Work\ELSA\Data Management\hwlestudytempfiles"

tempname handle
file open `handle' using "ONSdeathmonthscript.R", write replace
#delimit ;
foreach line in

        "library(readstata13)"
        "setwd('S:/Marty/PhD Work/ELSA/Data Management/hwlestudytempfiles')"
        "dat <- read.dta13('ELSAhwlestudy_sendtoRforONSdeath.dta')"
        "ELSA<-dat"
        "ELSA[,'death']<-ELSA[,'death6']"

        "ONSprobs<-c(9.803326125, 8.322035847, 9.161267372, 8.237223356, 7.4103558,
                8.140697632, "
         "         7.457425648, 7.326194045, 7.991462354, 7.843311635, 8.548274792,
```

```
        9.758425394)"

"#function to assign deathmonth"
"assigndeathmonth<-function(from,to){"
"  deathmonth<-  sample(c(from:to), "
"                       size = 1, replace = TRUE, "
"                       prob = c(ONSprobs[from:to]))"
"  return(deathmonth)"
"}"

"#function to impute death months based on death year and interview date/status"
"monthofdeath<-function(idauniq,deathmonth,interviewmonth,interviewyear,interviewstatus,
        deathyear) {"
"  if (is.na(deathmonth)&&interviewyear!=9999) {"
"    set.seed(idauniq)"
"    set.seed(runif(1, 0, 20000))"
"    deathmonth<-as.numeric(as.character(deathmonth))"
"    interviewmonth<-as.numeric(as.character(interviewmonth))"
"    interviewyear<-as.numeric(as.character(interviewyear))"
"    interviewstatus<-as.numeric(as.character(interviewstatus))"
"    deathyear<-as.numeric(as.character(deathyear))"
"    if (deathyear<=interviewyear) {"
"      if (deathyear<interviewyear) {"
"        newdeathmonth<-assigndeathmonth(1,12)"
"        return(newdeathmonth)"
"      }"
"      else {"
"        if (interviewstatus==5){ #deathmonth needs to be before or equal to interviewmonth"
"          newdeathmonth<-assigndeathmonth(1,interviewmonth)"
"          return(newdeathmonth)"
"        }"
"        else { #deathmonth needs to be AFTER interviewmonth"
"          if (interviewmonth==12){"
"            newdeathmonth<-12"
"            return(newdeathmonth)"
"          }"
```

```
"          else {"
"            newdeathmonth<-assigndeathmonth(interviewmonth,12)"
"            return(newdeathmonth)"
"          }"
"        }"
"      }"
"    }  else return(NA)"
"  } else return(deathmonth)  "
"}"



"#separate months and years of interview and death"
"ELSA[,'interviewmonth1']<-as.numeric(as.character(sub('/.*', '',
        ELSA[,'interviewdate_1'])))"
"ELSA[,'interviewyear1']<-as.numeric(as.character(sub('.*/', '',
        ELSA[,'interviewdate_1'])))"
"ELSA[,'interviewmonth2']<-as.numeric(as.character(sub('/.*', '',
        ELSA[,'interviewdate_2'])))"
"ELSA[,'interviewyear2']<-as.numeric(as.character(sub('.*/', '',
        ELSA[,'interviewdate_2'])))"
"#head(ELSA[,c('interviewdate_2','interviewmonth2','interviewyear2')],n=50)"
"ELSA[,'interviewmonth3']<-as.numeric(as.character(sub('/.*', '',
        ELSA[,'interviewdate_3'])))"
"ELSA[,'interviewyear3']<-as.numeric(as.character(sub('.*/', '',
        ELSA[,'interviewdate_3'])))"
"ELSA[,'interviewmonth4']<-as.numeric(as.character(sub('/.*', '',
        ELSA[,'interviewdate_4'])))"
"ELSA[,'interviewyear4']<-as.numeric(as.character(sub('.*/', '',
        ELSA[,'interviewdate_4'])))"
"ELSA[,'interviewmonth5']<-as.numeric(as.character(sub('/.*', '',
        ELSA[,'interviewdate_5'])))"
"ELSA[,'interviewyear5']<-as.numeric(as.character(sub('.*/', '',
        ELSA[,'interviewdate_5'])))"
"ELSA[,'interviewmonth6']<-as.numeric(as.character(sub('/.*', '',
        ELSA[,'interviewdate_6'])))"
"ELSA[,'interviewyear6']<-as.numeric(as.character(sub('.*/', '',
```

```
                ELSA[,'interviewdate_6'])))"
        "#assign all months of death as NA"
        "ELSA[,'deathmonth']<-NA #remove the Stata imputation"
        "ELSA[,'deathmonth'][c(which(ELSA[,'death']=='99/9999'))]<-99"
        "ELSA[,'deathmonth']<-as.numeric(as.character(ELSA[,'deathmonth']))
                 #remove the Stata imputation"
        "ELSA[,'deathyear']<-as.numeric(as.character(sub('.*/', '', ELSA[,'death'])))"

        "#impute deathmonths"
        "ELSA[,'deathmonth']<-as.numeric(unlist(as.character(apply(ELSA,1,
                function(x) monthofdeath(x['idauniq'],x['deathmonth'],x['interviewmonth1']
                ,x['interviewyear1'],x['status_1'],x['deathyear']))),use.names=FALSE))"
        "ELSA[,'deathmonth']<-as.numeric(unlist(as.character(apply(ELSA,1,
                function(x) monthofdeath(x['idauniq'],x['deathmonth'],x['interviewmonth2'],
                x['interviewyear2'],x['status_2'],x['deathyear']))),use.names=FALSE))"
        "ELSA[,'deathmonth']<-as.numeric(unlist(as.character(apply(ELSA,1,
                function(x) monthofdeath(x['idauniq'],x['deathmonth'],x['interviewmonth3'],
                x['interviewyear3'],x['status_3'],x['deathyear']))),use.names=FALSE))"
        "ELSA[,'deathmonth']<-as.numeric(unlist(as.character(apply(ELSA,1,
                function(x) monthofdeath(x['idauniq'],x['deathmonth'],x['interviewmonth4'],
                x['interviewyear4'],x['status_4'],x['deathyear']))),use.names=FALSE))"
        "ELSA[,'deathmonth']<-as.numeric(unlist(as.character(apply(ELSA,1,
                function(x) monthofdeath(x['idauniq'],x['deathmonth'],x['interviewmonth5'],
                x['interviewyear5'],x['status_5'],x['deathyear']))),use.names=FALSE))"
        "ELSA[,'deathmonth']<-as.numeric(unlist(as.character(apply(ELSA,1,
                function(x) monthofdeath(x['idauniq'],x['deathmonth'],x['interviewmonth6'],
                x['interviewyear6'],x['status_6'],x['deathyear']))),use.names=FALSE))"

        "#make death variable from month and year"
        "ELSA[,'death']<-paste(ELSA[,'deathmonth'], ELSA[,'deathyear'], sep='/')"
        "ELSA[,'deathONS']<-ELSA[,'death']"
        "ELSAbacktostata<-subset(ELSA,select=c('idauniq','deathONS'))"
        "save.dta13(ELSAbacktostata, file='ELSAhwlestudy_ONSdeath.dta')"

{;
  #delimit cr
```

```
  file write ‘handle’ "‘line’" _n
}
file close ‘handle’

shell "C:/Program Files/R/R-3.6.1/bin/Rscript" -e "source('<filepath>/ONSdeathmonthscript.

merge 1:1 idauniq using ELSAhwlestudy_ONSdeath, gen(ONSdeathmerge)

save ELSAhwlestudy_withONSdeath, replace


...
[VARIABLE MANAGEMENT]
...




***************************
*SAVE FOR IMACH
***************************
*England overall***********


use ELSAforPublication/ELSAforPublication_includingmissing, clear

*drop people with missingness
drop if droppedduetomissing==1
save ELSAforPublication/ELSAforPublication_excludingmissing, replace


*prep and save just the imach file

keep ///
sex ///
socialclass ///
```

```
raeducl ///
region ///
birth ///
deathONS ///
interviewdate_1 ///
status_1 ///
interviewdate_2 ///
status_2 ///
interviewdate_3 ///
status_3 ///
interviewdate_4 ///
status_4 ///
interviewdate_5 ///
status_5 ///
interviewdate_6 ///
status_6 ///


order ///
sex ///
socialclass ///
raeducl ///
region ///
birth ///
deathONS ///
interviewdate_1 ///
status_1 ///
interviewdate_2 ///
status_2 ///
interviewdate_3 ///
status_3 ///
interviewdate_4 ///
status_4 ///
interviewdate_5 ///
status_5 ///
interviewdate_6 ///
```

```
status_6 ///



gen id = _n, before(sex)
gen weight = 1, before(birth)

save ELSAforPublication/ELSAforPublication_imachEngland, replace
label drop _all // so that saved text file has values and not labels
outfile using ELSAforPublication/imachEngland.txt, wide replace noquote




*By sex********************
use ELSAforPublication/ELSAforPublication_excludingmissing, clear

keep ///
sex ///
socialclass ///
raeducl ///
region ///
birth ///
deathONS ///
interviewdate_1 ///
status_1 ///
interviewdate_2 ///
status_2 ///
interviewdate_3 ///
status_3 ///
interviewdate_4 ///
status_4 ///
interviewdate_5 ///
status_5 ///
interviewdate_6 ///
status_6
```

```
order ///
sex ///
socialclass ///
raeducl ///
region ///
birth ///
deathONS ///
interviewdate_1 ///
status_1 ///
interviewdate_2 ///
status_2 ///
interviewdate_3 ///
status_3 ///
interviewdate_4 ///
status_4 ///
interviewdate_5 ///
status_5 ///
interviewdate_6 ///
status_6

drop if sex==0 // drop females
drop sex

*create ID variable
gen id = _n, before(socialclass)
gen weight = 1, before(birth)

save ELSAforPublication/ELSAforPublication_imachEngland_MALES, replace
label drop _all // so that saved text file has values and not labels
outfile using ELSAforPublication/imachEnglandMALES.txt, wide replace noquote



use ELSAforPublication/ELSAforPublication_excludingmissing, clear

keep ///
```

```
sex ///
socialclass ///
raeducl ///
region ///
birth ///
deathONS ///
interviewdate_1 ///
status_1 ///
interviewdate_2 ///
status_2 ///
interviewdate_3 ///
status_3 ///
interviewdate_4 ///
status_4 ///
interviewdate_5 ///
status_5 ///
interviewdate_6 ///
status_6


order ///
sex ///
socialclass ///
raeducl ///
region ///
birth ///
deathONS ///
interviewdate_1 ///
status_1 ///
interviewdate_2 ///
status_2 ///
interviewdate_3 ///
status_3 ///
interviewdate_4 ///
status_4 ///
interviewdate_5 ///
```

```
status_5 ///
interviewdate_6 ///
status_6

drop if sex==1 // drop males
drop sex

*create ID variable
gen id = _n, before(socialclass)
gen weight = 1, before(birth)



save ELSAforPublication/ELSAforPublication_imachEngland_FEMALES, replace
label drop _all // so that saved text file has values and not labels
outfile using ELSAforPublication/imachEnglandFEMALES.txt, wide replace noquote
```

Appendix E

R code to impute death dates written by Stata '.do' file

```
library(readstata13)
setwd('S:/Marty/PhD Work/ELSA/Data Management/hwlestudytempfiles')
dat <- read.dta13('ELSAhwlestudy_sendtoRforONSdeath.dta')
ELSA<-dat
ELSA[,'death']<-ELSA[,'death6']
ONSprobs<-c(9.803326125, 8.322035847, 9.161267372, 8.237223356, 7.4103558, 8.140697632,
           7.457425648, 7.326194045, 7.991462354, 7.843311635, 8.548274792, 9.758425394)
#function to assign deathmonth
assigndeathmonth<-function(from,to){
  deathmonth<-  sample(c(from:to),
                       size = 1, replace = TRUE,
                       prob = c(ONSprobs[from:to]))
  return(deathmonth)
}
#function to impute death months based on death year and interview date/status
monthofdeath<-function(idauniq,deathmonth,interviewmonth,interviewyear,interviewstatus,
                deathyear) {
  if (is.na(deathmonth)&&interviewyear!=9999) {
    set.seed(idauniq)
    set.seed(runif(1, 0, 20000))
    deathmonth<-as.numeric(as.character(deathmonth))
    interviewmonth<-as.numeric(as.character(interviewmonth))
```

```
    interviewyear<-as.numeric(as.character(interviewyear))
    interviewstatus<-as.numeric(as.character(interviewstatus))
    deathyear<-as.numeric(as.character(deathyear))
    if (deathyear<=interviewyear) {
      if (deathyear<interviewyear) {
        newdeathmonth<-assigndeathmonth(1,12)
        return(newdeathmonth)
      }
      else {
        if (interviewstatus==5){ #deathmonth needs to be before or equal to interviewmonth
          newdeathmonth<-assigndeathmonth(1,interviewmonth)
          return(newdeathmonth)
        }
        else { #deathmonth needs to be AFTER interviewmonth
          if (interviewmonth==12){
            newdeathmonth<-12
            return(newdeathmonth)
          }
          else {
            newdeathmonth<-assigndeathmonth(interviewmonth,12)
            return(newdeathmonth)
          }
        }
      }
    }  else return(NA)
  } else return(deathmonth)
}
#separate months and years of interview and death
ELSA[,'interviewmonth1']<-as.numeric(as.character(sub('/.*', '',
                ELSA[,'interviewdate_1'])))
ELSA[,'interviewyear1']<-as.numeric(as.character(sub('.*/', '',
                ELSA[,'interviewdate_1'])))
ELSA[,'interviewmonth2']<-as.numeric(as.character(sub('/.*', '',
                ELSA[,'interviewdate_2'])))
ELSA[,'interviewyear2']<-as.numeric(as.character(sub('.*/', '',
                ELSA[,'interviewdate_2'])))
```

```
#head(ELSA[,c('interviewdate_2','interviewmonth2','interviewyear2')],n=50)
ELSA[,'interviewmonth3']<-as.numeric(as.character(sub('/.*', '',
                ELSA[,'interviewdate_3'])))
ELSA[,'interviewyear3']<-as.numeric(as.character(sub('.*/', '',
                ELSA[,'interviewdate_3'])))
ELSA[,'interviewmonth4']<-as.numeric(as.character(sub('/.*', '',
                ELSA[,'interviewdate_4'])))
ELSA[,'interviewyear4']<-as.numeric(as.character(sub('.*/', '',
                ELSA[,'interviewdate_4'])))
ELSA[,'interviewmonth5']<-as.numeric(as.character(sub('/.*', '',
                ELSA[,'interviewdate_5'])))
ELSA[,'interviewyear5']<-as.numeric(as.character(sub('.*/', '',
                ELSA[,'interviewdate_5'])))
ELSA[,'interviewmonth6']<-as.numeric(as.character(sub('/.*', '',
                ELSA[,'interviewdate_6'])))
ELSA[,'interviewyear6']<-as.numeric(as.character(sub('.*/', '',
                ELSA[,'interviewdate_6'])))
#assign all months of death as NA
ELSA[,'deathmonth']<-NA #remove the Stata imputation
ELSA[,'deathmonth'][c(which(ELSA[,'death']=='99/9999'))]<-99
ELSA[,'deathmonth']<-as.numeric(as.character(ELSA[,'deathmonth'])) #remove
                the Stata imputation imputation
ELSA[,'deathyear']<-as.numeric(as.character(sub('.*/', '', ELSA[,'death'])))
#impute deathmonths
ELSA[,'deathmonth']<-as.numeric(unlist(as.character(apply(ELSA,1,function(x)
                monthofdeath(x['idauniq'],x['deathmonth'],x['interviewmonth1'],
                x['interviewyear1'],x['status_1'],x['deathyear']))),use.names=FALSE))
ELSA[,'deathmonth']<-as.numeric(unlist(as.character(apply(ELSA,1,function(x)
                monthofdeath(x['idauniq'],x['deathmonth'],x['interviewmonth2'],
        x['interviewyear2'],x['status_2'],x['deathyear']))),use.names=FALSE))
ELSA[,'deathmonth']<-as.numeric(unlist(as.character(apply(ELSA,1,function(x)
                monthofdeath(x['idauniq'],x['deathmonth'],x['interviewmonth3'],
                x['interviewyear3'],x['status_3'],x['deathyear']))),use.names=FALSE))
ELSA[,'deathmonth']<-as.numeric(unlist(as.character(apply(ELSA,1,function(x)
                monthofdeath(x['idauniq'],x['deathmonth'],x['interviewmonth4'],
                x['interviewyear4'],x['status_4'],x['deathyear']))),use.names=FALSE))
```

```
ELSA[,'deathmonth']<-as.numeric(unlist(as.character(apply(ELSA,1,function(x)
                monthofdeath(x['idauniq'],x['deathmonth'],x['interviewmonth5'],
                x['interviewyear5'],x['status_5'],x['deathyear']))),use.names=FALSE))
ELSA[,'deathmonth']<-as.numeric(unlist(as.character(apply(ELSA,1,function(x)
                monthofdeath(x['idauniq'],x['deathmonth'],x['interviewmonth6'],
                x['interviewyear6'],x['status_6'],x['deathyear']))),use.names=FALSE))
#make death variable from month and year
ELSA[,'death']<-paste(ELSA[,'deathmonth'], ELSA[,'deathyear'], sep='/')
ELSA[,'deathONS']<-ELSA[,'death']
ELSAbacktostata<-subset(ELSA,select=c('idauniq','deathONS'))
save.dta13(ELSAbacktostata, file='ELSAhwlestudy_ONSdeath.dta')
```

Appendix F

HSE sample size: number of respondents at each year of age 50-75 for years 1996-2017

		Males		*Females*	
Year	Age	Sample size	Proportion both healthy and working	Sample size	Proportion both healthy and working
1996	50	136	0.68	148	0.59
	51	138	0.66	149	0.56
	52	119	0.64	138	0.57
	53	109	0.57	138	0.46
	54	104	0.59	119	0.48
	55	102	0.60	98	0.45
	56	95	0.62	107	0.37
	57	91	0.53	112	0.38
	58	107	0.48	110	0.39
	59	84	0.42	108	0.24
	60	118	0.41	130	0.29
	61	104	0.38	100	0.18
	62	101	0.39	86	0.17
	63	101	0.30	120	0.15
	64	93	0.28	116	0.12
	65	98	0.14	103	0.09
	66	103	0.12	136	0.04
	67	93	0.10	128	0.06
	68	100	0.05	125	0.02
	69	85	0.07	90	0.04
	70	84	0.08	108	0.02
	71	93	0.08	100	0.02
	72	85	0.07	107	0.00
	73	80	0.01	92	0.01
	74	74	0.01	111	0.01

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Table F.1 – continued from previous page

		Males		*Females*	
Year	Age	Sample size	Proportion both healthy and working	Sample size	Proportion both healthy and working
	75	71	0.03	99	0.03
1997	50	84	0.75	80	0.48
	51	55	0.62	82	0.55
	52	67	0.67	67	0.51
	53	55	0.75	78	0.47
	54	67	0.70	72	0.51
	55	53	0.57	66	0.41
	56	48	0.52	46	0.46
	57	64	0.36	58	0.38
	58	50	0.52	72	0.25
	59	57	0.51	58	0.45
	60	61	0.43	59	0.17
	61	61	0.43	61	0.25
	62	49	0.35	52	0.27
	63	45	0.33	52	0.19
	64	47	0.32	61	0.13
	65	52	0.13	71	0.07
	66	48	0.04	48	0.04
	67	53	0.04	59	0.02
	68	57	0.02	61	0.07
	69	45	0.09	53	0.00
	70	38	0.08	59	0.05
	71	37	0.08	54	0.06
	72	49	0.04	50	0.02
	73	44	0.05	52	0.00
	74	31	0.00	37	0.03
	75	33	0.00	44	0.00
1998	50	148	0.73	144	0.63
	51	139	0.69	193	0.55
	52	119	0.71	136	0.54
	53	113	0.60	145	0.58
	54	120	0.64	145	0.47
	55	105	0.62	133	0.45
	56	98	0.55	119	0.50
	57	97	0.55	99	0.41
	58	87	0.67	117	0.36
	59	89	0.46	103	0.41
	60	114	0.46	120	0.24
	61	109	0.43	113	0.21
	62	86	0.37	119	0.24
	63	105	0.21	116	0.23
	64	96	0.22	107	0.12
	65	105	0.16	102	0.07
	66	98	0.10	106	0.01
	67	95	0.08	103	0.04
	68	79	0.04	110	0.01
	69	87	0.07	97	0.03

Continued on next page

* **Table F.1 – continued from previous page** *

		Males		*Females*	
Year	Age	Sample size	Proportion both healthy and working	Sample size	Proportion both healthy and working
	70	80	0.05	83	0.00
	71	79	0.04	87	0.01
	72	64	0.11	96	0.02
	73	73	0.03	90	0.01
	74	75	0.03	92	0.02
	75	73	0.07	91	0.02
1999	50	64	0.66	92	0.60
	51	63	0.65	92	0.53
	52	77	0.70	80	0.50
	53	56	0.64	85	0.53
	54	56	0.57	72	0.58
	55	48	0.60	56	0.30
	56	62	0.55	47	0.51
	57	58	0.59	52	0.35
	58	61	0.59	52	0.48
	59	49	0.61	43	0.53
	60	42	0.50	46	0.24
	61	47	0.40	60	0.22
	62	49	0.35	52	0.12
	63	48	0.42	55	0.11
	64	51	0.18	50	0.16
	65	50	0.06	57	0.12
	66	50	0.10	40	0.03
	67	50	0.06	44	0.02
	68	44	0.05	45	0.00
	69	41	0.05	57	0.04
	70	50	0.04	56	0.04
	71	38	0.03	43	0.05
	72	38	0.05	45	0.02
	73	43	0.07	40	0.00
	74	31	0.00	44	0.00
	75	34	0.03	34	0.00
2000	50	57	0.53	58	0.71
	51	84	0.64	68	0.57
	52	66	0.67	77	0.57
	53	52	0.54	86	0.60
	54	57	0.54	78	0.46
	55	61	0.57	64	0.41
	56	64	0.56	67	0.40
	57	70	0.57	66	0.47
	58	49	0.53	65	0.37
	59	49	0.47	50	0.34
	60	43	0.51	57	0.21
	61	60	0.45	58	0.17
	62	59	0.41	59	0.12
	63	43	0.19	45	0.16
	64	34	0.29	49	0.06

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Table F.1 – continued from previous page

Year	Age	*Males* Sample size	*Males* Proportion both healthy and working	*Females* Sample size	*Females* Proportion both healthy and working
	65	61	0.15	55	0.04
	66	53	0.08	60	0.07
	67	49	0.08	41	0.12
	68	63	0.08	48	0.06
	69	43	0.02	64	0.02
	70	42	0.02	63	0.03
	71	45	0.00	52	0.00
	72	61	0.02	60	0.02
	73	35	0.00	60	0.00
	74	42	0.07	70	0.01
	75	42	0.00	59	0.00
2001	50	123	0.71	125	0.62
	51	113	0.65	152	0.59
	52	120	0.68	160	0.53
	53	124	0.60	170	0.59
	54	160	0.63	177	0.52
	55	141	0.60	128	0.57
	56	110	0.54	142	0.48
	57	107	0.53	141	0.43
	58	98	0.49	108	0.31
	59	107	0.53	111	0.40
	60	104	0.47	94	0.20
	61	88	0.35	87	0.24
	62	87	0.31	117	0.22
	63	107	0.24	119	0.16
	64	104	0.27	107	0.11
	65	106	0.18	111	0.11
	66	93	0.18	107	0.08
	67	92	0.04	99	0.09
	68	87	0.09	106	0.04
	69	87	0.05	110	0.05
	70	96	0.08	86	0.03
	71	74	0.07	118	0.02
	72	77	0.03	98	0.03
	73	83	0.02	92	0.00
	74	86	0.02	100	0.01
	75	66	0.03	66	0.02
2002	50	46	0.65	76	0.58
	51	58	0.69	66	0.45
	52	52	0.67	49	0.45
	53	52	0.58	70	0.59
	54	59	0.63	69	0.48
	55	71	0.58	76	0.51
	56	51	0.75	64	0.36
	57	38	0.42	56	0.45
	58	58	0.43	74	0.30
	59	40	0.45	60	0.35

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* Table F.1 – continued from previous page *

		Males		*Females*	
Year	Age	Sample size	Proportion both healthy and working	Sample size	Proportion both healthy and working
	60	40	0.40	43	0.37
	61	53	0.47	58	0.26
	62	41	0.59	45	0.18
	63	58	0.41	54	0.19
	64	43	0.23	51	0.08
	65	45	0.09	52	0.12
	66	38	0.11	53	0.08
	67	34	0.15	63	0.11
	68	43	0.07	40	0.08
	69	46	0.07	37	0.05
	70	46	0.09	37	0.03
	71	36	0.03	44	0.02
	72	29	0.10	46	0.02
	73	35	0.06	33	0.03
	74	25	0.04	46	0.04
	75	23	0.04	48	0.06
2003	50	121	0.74	126	0.63
	51	93	0.60	113	0.60
	52	126	0.66	128	0.52
	53	118	0.65	118	0.54
	54	113	0.67	144	0.57
	55	132	0.62	163	0.55
	56	138	0.61	183	0.53
	57	126	0.55	144	0.47
	58	113	0.47	115	0.41
	59	103	0.46	139	0.50
	60	128	0.42	124	0.27
	61	100	0.43	118	0.22
	62	92	0.42	107	0.22
	63	86	0.37	96	0.20
	64	82	0.30	116	0.13
	65	84	0.20	96	0.09
	66	93	0.15	110	0.12
	67	85	0.08	99	0.02
	68	83	0.10	91	0.05
	69	86	0.06	89	0.06
	70	79	0.05	86	0.01
	71	65	0.06	79	0.01
	72	65	0.02	114	0.02
	73	99	0.03	99	0.03
	74	68	0.04	86	0.02
	75	65	0.02	92	0.01
2004	50	43	0.65	67	0.48
	51	38	0.68	67	0.61
	52	52	0.63	62	0.61
	53	46	0.67	51	0.67
	54	48	0.42	53	0.51

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Table F.1 – continued from previous page

		Males		*Females*	
Year	Age	Sample size	Proportion both healthy and working	Sample size	Proportion both healthy and working
	55	48	0.67	58	0.50
	56	48	0.58	64	0.42
	57	61	0.56	71	0.55
	58	55	0.60	59	0.36
	59	48	0.52	56	0.50
	60	47	0.47	72	0.22
	61	55	0.45	63	0.24
	62	47	0.40	48	0.33
	63	56	0.41	68	0.12
	64	40	0.25	62	0.18
	65	42	0.14	56	0.14
	66	33	0.15	47	0.04
	67	39	0.08	49	0.10
	68	43	0.07	44	0.05
	69	31	0.00	53	0.06
	70	38	0.03	47	0.00
	71	45	0.07	58	0.03
	72	29	0.00	45	0.00
	73	52	0.04	45	0.02
	74	27	0.04	41	0.10
	75	31	0.00	39	0.03
2005	50	67	0.70	62	0.60
	51	56	0.68	60	0.62
	52	53	0.70	84	0.60
	53	59	0.59	71	0.59
	54	72	0.72	49	0.45
	55	61	0.62	63	0.62
	56	52	0.50	74	0.45
	57	66	0.56	69	0.39
	58	65	0.66	74	0.46
	59	63	0.43	76	0.30
	60	46	0.57	64	0.27
	61	63	0.48	70	0.23
	62	56	0.34	60	0.30
	63	51	0.39	73	0.21
	64	61	0.41	53	0.32
	65	119	0.15	112	0.14
	66	124	0.12	141	0.08
	67	127	0.12	136	0.07
	68	126	0.10	128	0.08
	69	113	0.11	127	0.02
	70	114	0.07	134	0.04
	71	94	0.07	109	0.00
	72	107	0.06	135	0.04
	73	104	0.04	117	0.03
	74	87	0.05	101	0.00
	75	79	0.04	98	0.01

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Table F.1 – continued from previous page

		Males		*Females*	
Year	Age	Sample size	Proportion both healthy and working	Sample size	Proportion both healthy and working
2006	50	102	0.71	133	0.65
	51	101	0.62	126	0.63
	52	99	0.65	103	0.58
	53	106	0.65	106	0.63
	54	94	0.74	140	0.54
	55	120	0.57	120	0.50
	56	109	0.61	131	0.51
	57	126	0.56	126	0.47
	58	117	0.71	153	0.42
	59	145	0.54	153	0.52
	60	114	0.57	130	0.33
	61	97	0.53	122	0.20
	62	94	0.40	107	0.28
	63	108	0.43	113	0.13
	64	94	0.21	113	0.17
	65	86	0.19	88	0.15
	66	88	0.11	108	0.10
	67	91	0.13	101	0.05
	68	87	0.13	114	0.09
	69	84	0.10	106	0.05
	70	92	0.08	94	0.05
	71	88	0.07	94	0.01
	72	79	0.04	72	0.04
	73	84	0.06	79	0.01
	74	73	0.04	77	0.01
	75	63	0.05	96	0.01
2007	50	45	0.51	69	0.75
	51	59	0.64	52	0.63
	52	49	0.67	70	0.56
	53	41	0.68	54	0.57
	54	58	0.71	60	0.50
	55	43	0.72	69	0.54
	56	39	0.67	49	0.55
	57	52	0.63	54	0.44
	58	50	0.42	64	0.53
	59	65	0.52	50	0.48
	60	59	0.47	72	0.28
	61	36	0.47	67	0.27
	62	48	0.42	65	0.23
	63	61	0.41	61	0.21
	64	40	0.43	51	0.14
	65	44	0.23	49	0.10
	66	44	0.09	62	0.11
	67	48	0.06	45	0.13
	68	56	0.05	54	0.07
	69	50	0.06	64	0.02
	70	36	0.03	49	0.12
	71	39	0.03	47	0.04
	72	33	0.03	54	0.04

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Table F.1 – continued from previous page

Year	Age	Males Sample size	Males Proportion both healthy and working	Females Sample size	Females Proportion both healthy and working
	73	31	0.06	33	0.00
	74	40	0.03	37	0.03
	75	36	0.03	36	0.03
2008	50	139	0.76	143	0.57
	51	117	0.67	142	0.51
	52	103	0.69	147	0.61
	53	119	0.69	108	0.57
	54	96	0.69	114	0.53
	55	90	0.69	141	0.62
	56	120	0.68	123	0.57
	57	126	0.63	146	0.51
	58	115	0.54	133	0.42
	59	126	0.54	128	0.45
	60	139	0.49	170	0.26
	61	142	0.44	147	0.23
	62	129	0.36	138	0.24
	63	95	0.33	125	0.26
	64	99	0.33	115	0.11
	65	111	0.18	109	0.16
	66	97	0.12	103	0.16
	67	102	0.16	96	0.11
	68	85	0.11	105	0.07
	69	93	0.13	108	0.07
	70	71	0.10	111	0.05
	71	84	0.14	103	0.06
	72	83	0.02	102	0.01
	73	78	0.04	93	0.03
	74	70	0.04	65	0.02
	75	64	0.06	90	0.01
2009	50	40	0.75	45	0.64
	51	21	0.67	29	0.59
	52	37	0.65	24	0.75
	53	26	0.73	39	0.59
	54	32	0.59	32	0.72
	55	39	0.67	34	0.59
	56	36	0.67	30	0.43
	57	31	0.71	41	0.41
	58	32	0.53	37	0.51
	59	25	0.48	41	0.51
	60	36	0.44	28	0.46
	61	38	0.42	43	0.30
	62	46	0.57	55	0.35
	63	38	0.26	32	0.16
	64	38	0.37	49	0.14
	65	41	0.24	45	0.22
	66	38	0.24	54	0.19
	67	29	0.10	35	0.20

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Table F.1 – continued from previous page

		Males		*Females*	
Year	Age	Sample size	Proportion both healthy and working	Sample size	Proportion both healthy and working
	68	27	0.07	32	0.13
	69	29	0.21	31	0.10
	70	37	0.11	21	0.05
	71	29	0.00	32	0.06
	72	26	0.04	28	0.04
	73	35	0.06	34	0.03
	74	24	0.04	27	0.04
	75	25	0.00	32	0.00
2010	50	53	0.64	87	0.71
	51	74	0.76	75	0.64
	52	61	0.66	79	0.52
	53	65	0.58	75	0.59
	54	52	0.63	90	0.53
	55	63	0.57	58	0.55
	56	60	0.57	65	0.48
	57	69	0.61	74	0.61
	58	60	0.58	65	0.38
	59	49	0.49	66	0.50
	60	66	0.45	83	0.31
	61	63	0.40	80	0.20
	62	76	0.46	71	0.20
	63	83	0.35	93	0.13
	64	53	0.40	67	0.18
	65	62	0.27	66	0.21
	66	60	0.17	74	0.16
	67	52	0.17	63	0.11
	68	62	0.15	54	0.06
	69	55	0.05	48	0.08
	70	51	0.08	46	0.04
	71	40	0.03	67	0.01
	72	46	0.04	40	0.10
	73	37	0.03	45	0.02
	74	53	0.06	63	0.02
	75	42	0.05	43	0.02
2011	50	68	0.72	73	0.66
	51	65	0.77	82	0.60
	52	78	0.67	88	0.65
	53	48	0.75	69	0.59
	54	62	0.66	70	0.51
	55	55	0.60	85	0.59
	56	55	0.60	59	0.53
	57	59	0.58	82	0.55
	58	51	0.51	61	0.51
	59	58	0.60	60	0.45
	60	67	0.54	74	0.32
	61	63	0.56	73	0.29
	62	74	0.36	91	0.21

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* Table F.1 – continued from previous page *

		Males		*Females*	
Year	Age	Sample size	Proportion both healthy and working	Sample size	Proportion both healthy and working
	63	69	0.39	80	0.18
	64	78	0.44	104	0.28
	65	42	0.19	70	0.07
	66	62	0.21	73	0.29
	67	59	0.10	78	0.09
	68	63	0.14	65	0.03
	69	42	0.07	56	0.09
	70	43	0.07	55	0.04
	71	40	0.08	60	0.07
	72	44	0.05	52	0.00
	73	55	0.07	61	0.03
	74	55	0.05	40	0.00
	75	45	0.04	48	0.00
2012	50	57	0.77	87	0.70
	51	54	0.69	81	0.63
	52	64	0.61	82	0.67
	53	74	0.68	77	0.70
	54	61	0.74	67	0.52
	55	70	0.69	70	0.53
	56	62	0.58	66	0.50
	57	65	0.63	65	0.54
	58	64	0.66	69	0.39
	59	60	0.67	64	0.48
	60	63	0.46	65	0.40
	61	45	0.58	74	0.34
	62	63	0.43	68	0.35
	63	65	0.31	79	0.19
	64	64	0.38	64	0.20
	65	93	0.29	86	0.15
	66	67	0.18	63	0.16
	67	68	0.10	62	0.15
	68	52	0.08	63	0.11
	69	60	0.17	59	0.07
	70	49	0.04	73	0.03
	71	57	0.16	53	0.04
	72	53	0.06	64	0.00
	73	55	0.04	60	0.05
	74	41	0.10	53	0.06
	75	42	0.02	46	0.02
2013	50	69	0.70	92	0.68
	51	57	0.65	84	0.63
	52	86	0.71	79	0.67
	53	71	0.73	74	0.65
	54	68	0.66	76	0.55
	55	71	0.55	86	0.62
	56	55	0.60	70	0.59
	57	58	0.59	63	0.71

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* **Table F.1 – continued from previous page** *

Year	Age	Males Sample size	Males Proportion both healthy and working	Females Sample size	Females Proportion both healthy and working
	58	63	0.67	67	0.45
	59	62	0.60	71	0.48
	60	50	0.42	69	0.39
	61	69	0.38	82	0.50
	62	56	0.45	81	0.27
	63	45	0.36	74	0.19
	64	75	0.35	80	0.20
	65	80	0.23	88	0.09
	66	92	0.22	89	0.15
	67	56	0.16	68	0.10
	68	73	0.18	63	0.10
	69	58	0.07	53	0.08
	70	57	0.14	68	0.07
	71	53	0.08	55	0.02
	72	50	0.06	60	0.02
	73	50	0.12	52	0.02
	74	44	0.05	55	0.02
	75	46	0.00	40	0.05
2014	50	79	0.73	67	0.70
	51	69	0.75	71	0.66
	52	72	0.72	79	0.66
	53	59	0.71	89	0.62
	54	59	0.66	79	0.59
	55	65	0.66	73	0.58
	56	55	0.64	57	0.40
	57	37	0.68	60	0.57
	58	49	0.65	60	0.55
	59	48	0.67	73	0.47
	60	60	0.42	63	0.44
	61	52	0.48	62	0.37
	62	67	0.45	54	0.24
	63	58	0.33	77	0.19
	64	72	0.40	63	0.16
	65	55	0.29	73	0.11
	66	81	0.22	86	0.09
	67	73	0.19	83	0.11
	68	43	0.07	54	0.11
	69	48	0.17	59	0.10
	70	64	0.19	64	0.05
	71	48	0.04	60	0.03
	72	45	0.07	46	0.07
	73	48	0.04	63	0.06
	74	44	0.09	51	0.02
	75	37	0.03	49	0.02
2015	50-54	309	0.69	393	0.64
	55-59	251	0.61	340	0.54
	60-64	314	0.44	361	0.32

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* Table F.1 – continued from previous page *

		Males		*Females*	
Year	Age	Sample size	Proportion both healthy and working	Sample size	Proportion both healthy and working
	65-69	356	0.21	384	0.09
	70-74	243	0.07	243	0.04
	75-79	199	0.03	239	0.01
	50-54	340	0.71	380	0.59
2016	55-59	296	0.61	354	0.54
	60-64	324	0.45	338	0.33
	65-69	317	0.16	348	0.09
	70-74	234	0.10	279	0.08
	75-79	202	0.02	215	0.01
2017	50-54	293	0.73	392	0.61
	55-59	321	0.62	406	0.53
	60-64	306	0.44	326	0.33
	65-69	282	0.16	332	0.14
	70-74	279	0.09	345	0.06
	75-79	201	0.04	243	0.02

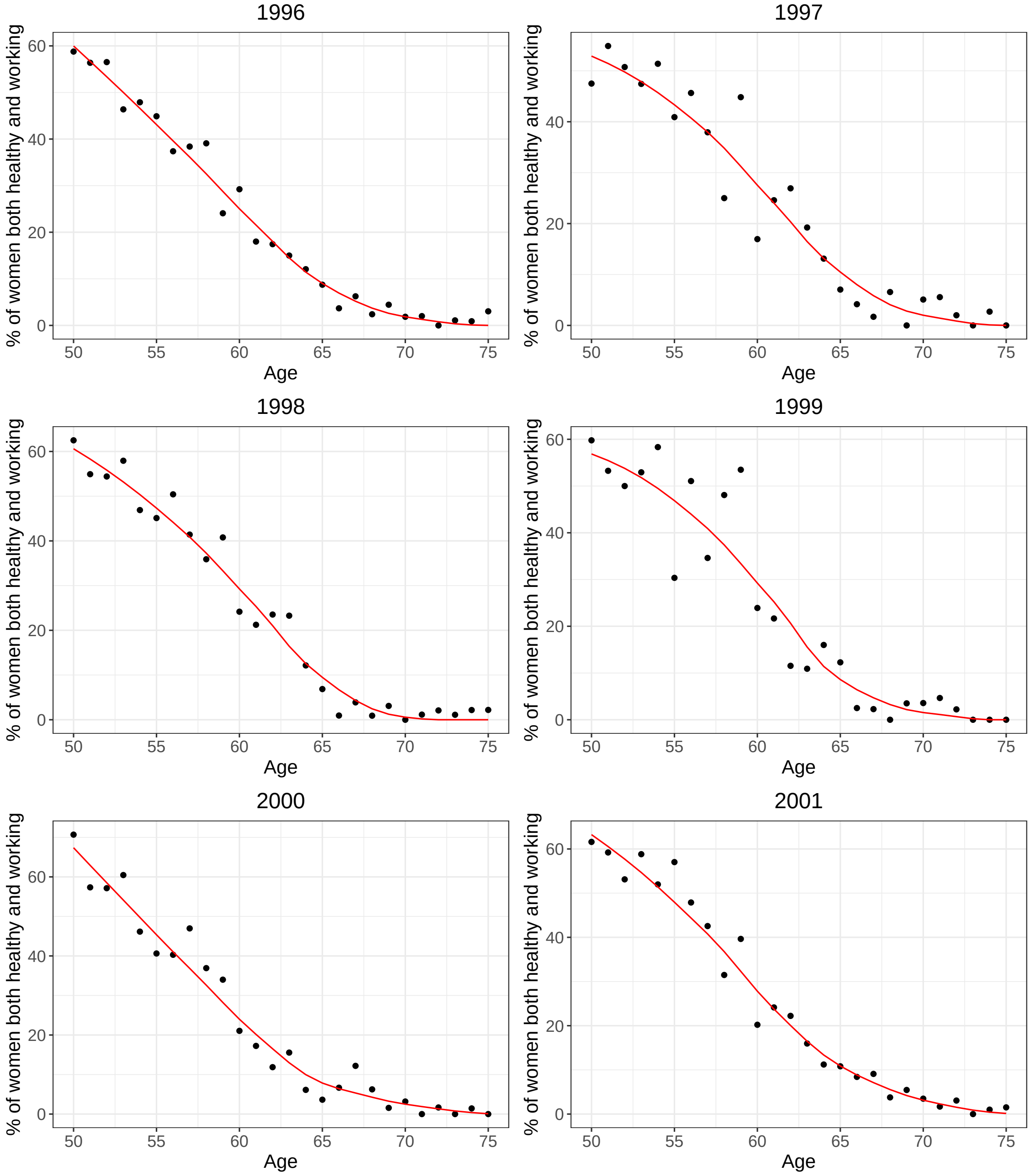
Source: Health Survey for England (HSE) 1996-2017 (NatCen 2017)

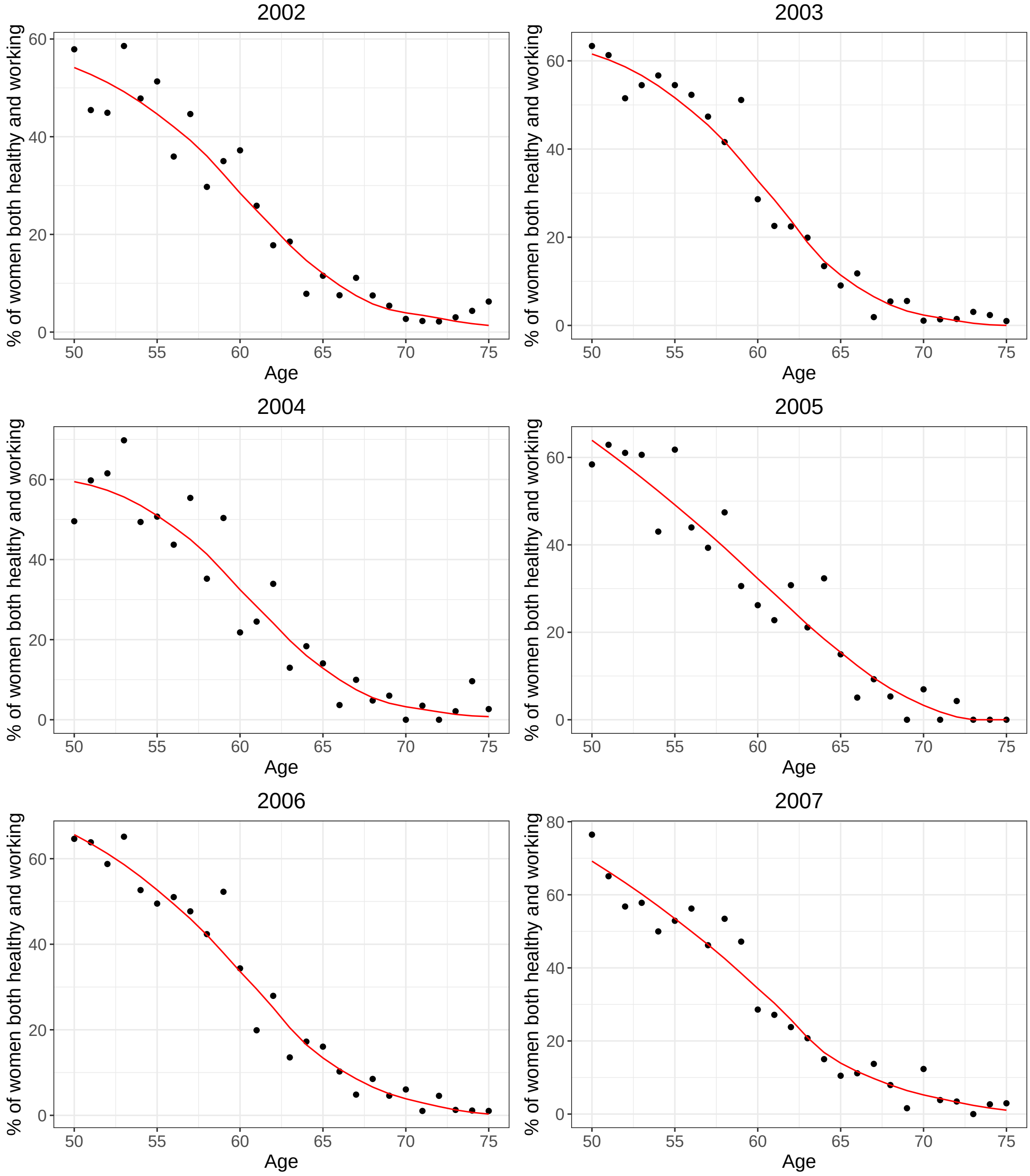
Appendix G

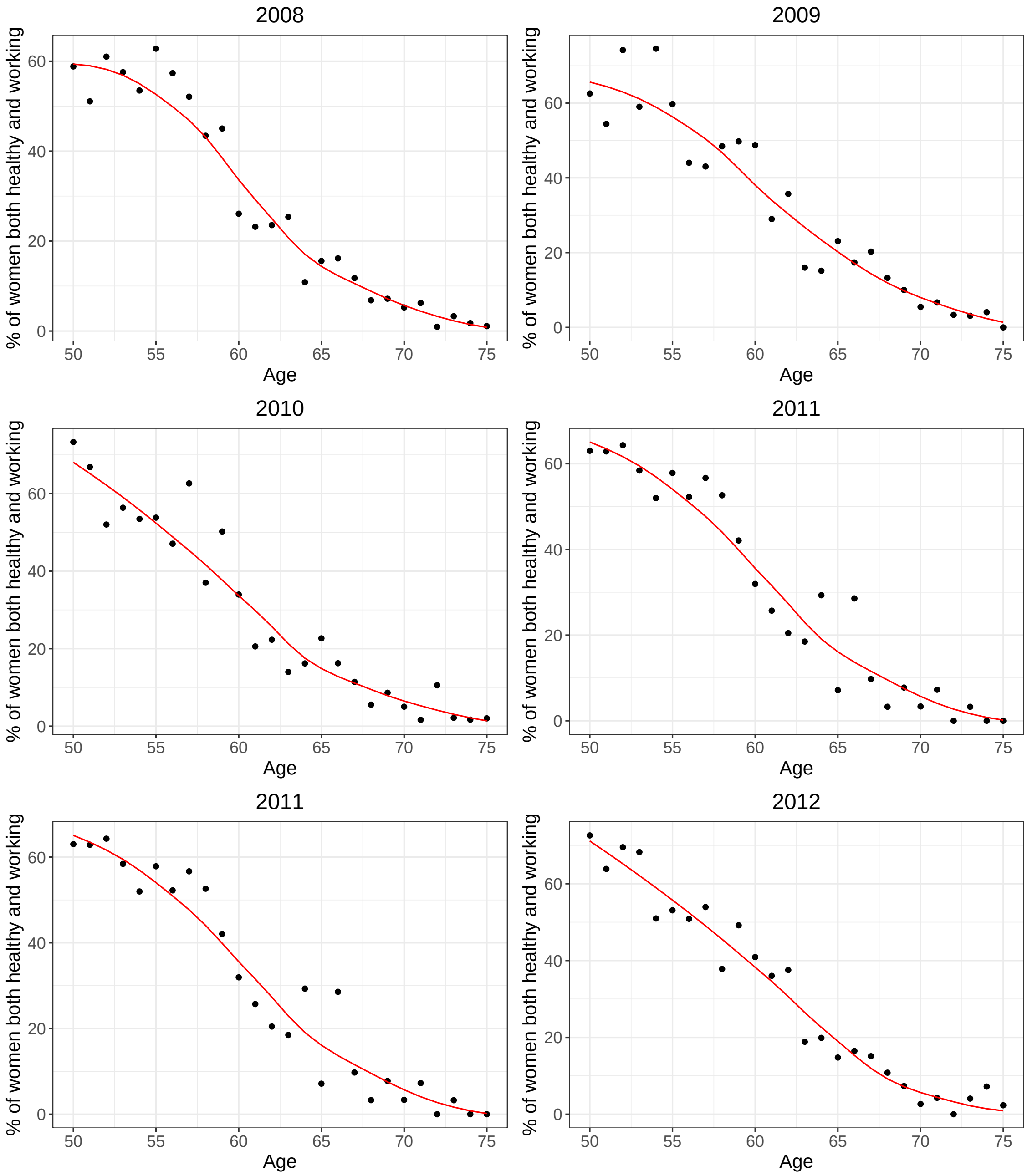
Raw and smoothed prevalence of being healthy and work among women and men aged 50-75 (for HWLE projections)

G.1 Females

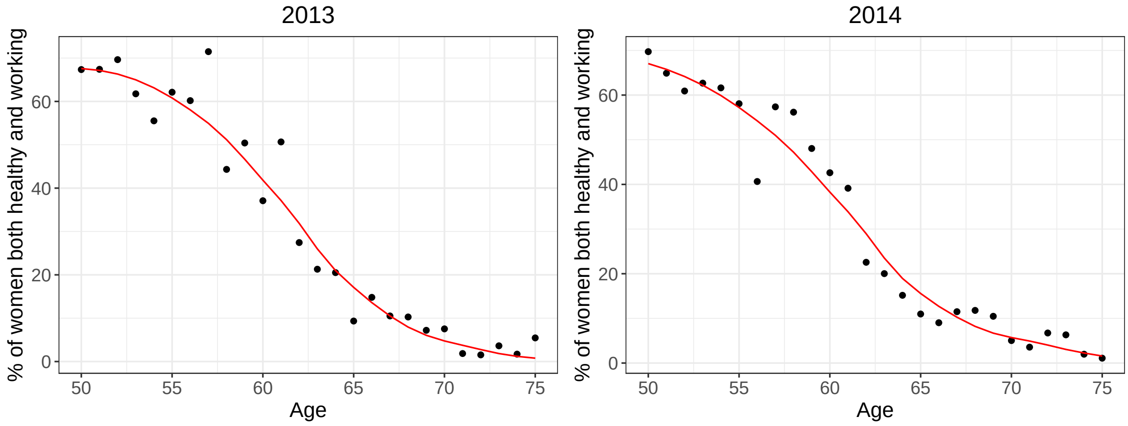
Scatterplots for each year of Health Survey for England data show observed population prevalence of being healthy and in work among females (using survey weights from 2003) with loess smoothed prevalence (red line) for ages 50-75.


1996
1997
1998
1999
2000
2001
% of women both healthy and working
Age


2002
2003
2004
2005
2006
2007
% of women both healthy and working
Age
0
20
40
60
80
50
55
60
65
70
75

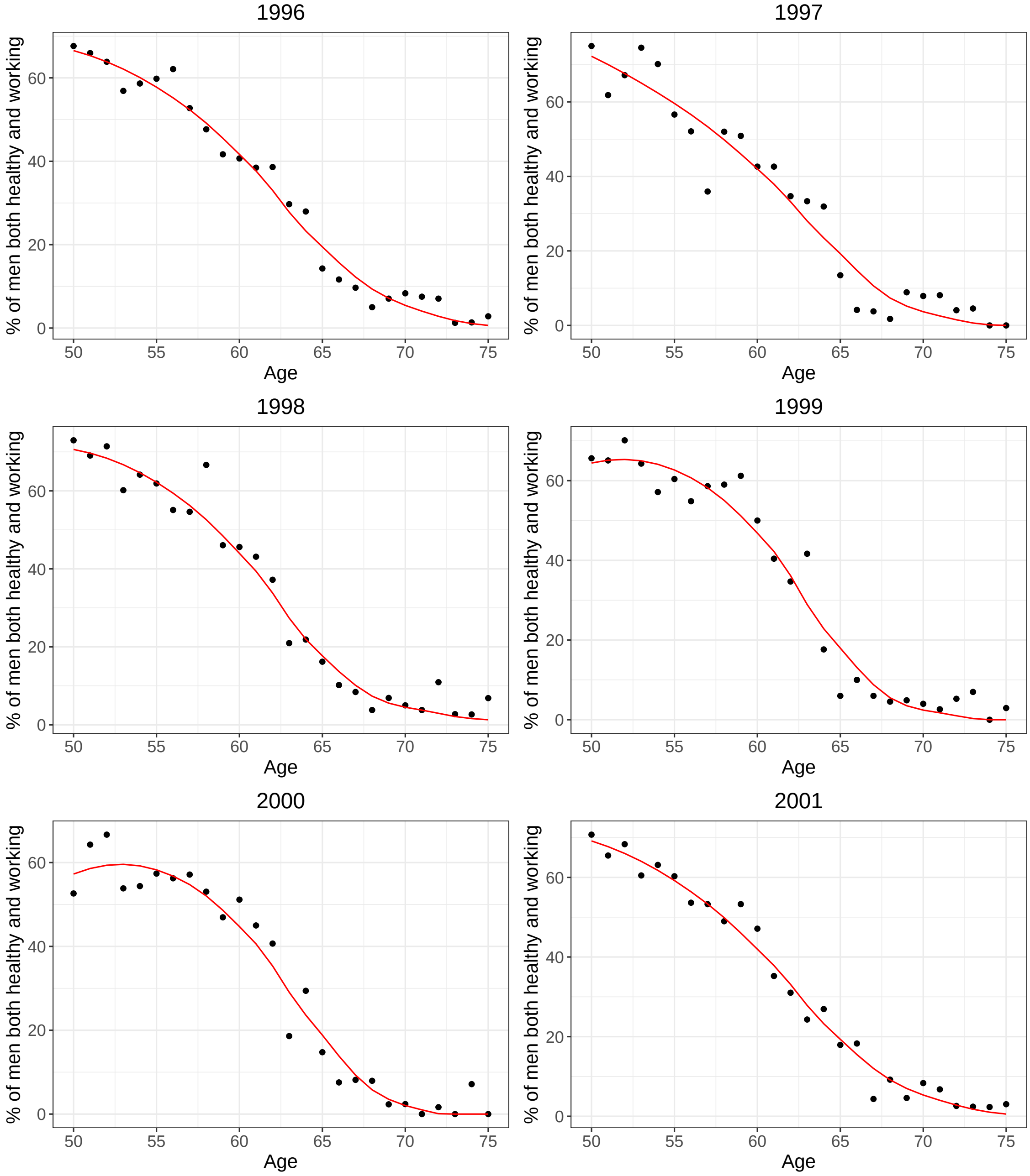


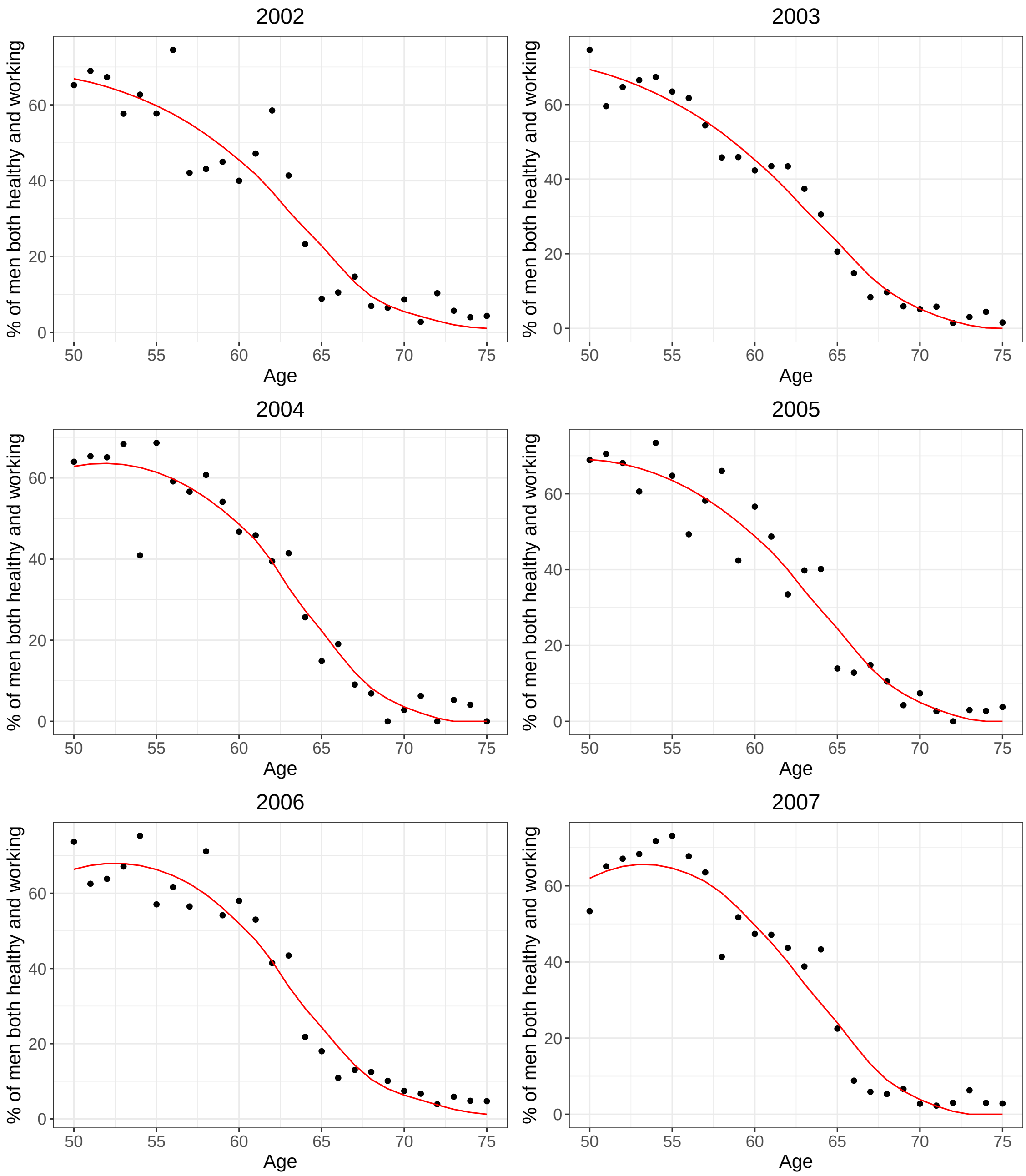
2008
2009
2010
2011
2011
2012
% of women both healthy and working
Age

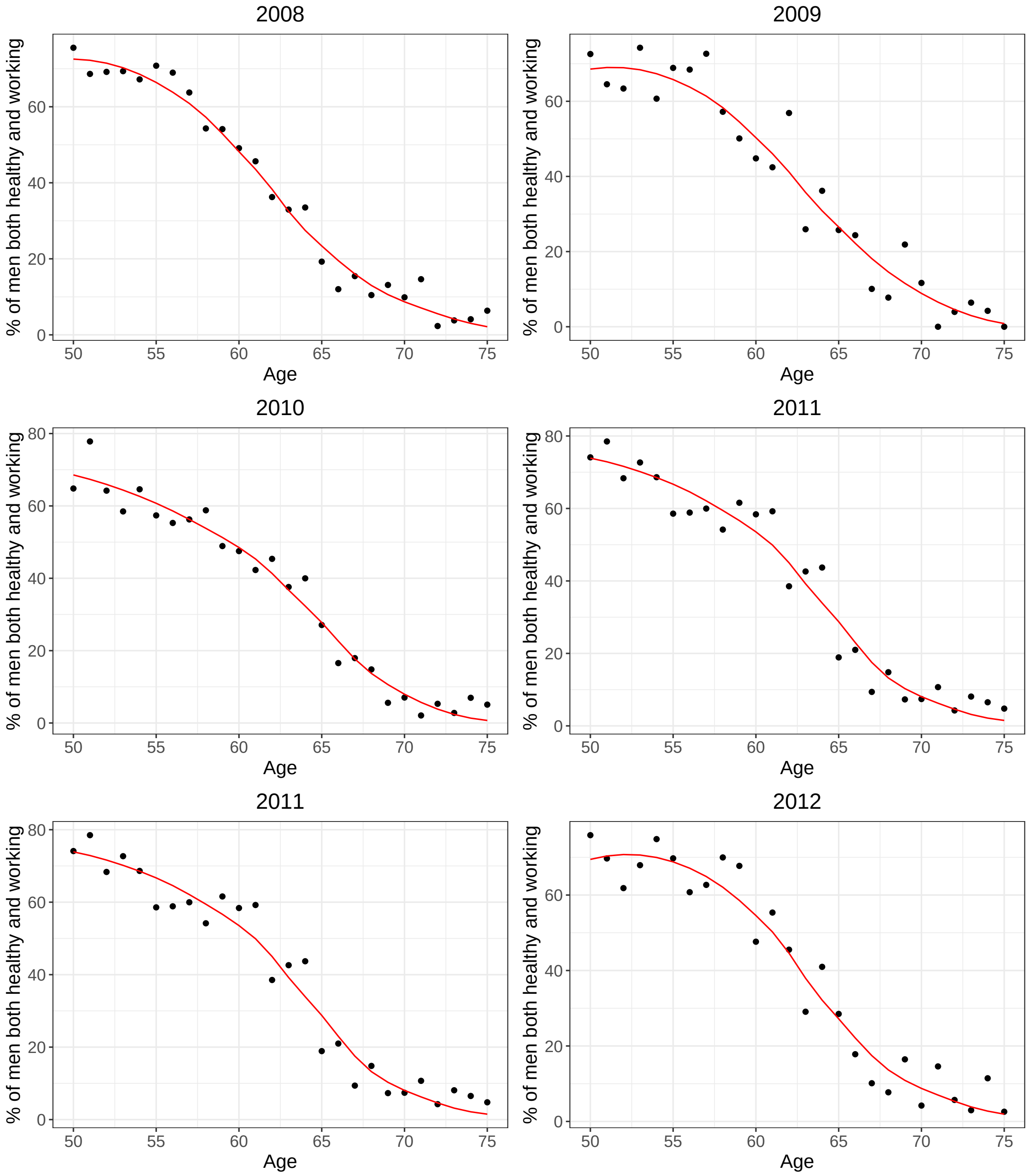


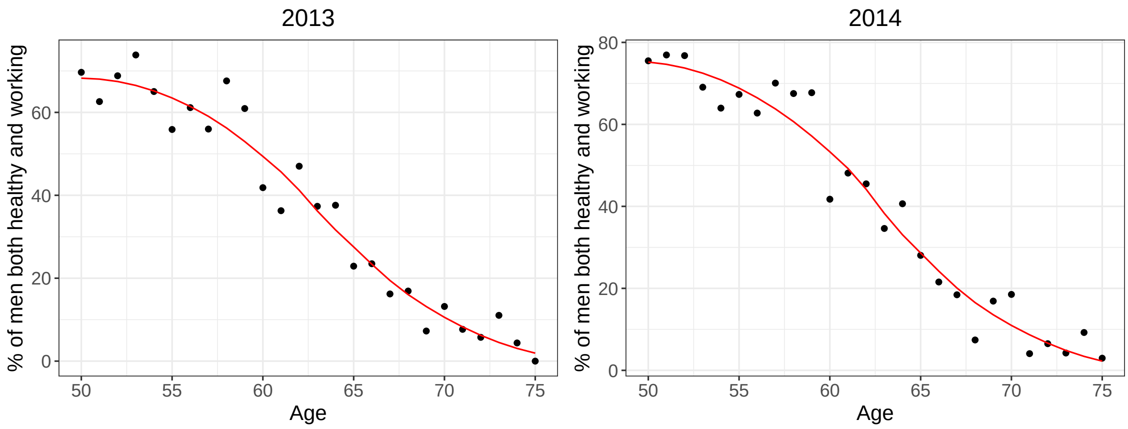
G.2 Males

Scatterplots for each year of Health Survey for England data show observed population prevalence of being healthy and in work among males (using survey weights from 2003) with loess smoothed prevalence (red line) for ages 50-75.


1996
1997
1998
1999
2000
2001
% of men both healthy and working
Age
0
20
40
60
50
55
60
65
70
75


2002
2003
2004
2005
2006
2007
% of men both healthy and working
Age
0
20
40
60
50
55
60
65
70
75


2008
2009
2010
2011
2011
2012
% of men both healthy and working
Age


2013
2014
% of men both healthy and working
Age
0
20
40
60
80
50
55
60
65
70
75