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The Worksome

Developing and Empirically Supporting a Theoretical Framework for Examining the Work-health Relationship

THE WORKSOME: DEVELOPING AND EMPIRICALLY SUPPORTING A THEORETICAL FRAMEWORK FOR EXAMINING THE WORK-HEALTH RELATIONSHIP

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ABSTRACT

Inequalities in health outcomes have received increasing attention both in the research landscape and in policy environments. Social determinants of health, especially those which are modifiable, have been examined thoroughly. One such determinant, occupation - in terms of the jobs and places people work - has been received less attention and scrutiny than the others, and it is often operationalised as social class. This lack of attention is further complicated because research into work and health has often been fairly heterogeneous in terms of contexts used, data deployed, and methodological approaches adopted and therefore conclusions are hard to reconcile. There have been calls for a theoretical framework to help link these disparate pieces of current and future research. Therefore, this thesis develops 'the worksome' out of the biological exposome, an epidemiologic life-course approach to exposure. The empirical portion of the thesis explores and supports the concept of the worksome, which emphasises the importance of context (geographical, temporal, and so on) and varying scales. This is done by employing two robust datasets: the European Working Conditions Survey (EWCS) and the British Household Panel Survey (BHPS), to examine a selected set of working conditions in the context of a variety of health outcomes using logistic regression techniques. The final set of models uses multilevel logistic regression. The various health outcomes, such as backache or anxiety, are characterised by differences in the effect of the working conditions, such as flexible time arrangements. The individual level accounts for a large part of the variance, and, with the BHPS, the observations over individuals through time were most relevant for general health. However, for specific health outcomes, the differences between individuals were most pertinent, meaning the conditions under which people live, and therefore work, are highly relevant. The contexts and scales within which the individuals are situated also have reasonably strong impacts on whether they report specific health outcomes. The heterogeneity of factors which promote and are of detriment to work has been clarified: feelings of control, certainty and security, and tasks which match skills can make two jobs with the same characteristics have different health impacts. The worksome emphasises the importance of examining the interactions between and within all of the elements in which an individual is situated. The concept of the worksome provides an empirically supported, solid theoretical framework for future research into work and health.

Author’s Declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University’s Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate’s own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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Author Name

July 11, 2021

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Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviation	Description
AQM	Advanced Quantitative Methods
BHPS	British Household Panel Survey
DIC	Deviance Information Criterion
ESRC	Economic and Social Research Council
EEA	European Economic Area
EU	European Union
ERI	Effort-Reward Imbalance model
EWCS	European Working Conditions Survey
GOR	Government Office Region
ICC	Intraclass Correlation
IGLS	Iterative Generalized Least Squares
ISCO	International Standard Classification of Occupations
JDC	Job-Demand Control model
MCMC	Markov Chain Monte Carlo
MLR	Multilevel Logistic Regression
NHS	National Health Service
NACE	Nomenclature of Economic Activities
NS-SEC	National Statistics Socio-economic Classification
ONS	Office for National Statistics
OR	Odds Ratio
OS	Ordnance Survey
NICE	National Institute for Health and Care Excellence
SES	Socioeconomic Status
SWDTP	South West Doctoral Training Partnership
UK	United Kingdom
VPC	Variance Partition Coefficient
WHO	World Health Organisation

Glossary

Advanced Quantitative Methods: A priority pathway for postgraduate training under the *ESRC*

Bayesian statistics: An approach to statistics based on Bayes' interpretation of probability, which uses prior knowledge to inform modelling strategies.

β: In *regression* analysis, the coefficient relating to the *covariate*.

British Household Panel Survey: A longitudinal survey with a representative British population, conducted every year from 1991-2008

Capital: Per Marx, a social relation characterised by the exclusive control of the means of production by the moneyed *social classes*, with influence on the conditions and activities of *labour*

Capitalism: The economic system characterised by private ownership of property.

Class: See *social class*

Constant: In *logistic regression*, the term which represents the *probability* of an *outcome* when all other *covariates* are 0.

Correlation: A statistical representation of how variables are associated with one another.

Covariate: A predictor variable in a *regression* analysis, expressed as x_i

Delocalisation: The fragmentation and geogrpahical dispersal of industries by global capital

Deregulation: The process of the repeal or reduction of government regulations related to the economy, often due to apparent inefficiencies in those regulations. Commonly promoted under *neoliberalism*

Deviance Information Criterion: A *Bayesian* measure of predictive accuracy, penalised by model complexity. [Eyles et al., 2019]

Domain: A conceptual context or scale employed in the *worksome*

Economically active: Those employed in any *working arrangement*, including informal arrangements, as well as the *unemployed* currently seeking or about to start work.

Economically inactive: Those without a job, who are not seeking work, generally students, carers, disabled people, and retired people.

Economic and Social Research Council : The funder of this PhD, a part of UK Research and Innovation.

Effort-reward imbalance model: A model of the relationships between*working conditions* and *health*, developed by Siegrist [1996], where the trade-off between effort, or risk, and reward is emphasised.

Employment: The relationship of an employee, who labours, with an employer, who pays for that *labour* towards a particular task or enterprise, or simply put, an individual having (usually paid) work

Employment Grade: A hierarchy of occupational status, related to income.

Error term: The term in the *regression* equation that represents everything the other terms, such as the *constant* and *covariates* do not capture. In *single level models*, there is just one, represented often by *e*, and in *multilevel models*, there are several, to represent the error at each level.

Eurofound: The European Foundation for the Improvement of Living and Working Conditions, which provides research and data to help develop better social policy.

European Working Conditions Survey : A repeated cross-sectional survey, with a representative European Union/European Economic Area population, conducted every 5 years from 1991-2015.

Exposome: A theoretical framework developed by Wild [2005] to encompass all exposures across the *life course*, primarily to examine environmental exposures. It is sometimes described as a measure of all of those exposures.

Exposure: For an individual or group, an occurrence of contact with a material, which is not necessarily physical, considered toxic or otherwise detrimental to health, i.e. a *hazard*.

Flexibility: Characterised by a pursuit of efficiency and cost-saving, leading to apparently seamless adjustments by capital, with total control, in wages, *employment* levels, job roles, locations, and other aspects. This principle first was applied to production, and then trickled through to the more abstract elements of *work* described above.

Flexible employment: A scheme of employment characterised by precarity, job insecurity, and often poor *income* as a consequence of *flexibility*.

Fordism: See *Taylorism*

FYROM: North Macedonia, the 'former Yugoslav Republic of Macedonia'

Gender: The social construction of characteristics (often also socially constructed) around masculine and feminine identities. Gender is a spectrum, and gender identity is the personal perception of what one's gender is. This may not match assigned *sex*. While surveys often ask for *sex*, as the recorded answer is based off of self determination, it is, effectively, gender.

Geocontextual: Geographic and contextual factors relating to *scales* and *domains*.

Globalisation: The internationalisation of capital as it seeks *flexibility*, i.e. to maximise efficiency and minimise costs.

Government Office Region: A subnational geographic division in the United Kingdom, including 9 areas in England, as well as the other constituent nations of the United Kingdom.

Hazard: A material, which is not necessarily physical, that is considered toxic or otherwise detrimental to health. Some examples could be cleaning chemicals, or stress at work.

Health: The state of *wellbeing* in all aspects: physical, mental, and social.

Health inequalities: Variations in the health outcomes or status of individuals, often by *socioeconomic status* or other characteristics, such as *sex*.

Health intervention: A policy effort or act which is executed in order to assess, promote or improve health and/or health behaviours, usually on the population level.

Health outcome: A general or specific health condition or *health status* that may result from particular events or conditions through an individual's *life course*.

Health status: A relative measure of an individual's health.

Heterogeneity: A characteristic of data meaning that it has high variability for particular data items.

Heteroskedasticity: Given two variables, when one varies differently across values of the second. It varies variably.

Idée force: An ideal with social power, proposed by [Bourdieu, 1998]

Income: The money gained through wages, salaries, or other payments in an individual's occupation.

International Standard Classification of Occupations: An occupation-based categorisation system developed by the International Labour Organisation.

International Labour Organisation: A United Nations agency, with the goal of promoting social justice through human and labour rights, by setting labour standards, and creating programmes and policy to forward good working conditions and work for all.

Intensification: In general, raising the workload for an employee, i.e. giving more work in the same amount of time, often for the same *pay*

Intraclass Correlation: See *VPC*

Job : See *occupation*:

Job-demand-control model: A model of the relationships between *working conditions* and *health* developed by Karasek [1979] and furthered by Karasek and Theorell [1990]. It describes how control modifies the potential impact of job demands.

Labour: The capacity for production of things of value sold for *pay* by individual workers in *employment*.

Labour market: The supply and demand of *labour* for *employment*

Labour market segmentation: Where a *labour market* is structured in a core-periphery manner, with the core having more secure *working arrangements*, and the periphery having less secure *flexible employment* arrangements.

Life course: An approach to analysis that looks across an individual's entire life.

Logistic regression: A special case of *regression* analysis for binary response *outcomes*

Log odds: The logarithm of the *odds*, produced by *logistic regression*, which are difficult to interpret, as their range is from $-\infty$ to $+\infty$ so often converted to *odds ratios*.

Markov chain Monte Carlo: A type of simulation used to sample from probability distributions to conduct *Bayesian statistics*

Morbidity: The state of having a condition or illness that impacts on *health*.

Mortality: Put simply, death, or the rate thereof.

Multicollinearity: When two or more *covariates* are linearly related.

Multilevel model: A type of *regression* model that accounts for clustering in the data.

National Health Service: The UK's public healthcare system.

National Institute for Health and Care Excellence: An institute in the UK which provides guidance on a variety of *health* topics to aid the *NHS*.

National Statistics Socio-economic classification: The UK's official *social class* classification

Neoliberalism: A political or economic system of belief, that is characterised by *deregulation* of *welfare states* and increasing privatisation.

Nomenclature of Economic Activities: An EU classification of economic processes, i.e. resources in, products out, mostly used for organisations and firms rather than individuals.

Occupation: The specific activity, task, or role undertaken by an employee, i.e. *labour*.

Odds: The ratio of probability an event will happen. It ranges from 0 to ∞.

Odds ratio: The increased or decreased *odds* of an event happening. An odds ratio of 1 can be interpreted as no effect occurring.

Office for National Statistics: The UK government statistics agency.

Ordnance Survey: The UK's national cartographic agency.

Outcome: The variable of interest in statistical analysis, often represented by y.

Pay: See *income*

Policy: A systematic procedure or process to guide interventions and decisions.

Policymaker: Those who develop or enact *policy*

Precarious employment: see *flexible employment*

Probability: The likelihood of an event occuring, ranging from 0 to 1.

Probability distribution: A mathematical function that encompasses all possible values of a random variable within a given range. The normal distribution, or bell curve, is a common probability distribution.

Psychosocial environment: "The sociostructural range of opportunities that is available to an individual person to meet his or her needs of well being, productivity and positive self-experience" [Siegrist and Marmot, 2004, pg1465]

Regression: A type of statistical analysis or model that seeks to estimate relationships between an *outcome* of interest and particular *covariates*.

Residuals: In regression, the difference between the observed *outcome* and the predicted values of that outcome.

Risk: In part, the likelihood of a *hazard* occurring through an *exposure*, and the idea of this as a future consequence of some particular action or event.

Risk analysis: The process of identifying and managing potential *risks*, and/or determining how things may change if the *risk* in question occurs.

Risk assessment: See *risk analysis*

Risk society: Beck [1992]'s perspective on *risks*, in that they "only exist in terms of the (scientific or anti-scientific) knowledge about them. They can be changed, magnified, dramatized or minimized within knowledge, and to that extent they are particularly open to social definition or construction." [Beck, 1992, pg23]

Scale: In the *worksome*, a fluid, interactive concept of levels, related to *domains*, the delineation of which at times is socially and politically mediated.

Self-esteem: Individual self-worth and the experience thereof.

Self-efficacy: Personal, individual belief in one's abilities.

Self-rated health: Individual perception of *health status*, often reported in survey data.

Sex: In survey data, generally male or female, and based on assignment at birth. For most people, this matches their *gender*.

Single level model: A simple *regression model* with only one *error term*, which conforms to the basic regression assumptions of independence of observations and so on.

Social class: A measure of position or ranking in society, dictated by social value, and, in effect, a hierarchical operationalisation of *socioeconomic status*, often largely based in *occupation*.

Social determinants of health: Individuals are born and live in these conditions and circumstances, which often are a result of social inequalities in health, or *health inequalities*

Socioeconomic status: A measure of social and economic position, which often includes not only *occupation*, but education and income. *Social class* is one way of measuring socioeconomic status.

Stakeholder: An individual or group who has an interest in a venture or initiative due to having a (perceived) effect on the initiative, or it affecting them directly or indirectly. For example, the stakeholders in a *workplace* safety initiative would be those in the workplace themselves, i.e. the employees and managers, but also the owner of the firm, and anyone in the wider community who may be affected by it.

South West Doctoral Training Partnership: An ESRC-funded successor to the South West Doctoral Training Centre, which funds postgraduate research on behalf of ESRC in the South West of England.

Survey data: Data collected through questionnaires or other similar means, generally on a representative population. The *EWCS* and *BHPS* are examples of survey data.

Taylorism: 'Scientific management' of production, whereby each process in production is broken down into discrete units or steps and examined for efficiencies above all else.

Unemployed: The state of not having an *employment* arrangement, for a person who is *economically active*

Variance components model: A special type of *multilevel model*, which is used to examine where variability lies in the data.

Variance Partition Coefficient: It describes the proportion of within-group variance in a multilevel model, or how related the observations within the group are to one another. In the case of this thesis, analogous to *ICC*.

Wages: See *income*

Welfare state: A form of government characterised by the prioritisation of socioeconomic wellbeing of its inhabitants.

Wellbeing: Not the presence of absence of illness, but a holistic state of positive existence, experience, and feeling.

Whitehall (II) Study: A cohort study of British civil servants of both genders between 1985 and 1988, following on from the first Whitehall Study, which examined male civil servants over 10 years form 1967. Its particular focus was the *social determinants of health*.

Work: See *occupation*

Working arrangements: See *employment*

Working conditions: The material and immaterial circumstances and characteristics of a particular workplace or occupation.

Workplace: A place of employment, where someone engages in work for their employer.

Worksome: A theoretical framework developed out of the *exposome* to focus on the relationships between *working conditions* and *health*, *social determinants of health*, a gradient of social-physical *exposures*, and the interactions within and between *scales* and *domains*.

World Health Organisation: A United Nations agency, whose fundamental role is to improve health globally.

Chapter 1

Introduction

1.1. Rationale and Context

The gap in health inequalities has widened over the past 35 years, despite extensive policy interventions and efforts to prevent this [Mackenbach et al., 2015]. The social determinants of these inequalities have thus been strongly emphasised as part of the ongoing research agenda in improving health [Raphael, 2015]. There has been an increasing amount of attention given by the literature to the influence of employment on health outcomes. Initially, interest attention was directed at the dichotomous unemployment/employment relationship [Bartley and Ferrie, 2001; Smith, 1985] and of course, most studies have found that being employed has a positive effect on health in comparison with not [Dodu, 2005; Payne, 1999]. Moreover, there has always been an undercurrent of research on the employed specifically [Benavides et al., 2000; Van der Doef and Maes, 1999]. The employed make up a large portion of the economically active population of the United Kingdom. The economically inactive include, for example, students, carers, disabled people, and the retired. According to the 2011 Census, the unemployed only account for around 6.4% of economically active individuals aged 16-74, while those in any form of employment account for approximately 88.7% of those individuals [ONS, 2011]. Most societies emphasise the cultural and economic importance of sustained employment [van der Noordt et al., 2014] . Work is also socio-culturally important [Bambra, 2011]. To be a member of society, one must work. Occupations are also unevenly distributed across a variety of axes, often due to social constraints, meaning that there should be differences both in working conditions and health outcomes between occupations [Benach et al., 2012]. Furthermore, work also has impacts on people's lives outside of the workplace [Kleiner and Pavalko, 2013]. While it may at first appear that the relationship between working conditions and health is one way, the health of workers is also important with regards to economic productivity. For example, the economic cost of absence due to sickness absence to the economy is substantial – according to a Department of Health [2004] white paper, it costs industry at least £11 billion each year; further, according to the Chartered Institute of Personnel and Development (CIPD), sickness absence costs around £550 per employee per year [C.I.P.D., 2015].

However, it is only recently that attention has been directed at specific conditions in the workplace [Siegrist et al., 2010], though working conditions in general have been thought of as a social determinant of health for some time [for example, Benach et al., 2012, 2014; Braveman et al., 2005; Karasek, 1979; Lewchuk et al., 2003; Marmot et al., 1995; Siegrist, 1996]. Often, though, study of health outcomes arising at least in part from working conditions has focused predominantly on those arising from exposure to physical hazards, such as chemical exposure [Arif and Delclos, 2012]. However, other working conditions can be operationalised as exposures, such as team cohesion (Fruhen and Keith 2014), working time (Dembe et al 2005, Kivimaki et al 2015), or social support (Niedhammer et al 2012). What often characterises exposure in the risk analysis literature are tangible hazards which individuals are involuntarily exposed to [Smith, 2013]. However, while an intangible exposure such as working time may appear voluntary, social constraints may cause it to be involuntary. What appears to be missing, though, from work on psychosocial working conditions and physical ones, is occupational specificity. That is to say that some research may focus on one particular industry or workplace, or on certain geographies, but little research compares individuals across different occupations or industries and geographies [Schutte et al., 2015]. Kim et al. [2012, pg100] critiqued the lack of 'precise conclusions' in research about the relationship between working conditions and health, naming factors such as:

"some inconsistent results in the majority of empirical studies, the lack of a sound interpretative framework that is capable of facilitating an understanding of different social and employment realities; and limited contextual and labour market-related variables that interact with individual employment situations."

If health is considered across the life-course, as advocated for by Ben-Shlomo and Kuh [2002], work takes up a large proportion of an individual's life course. Most people will work at some point during their life, as it is materially, socially, and culturally important [Bambra, 2011; Payne, 1999; Peck, 1996], and work may influence how individuals live their lives even outside the workplace [Kleiner and Pavalko, 2013]. Wild [2005, 2012, pg24] advocates for a concept he terms the 'exposome,' that is, "a comprehensive description of lifelong exposure history." With the exposome, like much of the prior occupational health research, there is a strong emphasis on measurable physical exposures rather than the more amorphous 'social determinants of health' [Wild, 2012].

The concept of the exposome is nonetheless a useful one, and informs the underlying theoretical framework of this work developed here. This new framework is called the worksome. The worksome can be considered as part of the greater exposome, though it will require far more integration of the aforementioned psychosocial elements into the broad domains of the exposome (internal/general external/specific external) than described by Wild [2012]. Of course, in emphasising the psychosocial aspects the physical exposures of course must still be considered too and remain important. The worksome consists of a wide array of exposures and pathways that are shaped by and contribute to social inequalities in health. Thus, factors that influence health are each a blend of physical and social components, represented as a gradient. A physical-social gradient will feature in the worksome. Changes in working conditions may originate in one an industry or occupational type and subsequently spread to other fields, so addressing the temporal element of these changes is important [Benach et al., 2014]. The concept of the worksome will be expanded on through the theoretical framework itself, developed in this thesis, and examined reinforced with empirical analysis of survey data, specifically data from the European Working Conditions Survey, and the British Household Panel Survey. As such, the worksome can contribute to the This therefore will provide the 'sound interpretive framework' that Kim et al. [2012, pg100] called for.

The worksome framework will be investigated empirically using the European Working Conditions Survey (EWCS), which is conducted every five years in the member states of the European Union, as well as associated states such as Norway and Turkey[Eurofound, 2020]. The inaugural survey was taken in 1991, followed by surveys in 1995, 2000, 2005, 2010, and 2015. Each individual country has a sample of between 500 and 1500 taken per wave, and individuals are classified by both International Standard Classification of Occupations (ISCO) and EU occupational types. This allows for the grouping of individuals by occupation and by country in multilevel models. The survey asks several questions with respect to health outcomes as well, allowing for a robust picture of the linkages between individual working conditions, contextual information such as occupation type or country of residence, and a wide variety of health outcomes.

Further empirical support exploration of the worksome is will be given through repeating the analysis using the British Household Panel Survey (BHPS), an 18 wave, nationally representative longitudinal panel survey, following individuals through time in the United Kingdom, between 1991 and 2008 [University of Essex, 2018]. The initial sample was 10,300 individuals in 5,500 households. Each individual has wave-observations through time, allowing for a longitudinal picture to be built through multilevel models, with wave-observations grouped in their respective individuals, who are classified into ISCOs, and then grouped into Government Office Regions (GORs). There is one general health outcome, and two specific health condition outcomes in this dataset.

In order to organise this thesis, a set of specific research questions and objectives was derived, and these are discussed below. The overarching aim of this thesis is to examine working conditions and their relationship with health, and to develop a theoretical framework which will allow the unification of disparate research in this area.

1.2. Research Objectives

In order to investigate the thesis aims, the following objectives have been defined:

1. **Investigate and confirm the relationship between work and health**: It is well known that there is a relationship between health and work. However, prior to exploring the detail

for the worksome it is necessary to provide a baseline analysis within the datasets under investigation

2. **Determine which specific working conditions underlie this relationship**: As prior work has established the relationship between work and health, it is key to expand on this work and understand which specific working conditions may impact on this relationship.
3. **Examine and explore the geographies of these relationships:** These relationships should vary geographically if only because there are significant regulatory and welfare-regime differences between European states, and because the data are naturally clustered into countries.
4. **Develop a transferable conceptual framework, the 'worksome', and apply it to the empirical examples**: A conceptual framework is a useful tool to ensure that research is transferable, and, as Kim and colleagues (2012) argue, a crucial missing link in research into work and health. By applying it to the empirical work carried out to meet the prior objectives, the framework can be substantiated.

1.3. Specific Research Questions

1. What is the relationship between work and health?
2. Which specific working conditions impact on this relationship? How do they vary across individuals (i.e. by gender, age, and so on)?
3. What is the impact of geography - in this case varying EU countries and UK regions? Does this vary by time?
4. How do responses change over time, and is this related to geography?
5. How might the impact on health vary across occupation types?
   - Do individuals vary more within the same occupation type or between occupation types?
   - What is the geography and temporality of this?
   - Does the system of occupational classification matter (e.g. either the Nomenclature of Economic Activities (NACE) or the International Standard Classification of Occupations (ISCO)?
6. What is the relationship between work, working conditions, and specific health outcomes such as backache or anxiety? Does this vary by occupation type, geography, and/or time?

1.4. Thesis Structure

The objectives listed above dictate the general thesis structure. After the introduction, the thesis proceeds through a further 11 chapters.

Chapter 2 is the literature review. It furthers the rationale and context for this thesis, providing background around the research questions, conceptual framework, and the landscape of work-health research. Specifically, it will define and discuss flexible employment and the new world of work, use the UK regulatory context as an example, and describe current models of the work-health relationship. Finally, extant research will be characterised and interpreted, moving towards Chapter 3, which is the outline of the theoretical framework, the worksome. This chapter forwards research objectives 1 and 2, and research questions 1, 2, 3, and 6.

Chapter 3 is based in large part on a paper published in *Social Science and Medicine* [Eyles et al., 2019], and describes the theoretical and philosophical basis for the worksome framework by first introducing the concept of risk, then linking epidemiological concepts to the task at hand. Further justification of the need for this framework is also provided. This chapter meets research objective 4.

Publication (Chapter 3, Chapter 7)

Eyles, E., Manley, D., Jones, K. 2019. Occupied with classification: Which occupational classification scheme better predicts health outcomes? *Social Science and Medicine*, 227: 56-62.

Chapter 4 describes the EWCS and BHPS datasets, through their data collection and sampling methodology, to the data structure and variables included, such as the individual health outcomes in the data, and the working conditions which will be examined. The methods are also specified, and the modelling strategy will be described. Part of the methods section is based on the same publication Chapter 3 was derived from [Eyles et al., 2019]. This chapter addresses research objectives 1-3, and research questions 1-6.

Chapter 5 is the first results chapter and features the single-level logistic regression results from the EWCS data. It uses a parsimonious modelling strategy to examine whether work and health are related, and to provide the groundwork for the multilevel models. It also examines each individual health outcome described in Chapter 4. Chapter 6 is the second single-level logistic regression modelling chapter, and examines the BHPS data in the same manner. Chapters 5 and 6 examine research objectives 1 and 2, and research questions 1, 2 and 6.

Chapter 7 extends the analytical implementation through the variance components model. It sets out the structure necessary for the multilevel models in Chapters 8 and 9. It looks at countries, years, welfare regimes, and occupational types as potential levels for the multilevel models. Some text in this chapter was taken from the paper published in Social Science and Medicine (Eyles, Manley, and Jones 2019) paper. It meets research objectives 1-3, and answers research questions 3-6.

Chapter 8 is the multilevel model results chapter for the EWCS data. It follows a similar structure to Chapters 5 and 6, however, it mitigates the natural clustering in the EWCS data through including a random component in the model, decided upon in Chapter 7. Chapter 9 is the corresponding BHPS data analysis. Chapters 8 and 9 forward research objectives 1-3 and research questions 1-6, as well as indirectly reinforcing objective 4.

Chapter 10 is the discussion chapter, where the results are put into context, especially with respect to the worksome framework and the existing literature. This chapter examines research objectives 1-4, and research questions 1-6.

Chapter 11 is the conclusion, which brings this thesis to a close. It will reiterate the rationale and context for the work, present the completed research objectives and questions, discuss strengths and limitations of the work, and provide directions for future research.

Chapter 2

Literature Review

2.1. Introduction and Background

This review primarily focuses on employment conditions and their relation to health. The meanings attached to these relations are not given, but constantly negotiated [Daykin, 1999]. First, a discussion of the previous research on health inequalities and recommendations made is undertaken, followed by a brief definition of flexible employment. While this study will examine all forms of employment, flexible employment is described in particular here as it is an increasingly common phenomenon with spill-over to other forms of employment be it in the form of working conditions or contracts. A case study discussion of the regulatory context and history of employment in the United Kingdom, one of the larger countries in one of the datasets used in the analysis, and the setting for the other, is used to explore the relationship between government policy and occupational health outcomes. This is followed up with a debate about the varying models of the employment-health relationship as well as a discussion of the indicators of working conditions and how they may be used both within the models and alone. It is important as well to understand the events and decisions leading to the emergence of certain forms of employment, such as flexible employment.

Occupation has been somewhat neglected in research on the social determinants of health [Siegrist et al., 2010] However, choosing an occupation is often socially constrained in some way or other. Occupations are unevenly distributed by class, gender, ethnicity, immigration status, geography, and other axes of discrimination though it may not be immediately obvious why [Benach et al., 2014]. There has been a large array of work on social class, often measured by employment grade or category, such as the Whitehall studies [Marmot et al., 1991], which found a sharp inverse association between mortality from an array of health conditions and diseases and social class. However, as the worksome chapter will later discuss, this is not necessarily the best approach to the question of the relationships between working conditions and health. This is mainly due to the hierarchical and changing nature of how class is measured. Indeed, that class is a separate axis of difference to occupation, though related.

According to van der Noordt et al. [2014], developed and advanced developing societies aim to get as many people as possible in some form of sustained employment. It is essential for most people to start and continue working, given that living in subsistence is generally impossible in modernised societies [Peck, 1996], as well as work being socially and culturally important [Bambra, 2011; Richter et al., 2013]. Work holds social value [Payne, 1999].

"... [W]ork affects not only job demands and job resources, but also how people live their lives when they are away from the job." [Kleiner and Pavalko, 2013, ,p985]

The multiple exposures and pathways of working conditions and the work environment contribute to social inequalities in health as work is a major social determinant of health [Niedhammer et al., 2008]. There has been a wide range of work on the health effects of unemployment [Bambra, 2010; Bartley and Ferrie, 2010; Giatti et al., 2008; Hergenrather et al., 2015; Lundin et al., 2009; Norstrom and Gronqvist, 2015; Smith, 1985], however, it cannot be assumed that employment itself or the transition to/from it will cause positive health effects [Ahs and Westerling, 2006; van der Noordt et al., 2014]. Furthermore, employment should be examined excluding unemployment, which is different in its mechanisms and well-explored.

It is possible for employment to cause both positive and negative health effects [Bambra, 2011; Dodu, 2005]. Clougherty et al. [2010] suggest that the act of working (employment in other words) itself may promote wellbeing. They emphasise that establishing what aspects of work as opposed to income or other material benefits improve health may be difficult [Clougherty et al., 2010]. Marmot and Bell [2010] underline the influence of working conditions and the nature of work on health, be it promoting or having adverse effect on both physical and mental health. Occupational health has explored the physical hazards faced by a variety of workers, but understanding exposure to the organization of work is as important for health as exposure to biochemical hazards in understanding (work-related) health outcomes [Lewchuk et al., 2003]. Empirical work-related health research often focuses on illness and does not generally address health promoting workplace conditions [Aronsson and Blom, 2010]. This may be due to the difficulty of operationalising good health or wellbeing as opposed to disease or ill health [Aronsson and Blom, 2010]. Wellbeing is not necessarily just the absence of illness or negative health effects, though its definition has proven to be challenging, with some proposing a meaning based on a state of balance [Dodge et al., 2012].

The workplace, though, is seen as a promising site for delivering health interventions, both for reasons of population (most adults are employed), and for financial and business reasons (improved work performance and safety) [Martin et al., 2009]. Further, the National Institute for Health and Care Excellence (NICE), which produces public health guidance in the UK, published guidelines for mental wellbeing at work, on request from the Department of Health in the United Kingdom [NICE, 2009]. The Black Report [Black, 2008] also argued for the promotion of healthy workplaces in improving general wellbeing. The Marmot Review into health inequalities in England identified work as a key domain for improvement [Marmot et al., 2008], although in the 10-year review of the Marmot Review, it was found that health inequalities had not improved, and most new employment was in lower quality jobs [Marmot et al., 2020]. While seeking out health promoting conditions is important, the availability of data or lack thereof may be a constraining factor. It is important too to consider how labour is organised and how the labour market is structured. Organizations are changing rapidly in most countries so older models of work and health may no longer be wholly appropriate [Richter et al., 2013].

2.2. Health Inequalities

Health inequalities, when measured, can show the range of variation in health, or the distribution of the population within the variation [Murray et al., 1999]. This variation is unlikely to be only due to chance, therefore health inequalities are likely due to systematic factors relating to risk and outcome [Murray et al., 1999]. Dahlgren and Whitehead [2006] in a WHO report affirm that inequalities in health are often caused by policy and lifestyle determined in part by structural factors. These inequalities have also been found to persist from working age adults into later life [Corna, 2013].

Oakes and Rossi [2003] describe that the “strong” relationship between socioeconomic status and health has been recorded since the times of ancient Egypt, China, and Greece, and argue that the inequality between socioeconomic status and health has persisted through time, despite a reduction in the impact of acute infections, due to improvements in medicine. Health inequalities, or social inequalities in health can be defined as “differences, variations, and disparities in the health achievements of individuals and groups” [Kawachi, 2002, pg647]. Siegrist and Marmot [2004]explain how despite significant focus on improving them from both science and government, social inequalities in health have widened. Marmot and Bell [2010] suggests that health inequalities arising due to social inequalities. These inequalities are also often termed as the health divide or the health gap [Shaw et al., 2000; Wilkinson, 2005].

Social inequalities in health can be measured by social determinants of health, i.e., “the conditions in which people are born, grow, live, work and age, and inequities in power, money and resources” [Marmot et al., 2020, pg5]. Simply put, they are factors that influence health, either positively or negatively, which also can be mediated by policy and other conditions, and crucially which occur **and interact** at several scales. Some of these scales are modifiable, such as working conditions [Dahlgren and Whitehead, 2006; Wilkinson, 2005]. Dahlgren and Whitehead [1991] developed a schematic framework of the social determinants of health [see Figure 2.1]. Marmot and Bell [2016] highlight the need to examine these determinants in detail in order to better understand what they term “the causes of the causes,” or those critical factors which lie beyond the immediate causes of poor health. Marmot [2005] emphasises the importance of taking action, be it undertaking research, or influencing policy on the social determinants of health, to reduce the inequalities in health between countries. The WHO report on Social Determinants of Health emphasised that fair employment with good working conditions was an important determinant of health, and should be a policy priority [WHO, 2008].

Despite their pervasiveness in all societies, it is important to study social inequalities

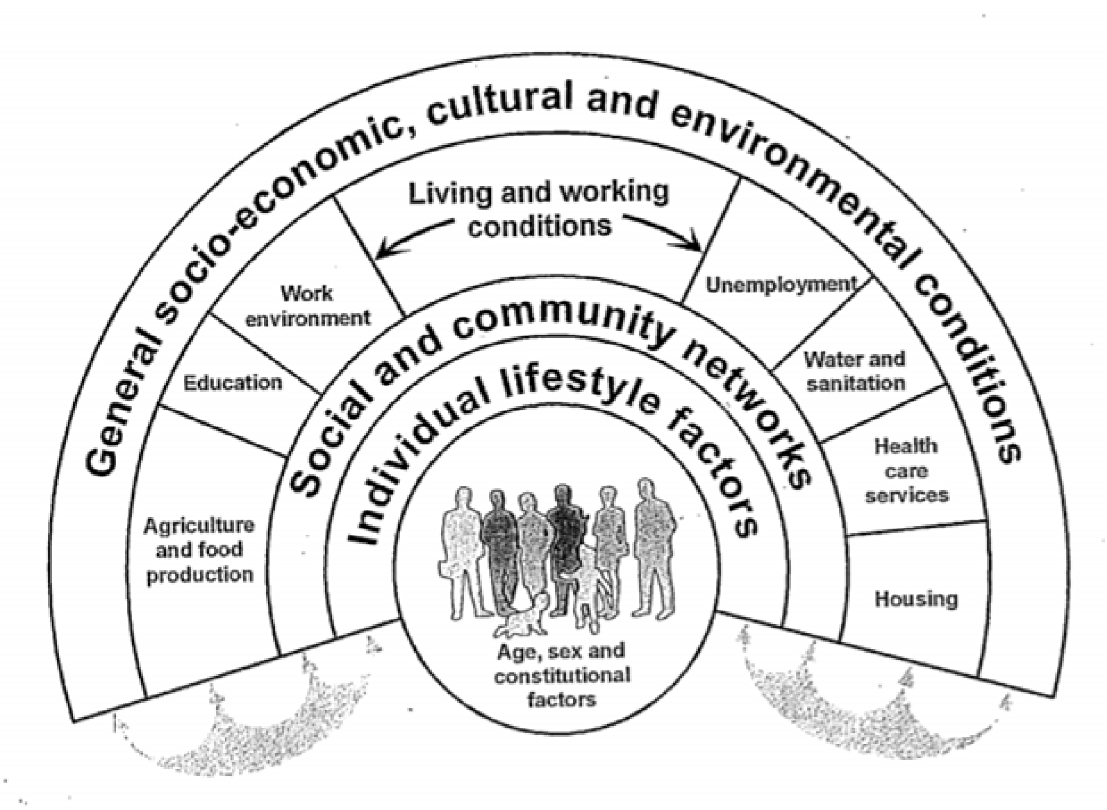


Figure 2.1: Social determinants of health [Dahlgren and Whitehead, 1991]

in health, as Siegrist and Marmot [2004] argue, because the magnitude of inequality may vary significantly between and within societies. Marmot and Bell [2010] argue that "health inequalities are not a natural and immutable feature of society," nor is it only a problem of access to care, especially given the National Health Service (NHS) in the UK, which provides care to all, regardless of social position, income, or ability to pay. Moreover, Cutler et al. [2006] highlight that some larger changes in access to healthcare have not shown similar improvements to health gradients. Eikemo and Bambra [2008] attribute some of these health inequalities to the structure and social policies of welfare states. Espelt et al. [2008] emphasise the importance of social policy in terms of reducing social inequalities, and Marmot and Bell (2010) observe that health inequalities appear to respond to changes in society, economy, politics, and culture.

Crucially, some of these inequalities are modifiable, avoidable and, hopefully could be mitigated, particularly those relating to working conditions. Marmot and Bell [2016] argue that the slope of the social gradient in health varies temporally and geographically, and while perhaps, according to them, social hierarchies are 'inevitable' in society, the variation in the slope implies that strategies to reduce health inequalities are possible, something reiterated in Marmot et al. [2008]. Mackenbach et al. [2008] found that the magnitude of inequalities in health between socioeconomic groups varied considerably between countries, but thought these differences may be amenable to change. Social inequalities in health can be argued as not being due to a free, individual choice, but due to a range of influences starting in early-life influences. In other words, individual life chances may depend on contextual factors which are not necessarily decided on by the individual, and in many cases, because they are out of the control of the individual being impacted, could be regarded as unfair [Kawachi, 2002]. Elo [2009] emphasises the importance of reducing these inequalities in health, in order to improve life for all, and to reduce unnecessary suffering [Marmot and Bell, 2010].

In the first Whitehall study a "steep, inverse association between social class, as assessed by grade of employment and mortality from a wide range of diseases [was found]" [Marmot et al., 1991, pg1387]. The follow up in in the late 1980s, the Whitehall II study, was conducted as an expansion of the first Whitehall study in the late 1960s, which found that the gradient remained despite major advances in health [Marmot et al., 1991]. Marmot et al. [1991] further stressed that this association is a gradient, rather than a strict dichotomy. That is to say, poor health is not only the domain of those of with lower social status, but those in other positions also have relative inequalities in their health [Marmot, 2005]. Marmot and Bell [2012] in their summary of their WHO report into the social determinants of health, describe the social gradient in inequalities in health as substantial. Similar gradients in health were found in Canada and other European countries [Cutler et al., 2006; Elstad and Krokstad, 2003; Mackenbach et al., 2008]. However, Marmot et al. [1991] suggested that established risk factors may not explain these differences, even when adjusting for lifestyle differences; adjusting for smoking only changes the difference in life expectancy between the highest and lowest categories by 2 years, from 6 to 4 Cutler et al. [2006]; Marmot [1994]. Social circumstances at work (e.g., low control, low satisfaction, social support) were also found to be related to these inequalities [Marmot et al., 1991]. However, the relation with employment grade for certain outcomes was less consistent for women than men. Those in lower status jobs reported low control, variety of work, and high pace, with less satisfaction [Marmot et al., 1991]. The work environment is perceived differently by different grades [Marmot, 1994; Marmot et al., 1991]. Often, occupational class or rank is used to measure social status, but it only is one element of social inequality. It may not, for example, adequately capture material resources, or qualifications, so a pluralistic approach may be necessary [Siegrist and Marmot, 2004]. Occupational class is often seen as a summary measure, which can capture early-life social status, and further, adult position in society [Elo, 2009].

One critical observation which arises from the literature above is that occupation is not merely something to be controlled for, but something which needs to be examined. Marmot et al. [1987] advocate for examining inequalities and their characteristics while maintaining a critical eye on how inequality is measured. Poor working conditions not only relate to the physical but also the psychosocial [Siegrist and Marmot, 2004]. Marmot and Bell [2012], describing the Strategic Review of Health Inequalities in England, named 'good work for all' as one of the six domains for action on social determinants of health; they emphasised the quality of this work, particularly related to working conditions as important. Different jobs will have different environments, and creating more precarious work will likely not improve health inequalities significantly (as will be described in the subsequent sections of this chapter). Indeed, most jobs created since 2010 in the United Kingdom were found to be of poor quality, leading to little improvement in health inequalities [Marmot et al., 2020, 2008]. Indeed, adverse working conditions are damaging to health, and reinforce the social gradient in health inequalities [Marmot and Bell, 2010]. Siegrist et al. [2010] describe the "significant contribution" working conditions make to social inequalities in health, and underline the importance of improving working conditions to reduce health inequalities.

2.3. Psychosocial Environment

According to Giddens [1976], the structures of society both influence and enable individual agency, rather than merely constraining them. A sense of belonging to these structures, be it through contributing to them, or acting in them unconstrained, creates positive self-experience [Siegrist and Marmot, 2004]. Siegrist and Marmot [2004, pg1465] define the psychosocial environment as: "the sociostructural range of opportunities that is available to an individual person to meet his or her needs of well being, productivity and positive self-experience," continuing by emphasising the importance of self-efficacy and self-esteem. Self-efficacy is defined as "the belief a person has in his or her ability to accomplish tasks," which is based on "a favourable evaluation of one's competence and of expected outcomes" [Siegrist and Marmot, 2004, pg1465-1466]. Therefore, in terms of self-efficacy, a good psychosocial environment allows for the practice of skills and the experience of a sense of control. Marmot et al. [1997] found that control also was related to the position in the social gradient with greater control being exhibited at the higher end of the slope.

Self-esteem is "the continued positive experience of a person's self-worth" [Siegrist and Marmot, 2004, pg1466]. In terms of self-esteem, a good psychosocial environment allows for appropriate, useful feedback for tasks, and enables connections with others, to increase belong, social approval, and success [Siegrist and Marmot, 2004]. The NICE [2009] public health guidelines for mental wellbeing at work argue that work itself is an important determinant of self-esteem. The Whitehall studies were some of the first to clearly show the importance of relative social position, created by psychosocial environments, over, for example, the material effects of income, in relation to health inequalities [Marmot et al., 1991; North et al., 1996]. North et al. [1996], as part of the Whitehall II Study, found that adjusting for socioecnomic status, measured by employment grade, was a strong predictor of sickness absence. However, other measures of material circumstances did not have a strong predictive effect, but aspects of the psychosocial environment did, some of which are likely mediated by grade [North et al., 1996]. That is to say, the psychosocial environment itself and the perception of that environment influences sickness absence.

Bambra et al. [2008a]. Pikhart et al. [2004] and Niedhammer et al. [2004] emphasise the importance of the psychosocial environment at work in particular as being important in studying health inequalities. Bambra et al. [2008a] emphasise that the psychosocial work environment in particular is under increased consideration by policymakers as a point of intervention to reduce health inequalities. Indeed, the NICE [2009] public health guidelines on mental wellbeing at work emphasise the interaction between the psychosocial environment, the working conditions and nature of the job, and the person in question. The (work) psychosocial environment i.e., that which helps an individual meet their wellbeing needs Siegrist and Marmot [2004], should encompass working conditions that allow for self-efficacy and self-esteem, often via a sense of control. This can have positive health impacts. Further, self-rated health has been found to vary across the psychosocial environment Pikhart et al. [2001].

2.4. Self-rated Health

Self reported health data, which relies on individual perception, is linked to other measures of health status [Marmot et al., 1991]). Self rated health has been consistently important across time. Perceived health is reflective of an individual's self awareness of integrated dimensions of health – physical, mental, and social, that may not be obvious to an outside observer [Kaplan and Camacho, 1983; Kaplan et al., 1996; Miilunpalo et al., 1997; Møller et al., 1996]. Møller et al. [1996] emphasise that all studies examining this relationship of self-rated health and future mortality had very different designs, including population, control variables, assessment of self-rated health, and follow-up, yet these studies consistently found this association to exist. Idler and Benyamini [1997, pg22] also emphasise that self-rated health is "relatively insensitive to the semantic variations in the questions eliciting it," as well as translation from English causing relatively few difficulties. Marmot et al. [1991, pg1391] describe it as reflecting "a burden of perceived ill-health, that shows a clear social class gradient." Rating health overall as poor or average was found by Marmot et al. [1991] in the Whitehall II study to be a very strong predictor of mortality.

Kaplan et al. [1996], in a Finnish population study (the Kuopio Ischaemic Hearth Disease Risk Factor Study), reinforced this result, with very few exceptions, noting it may be possible that the association may be weakened with more adequate objective measures of health status. McGee et al. [1999] found self-rated health to be a strong indicator of mortality even controlling for gender and ethnicity. However, for epidemiological research based on survey or secondary data, self-rated health is useful as it reflects underlying disease or other health problems, without requiring expensive, invasive, or complicated measurements of objective health. Idler and Benyamini [1997] found in their review that many investigations using self-rated health are studies of secondary data, and emphasise that it is economical and allows for improved replication or improvement of analysis. Further, Kaplan et al. [1996], in studying a healthy subsample, found that self-rated health had a much smaller association with objective health than in the whole sample; there should be emphasis on validity in different subpopulations [Miilunpalo et al., 1997]. Heliövaara et al. [1993] examined a nationally representative sample, comparing health interviews and health examinations, and found that they both gave a similar view of chronic morbidity in the population. Miilunpalo et al. [1997] suggested that self-rated health can be verified by objective measures of health, or health records, and did so on a sample cohort in an industrial town in Finland, finding it to be stable across time (individuals transition only to adjacent classes, and 60% did not transition at all one year later). Pikhart et al. [2001]

assert the importance of self-rated health for social and epidemiological research due to its stability and consistency in results across a large number of studies.

Self-rated health, then, is key in research with secondary data, which most geographical and health-related studies employ. It has been validated as a concept for use as a reflection of underlying health status, problems, and outcomes. It can be used to examine the health inequalities through the lens of occupation, discussed earlier. However, occupation is not static; standard employment relations have become less common. Over time, the world of work has changed towards a 'flexible' model of employment, something that will be discussed in the following section.

2.5. What is Flexible Employment?

"Flexible production," an innovation in how factories operated, developed in the 1970s, is commonly thought of as a positive, necessary step in labour organisation towards economic growth [Benach and Muntaner, 2007]. Its origins could be traced back to 'scientific management' principles, often called Taylorism or Fordism. Taylorism is characterised by a pursuit of efficiency, and a high level of control on the part of managers: each process is made into discrete units, and workers are thought of as cogs in a machine [Rosen, 1993]. These principles evolved to make the link between production and consumption more efficient with 'just in time' (JIT) production or 'total quality control' (TQC) [Canaan, 1999]. JIT aims to precisely meet demand with just about enough production, whereas TQC aims to produce high quality products [Canaan, 1999]. These approaches to production filter into the concept of flexibility. Flexibility has trickled not just to technological and industrial systems of production, such as the factory floor, but to more abstract elements of working, including schedules, tasks, and status [Benach and Muntaner, 2007; Ross, 2009]. This is a consequence of the dramatic socioeconomic changes of the late 20th century, primarily the shift to neoliberalism [Kim et al., 2012].

The neoliberal model of the economy insists that market principles percolate through all aspects of life, in order to increase market competitiveness and therefore growth and development [Standing, 2011]. Bourdieu [1998] expounds the dominant discourse around neoliberalism – that there is no alternative to place in opposition to it. Further, neoliberalism is never fully complete, so the process continues. Mechanisms within the legal system can allow for the adoption of these principles by interested parties. Bourdieu [1998] refers to the use of terms like flexibility and deregulation as a connotative game of metaphors. These metaphors serve to hide what these terms truly entail. Insecurity may be rationally managed by firms in order to engender obedience to the new cost-saving regime Bourdieu [1998]. Diverse contract types and higher flexibility are used by firms to adapt to competitive global markets Dawson et al. [2015].

Paradoxically, though, flexible employment both reduces and generates constraints on labour – unions and labour laws are removed, so workers are technically more mobile, but with that in mind, workers are thus constrained by a dearth of security and an increase in uncertainty. This widespread uncertainty may affect the health of those subject to it Daykin [1999]. Standing [2011, pg6] describes a number of types of flexibility:

"wage flexibility meant speeding up adjustments to changes in demand, particularly downwards; employment flexibility meant easy and costless ability of firms to change employment levels, particularly downwards, implying a reduction in employment security and protection; job flexibility meant being able to move employees around inside the firm and to change job structures with minimal opposition or cost; skill flexibility meant being able to adjust workers' skills easily."

These types of flexibility in the labour market are thought of by employers and policymakers as a system to develop worker performance and adaptability undeterred by technological change and globalisation [Bardasi and Francesconi, 2004]. However, it is globalization, labour market deregulation, and increasing competition which cause firms to restructure to include short term and temporary contracts, which can be perceived as threatening by employees, detrimentally impacting their performance, and in turn also changing the effectiveness of the firms they work for [D'Souza et al., 2003; Laszlo et al., 2010].

Globalisation causes competitive pressures within labour markets and the economy more generally. This is due in part to the supply of low-cost labour emerging from developing, or newly industrialising countries, making flexibility "a prerequisite for economic competition" [Standing, 2011, pg56]. Bourdieu [1998, pg34] terms globalisation as an 'idée force,' or an ideal with social force that can obtain belief; European workers are shown the harder working conditions in developing countries as the ideal, and thereby flexibility is imposed and normalised over time. Working conditions have therefore changed as the economy globalises.

The level of perceived control is important for employees as "social relations in the workplace (the labour process) involve negotiating a fragile balance between control and consent: managerial despotism is rarely the best way to secure *and reproduce* a productive workforce" [Peck, 1996, pg23-24, italics in original]. However, "today's precarity is, in large part, an *exercise* of capitalist control. Postindustrial capitalism thrives on actively disorganizing employment and socio-economic life in general so that it can profit from vulnerability, instability, and desperation," again, an idée force [Bourdieu, 1998; Ross, 2009, pg51]. Intensification of work erodes worker control over workplace practises, and this, again, becomes normalised [Canaan, 1999]. It would seem then that anxiety about instability is now endemic to the labour market [Bardasi and Francesconi, 2004].

The anti-regulatory environment which emerged through the 1980s fetishized marketization at the expense of trade unions and labour's power [Nichols, 1999]. Thus, neoliberalisation relocated the bargaining power of labour to labour's disadvantage, as individuals are seen to have power over their own economic destinies, though precarious types of employment did exist prior to this period [Quinlan, 2012; Ross, 2009]. The flexible labour market generally is structured in the form of core-periphery; the core is comprised of (more) secure workers surrounded by a periphery or buffer of a variety of unstable and insecure work arrangements, i.e., ‘labour market segmentation’ [Samuelsson et al., 2012; Virtanen et al., 2005a]. Industries are fragmented and geographically dispersed following the principles of global capitalism [Benach et al., 2014]. [Bourdieu, 1998] terms this ‘delocalization.’ Indeed, individual experiences of work are also increasingly fragmented and competitive [Daykin, 1999]. Peck [1996] argues that the premise of labour as commodity, i.e., the peripheral worker, is in direct denial of the social nature of labour and the (re)production of labour: it is a pseudo-commodity, as supply is relatively autonomous from the market. Insecurity is sometimes seen as a trade-off for retaining investments and jobs, and often under neoliberalism, each setback in the economy is blamed on a lack of ‘structural reform’ in the labour market and a lack of flexibility on the part of workers – carrying through that idée force [Standing, 2011]. Standing [2011] further asserts that firms themselves have become commodities, being bought and sold via a series of instruments. Due to this, workers and employers have little impetus to establish longer relationships based on trust, for example, as these relationships become increasingly contingent and re-negotiable [Standing, 2011].

There is a new expectation of labour to do the same or more work in fewer hours, or expectations or tasks have expanded – the increasing intensification of employment [McNamara et al., 2011]. The idée force of the flexible labour market is generalised and pervasive, and constantly moving the goalposts so that workers and firms are constantly on edge, engendering a permanent sense of insecurity. Precarious experiences do transcend contract types, though the constituent working conditions of this experience should theoretically vary.

Decomposing these experiences to their parts is an increasingly common approach in research [Scott-Marshall and Tompa, 2011], though it is important to understand how these experiences and their underlying parts may interact or influence one another. The impact of these structural changes is exacerbated by the slow evolution of the legislative, economic, and social mechanisms surrounding the labour market [Scott-Marshall and Tompa, 2011]. While there is general agreement on the processes encompassing new types of employment, the sheer variety of contract types and indeed working conditions which may only vary subtly particularly within differing contexts may cause analytical issues, as seen in the lack of consensus with respect to what is and is not flexible employment.

Flexible employment encompasses a variety of schemes and terminologies: precarious, casual, temporary, non-standard, atypical, non-permanent, unregulated, contingent, fixed-term, and so on [Benach and Muntaner, 2007; EMCONET., 2007; Kauskamp et al., 2013; Kim et al., 2012; Peck, 1996]. However, all of these seem to be essentially the same – not necessarily mutually exclusive, though terminology and analytic differences may raise issues, especially around the transferability of research. For example, Hadden et al. [2007] define contingent employment as having unpredictable hours and limited duration, while Connelly et al. [2011] define it as having no ongoing employment with a single employer. Bourdieu [1998, pg85] describes the casualization of employment as a component of a so-called ‘mode of domination’, “based on the creation of a generalized and permanent state of insecurity aimed at forcing workers into submission, into the acceptance of exploitation." A docile workforce, essentially one subject to what Bourdieu [1998] terms the 'structural violence' of insecurity, is an ideal one under neoliberal schemes. Lewchuk et al. [2003] describe precarious employment as the cumulative combination of a number of factors, inclusive of but not limited to atypical employment contracts, job insecurity, and low wages.

Kauskamp et al. [2013] emphasise the importance of taking the heterogeneity of precarious employment into account as it will not necessarily be inferior in all contexts. To put it plainly, sometimes it is a matter of choice. Some workers with higher levels of control in their temporary position use it as a pathway towards lasting employment, or they may hold a preference for project-based work [Samuelsson et al., 2012; Virtanen et al., 2005b]. Others take lesser jobs for tax or regulatory reasons – earning under a certain threshold (1.03 million yen, £5630) is tax exempt for secondary earners in Japan, for example [Kachi et al., 2014]). Domestic constraints may also limit the choice of job for women, as proximity to the home and complementary hours will be likely requirements [Weststar, 2011]. Job loss negatively effects future career prospects, so workers may take less than ideal employment in order to continue to earn [Virick, 2011]. Furthermore, while flexible employment types may benefit some, it, all things considered, undermines employment conditions [Benach et al., 2014]. Peck [1996]'s insistence that labour market allocation processes themselves must be questioned due to the pervasiveness of inequalities in the labour market, partly self-created and self-shaped is highly relevant.

There is indeed a social gradient in health and health outcomes, some of which has been evidenced using occupational classes [Marmot et al., 1995], and understanding these social inequalities is important for mitigating the effects of it [Niedhammer et al., 2008]. Popham and Bambra [2010] found this gradient in self-rated health by employment status, as well as a social gradient in unemployment risk. Benach et al. [2014] present a summary table of reviews of work and health by health outcomes, and nearly all studies found adverse effects of particular conditions, be it job insecurity or on call work. Morrison and Berezovsky [2003] argue that labour market risk is unevenly distributed, which may be reflected in those conditions having more or less adverse effects depending on occupation or workplace. Bambra [2011] further asserts that production is driven by the hunger of capital accumulation rather than by what is best for the health of workers. Daykin [1999] emphasises, though that as contexts shift, traditional understandings of the work-health relationship must also change, and modes of political organisation should no longer be assumed. The UK context, for example, has changed greatly over the past fifty or so years, as the following section shows.

2.6. The Historical and Regulatory Context of Work, Health, and Inequality: United Kingdom Case Study

While the European Working Conditions Survey, the first major dataset used in this thesis, covers all EU, EEA and candidate countries, for the purpose of this thesis, one particular context, the

United Kingdom, will be examined as a case study as it forms the focus of the second dataset – the British Household Panel Study.

During the First World War, the UK Government Industrial Fatigue Research Board investigated workplace injuries, concluding that the cause of accidents is mostly found in the psychology of individual workers [Nichols, 1999]. This was broadly rejected on methodological grounds, however notions about victims and their culpability in workplace accidents still remain [Nichols, 1999]. The classic welfare state did not fully exist until post-World War Two and was laid out in detail in the 1942 Beveridge Report ('Social Insurance and Allied Services') [Lowe, 2005]. The Beveridge Report developed the welfare state from past practice but ultimately its significance related to the tenets of universalism and comprehensiveness: "all citizens were to be insured 'from the cradle to the grave' against every eventuality which might lead to the inadvertent loss of their income" [Lowe, 2005, p17]. A high level of employment, or 'full employment' was proposed as the best guarantor of individual welfare, and this philosophy persisted in British government up until the mid-1970s; 'full employment' was delineated as under 3% unemployment [Lowe, 2005]. In a modern reflection of this philosophy, one of the Employment Conditions Knowledge Network's (EMCONET) key recommendations to reduce worldwide health inequalities through employment conditions was a return to full employment [EMCONET., 2007]. Inequality fell rapidly under Wilson between 1964 and 1970, and did not rise back above its previous peak until the Thatcher administration in the eighties [Shaw et al., 2000]. Full employment was abandoned 1975, as it exists in conflict with economic growth-related goals, as growth requires a more mobile (i.e., flexible) labour force [Lowe, 2005]. In the 1975 April budget, Labour abandoned the goal of full employment to avoid reflation of economy; Lowe [2005, pg1] states that "one of the 'props' of the welfare state, that government could *and should* guarantee a high level of employment – was thereby kicked away." The next year, Keynesian demand management was also abandoned, and in 1978-9, the 'Winter of Discontent' of strikes occurred mainly due to Labour failing its so-called social contract with the unions [Lowe, 2005]. Lowe [2005] argues that Labour's failure effectively elected Thatcher in 1979 and led to the adoption of neoliberalism.

There was a longstanding belief by both Labour and Tory governments that workers in the UK were unproductive, and even deliberately idle [Nichols, 1999]. Throughout the 1980s, the government held an almost antagonistic stance towards occupational health; it reduced funding and support of regulatory agencies, held deregulation philosophies, and actively resisted EU directives, as discussed below in subsection 2.6.1 [Daykin, 1999]. Standing [2011] argues that 'deregulation' is really 'reregulation' as more increasingly directive regulations were introduced, mainly, it seems, to dictate what people had to do to benefit from social policy. Bourdieu [1998] claims that Thatcher presents a restoration of the oldest capitalist tactics as a revolution, appealing to progress, through writing off progressive thought as archaic. Indeed, in that decade, Thatcher claimed to have turned around productivity, growth rates, and cured 'the British disease,' though these 'triumphs' were contingent on the power of labour being diminished economically, politically, and ideologically, rather than any neutral policy masterstroke [Nichols, 1999]. Thatcherite policy generally resulted in insecurity not only in the lower classes but in the middle classes as well [Bourdieu, 1998]. Hutton [1997] claims that the Thatcherite reforms since 1979 only dealt with the consequences and not the root of UK decline, adopting a fundamental amorality which emphasises the market at the cost of social exclusion. Unions were systematically dismantled by 1993, with nine major pieces of legislation leading to, for example, the abolishment of closed shops, the reduction of union membership, and the loss of collective bargaining agreements [Hutton, 1997]. The work day became more porous as the workplace adapted to the new neoliberal climate, reducing labour's confidence to endure due to higher levels of uncertainty and even, in some cases, fear [Nichols, 1999].

In the 1990s, the Labour opposition focused on increasing equality [Shaw et al., 2000]. After 'New Labour,' which as a social democratic focus as opposed to 'old' Labour's democratic socialist focus, was elected in 1997, there was a change in tack, and decreasing inequalities, especially in health, dropped rapidly down the policy agenda [Shaw et al., 2000]. Thatcher herself famously claimed that New Labour was her greatest political achievement [Burns, 2008]. However, it was not all necessarily Labour's fault, as it had to maintain the previous (Conservative) government's financial framework. There was generally movement away from the rhetoric of collective responsibility that carried Labour to election towards the (neoliberal) idea of individual responsibility for inequalities, something that has continued to present.

2.6.1. EU Regulations in the UK

While there are regulations to counter certain negative aspects of fixed term and part time employment, for example, (such as EU directives 1999/70/EC; 1997/81/EC; 1998/23/EC [Bardasi and Francesconi, 2004; EU, 1993, 1997, 1998, 1999, 2000, 2003], the majority of public policy appears aimed at increasing equality in pay, but not necessarily on the "non-monetary" conditions around atypical employment [Bardasi and Francesconi, 2004]. The UK government passed the Working Time Regulations 1998 [UK, 1998] in response to the European Working Time Directive (1993/104/EC [EU, 1993] and 2000/34/EC [EU, 2000] consolidated and superseded by 2003/88/EC [EU, 2003]). However, there are a number of professions with exceptions, up to 2003, when the Regulations were amended to include more exceptions (WTR 1998 [UK, 1998], (18(1); The Working Time (Amendment) Regulations 2003 [UK, 2003], 18(1)/18(2)). Such workers are exempted, for example, from "an employer shall take all reasonable steps, in keeping with the need to protect the health and safety or workers, to ensure that the limit specified in paragraph (1) [work no more than an average of 8 hours in each 24 hour period] is complied with in the case of each night worker employed by him" (6(2)); these workers are also excluded from having adequate rest breaks from strenuous work (8), and other further articles of the Act (WTR 1998 [UK, 1998], (18)). Further exemptions are specified, whereby the above exclusions (and others) also apply to cases "where the worker's activities involve the need for continuity of service or production [...]" (ibid. 21(c)); "where there is a foreseeable surge of activity [...]" (ibid. 21(d)). Arguably many jobs could be classified under these exclusions: retail employees during holiday shopping, or programmers before a production deadline. Indeed, these workers may ‘voluntarily’ decide to exceed reasonable working hours and limit rest breaks; the Act does suggest a maximum 48-hour work week, for example, but this is not required (WTR 1998 [UK, 1998], 4(1)). It was further amended in 2007 regarding entitlements to additional annual leave, and in 2013 with smaller amendments (Working Time (Amendment) Regulations 2007 [UK, 2007], 2013 [UK, 2013]).

Temporary agency work is one aspect of temporary work, whereby an agency supplies employees to a client, who is effectively the employer, but the employee is administered and paid through the agency. This means that there may be different pay schemes for agency workers and those employed by the firm itself [Connelly et al., 2011]. There is also a substantial amount of heterogeneity between temporary employment organisations [Benach et al., 2014]. Until 2010, temporary agency workers in the UK were not entitled to the same rights, entitlements, and protections as their permanent counterparts under the Employment Rights Act 1996. However, through the EU Temporary Agency Work Directive (2008/104/EC [**?**]), the UK was compelled to pass the Agency Workers Regulations 2010 [UK, 2010]. The UK government negotiated with the EU over this directive for six years, only capitulating so it would not lose its opt-out from the working time directives (1993/104/EC [EU, 1993] and 2000/34/EC [EU, 2000] consolidated and superseded by 2003/88/EC [EU, 2003], referred to above), according to The Guardian [Wintour, 2008]. The Agency Workers Regulations 2010 [UK, 2010] asserts that an agency worker is entitled to the same working conditions someone permanently in the same role, subject to a twelve-week continuous qualifying period working in the same job (The Agency Workers Regulations 2010 (5), (7)). The Regulations state that the worker is in the same role unless:

(a) ”the agency worker has started a new role with the same hirer, whether supplied by the same or by a different temporary work agency;

(b) the work or duties that make up the whole or the main part of that new role are substantively different from the work or duties that made up the whole or the main part of the previous role; and

(c) the temporary work agency has informed the agency worker in writing of the type of work the agency worker will be required to do in the new role.” (AWR 2010 [UK, 2010] (7(3(a-c)))).”

Again, the language of these exceptions, similar to the Working Time Regulation Act 1998 [UK, 1998], leaves enough ambiguity for any enterprising hirer of agency staff to supply workers with a ‘new’ role before the 12-week period is met. According to a report by the Liverpool City Council, the EU Regulation has a loophole, called the ‘Swedish derogation,’ which means that agency workers are not entitled to equal compensation, as long as they have a permanent contract, are compensated between assignments, and this must be explained to the worker [Kushner, 2014]. According to the Trades Union Congress, TUC [2013, pg1]:

”a Swedish derogation contract exempts the agency from having to pay the worker the same rate of pay, as long as the agency directly employs individuals and guarantees to pay them for at

least four weeks during the times they can't find them work. In Sweden, where these contracts originate, workers still receive equal pay once in post and 90 per cent of normal pay between assignments. However in the UK workers have no equal pay rights and are paid half as much as they received in their last assignment, or minimum wage rates, between assignments. Agencies can also cut their hours, so receive as little as one hour of paid work a week."

Rossman [2013] reported that some union members were pressured to sign 'derogation' contracts which effectively reduced their weekly pay by up to £200 per week. Furthermore, those agency workers who do not sign such contracts often found that the comparator for 'equal pay' was the lowest starter pay for a permanent employee, or the legal minimum [Rossman, 2013]. Indeed, the Association of Labour Providers (ALP)in the UK offers a course specifically aimed towards agencies and hirers considering using the Derogation, specifically how to transfer workers to this type of contract and how to avoid any 'risk' [ALP, 2015]. It seems that there are a dizzying array of contracts and categories for workers to fall under, especially when some of these allow a firm to revoke or alter concessions made to workers, such as the Swedish derogation and the Temporary Agency Work Directive (2008/104/EC [EU, 2008]). This makes defining and understanding the conditions and outcomes of these a complicated proposition. A model-based approach can help simplify these contexts and make research transferable. Of course, on 1st January 2021, the UK left the European Union and whilst some of the previous directives remain in place, there may over time be divergence and the impact of this on health remains to be seen.

2.7. Models of employment and health

Two decades of scholarship on precarious employment arrangements have not generated precise conclusions on the relationship between precarious employment and health. This is due to several factors: some inconsistent results in empirical studies, the lack of a sound interpretative framework that is capable of facilitating an understanding of different social and employment realities; and limited contextual and labour market-related variables that interact with individual employment situations." [Kim et al., 2012, pg100]

Despite continued recommendations and agendas for research [EMCONET., 2007], there is inconsistency within research on precarious working conditions. Kauskamp et al. [2013] attribute this inconsistency to differences on several fronts: the specific form(s) of employment, sample composition, health outcomes, and location or context [Virtanen et al., 2005b]. Pikhart et al. [2001] also note a dearth of research into the quality of working conditions and health. Further, [Siegrist and Marmot, 2004], emphasise that some processes and variables cannot be measured directly, and require theoretical concepts to operationalise particular working conditions or other characteristics at a generalizable level, allowing for comparison between and within occupations. This suggests a model-based approach may be appropriate to unite disparate areas of research.

The mechanisms linking health and employment conditions are still unclear, but an array of models, approaches, and frameworks have tried to resolve this Kauskamp et al. [2013]. The workplace psychosocial environment is a result of employment relations and not unrelated to them [Benach et al., 2014]. It is not only the work itself, but the hierarchies and structures of the workplace that can create both negative physical and mental health effects [Canaan, 1999]. Psychosocial exposures at work are often thought of as disconnected to physical hazards [Karasek and Theorell, 1990], but they are indeed linked (see Chapter 3).

Many newer models have built upon older models [Lewchuk et al., 2008]. EMCONET. [2007] also emphasises a need for more research surrounding working conditions and health, particularly on the mechanisms of, routes to, and the effects themselves. This can be difficult, though, as there is little agreement on the distribution of health effects among different types of worker [Virtanen et al., 2005b]. Watterson [1999] argues that occupational disease is a social construction, as the relationship between the disease and the occupation may be tenuous or confounded by other factors. A model-based approach could mitigate this tenuousness.

2.7.1. The Job-Demand-Control Model

The job strain or job demand-control (JDC) model developed initially by Karasek [1979], expanded with a colleague approximately ten years later to integrate support and develop questionnaires are some of the main models used in analysing working conditions and health. [Karasek and Theorell, 1990].

"Job control refers to employees' ability to make decisions about how and when they perform their work as well as the extent to which their job entails using and developing their skills. Job demands encompasses the amount and pace of work" [D'Souza et al., 2003, pg849].

Low levels of control are associated with poor health outcomes (e.g., distress, cardiovascular disease mortality) and employment outcomes (high absenteeism and turnover) [Johnson et al., 1996; McNamara et al., 2011]. Siegrist and Marmot [2004] emphasise that this model links the experience of self-efficacy with the way work is structured. Lewchuk et al. [2003] emphasise the importance of control but also that it can vary. Mohren et al. [2003] found among workers reporting job insecurity that demands were higher and decision latitude was lower. McNamara et al. [2011] found that employment status in general did not affect workers' perceptions of job security, though.

Indeed, while the control dimension produces consistent results, such as Marmot et al. [1997]'s finding that low control predicts coronary heart disease independent of socioeconomic status, the full model has produced mixed results [Siegrist and Marmot, 2004]. This was found by Godin and Kittel [2004] in their study of psychosocial stress at work, where control was significant but high demand had negligible impact on the health outcomes studied. The JDC model has a very specific allocation of power and support, which limits its usefulness in understanding new forms of employment [Lewchuk et al., 2003]. Furthermore, it exists at a task-level scale using only 'objective' measures whereas individual level data appears more commonly collected and analysed [Ostry et al., 2003; Van der Doef and Maes, 1999]. Egan et al. [2007] systematically reviewed organisational-level control, finding that interventions focusing

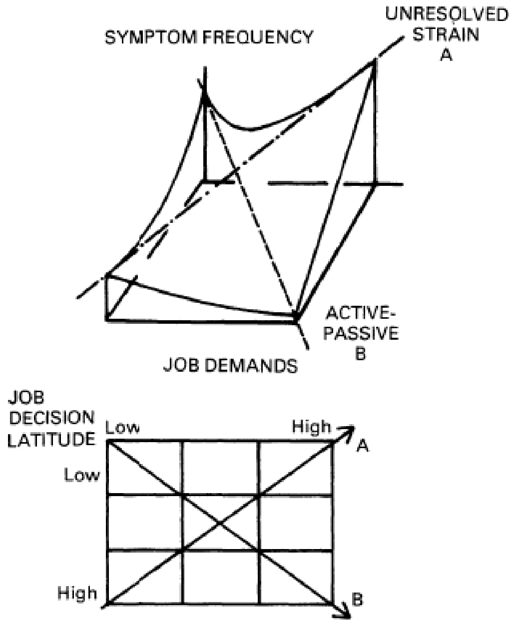


Figure 2.2: The job-demand-control model [Karasek, 1979]

on control or support improved health, and demand-reduction interventions also improved health, but warned that some evidence is inconsistent in terms of the direction of the effects, such as when interventions increased demands.

2.7.2. The Effort-Reward Imbalance Model

The effort-reward imbalance model (ERI, figure 2.3), the other major model used in this work-health research, is based on the notion that chronic stress (such as that at work) can be strongly associated with adverse long-term health effects [Muntaner et al., 2006]. It was developed in response to the JDC model, in order to integrate individual coping and the social reciprocity of modern work contracts, i.e., labour market and workplace related features [Siegrist, 1996; Siegrist and Marmot, 2004; Tsutsumi et al., 2001]. Niedhammer et al. [2004] found that the ERI was a significant risk factor for poor self-reported health in both men and women, under several different types of ERI, however under one year of follow up, some formulations of ERI were unpredictive of poor self-rated health. Godin and Kittel [2004] found ERI an excellent predictor of absenteeism and poor self-rated health. Further, Siegrist and Marmot [2004] describe the effort-reward imbalance model as linking the individual worker's self-esteem and the structure of work. Control is defined as a generalised belief on the part of the individual in question about the extent that outcomes important to them are under their own influence, or, controllable. It is therefore modelled at the individual level. The job-demand-control model does not distinguish this clearly. Therefore, the ERI improved on this by shifting the focus onto

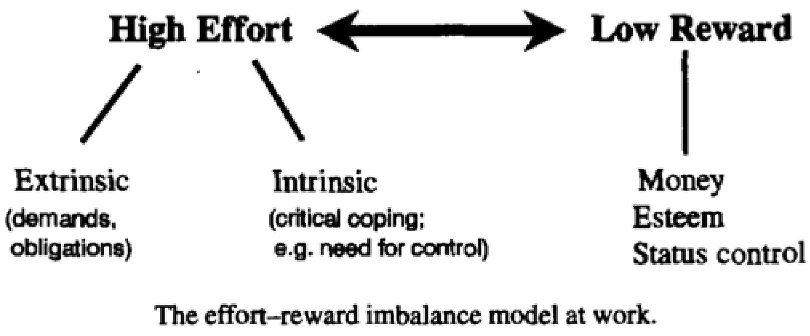


Figure 2.3: The effort-reward imbalance model [Siegrist, 1996]

reward. The effort-reward imbalance model is essentially about costs and gains, though it may not always adequately capture trade-offs. Siegrist [1996] rightfully points out that people may 'choose' to be in high effort/low reward situations due to social constraints, and a lack of control often characterises these situations. These situations are conceptualised in the ERI model as an absence of reciprocity [Siegrist and Marmot, 2004], i.e., high effort, low reward, which is not necessarily uncommon in certain occupations [Niedhammer et al., 2004]. This absence of reciprocity can impact negatively on self-esteem and self-efficacy.

Similar results, though, have been found by both models at both levels, and it has been proposed that these models complement one another, as Siegrist and Marmot [2004] discuss, they model both self-efficacy (JDC) and self-esteem (ERI). Further, in a study of depression and job stress in Japan, Tsutsumi et al. [2001] found that the measures in the two models were also relatively statistically independent to one another in relation to depression.

The Karasek model relies solely on objective measures of 'work' that do not adequately capture individual-level variation, although more recent adaptation also includes social support [Karasek and Theorell, 1990]. The Siegrist model was developed to integrate individual responses to conditions, however, it does not include any measure of task-level control [Siegrist, 1996]. Furthermore, Benach and Muntaner [2007, pg277] claim such psychosocial models may be unable to include other "more distal social and organizational determinants of health." Thus, factors relating to both structural and social inequalities, especially labour market variables, should be taken into account [Benach and Muntaner, 2007].

In terms of model success, regulatory context may also be important. For example, Virtanen et al. [2005b] found that, in Scandinavian countries, those working on a fixed term did not experience many differences to permanent employees, but this was partially attributed to its welfare regime. Lowe [2005, pg14] explains that the 'ultimate objectives' vary and reflect different cultures and political regimes. Finally, it is important to reflect on when these models were developed. Employment has, as argued, changed significantly in the past few decades, and some of the models were developed when standard employment relationships were the norm [Scott-Marshall and Tompa, 2011]. However, few recent models have attempted to be as generalised as Karasek's or Siegrist's, perhaps due to increased uncertainty, stemming from the idée force of the neoliberal, globalised economy [Lewchuk et al., 2008, 2003; Underhill and Quinlan, 2011]. There is also uncertainty to be found in applying these models to analyses, as there are many possible indicators to use.

2.8. Indicators of Working Conditions and Health

While a lot of work has been done on examining the social gradient in health, such as in the Whitehall studies [Marmot et al., 1991], which have influenced a large portion of further work on the role of working conditions on health, more detail about the factors underlying this gradient and social inequalities in health should be examined, as the understanding of them is somewhat unclear [Elo, 2009]. Examining more specific elements of working conditions and how they relate to health is needed to help mitigate these inequalities with effective policy and interventions.

Choosing which indicator(s) will be suitable within the model-based approach and useful for analysis can be a difficult proposition. "For example, job satisfaction is not a direct measure of health status, and health-absenteeism may be a poor proxy for health outcomes" [Benavides et al., 2000, pg500]. Focusing on a single indicator may cause estimation problems [Scott-Marshall and Tompa, 2011]. It is necessary to clearly define concepts, though often there may be subtle variation due in part to the terminological differences discussed earlier. Scale is also important – how can working conditions vary across, between, and within workplaces, individuals, labour markets, and states? People with better jobs are more likely to be healthier, but by how much, and is this difference significant and independent [Clougherty et al., 2010; Honjo et al., 2015]? Employment status or occupational type are a commonly used indicator in this type of analysis, as is job insecurity and working hours in several forms. There is variation across disciplines and even across the specific occupation examined in how outcomes or conditions, like stress, for example, are measured.

In McNamara et al. [2011, pg230] analysis of hospitality workers in Australia, they found that employment status did not cause any effect on workers' perception of job security, suggesting "the taxonomic approach has limited value." Workers surveyed felt similarly insecure, regardless of permanent or casual status [McNamara et al., 2011]. Perhaps, then, it is important to not only consider employment status in examining health outcomes but other measures of working conditions. Researchers have found that agency workers' employment can create downward pressure on working conditions, safety, and wages for other workers [Arrowsmith, 2006; Davidov, 2004; Underhill and Quinlan, 2011]. Temporary workers, according to Standing [2011], may be used to wrest concessions from permanent employees, as they can be replaced with temporary ones. A study of Japanese workers between 2001 and 2007 found workers' health was negatively changing over time, even if variation in employment contracts were adjusted for [Nishikitani et al., 2012]. In the Japanese context, the relationship between self-rated health and type of contract varied by household structure for women but not for men;

women in single parent families, for example suffered from fair/poor health [Kachi et al., 2014].

Indeed, consistent results are not always found – Bardasi and Francesconi [2004] assert that there was not a significant association with poor general health and a variety of types of flexible employment, though some types (seasonal/casual jobs across both genders), for example, were associated with higher chances of experiencing poor mental health. Scott-Marshall and Tompa [2011] found that exposure to nonstandard employment contracts was not associated with negative health impacts, though exposure to aspects of work precariousness were. Bardasi and Francesconi [2004] propose that, theoretically, the health effects of atypical types of employment are ambiguous, due to the preferences, expectations, and financial constraints of the individuals under consideration. Social constraints should also be considered. Indeed, effects may be dependant, for example, on the level of volatility in an atypical employment situation [Virtanen et al., 2005b]. Scott-Marshall and Tompa [2011] suggest that focusing exclusively on the type of contract may obscure that labour market experiences in 'the new economy' inclusive of 'standard work' exhibiting insecure characteristics, so it is key to determine what is associated with the effects.

Another issue to consider in determining the health effects of employment is reverse causation or selection bias, whereby it is not that atypical types of employment lead to health effects but that people more likely to be working those types of job are already unhealthy [Bardasi and Francesconi, 2004; Carpenter, 1987; Muntaner et al., 2010; Payne, 1999]. Clougherty et al. [2010] posit that those of more advantageous backgrounds are often already healthier, and will be healthier, as well as being more likely to be employed in better jobs as opposed to their less privileged colleagues. Moreover, what Virtanen et al. [2005b] and Kim et al. [2012] refer to as the 'healthy worker effect' posits that healthier people are more likely to look for a job, and to get a job. Bartley and Owen [1996] characterize this effect as weaker in non-manual versus manual workers. Watterson [1999] argues that employees needed to be healthier in 1997 than in 1977 to keep the same jobs. Further, Martikainen and Valkonen [1999] found that the healthy worker effect wore off with increasing duration of follow-up. However, George [2005] argues that the dominant direction of causation is from socioeconomic status to health, though Cutler et al. [2006] discuss that poor health can lead to low income. Perhaps insecurity, which may not be related to health at baseline, may be a useful indicator?

Job insecurity has been defined as "the discrepancy between the level of job security a person experiences and the level she might prefer"; while the concept is sometimes limited to the threat of job loss, it may also include "the loss of any valued condition of employment" [Bartley and Ferrie, 2001, pg778]. This implies a certain degree of subjectivity. Greenhalgh and Rosenblatt [1984, pg438, cited in[Richter et al., 2013]] define job insecurity in their framework as "the perceived powerlessness to maintain the desired continuity in a threatened job situation." Lau and Knardahl [2008] separate job insecurity and employment insecurity, emphasising that employment insecurity focuses on the ability to find an equally satisfactory job. Bourdieu [1998, p84] describes flexibility as an 'insecurity-inducing strategy,' claiming insecurity not as an economic inevitability but as a product of political will and idées forces. Costs are reduced for firms by creating insecure working arrangements – insecure workers are less demanding [Bourdieu, 1998]. For example, Bartley [2004] suggest that the deterioration of job security over time may be a key reason of the increasing prevalence of limiting illness (an increase of 14% between 1972 and 2000). Ferrie et al. [2005] found poor self-rated health was related to job insecurity, as well as the General Health Questionnaire score and depression. People reporting insecure working conditions were four times as likely to report depression and poor self-rated health, and those claiming moderate insecurity were nonetheless also more likely to be depressed [D'Souza et al., 2003].

Job security is related to poor mental health [Benach et al., 2002; Lau and Knardahl, 2008]. Self-reported morbidity was higher among the insecure [Benach and Muntaner, 2007]. Job insecurity can be viewed as an exposure resulting in impaired mental and physical health [Kim et al., 2012; Mohren et al., 2003]. Potential explanations of the relationship between job insecurity and health have not been thoroughly explored, however [Ferrie et al., 2005]. Richter et al. [2013] also suggest that more research is required to determine the conditions under which job insecurity relates to documented health outcomes. It has been found that "a combination of personal characteristics [. . . ,] material factors [. . . ,] and other psychosocial characteristics of the work environment [. . .] explained 68% of the association between self-reported job insecurity and self-rated health in women and 36% in men" [Ferrie et al., 2005, pg1598].

The regulatory context, as indicated earlier, is also highly important – in a review of studies published stratified by welfare regime, those in Scandinavian countries, for example often reported no or little association between experiences of insecurity and ill health [Kim et al., 2012]. It was theorised that more egalitarian welfare employment societies buffer the negative effects of insecurity; all other welfare regimes were found to have a strong relationship between ill health and job insecurity [Kim et al., 2012]. Including a welfare regime component in analysis may be prudent. Work involvement, or in this case, the psychological identification of work, was found to moderate the negative effects of job insecurity on satisfaction [Richter et al., 2013]. Insecure workers withdraw from their roles, reducing their commitments and productivity [Scott-Marshall and Tompa, 2011]. It is the anticipation of change that causes more adverse effects than the change itself – losing a job allows one to use certain coping mechanisms that are not viable when there is merely the threat of job loss [Scott-Marshall and Tompa, 2011]. Precarious employment and job insecurity are associated with significantly worse occupational health and safety outcomes [Quinlan et al., 2001].

Sickness absence (SA) has been related to job insecurity by Kivimaki et al. [1997]. Job insecurity and low social support were found to increase the number of absent days across both genders [Niedhammer et al., 2013]. North et al. [1996] using the Whitehall II study, found that self-reported work characteristics were predictive of sickness absence spells of varying lengths, especially in relation to work demand, or social support at work. Kinnunen et al. [1999] modelled this relationship using their sample of Finnish employees in three industries over a three-year period: the more likely a job change was perceived to be negative or insecure, the more likely the employee was to feel job exhaustion one year later, and it was more likely that

that employee would be absent due to illness. The costs of sickness absence to the economy and business are considered substantial [C.I.P.D., 2015; Marmot et al., 1995]. Long term sick leave is also a significant public health problem [Ahlstrom et al., 2010]. Head et al. [2008, pg1] claim that diagnosis-specific sickness absence is a useful total health measure, in that “it reflects day to day functioning in occupational setting and predicts mortality at least as well as more established indicators of health.” Indeed, Head et al. [2008] found a dose-response association between mortality and diagnosis-specific sickness absence (hazard ratio 1.97 for 2+ certified absences and 1.48 for one absence, compared to no absences). Aronsson and Blom [2010] use measures of sickness absence and presence (as well as self-rated health) to create a long-term-health outcome variable measuring ‘good’ health. Being in a preferred occupation and workplace had an odds ratio of 1.34, compared to not, and was therefore the most important labour market aspect [Aronsson and Blom, 2010].

Absenteeism captures the range of ill health that is experienced within an organisation, though its inverse, presenteeism, should be considered also – Wada et al. [2013] claim that presenteeism reduces worker performance. Presenteeism can mask serious health problems that may emerge later in life; it may decrease productivity. Sickness absence and presenteeism both stem from the same decision process, so understanding of both can be enhanced [Hansen and Andersen, 2008]. Gerich [2015] argues that a combination of sickness absence and sickness presence is a more valid indicator of health. It may remain difficult to define and measure, though, as perception (both of the employee and employer) is heavily involved [Hansen and Andersen, 2008]. Presenteeism stems from ”the moral evaluation of sick employees by peers and superiors depends not only upon the biological reality of illness but on pre-existing attitudes and patterns of power and control” [Daykin, 1999, pg2]. The culture of a workplace is clearly important: presenteeism may be a part of professional identity, as it is perceived by those working in nursing as ‘not letting anyone down,’ or management may be unresponsive or uncaring, perhaps promoting presenteeism [Dew et al., 2005]. Demands for presence are therefore both work and personally related, and related to more than one causal mechanism [Hansen and Andersen, 2008].

Fixed term and temporary forms of employment are both related to a lower rate of sickness absence than the rate for those permanently employed, likely due to higher job insecurity [Virtanen et al., 2003, 2005b]. [Virtanen et al., 2003] found that an employee transitioning from fixed term to permanent contract was associated with increases in job security and satisfaction and also, importantly, medically certified sickness absence. Dew et al. [2005] found that the organisation of workplaces mattered in terms of illness reporting – workplaces with well-organised trade unions tended to have better reporting, and the rationalisation of presenteeism varied across sites. Sector or workplace organisation may therefore be related to health. An agency worker interviewed by [Underhill and Quinlan, 2011, pg406] they quoted explained that agency workers had more pressure to keep working and to work rapidly, stating “you can just see the permanents work slower, because they know they’ve got a job.” Agency workers too often work longer hours.

"Work time poses a unique challenge, theoretically and methodologically, because it can potentially channel several health-relevant mechanisms" [Kleiner and Pavalko, 2013, p985]. This can include things like night or shift work, the amount of work, or the structure and organisation of that time. Erren et al. [2008] describe the medium to long term disruptions of the circadian rhythm and its effect on bodily systems as 'chronodisruption.' Artificial light sources provide the body with 'inappropriate and confusing information' which desynchronises the internal clock and can bring about short- and long-term adverse health effects Erren et al. [2008, p369]. Bambra et al. [2008b] also discussed the health problems reported with shift work, which can include fatigue, digestive issues, stress, and sleep disturbances, which can be associated with the disruption of the natural circadian rhythm. Shift workers are at greater risk of cardiovascular and gastrointestinal disease [Knutsson, 2003]. A Danish study of women aged 30-54 who mostly worked at night found an increased risk of breast cancer compared to those who did not (OR = 1.5, 95%CI = 1.3-1.7, [Hansen, 2001]). In their meta-analysis, Erren et al. [2008] found a 70% increase in relative breast cancer risk across 12 studies, and a 40% excess relative risk for prostate cancer across nine studies. For the shift work meta-analysis, in seven studies, female shift workers faced a 40-50% increase in breast cancer risk [Erren et al., 2008].

Bannai and Tamakoshi [2014] emphasise the importance of separating shift workers from regular workers in analysis as they can skew results. For example, while Wong et al. [2011] found a 27.9% decline in reported workplace injuries in Canada between 1996 and 2006, for night shift workers, the injury rate did not change. Furthermore, when Kobayashi et al. [2012] presented their results of long working hours of male manufacturing workers in Shuzoka, Japan both with and without shift workers, the significant negative impact on health they found disappeared when the shift workers were removed from the analysis. However, there was nonetheless a positive association with working hours and metabolic syndrome after adjusting for shift work [Kobayashi et al., 2012]. Interestingly, Kobayashi et al. [2012] found a nonlinear pattern, with an OR drop from 8-9 hours and 9-10 hours, and a rise at >10 hours. Wong et al. [2011, p54] point out that shift work may be confounded by workplace characteristics, which can vary across shifts, as "the shift length, type of tasks, and number of staff and level of supervision may differ between day and night shifts thereby making it difficult to compare risks." Bambra et al. [2008a] describe shift work as important but overlooked in terms of being a working condition that is determinant of health, and emphasise that it is socially patterned. Harrington [2001]'s review of shift and extended-hours work found a consensus on the negative effect on sleep of these types of work, arguing that fatigue is a common complaint, though difficult to measure. Standing [2011, pg115] cites a "growing disrespect for the 24-hour body clock." Wong et al. [2011] stress that it is not only the disruption to normal biological processes that can cause harm, but also changes to sleeping routines leading to fatigue which may increase the risk of accidents.

Flexible workers are less likely to have control over their hours than those more securely employed [Bohle et al., 2004]. Bannai and Tamakoshi [2014] reviewed the literature on long working hours, emphasising the difficulty of drawing overarching conclusions when the question of how long is too long remains inconsistently answered. Accounting for this issue in the analytic phase, they concluded that long working hours are associated with CHD, sleep disorders, anxiety, and depressive states [Bannai and Tamakoshi, 2014]. Associations were drawn between women's low level of control over working time and poor self-rated health and psychological distress, and interaction analyses revealed that this effect was gender-dependent [Ala-Mursula, 2004]. Women, despite increasing workforce participation, still perform the majority of domestic labour [Weststar, 2011]. It could be that similar 'caring' labour is unequally assigned to female employees at the workplace as well [Cottingham et al., 2015]. Indeed, Standing [2011, pg117] points out that work is defined not only by "what was done but for whom it was done." Similar associations were found between control of working time and work stress with sickness absence at individual and aggregate scales [Ala-Mursula et al., 2005]. This is important as risk factors may not remain static across workplaces and individuals [Benach et al., 2002]. "[H]osts too often appeared to assume that casual observation of others and 'common sense' could replace training" [Underhill and Quinlan, 2011, pg408]. Further, as Nichols [1999] indicates, the moment the human factor is considered, everything that is done or not done by the victim or other workers can be blamed. Medical staff may be hostile towards writing about any sort of 'occupational epidemic' due to evidentiary issues or value judgments about the nature of the injury [Canaan, 1999; Watterson, 1999]. More weight may be allocated to a doctor's examination of visible symptoms as opposed to the patient's experience: essentially value judgements made in the name of science [Canaan, 1999].

2.9. Conclusions

Health inequalities have persisted through time, despite efforts to mitigate them [Marmot et al., 2020]. This chapter has argued that the workplace, and therefore, occupation, are factors in influencing health and health outcomes, as social determinants of health. Decomposing the work experience to working conditions and environments of work allows for the closer examination of these influences on inequalities and individual health [Scott-Marshall and Tompa, 2011]. Changes over time in employment arrangements have increased precarity, insecurity, and other negative aspects of these changes via flexibility, and are unequally distributed [Bambra, 2011]. As a consequence, this may increase inequalities in health. Through this literature review, it has been shown that working conditions, such as working time [Ala-Mursula et al., 2005; Artazcoz et al., 2013; Bohle et al., 2004], do have an impact on health and health outcomes. Several models were proposed to better understand thesse relationships, such as the effort-reward imbalance model Siegrist [1996], yet they miss certain aspects of these relationships, such as individual variation, or less immediate social determinants of health [Benach and Muntaner, 2007]. Therefore a reasonably broad approach should be taken, inclusive of the life course approach [Ben-Shlomo and Kuh, 2002], as well as general and specific social determinants of health [WHO, 2008].

EMCONET. [2007] calls attention to the frequent underestimation of data around occupational diseases and exposures. Clougherty et al. [2010, pg8] found that "the distribution of hazardous exposures is sufficiently parallel to the social gradient of health that a significant contribution of this is plausible," though it is generally assumed so obvious that evidence is rarely if ever produced empirically of these relationships. Some 'safety' improvements may exist more in the name of increasing profits than protecting workers: Nichols [1999] gives the example of the Davy lamp in mining, which, while partially increasing safety, also allowed for more dangerous veins to be exploited. Other safety interventions may have better improved workers' situations. More intangible variables should be examined. Changing patterns of employment are echoed in new arrangements of the production and distribution of risk and exposure, such as the externalisation of risk and cost to the employee from the employer [Daykin, 1999; Standing, 2011]. These considerations should be incorporated into a theoretical framework, similar to the models described in this chapter, but with an epidemiological approach to integrate concepts of risk, hazard, and exposure. This framework is called the worksome.

Chapter 3

The Worksome Theoretical Framework

3.1. Introduction

1

The models presented in the literature review, such as Siegrist [1996]'s effort-reward imbalance model which address the employment-health relationship have been found to be insufficient in terms of i) adequately explaining the relationship as it may occur in varying contexts; ii) operationalising concepts discretely and unambiguously, and iii) not considering how results may be presented to and perceived by a political or lay audience. The risk assessment and analysis concepts are introduced in this chapter as a bridge towards the worksome – while much of the literature using the concepts of hazard and risk addresses only tangible exposures, it is possible to adapt risk analytic models and language to intangible ones. There is a clear gap within research around the work-health relationship and risk that may be closed through applying the worksome framework to the work-health relationship.

The exposome is an epidemiological model developed by Wild [2005] in response to the sequencing of the human genome, the development of biomarkers, and the (at the time) strong emphasis on genotyping. Whilst the exposome is very useful for epidemiological work it does not allow for the accurate assessment of environmental exposures. The worksome as a framework was developed to reorient the exposome towards improving this area. Looking towards the life-course approach [Ben-Shlomo and Kuh, 2002], and through the lens of exposure, a framework linking concepts in epidemiology, occupational health, and inequalities research is developed and described: the worksome.

Lynch and Smith [2004] describe many chronic conditions, such as cardiovascular diseases, as developing over a long period of time, attenuated or amplified by other life

[1] A part of this chapter has already been published in Social Science and Medicine [Eyles et al., 2019]

course factors. The worksome includes the interactions between scales, individuals, times, and geographies. This furthers our understanding of the complexities of this landscape. As work too consumes a large part of any given individual's life, the life course approach is key to understanding work as a social determinant of health. George [2005] emphasises how critical it is to study the relationships between health and socioeconomic status with a life course approach and argues that the consistent causal direction is from SES to health.

This chapter describes the process of risk analysis and the concept of hazard or exposure, and then moves towards the idea of an intangible exposure that crosses physical and social/psychological boundaries. The language of risk analysis and assessment, even in relation to epidemiology, is familiar ground to many policymakers. This is important because policymakers often require time-efficient briefs that are easily understood. Using familiar concepts is one way to ensure that policy-focused research will be effective.

Integrating these concepts into the worksome allows for easier adoption of the framework in research that aims to influence policy. The chapter takes the interconnected 'whole person' view of physical and mental health [Carter et al., 2015]. The worksome will be then situated into health inequalities research, particularly in relation to the use of social class. A critique of current class-based approaches to research will be made. Finally, a rationale for using the worksome will be provided.

3.2. Risk assessment, risk analysis, and epidemiology: Developing a new paradigm for assessing intangible hazards

Policymakers use risk frameworks to decide on exposures and hazards, so using the language and concepts of risk assessment in a framework focusing on the social determinants of health proximate to occupation may allow for better translation of research to policy. This section forms a bridge from the exposure science and risk analysis concepts from tangible to intangible exposures and sets the base for the worksome framework. The risk literature will be briefly overviewed, followed by a short discussion on the sociocultural construction of risk.

Prior to the 20th Century, risk was generally considered as a neutral term, but now it is primarily used in the context of negative outcomes over words like 'danger' or 'hazard' [Fox, 1999; Gabe, 1995]. Hazards are those circumstances which may give rise to harm, whereas risk is the likelihood of a given hazard occurring [Fox, 1999]. However, these circumstances are not always without controversy. Risk is inherently uncertain, and the way it is characterised can be controversial. John Snow, arguably one of the fathers of modern epidemiology, was recommended to withhold his results of his famous cholera study as there was worry of a panic [Brown, 1995]. [Bourdieu, 1998, pg40] put this sort of recommended censorship as such: "You cannot cheat with the *law of conservation of violence*: all violence is paid for [. . .]." Violence, in this case, is the exposure to risk and hazard. Who 'pays' for the violence is determined by many factors, be it structural factors (government policy, employment relations) or individual ones (lifestyle choices)? Those under risky conditions can still suffer from them even if they are unaware of them, but as there are many ways of examining risk, characterisations and interpretations can still differ [Gabe, 1995].

*"The technical concept of risk focuses narrowly on the **probability** of events and the **magnitude** of specific consequences. Risk is usually defined by multiplication of the two terms, assuming that society should be indifferent towards a low-consequence/high-probability risk and a high-consequence/low-probability risk with identical expected values." [Kasperson et al., 1988, pg177-8, emphasis in original]*

A more discriminating sort of analysis than this simplistic approach is, therefore, required in order to distinguish between these forms of consequence and probability discussed by Kasperson et al. [1988]. Risks are, by definition, scientifically uncertain as they relate to future consequences of an action. The future is generally unpredictable: if the environment and human behaviour are taken into account during the course of analysis, uncertainties will exist throughout the entire scientific process [Fisher, 2010]. Relationships are not always linear or obvious and people make choices that cannot always be predicted. Different people will accept different risks at different thresholds, and this can vary culturally and contextually. Different people are subjected to different risks at different levels, and some pay for risks they are not at all involved in creating nor benefit from. This calls back to the 'law of conservation of violence,' in that these risks, i.e., 'violence,' are paid for not necessarily by those who enact them [Bourdieu, 1998].

Risks are open to social definition by those with power and access to knowledge [Fox, 1999]. Fox [1999] describes hazards as 'natural,' and risks as 'cultural.' The externalisation of risk from firms is common in neoliberal economies, and there lies inequality in the probabilities of the negative consequences of these risks. There are nonetheless efforts to include multiple voices in these decisions around how risk is characterised and analysed, in order to better mitigate or control exposure to risks. Risk characterisation and evaluation can be improved through an analytic-deliberative process, whereby analysis is defined as using "rigorous, replicable methods developed by experts to arrive at answers to factual questions," and deliberation as using "processes such as discussion, reflection, and persuasion to communicate, raise and collectively consider issues, increase understanding, and arrive at substantive decisions" [Stern and Fineberg, 1996, pg20]. This is an iterative process, as analysis may be framed by deliberation, and deliberation informed by analysis [Stern and Fineberg, 1996]. That is not to say that this process is without problems: those in power can use these structures to claim that the processes around risk assessment are fair, when the probabilities and consequences of those risks are unevenly distributed.

As risk is 'cultural,' differing viewpoints and the structures of power in society can make it a moral issue in several respects. Beck [1992, pg23]'s 'risk society' perspective should also be considered here:

"[risks] only exist in terms of the (scientific or anti-scientific) knowledge about them. They can be changed, magnified, dramatized or minimized within knowledge, and to that extent they are particularly open to social definition or construction."

Those who are exposed to risks can be subject to blame. The moral dimension of risk and blame is important to address. Those on the margins may be subject to higher levels of risk, and this distribution blamed on 'choices' they have made. For example, an individual may 'choose' to work at a hazardous job, because they have to work to survive, not because they truly want to work in those conditions. This 'choice' comes into play when the consequence of the risk is considered: the individual may be blamed for what may happen, since they were aware of the risk. It should therefore not be assumed that science and values are so easily distinguishable. Risk decision-making is not, fundamentally, a conflict between these two, but a balance. It is important to consider the potentially numerous subsets of the population: those who die, who become ill, who are infected or otherwise affected, who are exposed, and who are susceptible [Katz et al., 2014].

Further, individuals can be socially constrained and afflicted by risks (not solely physical ones) 'voluntarily.' A worker may 'choose' to continue to work in an office where they experience workplace harassment, for example, because finding a new job may be too difficult or impossible. Not working is an impossibility for many considering the neoliberalisation of welfare systems worldwide, a consequence of which is the individualisation of responsibility. Put simply, under neoliberal welfare systems, the individual, not the state, must help themselves. Not all exposures are equally likely to engender negative health effects, and Anderson and U. S. E. P. Agency [1983] call for 'reasonableness' (again) around low dose and low risk thresholds, though there remains uncertainty. To reiterate, a more discriminate form of analysis is required, that includes both substantively- and theoretically-driven objectives. The worksome, which explicitly articulates this kind of interaction between exposure and risk, does this.

The assessment of risk, and the actions to take from this assessment form an important part of public policy, especially that around the health consequences of those risks. Risks are uncertain, and subject to what Bourdieu [1998] termed the 'law of conservation of violence,' whereby risks and exposures must be paid for in some sense. Risks are largely socially defined, and inequalities arise when risks are externalised from firms outwards in neoliberal economies, which, as discussed in Chapter 2, are an idée force, or an ideal with social power. These risks are imposed or shifted often through the flexibilisation of employment, which Peck [1996, pg23] (1996, p23, emphasis in original) argues is 'an *exercise* of capitalist control.' This is a source of health inequalities: those who take on the risks are often not those who create them, yet as described earlier, suffer the consequences and blame for what occurs. It is often the constrained worker who must 'pay' for the risk or exposure, due to increased instability and decreased control over work practices and organisation. These changes occur over the life course, and in order to examine and understand how these exposures, both tangible and intangible, happen and are processed, a robust conceptual framework is required, as suggested by Kim et al. [2012].

3.3. The Worksome

The worksome is a theoretical framework that organizes the factors that impact human health. It is a representational model of the factors and interactions that can impact health. Extending the past concept of the "exposome," the worksome is innovative in the way it classifies and models interactions between the social and physical components of exposure. It is precisely these interactions that recognize the fact that not all individuals may be harmed by a given workplace, but that the interactions between the workplace and other social factors drive health outcomes.

Paracelsus established the concept of dose-response by stating "solely the dose determines that a thing is not a poison" [Borzelleca, 2000; Paracelsus, 1538]. This can be applied to many models of exposure and contexts. Not all effects caused by an exposure are harmful, which is similar to not all jobs causing ill health. The occurrence and intensity of effects are related to dose in the toxicologic framework; dose is thought of as meaningful when its pathway and interval of exposure are indicated [Loomis and Hayes, 1996]. These concepts underpin much of exposure science and epidemiology, and one such model of how exposures may come together is the exposome (figure 3.1), which is the precursor to the worksome.

The exposome was developed by Wild [2005] in response to the sequencing of the human genome, and to incorporate the life-course approach to exposure into epidemiology [Ben-Shlomo and Kuh, 2002]. The exposome includes three separate - but related- domains that encompass pathways to and effects on health, the internal, specific external, and general external [Wild, 2005, 2012] whilst also capturing both nature and nurture [Miller and Jones, 2014]. This sort of life-course approach is appropriate for work (which we can define as a 'general external' element) as it accounts for a large proportion of time in a life-course [Bambra, 2011; Payne, 1999; Peck, 1996], and it can impact how lives are lived outside the workplace [Kleiner and Pavalko, 2013]. Working consumes a large part of any life course, regardless of whether that work is formal or informal. The general external elements, like work, of the framework are, in the general version of the exposome assumed rather than measured, as work with the exposome is predominantly top-down, focusing on physically measurable exposures [Rappaport, 2011].

The exposome has been adapted for health inequality research, notably by Juarez et al. [2014] who created 'the public health exposome,' which focuses primarily on environmental health. Research creating various types of exposome, for instance the exposomics project [Vineis et al., 2017], the public health exposome [Juarez et al., 2014], and the occupational exposome [Faisandier et al., 2011], focuses on the use or adaption of the exposome more with respect to biological analyses and issues which may arise thereof, without realising that other approaches using survey data may also be suitable under the paradigm [Brunekreef, 2013]. The worksome is an expansion of the exposome, in order to account more strongly for the social determinants of health, and the interactions between the scales of exposure.

The worksome expands on the idea of exposure to include a social-physical gradient,

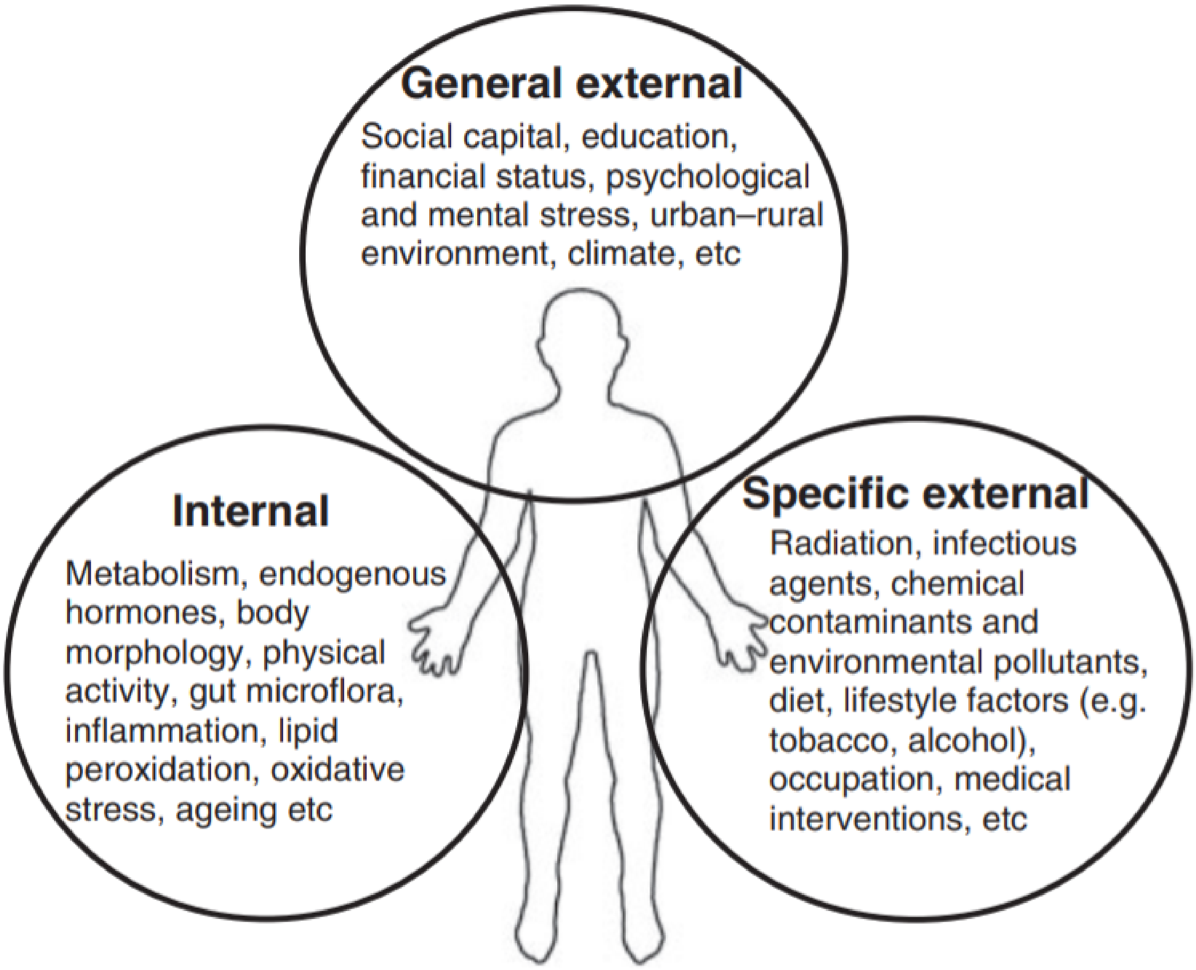


Figure 3.1: The exposome [Wild, 2012]

integrating the idea of intangible exposure (Figure 3.2). The worksome is necessary to explicitly model workplace in order to draw out lower-level scale (micro/meso) exposures, vectors, and effects. The worksome emphasises the importance of the scale of exposure and the interactions both within and between scales. It can include individuals, work groups, firms, industries, with other geographic and contextual (geocontextual) factors existing at the same or different levels, such as the workplace, the city, or the regulatory regime at varying levels of government. When data are collected, they are often structured consciously on particular scales, and therefore particular social structures, which are historically contingent, and subject to production or alteration by those in power [Sayre, 2005]. Jonas [2006] argues that "scalar-defined geographic processes" can empower or disempower individuals, and this can impact, for example, on their health outcomes. Therefore, including scales is important, and finding the right scales to include in an analysis using the worksome is therefore highly important. As a practical matter, the extent of an analysis is in part determined by scale and data availability.

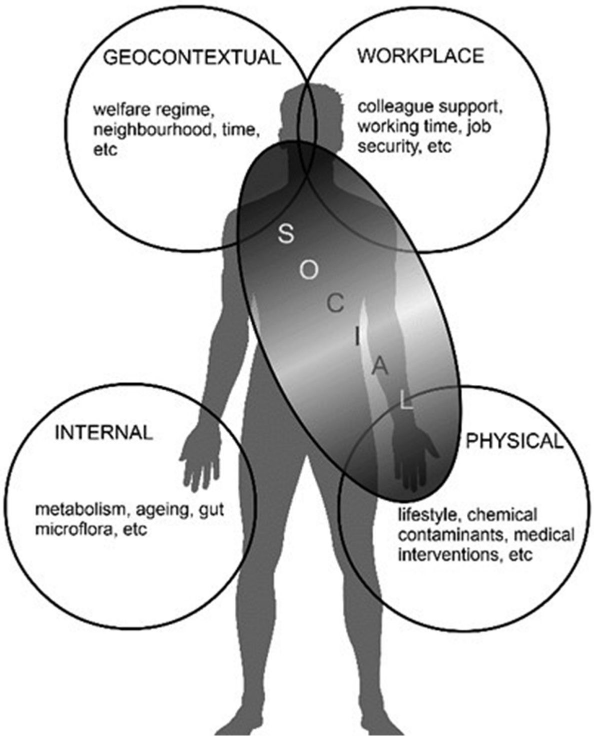


Figure 3.2: The worksome, published in [Eyles et al., 2019]

Scale can be seen in the worksome (figure 3.2), as each bubble can represent a single scale (i.e., the internal) or a set of scales (the geocontextual). In geography, scale refers to, most simply, the levels, or sociospatial categories (e.g., local, international) at which geographical units, or what could be termed 'places' (e.g., cities, regions) may sit, as well as their size and how they relate to one another [Marston, 2000; Sayre, 2005]. The geographies are highly relevant to research into health as place "*constitutes* as well as *contains* social relations and physical resources" [Cummins et al., 2007, p1825, italics in original]. The temporal element must not be neglected either, as analysis can be conducted along different timescales, and life courses are, of course, different lengths.

Specific delineation, however, does not mean that scales are rigid. Delaney and Leitner [1997], argue that scale is often constructed. The worksome takes scale as a fluid, interactive concept of levels, while keeping in mind that the scale at which an effect is experienced, as well as the delineation of those scales are often socially and politically mediated. This in turn goes along with how Sayre [2005, pg280] describes scale as "an attribute of how one observes something rather than of the thing being observed". Thus, scale is relational, and taking it as an interactive concept allows for the linking of research, which may vary over scales, in different contexts (i.e., differing regions, countries, or times).

The physical-social aspects of exposure are represented in the worksome model (figure 3.2) by the social gradient linking the physical to the geocontextual and the workplace. This encompasses largely physical exposures such as chemical handling [Arif and Delclos, 2012]

, predominantly social exposures including social support [Niedhammer et al., 2013], and exposures which are inherently both physical and social and fall between the extremes, such as working time [Dembe et al., 2005; Kivimäki et al., 2015]. Working time is both physical and social. It is physical, since the time spent exerting oneself or being present at work is a physical aspect of work, but it too is social, in the sense that it is also the time spent being exposed to a variety of (physical and social) working conditions. To expand on the social aspect of working time, it, in a meta sense, mediates how other working conditions are received and is mediated itself by interactions within the workplace, e.g., an individual's relationship with their manager. As well, the specific contacts with a variety of people, be it colleagues, or perhaps clients, are a part of working time.

Social exposures are essentially intangible, something which is emphasised in the social-physical gradient of the worksome, and it is an exposure type not emphasised by the exposome. Social exposures can be related to the social determinants of health in some respects. The social-physical gradient of exposure in the worksome model allows for flexibility in analysis as it provides a framework within the worksome for disparate and similar-but-different measures of exposure to be compared. Siegrist et al. [2010] argues that these are all measurable, through the careful application of theoretical concepts and reliable, valid social science research methods. Moreover, individual-level exposures and workplace level exposures interact: individuals within a workplace are affected and have effects upon workplace-level characteristics. Individuals, therefore, cannot be considered solely as discrete entities, but as relational ones, with respect to the work-health relationship along the life course. The worksome is novel, since it represents the pathways and direction of the relationships.

Returning to the life course approach, Ben-Shlomo and Kuh [2002] describe four pathways which should be integrated into research, using the example of adult respiratory disease. The pathways are labelled as predominantly biological, predominantly social, sociobiological, and biosocial. These are partly accounted for in the exposome, but its approach to the social aspects of exposure is weak. The worksome improves on this through the physical-social gradient of the worksome. The examples for each pathway, using adult respiratory disease as the endpoint are: impaired fetal lung development leading to impaired adult lung function (biological), adverse childhood SES influencing adverse childhood exposures and lifestyle choices in adulthood (social), adverse childhood SES being associated with the 'likelihood of exposure to infectious agents' (sociobiological), and finally, 'repeated childhood infections' leading to poorer educational attainment and adult SES (biosocial) [Ben-Shlomo and Kuh, 2002, pg285]. This can be seen in the worksome's integrated, interactive approach to scale and exposure: the directions and pathways to the endpoint of a health outcome are not always linear. Some of these pathways are influenced by those above the individual and workplace, or by interactions within the workplace and between individuals, or even within individuals (internal scale).

The worksome has an explicit model for geo-contextual factors. This is because workplaces are also located within geographical contexts, be it in relation to other firms, related industries, as well as in social and regulatory contexts. Geocontextual influences are an undercurrent and require consideration in work-health research. Geocontextual effects have long been considered of high importance and relevance to understanding health outcomes [Jones et al., 1987]. Further, a geographical approach has been argued to help support public health policy [Dummer, 2008]. Interactions within and between the domains of the worksome must be emphasised – people exist at multiple scales simultaneously: 'echoes' of past actions or consequences are reflected in these interactions as well. Time, or the life course, is an important element of the worksome. A given individual's contribution can prevail and the residual impacts remain with people for a long time after the initial exposure, as well as influencing their and others' behaviours. In addition, a person can change jobs, move to different areas, and live many different types of life in an individual life course. Trajectories can change, be it due to individual choice or structural factors. In terms of exposures, and the health outcomes arising from them, there can often be a time lag, or latency period between exposure and outcome.

With respect especially to time, the life course approach allows the worksome to also cover those who are unemployed or engaged in informal work. The former are incorporated as they move in and out of the workforce. The latter are encompassed as the worksome does not distinguish between formal and informal work, in the sense that they are both considered equally under the framework. Indeed, there are a number of papers examining life trajectories and career typologies with respect to occupational mobility, for example, and these approaches, often using sequence analysis or latent class analysis, can and should be emulated in work that examines the relationships between working conditions and health [Anders and Dorsett, 2017; Corna and Sacker, 2013; Haapakorva et al., 2017; Scott and Zeidenberg, 2016].

Movement between occupation types, such as from manufacturing to low-paid service sector, has been connected with poorer health using these approaches [Kampanellou and Houston, 2016]. Employing latent class models, Corna and Sacker [2013] modelled the lifetimes of older British adults, particularly around the labour market and family experiences, finding significant differences in the mental health domain. The worksome is useful in this respect over the exposome as it adds specificity and interaction between the domains, meaning that those experiences can be modelled both where they occur and how these occurrences interact with experiences in other domains. This is a result of the strong emphasis on the scales of these exposures and experiences. Further, it has a social-physical exposure gradient which allows more explicitly for intangible exposures.

One important emphasis of the worksome is on using occupation specifically. Ideally, workplaces themselves would be modelled or examined. However, it is often not practicable to survey or conduct qualitative research on multiple individuals in multiple workplaces. Further, epidemiological and social health research often use secondary data, which are economical and reproducible [Idler and Benyamini, 1997]. This means that reliable occupational classification systems are necessary. However, as the next section will discuss, social class is often used in place conceptually over occupation, or as a proxy for occupation when it is a separate social determinant of health, and when looking at work and health, occupation is a more appropriate dimension.

3.4. Why Occupation, and not Social Class?

According to Liberatos et al. [1988, pg89], “many sociologists feel that occupation is a reliable single indicator of relative standing in industrial societies”. Most social class classifications are based in some notion of the social value of particular occupations, but as will be argued, the divisions between classes are often arbitrary and atheoretical. There is a certain inconsistency, whereby classes both are hierarchical, and they are not – sometimes labelled as ‘relational’. Inequalities of opportunity are socially constructed and politically mediated; it is not only the job itself that is important but the type and nature of it and its social (and arguably, geographical) distribution [Peck, 1996]. The worksome takes these factors into account, through time and context. Bambra [2011] maintains that labour types and statuses have an inherent social status, which leads to those of differing statuses selecting into different occupations. This selection bias reflects the circumstances of those in those jobs and their ‘choices’. Siegrist et al. [2010] argue that the distribution of working conditions is “socially patterned”, in that those of lower status tend to experience more adverse working conditions, and attribute it to a social gradient overall in these conditions. Social status and occupation are linked and reflected in the ‘occupational’ class classifications still used today in many studies [Liberatos et al., 1988].

Occupation in some form is widely used as an explanatory variable to represent social class in health research MacDonald et al. [2009]. Often education, income, and occupational class are interchangeably analysed in studies in health inequalities [Geyer et al., 2006; Lahelma et al., 2004; Liberatos et al., 1988; Macintyre et al., 2003]. Geyer et al. [2006] concluded that these factors, though correlated, measure different latent social and causal phenomena, and should not be used interchangeably. This was done by examining the independent effects via Cox and logistic regressions of education, income, and occupational class on four separate health outcomes on German and Swedish populations [Geyer et al., 2006]. Whether education, income, or occupational class showed strong effects on health was dependent on the outcome measured, but the effects were still nonetheless independent [Geyer et al., 2006]. Careful consideration of the health outcome in question is also necessary, in order to avoid pragmatic or convenient choices not driven by substantive or theoretical rationale [Macintyre et al., 2003]. Social class is more complicated than occupation alone – it is a hierarchical measure of socioeconomic positioning.

The variety of ways in which social class has been historically articulated, and the difficulty of comparison, e.g., where does a skilled, successful tradesman lie compared with an unskilled white-collar worker, means that social class is less than ideal as a social determinant of health, especially considering working conditions [Savage et al., 2015]. Savage et al. [2015] also point out that income and social class do not always match – some in the higher managerial and professional class are in the bottom 20% of income earners: incomes within each social class can vary significantly. The selection of certain occupational groups into particular social classes, in some regards, then, lacks substantive validity.

Occupations can be ranked in multiple ways. The two most common are prestige-based, i.e. social-value based classifications and socioeconomic-based, i.e. education- and income-based classifications. Marmot et al. [1991], in the Whitehall II study, use the civil service grades, which are, essentially, a hierarchy of job status, strongly related to income. Social class can also be articulated through education, background, or even in relation to something people have or do not have [Leiulfsrud et al., 2010]. Social classes should and do change over time as (the nature of) work changes as the social prioritisation of certain types of status shifts. However, this change over time makes them unsuitable for the type of life course analyses that the worksome advocates for – while it is plausible for an individual to change classes through their life, if the classes themselves continue to change, it makes for unwieldy or irreconcilable analyses that cannot be carried into the future.

Social class was defined occupationally by the Registrar General's Office in 1911 into five categories [Pamuk, 1985]. Savage et al. [2015, pg35] assert that the "'occupational' measure of class was actually a way of making cultural judgements about the ranking and social importance of jobs." Indeed, this classification did change over time, as, for example, approximately a quarter of occupations changed classes between the 1951 and 1961 revisions [Liberatos et al., 1988]. Occupations in this scheme change class every census, and Pamuk [1985] points out that the Registrar General's Office warned that the classes should not be compared longitudinally. Distinctions between classes can be difficult to identify, especially through time, due to their 'inherently relational logic,' which is readily impacted by social change [Leiulfsrud et al., 2010]. Cambois et al. [2001] emphasise the importance of limiting intergroup mobility in order to measure more permanently individual SES, but, as argued above, social class is far too erratic over time to be used in this way. Furthermore, social class measures struggle to find the same strength of difference or inequality amongst women, meaning they fail on gender [Cambois et al., 2001; Leiulfsrud et al., 2010; Marmot et al., 1991].

Occupational classification systems change far less over time; the ISCO classification system was created in 1957, and was revised in 1968, 1988, and 2008 [ILO, 2010]. This is more due to occupations being created (computer programmers, for example, were only just starting to exist in 1957) rather than the social value of any given occupation changing, as they do in social class classifications. It is unlikely that the lawyer classification will change into the travel guide one. Cambois et al. [2001] give the example of French teachers, who historically have some of the lowest mortality rates, despite low incomes and classification. Using social class would miss these finer nuances at the occupation level.

Using occupation alone also requires little practical change, as the procedure of generating many modern social class classifications often begins with occupational information, often as International Standard Classification of Occupations (ISCO) codes, which are adapted for use in different countries [Connelly et al., 2016]. Furthermore, there is likely to be more consensus both between actors and contexts through time about who constitutes any given occupation, and generally what this occupation entails. Occupational classifications can even allow for those who are working informally or under other unusual arrangements [Eurostat, 2020b]. Martikainen and Valkonen [1999] found that the economically inactive are not well captured by social class, based on occupation, but this can be mitigated by the life course approach of the worksome, whereby previous occupation can be accounted for.

Corna [2013] argues that socioeconomic position is not fixed over time and should not be considered as such. Further, in the British context, and many others, the labour market has changed radically over the last 30 years, with large changes to dominant industries, employment arrangements, and occupational structure [Siegrist et al., 2010]. This means that social class, while important as a unit of analysis in some cases, at the very least needs supplementation with alternative views, as well as careful consideration of whether it is appropriate to use in any given study. Therefore, the worksome framework will recommend using a system of classification that is relatively fixed, to allow for the robust inter-temporal and contextual comparisons and analyses.

To summarize, how occupation is conceptualised, and operationalised as well as how it is measured. is key to identify the linkages between observed conditions and health [MacDonald et al., 2009]. Operationalising occupation as a measure of class may confound the actual impact of occupation itself and the conditions therein. The role occupation plays in analysis and how it is controlled may have consequences for any study [Liberatos et al., 1988]. While socioeconomic status is inclusive of occupation to some degree, it usually is measured through the 'class' system, income, or educational attainment rather than working conditions within occupations themselves.

The problem with using occupation as a stand-in for socio-economic status is that there are nuances within and between each class with regards to working conditions and exposures. Social class is also articulated differently in different societies, as what holds social value can vary significantly between contexts. This can reduce the transferability of results because of variation in social class measures and contexts. An occupation-specific classification system is therefore required. Fortunately, the International Standard Classification of Occupations (ISCO) was developed to allow for international comparison of occupations for research and policy. The ISCO has influenced the development of national-level standard occupational groups which are readily translatable to ISCO, including the British Standard Occupational Classification (SOC), the UK adaptation [Connelly et al., 2016].

Furthermore, as Braveman et al. [2005] rightly point out, questions on socioeconomic comparability arise when individuals have one similarity alone (i.e., same level of education, but other characteristics may be different). Liberatos et al. [1988] warn that misleading results may be obtained due to either using the wrong indicators or random misclassification during data collection. Inequalities can and do exist outside of the (institutional) class system [Leiulfsrud et al., 2010]. Individual socio-economic indicators do not all relate in the same way to health outcomes. Using measures as a proxy for one underlying phenomenon is poor practice, though one often done, i.e., occupation for class [Shaw et al., 2000].

3.4.1. Example: The Genesis of Mortality and Class Demography in England and Wales

The stratification of mortality by social class began in England and Wales in 1851, in the *'Decennial Supplements to the Annual Report of the Registrar General'* [Elo, 2009]. Further, from the 1920s, they were linked to the Registrar General's social classes, first developed in 1911, and these class inequalities in mortality persist even to today [Elo, 2009]. Cambois et al. [2001] suggest that a there was a lag in survival improvement, with decreases in mortality filtering downward from high to low status groups. These assume a constant, or widening gap, perhaps this due to "equivalent changes in mortality and disability" for each group, or disproportionate experiences of improvements [Cambois et al., 2001, pg515]. This may be indicative of a problem with the way these groups are operationalised [Murray et al., 1999], which is often a function of method or dataset, or even due to a standardised approach rather than having solid theoretical ground. Further, these classifications may be reflective of bias on the part of their creators, who, like everyone, are influenced by and influence the class system.

Macintyre et al. [2003] argue that the Registrar General's scale was in part calibrated by class differences in mortality. In effect this makes analysing mortality by social class an endeavour with a redundant conclusion, as what is used to make the classes contains a hierarchy based on a particular result, i.e., a class gradient of mortality. Jones and Cameron [1984, p37] argue strongly against the use of the Registrar General's social classes, calling them "engineered to conform to the prejudices of narrow-minded professionals and blatantly manipulated to produce smooth mortality gradients." Pamuk [1985] further argues that 'a continuous decline in mortality differentials' is empirically unsupported, and the notion of it is victim to the old-fashioned scientific ideal of 'perpetual progress,' with a unilinear history.

Scott [2002] describes the development of the class system by Stevenson and his colleagues in the General Registrar's office, which was largely based in their own experiences and instincts of class. Grusky and Sorensen (1998) argue that these sorts of classifications often echo "the interests and assumptions of the classifiers themselves (i.e., statisticians) rather than the operation of more fundamental technical or social boundaries." The rationale for tinkering with the classification system often appears to be arbitrary and atheoretical. In order to adjust the Registrar General classes, for example, Scott [2002] further claims that the standardised mortality ratio (SMR) was used to decide on cut-offs for the classes. This was done to create a smooth gradient and emphasise contrast. As a system, these classes and similar may not be entirely based in theory or principle, and indeed, are designed to generate a particular statistical result. This means that another approach is necessary.

The National Statistics Socio-Economic Classification (NS-SEC) was developed to solve the (partly hierarchical) issues with the Registrar General's scale, based on employment relations and status. The NS-SEC is said to group people who experience similar life chances and lifestyles partly due to employment relations [Connelly et al., 2016]. The NS-SEC allegedly does not have an implied hierarchy, and is a 'relational' scheme rather than an ordinal one [Oakes and Rossi, 2003]. But as Macintyre et al. [2003] rightly point out, the terminology used for the classifications show a clear hierarchy. Indeed, in the threefold version of the NS-SEC, the third level is 'lower occupations.' Scott [2002, p27] argues that "there is not, however, a straightforward linear hierarchy across all classes for all variables." A final argument against social class schemes of this sort is the heterogeneity within classes [Connelly et al., 2016; Pamuk, 1985; Scott, 2002]. That is to say, people within the same category can hold fairly different social positions, and can have vastly different life chances and experiences, as well as, more relevant to work, working conditions and employment relations. If social class groups are fairly heterogeneous, and generated in part with the outcome under analysis (i.e., mortality rates), more discriminate and homogeneous groups are required. This is why the worksome advocates for analysing individuals using occupation, rather than class, especially with respect to working conditions and how they may relate to health.

MacDonald et al. [2009] found in their review of occupation use in epidemiological research that while 83% of projects collected descriptive occupational measures, less than half used these data in published analyses. Often, only broad categories are used [Elo, 2009], which do not always add much to the analysis, especially with new, precarious modes of work that transcend the manual/nonmanual or white/blue collar divisions. In addition, most research used occupational and workplace information to represent environmental exposures or to control for socioeconomic status, though MacDonald et al. [2009, pg1416] argue that "authors rarely acknowledged the likely interdependence and interaction of SES and workplace conditions, despite considerably theoretical and empirical evidence linking the two." Elo [2009, pg555] argues that the various measures of SES are "linked to distinct proximate determinants of health and mortality," emphasising the importance of examining "multiple dimensions of social class that may have an independent influence on health outcomes."

Unpacking the dimensions of SES is important in matters of effective public policy, though social ranking should not be used as a determinant of health, if structural elements of inequality are to be properly uncovered. This is why the worksome accounts for multiple dimensions, pathways, and interactions between occupation, income, employment, and health. Social ranking is undeniably socially mediated, and the measurement, operationalisation, and validation of measures of this are created by those who experience the system in particular ways, and therefore contains some element of bias. [Murray et al., 1999, pg540] argue that, via the definition of health inequalities as "the difference in health status between social groups, with lower as compared to higher social position, does not allow for scientific inquiry into other determinants of health inequality across individuals." Further, there is likely not one latent underlying social dimension represented by class, a convenient catchall often integrating occupation, education, income, and job status. There are multiple dimensions, pathways, and interactions at play, which the worksome framework accounts for.

Macintyre et al. [2003] argue that measures of SES are often used interchangeably to examine ‘similar underlying constructs.’ Also, Leiulfsrud et al. [2010] assert that often social class systems can not be decomposed, such as occupation, even if occupation is an important element in the classification. The NS-SEC, for example, is partly composed of the UK version of the ISCO classification codes. There is nonetheless still a strong belief, despite awareness to the contrary, that due to this alleged single latent social phenomenon, one SES indicator can be substituted easily for another in analysis [Geyer et al., 2006]. This is an ultimately unproductive belief, as effective policy requires effective research, that is able to articulate the social determinants of health inequalities. While class may have a place in this, its dominance in the research landscape should be called to question.

To conclude, it is not just the theory of SES but how they are operationalised that matters, in terms of understanding social inequalities, especially with respect to reliable comparisons and analyses of data from a variety of contexts [Leiulfsrud et al., 2010]. It is indeed possible or desirable to employ more than one standard classification system, to allow for alternative views which may hold advantages for particular types of analysis. This is especially true substantively, where one measure of SES may show a stronger effect on a given outcome, though the effects of the others should be considered [Geyer et al., 2006]. If the relationship between working conditions and health is of interest, then stratifying or analysing by occupation rather than social class is likely to be more appropriate, as will be shown in Chapter 7. This is where empirical validation of occupational classifications over social class is undertaken. Macintyre et al. [2003] assert that while research often asks which classification “‘best’ measures socioeconomic gradients in health,” there is an implication that a universal relationship between SES and health exists. They warn against looking for the ‘best’ measure by simply finding the strongest association or effect [Macintyre et al., 2003]. While the strongest association might nonetheless be indicative of substantive importance, theoretical importance and relevance should also be crtieria for which classification system to employ. Indeed, Connelly et al. [2016] argue for a flexible approach, being inclusive of theory (which they contend does not always influence substantive results). Considering research objectives and policy goals substantively and theoretically when making these choices is also important.

Therefore, justifying one classification over the other requires ”robust empirical and theoretical adjudication” [Leiulfsrud et al., 2010, p1]. I provide this justification later, both in Chapter 7 and in Eyles et al. [2019]. In both cases, an empirical justification for the worksome framework is provided that supports its explicit focus on occupation by comparing different classification systems in the context of working conditions and health [Eyles et al., 2019].

3.5. Conclusion

Using the language of biomedical epidemiology is key to the worksome approach; the goal is to not only forward a clearer and comparable set of social research projects but also to develop clearer research findings for policymakers and other scientists. This allows for informed decision-making and more effective policy. Policymakers are familiar with risk assessment information, as it has been used by many governments for years, and therefore research using this combined framework will be more visible and adoptable [Anderson and U. S. E. P. Agency, 1983]. The worksome makes explicit the elements that the exposome treats as givens, allowing for the use of language familiar to policymakers while including effects that may not be considered explicitly in the biomedical approach. This framework can help fit disparate pieces of research together and contextualise them to form a wider collective of research.

The explicit focus on workplace and occupation allows for the examination of finer differences between individuals. Cutler et al. [2006] argue that the catchall of socioeconomic status (SES) covers a range of concepts, but that its constituent parts may have separate effects on health. Furthermore, they argue that these groupings can be ultimately unhelpful for the implementation of research in policy, where more discriminating classifications are required to test and implement policy. Scott [2002, pg26] argues “for most purposes a far more fine-grained economic classification is likely to prove useful.” This approach also allows for the examination of differences at the occupational level that may be obscured by the larger categories of social class classifications [Connelly et al., 2016]. Flexibility is important, as for research involving people, a complete body of research is impossible as society is constantly changing, so gaps in research are to be expected, and can be filled. The current paradigm of research, where social class is used as a proxy for a wide range of different circumstances, rather than occupation, misses out on the specificity of occupation-specific classifications, and the ready transferability between contexts. Without quantifying the risk, there is less information for policymakers to go on in order to balance risk with (socio)economic concerns [Anderson and U. S. E. P. Agency, 1983]. Furthermore, these models are widely used by government agencies often to address environmental health, and therefore are more familiar to a wider variety of audiences [Stern and Fineberg, 1996]. As risks themselves are socially defined and constructed [Beck, 1992], it is therefore acceptable to address the work-health relationship within this framework. It is therefore important then, in analysing this relationship through the worksome which includes aspects of the risk model and the exposome, to take into account different contexts and scales – not all jobs are the same, and not all people in the same job will be similarly affected, but some will be.

Social class has its place in analyses, but something more exists, so through the worksome, I argue, we can look for what is missing from contemporary analysis into SES and health. Employment relations and the hierarchies that result from them in terms of social class are complex. It is therefore more appropriate to perhaps take into account these conditions in analysis, rather than having the ‘black box’ of social class schemes, so that we may examine the constituent parts in order to be able to influence policy. There are a variety of reasons occupation is preferable as a unit of analysis in the worksome framework. Social class classifications can reflect the bias or class experience of their creators, and at times, the criteria used to create the groups themselves may use the outcomes we are interested in analysing as criteria for group assignment itself. For example, if the groups are based in part on particular morbidities, then this will influence, I suggest detrimentally, any analysis of morbidities using those groups. They have smaller numbers of groups, which can be fairly heterogeneous in terms of social position, especially in the middle. These sorts of schemes also change significantly over time as social priorities and value shifts. Most simply, the identified composition of social classes can vary between places and times, meaning research using these is difficult to compare and translate into policy. Therefore, occupation provides a temporally and geographically more sound system for examining working conditions and health.

The worksome can provide a transferable framework for research into work and health across these contexts. Through its flexibility, it can accommodate research from a variety of scales and contexts, allowing for the conceptual linking of disparate yet related studies. Further, by examining occupation, it eliminates the aforementioned difficulty of comparing class contexts. Occupations, while socially mediated, are not, like class, socially defined, and are more readily conceptually transferable between contexts.

The worksome is an expansion of a familiar concept, the exposome [Wild, 2005, 2012], and encompasses a life-course approach, as work is something which generally consumes a large part of any given individual's time. The exposome was explicitly chosen as a base, as its biomedical language and approach is well understood by policymakers. The worksome is useful over the exposome as it adds specificity and interaction between the domains, has a social-physical exposure gradient, allows more explicitly for intangible exposures, and emphasises scale more strongly. The worksome reorients the way in which the relationship between occupation and health is understood – as an interactive, multi-scalar framework of exposures set along a social-physical gradient (figure 3.2). By integrating scales, times, individuals, and geographies and their interactions, the complexities of these relationships become clearer. Further, the worksome promotes a new paradigm for health inequalities research, namely an approach which prioritises looking at finer details and the interactions between individuals, scales, and contexts. Finally, the worksome also allows for alternative views on sources of and influences on inequalities, due to its flexible approach to exposure, and interaction between individuals, scales, and contexts. The following chapter will present the datasets chosen to empirically investigate the worksome, as well as the methods employed for the analyses.

Chapter 4

Data and Methods

4.1. Introduction

[1] The worksome provides a theoretical framework for examining the relationships between working conditions and health. While one major research objective of this thesis is to develop this transferable conceptual framework, other objectives also include identifying and confirming these relationships, as well as specifying working conditions which underlie them. The worksome framework allows for these objectives to be met, through specific research questions, importantly those addressing changes through geographies, over time, across occupation types, and within individuals. The specific research questions address these changes, and, the final research question is to examine them in the context of specific health outcomes. The structure of the worksome answers this: it explicitly includes scales of exposure and a social-physical gradient of exposure, which draws out the relationships between working conditions, demographic variables, structural scales and health outcomes.

In order to answer the research questions posed by this thesis and meet the research objectives, quantitative analysis is employed to examine general health, as well as a set of specific health outcomes. This will provide empirical support of the worksome concept. Temporal, spatial, and occupational variation will also be examined at the national level with the European Working Conditions Survey (EWCS) data [Eurofound, 2020], and at the subnational level with the British Household Panel Survey (BHPS) data [University of Essex, 2018]. This chapter will describe the datasets, provide some exploratory descriptive statistics and maps, and discuss the most appropriate approach to analysing the data, namely (multilevel) logistic regression.

4.2. Data Choice

The European Working Conditions Survey (EWCS) and the British Household Panel Survey (BHPS) were chosen over several other datasets. The Whitehall and the Census datasets were also considered but excluded for a number of reasons. The Whitehall data were excluded because

[1] Some text in this chapter was taken from the paper published in Social Science and Medicine [Eyles et al., 2019]

it is only about a specific population within the UK Civil Service, whereas research question 5 is about the impact on different types of occupations, not all of which exist in the Civil Service. Furthermore, conclusions drawn from the Whitehall data may be more difficult to generalise because of this specific population, meaning empirically supporting the worksome, a broad theoretical framework, would be difficult. The Census was not chosen as it does not have many variables with respect to working conditions, and it is difficult to obtain specific individual-level data. By contrast, the richness and depth in the EWCS data is ideal for exploring the worksome across countries.

The BHPS was chosen to complement the EWCS data, because it matches in terms of time with the EWCS waves: the EWCS was collected between 1991 and 2015, the BHPS between 1991 and 2008. This means that they are more readily comparable than data collected later, like Understanding Society, the continuation of BHPS. Furthermore, where the EWCS data are repeated cross-sectional, the BHPS data are longitudinal, and do have several health outcomes and working conditions assessed throughout. The EWCS data are tailored towards examining working conditions specifically, and have many health outcome variables, though this does vary by wave. Furthermore, the international extent of the EWCS data is of particular interest, because of the differing legislative environments.

The EWCS data in particular are very rich, but poorly explored in health research. Other work using the EWCS has not approached health with a holistic theoretical perspective. With the worksome as a theoretical framework, however, a more purposeful, broad approach is possible. However, the EWCS does not have subnational data, and further, was taken as repeated cross-sectional surveys, rather than a longitudinal survey. Therefore, the BHPS was also chosen in order to investigate finer subnational geographic variation, primarily at the region level, and examine in more detail the longitudinal aspects of the research questions, using the same broad approach.

4.3. Data: European Working Conditions Survey

The EWCS dataset, specifically the 1991-2015 integrated data file, was obtained from the UK Data Service [Eurofound, 2020]. EWCS is administered by the European Foundation for the Improvement of Living and Working Conditions, or Eurofound for the European Union (EU). The survey was conducted approximately every five years starting in 1991, repeating cross-sectional waves in 1995/6, 2000/1, 2005, 2010, and 2015. Generally, the target sample size in larger countries was between 1,000-1,500 individuals and 500-1,000 in smaller countries (see figure 4.1). It should also be noted that not all countries are in all waves, and some dropped out of waves and returned to the survey later. For example, Serbia was only in the 2015 wave, while Kosovo was only present in the 2010 wave and Switzerland was omitted from the 2010 wave. The survey years 2000 and 2001 are presented separately here to show that they are mutually exclusive and can be treated as one wave for the purposes of analysis. EU countries were surveyed in 2000 and candidate countries in 2001 – candidate countries are those countries which are not in the EU but may be in the future [Eurofound, 2015; Paoli and Merllié, 2001]. However, despite the different status of these countries, the survey was administered with the same questionnaire and approach [Eurofound, 2015; Paoli and Merllié, 2001]. To prepare for the exploratory analysis conducted in Chapter 7, the countries have been sorted into welfare regimes, following Bambra [2007]'s classification. The classification can be found in table 4.1. The graphs in this section are sorted into these regimes, so that more similar countries are grouped together.

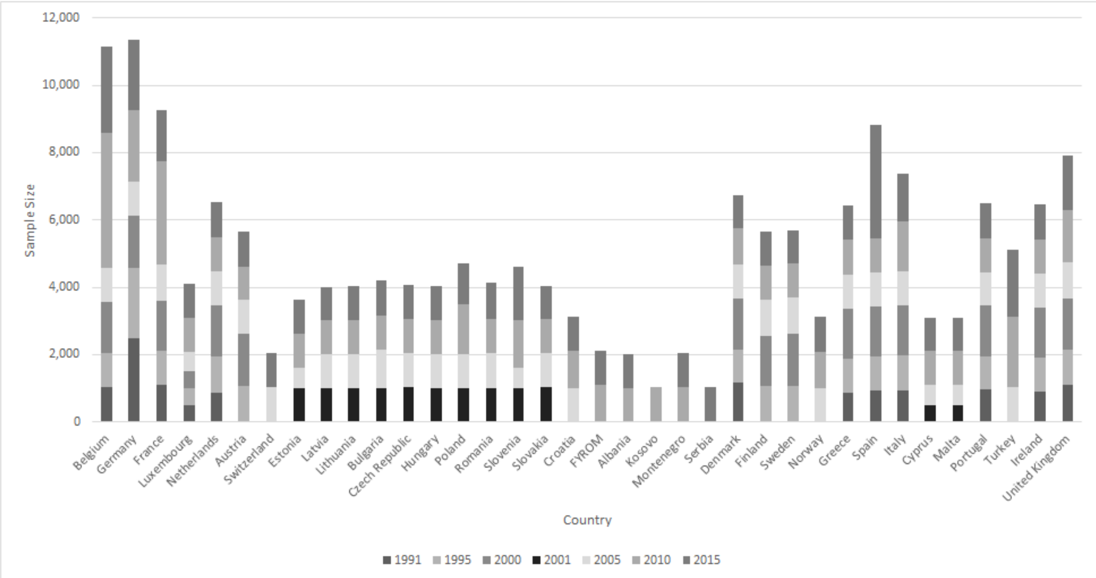


Figure 4.1: EWCS Countries through Survey Years. The 2000 and 2001 years comprise one wave of the survey. The countries are sorted into welfare regimes

The sampling methodology varied in some minor respects by survey wave, and in some cases by country. For example, Switzerland dropped out of the survey in 2010, but returned in the following 2015 wave. In the case of this thesis, 1991 data have only been included in some simpler preliminary descriptive analysis, as the data collection was much sparser; the survey questionnaire itself only had 19 questions [Paoli, 1992]. All sample designs aim to include only the 'total active population,' (i.e., employees or self-employed) excluding the non-working population, aiming to only include those 15-65, though members of the respondents' households were also asked some basic questions, e.g., their sex, age, and employment situation [Eurofound, 2007, 2011; Paoli, 1992, 1997; Paoli and Merllié, 2001].

In 1991, the Survey was carried out by INRA, a European research institute, using a multi-stage random design, whereby sampling points were drawn from 'administrative regional units' post-stratification (in the United Kingdom, electoral registers were used) [Paoli, 1992]. In 1995, it was carried out by INTRA-EUROPE, using a multi-stage random design, and includes non-EU workers working in the EU speaking the respective national language [Paoli, 1997]. In 2000, the multi-stage random sampling methodology (for 1991, 1995, and 2000) was described as using a 'random walk' procedure: using the Eurostat or national institute territorial breakdowns and

Table 4.1: Welfare regime classification and component countries

Welfare Regime Classification	Percent	Component Countries
Conservative Corporatist (Bismarckian)	28	Belgium, Germany, France, Luxembourg, Netherlands, Austria, Switzerland
Former USSR	6.52	Estonia, Latvia, Lithuania
Post-Communist	22.99	Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovenia, Slovakia, Croatia, Albania, North Macedonia (FYROM), Kosovo, Montenegro, Serbia
Social Democratic	11.85	Denmark, Finland, Sweden, Norway
Mediterranean/ Southern	22.6	Greece, Spain, Italy, Cyprus, Malta, Portugal, Turkey
Liberal	8.05	Ireland, United Kingdom

population densities, a list of sampling points was created [Paoli and Merllié, 2001]. Starting points are then chosen for each sampling point and each interviewer follows the ‘random walk procedure’; when a household is encountered where several individuals are within the survey scope, the individual whose upcoming birthday is the nearest to the current date is chosen [Paoli and Merllié, 2001, ’first birthday method’]. In 2005, the sampling design was further described as stratified and clustered, though in Belgium, the Netherlands, Sweden, and Switzerland, a different procedure was undertaken, as the ‘random walk’ had low response rates in previous waves: telephone directories were used to select interviewees [Eurofound, 2007]. In 2010, the survey was conducted by Gallup Europe, and the sampling methodology appears to be similar to previous years, though samples in Finland and Denmark were not clustered [Eurofound, 2011]. In 2015, the Survey was carried out by Ipsos NV, and the sampling strategy was similar to previous years [Eurofound, 2015].

The samples were also weighted in each wave in order to be nationally representative of the economically active population, generally by assigning a weight to each individual varying according to their ‘rarity,’ that is, said individual would have a higher weight if the group they represent is under-represented in the sample [Eurofound, 2007, 2011; Paoli, 1992, 1997; Paoli and Merllié, 2001].

4.3.1. EWCS Data Structure and Variables

In terms of the data themselves, many of the data items in earlier waves are not comparable with later waves, especially in terms of health outcomes, but also for explanatory ones. Omitting data from 1991, 1995, and 2000, due to missing information from both outcome and explanatory variables, resulted in a loss of 61,559 observations, accounting for 34.4% of the initial dataset. Questions about specific health outcomes, such as backache, were not asked to all respondents in those years. There did not appear to be any pattern to the missingness on the explanatory variables, so observations with missing data on explanatory variables were also removed from the dataset, as their exclusion should not induce bias. Table 4.2 shows the exclusions from the data. Those over 65 were also excluded, as the EWCS sampling frame consists of those aged

15-65 [Eurofound, 2007, 2011; Paoli, 1992, 1997; Paoli and Merllié, 2001]. Figure 4.2 shows the data by country and year after the exclusions.

Table 4.2: Exclusions from the EWCS Data.

Exclusion		**n**
	178,905 (total initial sample)	
Full Exclusion	**Cases removed**	**Cases remaining**
1991	12819	166,086
1995	15986	150,100
2000	32754	117,346
Over 65s	3168	114,178
	Exclusions due to Missingness	
Education	806	113,372
Shiftwork	835	112,537
Weekly Hours	3427	109,110
Time Arrangement	659	108,451
Skill-Duty Match	1269	107,182
Satisfaction with Working Conditions	702	106,480
Appropriate Pay	1639	104,841
Night Work	1263	103,578
ISCO 1 digit (1988) (missing code)	520	103,058
ISCO 2 digit (1988) (missing code)	48	103,010
Converted ISCO 2-digit 2008 (missing code)	59	102,951
	Total n:	102,951

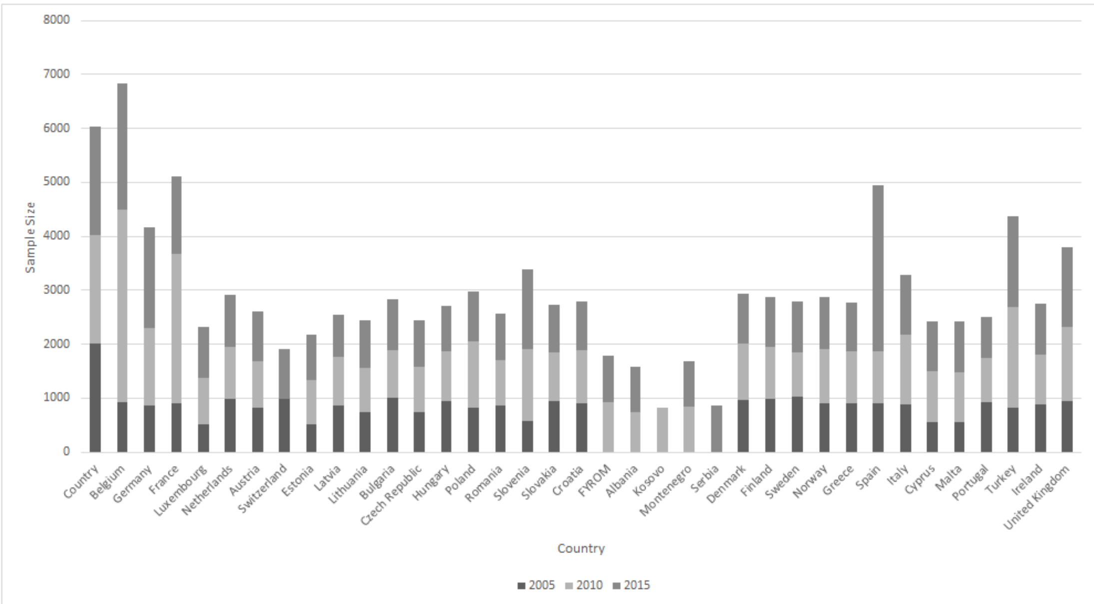


Figure 4.2: EWCS Countries through Survey Years after Exclusions. The countries are sorted into welfare regimes

The EWCS data include highly detailed information on occupations. However, in 2008 the International Labour Organisation's (ILO) International Standard Classification of Occupations (ISCO) was changed. As such, to ensure it was possible to use as many waves as possible the 2005 wave was reclassified from the original 1988 classification into the new 2008 standard using the International Labour Organisation's (ILO) International Standard Classification of Occupations (ISCO) correspondence tables [ILO, 2016]. The ISCO is a classification system which is structured (from finest to coarsest) into unit groups, minor groups, sub-major groups, and major groups, "based on their similarity in terms of the skill level and skill specialization required for the jobs" [ILO, 2016, np]. Table 4.3 shows the data split into the ISCO major groups, which include categories such as technicians and associate professionals, and skilled agricultural, forestry and fisheries workers. A sub-major group from the former major group is, for example, information and communications technicians, and within that classification fall several minor groups, including telecommunications and broadcasting technicians.

Table 4.3: ISCO 2008 Major (1-digit) Categories (n=10)

Occupation	Frequency	Percent
Armed forces occupations	477	0.46
Managers	7,251	7.04
Professionals	18,365	17.84
Technicians and associate professionals	14,236	13.83
Clerical support workers	9,035	8.78
Service and sales workers	19,282	18.73
Skilled agricultural, forestry and fisheries workers	3,303	3.21
Craft and related trades workers	12,642	12.28
Plant and machine operators, and assemblers	7,312	7.1
Elementary occupations	11,048	10.73

Facilitating international occupational comparisons is one of the objectives of the ISCO, so therefore it should in theory be the most suitable classification system in the data. There is also the Statistical Classification of Economic Activities in the European Community (NACE), which is an industrial classification system. The data broken down into the major ISCO categories (n in data=43) and 1-letter NACE categories are shown in tables 4.3 and 4.4 respectively. The most common ISCO occupations at the major level are service and sales (18.73%) and professionals (17.84%); the least common are armed forces (0.46%) and skilled primary industries (3.21%). The most common NACE classifications are wholesale and retail (15.29%) and manufacturing (14.65%), and the least common are extraterritorial organisations (0.12%) and fishing (0.10%).

For gender, the total sample is a 50/50 split, men to women, as would be expected with a representative sample of the European population. The gender split for most countries is roughly similar, although Kosovo, Turkey, Malta, Greece, the FYROM, and Switzerland have 45% or less proportion of women in the sample, with the first three having under 40% women in the sample. Portugal, Finland, Slovakia, Bulgaria, Latvia, Estonia, and Lithuania have 55% or more proportion of women in the sample, with the last three having more than 60% women in the sample (see figure 4.3). This country-level variation means that it may be necessary to account for geography in the modelling strategy.

In terms of education (see table 4.5), most of the sample has finished (upper) secondary education (42.24%) or the first stage of tertiary education (29.32%). The questionnaire uses the International Standard Classification of Education (1997 version). The lower secondary stage goes up to the end of compulsory education; the upper secondary stage tends to have an

Table 4.4: NACE (1-digit) Categories (n=17)

Classification	Frequency	Percent
A Agriculture, hunting, and forestry	4,642	4.54
B Fishing	103	0.1
C Mining and quarrying	527	0.51
D Manufacturing	14,992	14.65
E Electricity, gas, and water supply	1,324	1.29
F Construction	6,676	6.52
G Wholesale and retail trade; repair of motor vehicles and motorcycles	15,651	15.29
H Hotels and restaurants	5,018	4.9
I Transport, storage and communication	6,309	6.16
J Financial intermediation	3,128	3.06
K Real estate activities	9,214	9
L Public administration and defence; compulsory social security	6,779	6.62
M Education	9,171	8.96
N Health and social work activities	10,470	10.23
O Other service activities	6,750	6.6
P Activities of households as employers	1,161	1.13
Q Activities of extraterritorial organisations	120	0.12
Not classified	314	0.31

entrance requirement [U.N.E.S.C.O., 1997]. The first stage of tertiary education can include both Bachelor's and Master's degrees, and the second stage is research oriented and includes PhDs [U.N.E.S.C.O., 1997]. For the purposes of analysis, the education variable was split into those with tertiary or above education, and those without, leading to a split of 69.34% without tertiary education, and 30.66% with tertiary education. This was done as there would be a small number of observations per country, per year, and per occupation, leading to the educational effect being poorly estimated, following the example of von dem Knesebeck and Geyer [2007]. Tertiary education was chosen as the split, as it is a commonly researched transition point in education research worldwide [Aizawa, 2016; Gueudet, 2008; Pampaka et al., 2012; Raffe, 2008; Schindler and Lörz, 2012].

Table 4.5: Educational Attainment

Classification	Frequency	Percent
Pre-primary education	528	0.51
Primary education or first stage of basic education	5,271	5.12
Lower secondary or second stage of basic education	14,617	14.2
(Upper) secondary education	43,489	42.24
Post-secondary non-tertiary education	7,505	7.29
First stage of tertiary education	30,183	29.32
Second stage of tertiary education	1,358	1.32

For variables relating to working conditions, several were selected, rather than using all the variables available in EWCS, primarily to avoid overparameterisation of the model, and difficulty in interpreting a large amount of effects. This is especially important given the multilevel structure required by the worksome conceptual framework, which increases the number of model parameters. These variables were selected for the set of theoretical reasons presented in Chapter 2. To measure working conditions concerning working time, the variables are shift

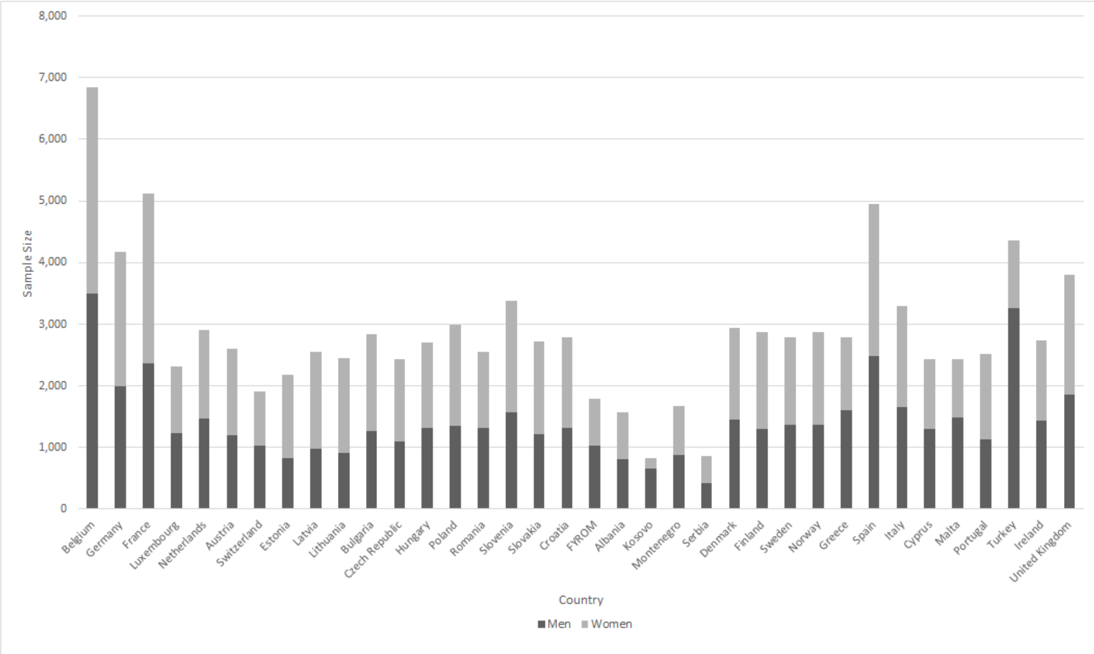


Figure 4.3: Gender Ratio by Country. The countries are sorted into welfare regimes

work, nights per month, working time arrangements, and hours worked per week. Working time is of particular importance, as discussed in the literature review, since working time regulations are a particularly contentious policy issue in the UK. Further, Dembe et al. [2005] argue that working overtime is associated with a disproportionately higher level of occupational illness and injury Appropriate pay for work was included because it can proxy job insecurity according to Siegrist [1996]'s effort-reward imbalance model. Alternatively, people are willing to accept risk for reward (i.e., pay), as Katz et al. [2014] argue. Skill-demand match, which includes both control and efficacy in meeting tasks and the demands behind them was included. Finally, satisfaction with working conditions was included firstly to ensure the other working conditions still had an effect when this was accounted for, and secondly as it is an overall measure of an individual's feeling on the conditions of their occupation, which is relevant to health.

In terms of shiftwork, 19.57% of the sample works shifts. Splitting working time arrangements by shiftwork shows that shift workers primarily have hours set by the company (75.92%), whereas non-shift workers have more heterogeneity in terms of their working time arrangements. Nights worked per month is a reasonably right-skewed variable, with a mean of 1.36 nights, but a median of 0, with a standard deviation of 3.92 nights per month; 81.39% of participants did not work any nights. Continuing to the final time-related variable, working hours per week had a median of 40, a mean of 38.89, and a max of 168. The first quartile is 35 hours per week, and the 95 percentile is 60 hours per week, meaning there is a reasonably long tail of low numbers of participants working from 60-168 hours per week.

Whether or not a participant's skill levels allow them to cope with the duties of their job (following Siegrist [1996]'s skill-demand match) was another variable of interest. This also uses concepts from Karasek and Theorell [1990]'s job-demand control model and measures self-efficacy in the context of the requirements and tasks of their occupation. 30.94% of participants felt that the demands of their job were *too low*, 56.61% felt they *matched*, and 12.44% felt they were *too high*. Further, in terms of whether a participant felt they are paid appropriately considering "all efforts and achievements", most tended to *agree* (32.08%), followed by *neither agree nor disagree* (23.05%), with *strongly agree* coming last (11.70%), see table 4.6. The variable was grouped into three categories and compared with *neither agree nor disagree*, leading to proportions of 33.17% for *disagree*, 43.78% for *agree*, and 23.05% for *neither agree nor disagree*. Again, appropriate pay was selected because the EWCS data covers several European countries with diverse economies, between which gross pay may not be directly comparable. Further, it helps operationalise the risk-reward relationship, in that people often are willing to take on more risk for higher compensation, described in the effort-reward imbalance model [Siegrist, 1996]. Finally, in terms of satisfaction with working conditions, an overall measure of an individual's assessment of their working conditions, 3.50% are *not at all satisfied*, 14.87% were *not very satisfied*, 76.09% were *satisfied*, and 23.91% were *very satisfied*.

Table 4.6: Considering all efforts and achievements, participant's job is paid appropriately.

Job is paid appropriately	Frequency	Percent
Strongly disagree	12,978	12.61
Tend to disagree	21,169	20.56
Neither agree nor disagree	23,733	23.05
Tend to agree	33,030	32.08
Strongly agree	12,041	11.70

For outcome variables, the primary one was whether the participant felt that their work affected their health. The question was phrased "Does your work **effect** your health?" in the EWCS survey questionnaire rather than 'affect,' but for the purpose of this thesis, it will be referred to with 'affect.' This is a self-rated health variable that covers both physical and mental health. Self-rated health assessments show consistent results even with differing assessment types or wordings of questions [Idler and Benyamini, 1997; Møller et al., 1996]. Over the whole sample, the ratio of No/Yes was 59.93%/40.07%, and this changed very slightly from 2005 to 2015 – the proportion of naysayers increased slightly. Indeed, geography too appears to matter: the proportion varies across countries (see figure 4.4), with Italy, Belgium, the United Kingdom, and Ireland, for example, having much higher proportions of those who feel their work does not affect their health, and Latvia, for example, having a much greater proportion of those that do feel that their work affects their health. This geographic variation means that there is likely clustering in the data, and methods which account for this should be considered. Returning to the map (figure 4.5), there appears to be a concentration in Finland, Scandinavia and the Baltic and Balkan countries in saying that their work does affect their health, whereas Germany, Austria, Ireland, and the UK report lower proportions of those saying their work affects their health. This could be due to differing perceptions of work in these countries, as Finland and Scandinavia have similar political and economic environments, for exmaple.

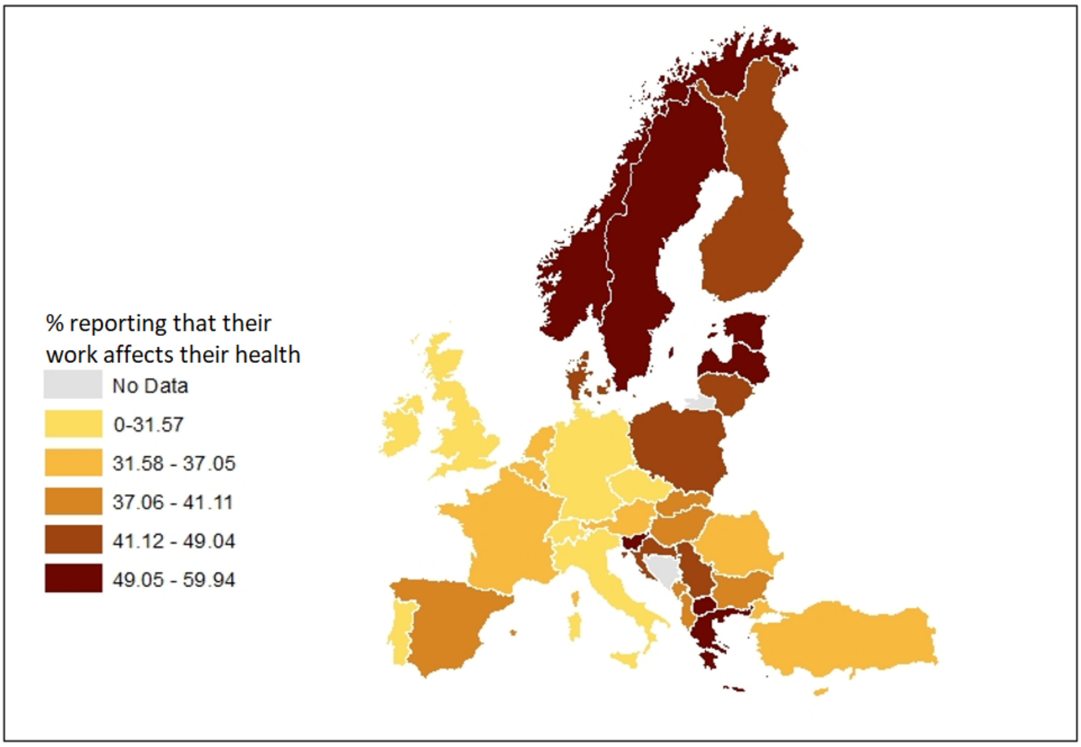


Figure 4.4: "Does your Work Affect your Health?", by Country, boundary data [Eurostat, 2020a]

As for the other specific health outcomes, there was one difference between the 2005 and 2010/2015 waves, in that the specific condition questions were asked in 2005 only if they had answered that their work affected their health, effectively putting them in the *not mentioned* category. Those missing values were put into the *not mentioned* category. Muscular or joint-related pain or problems appeared to have the highest proportion of *mentions* to *not-mentioneds* (see Table 4.7). All of the health outcomes appeared to vary by geography, particularly anxiety and fatigue (see figure 4.5a-i).

To look over the specific health outcomes: hearing problems (Figure 4.5a) in the last 12 months appear to be concentrated in Finland, Scandinavia, The Netherlands, and Slovenia. Skin problems (Figure 4.5b) appear to be more commonly reported in France, Sweden, Finland, the Balkans, and Slovenia. Back problems (Figure 4.5c) seem to be more common in Portugal, France, the Balkans, and the Baltic states. Headaches and eyestrain (Figure 4.5d) appear to be mentioned more frequently in Eastern Europe, particularly the Balkan states, FYROM, and Montenegro. Shoulder and neck pain, or upper muscular pain (Figure 4.5e) appears most common in Finland, Scandinavia, France, and Croatia, as well as Estonia. Pain in the lower limbs, lower muscular pain (Figure 4.5f) seems to be most common in Eastern Europe, particularly the Baltic states, Finland, Turkey, Greece, and, in Western Europe, Portugal.

Table 4.7: Specific Health Outcomes in the EWCS

Condition	Percent Mentioned	Percent Not Mentioned
Hearing problems in the last 12 months	6.45	93.55
Skin problems in the last 12 months	7.94	92.06
Back problems in the last 12months	40.73	59.27
Headaches and/or Eyestrain in the last 12 months	34.54	65.46
Shoulder or Neck pain (upper muscular pain) in the last 12 months	40.10	59.90
Pain in the lower limbs (lower muscular pain) in the last 12 months	31.59	68.41
Injury(ies) in the last 12 months	8.48	91.53
Anxiety in the last 12 months	13.10	86.90
Fatigue in the last 12 months	37.57	62.43

Injury(ies) (Figure 4.5g) in the last 12 months appear more frequently reported in France, Turkey, Greece, the Netherlands, and Latvia. Anxiety (Figure 4.5h) seems to be most commonly mentioned in France, Greece, and the Baltic states. Fatigue (Figure 4.5i) has a large range, and is more common in Eastern Europe, particularly the Baltic and Balkan states, as well as Turkey. This variation in the reporting of outcomes is therefore important to account for in the modelling strategy - there are country-level differences that may impact on any results. This could be due to differences in political or economic regimes, i.e. welfare regimes, or to differences in the geographical distribution of occupations that may engender these outcomes more than others. For example, the injury(ies) may be more common in jobs with physical tasks, such as manufacturing jobs, whereas headaches and/or eyestrain may be common in jobs that require a lot of computer work. Therefore, occupation too should be included in the modelling strategy.

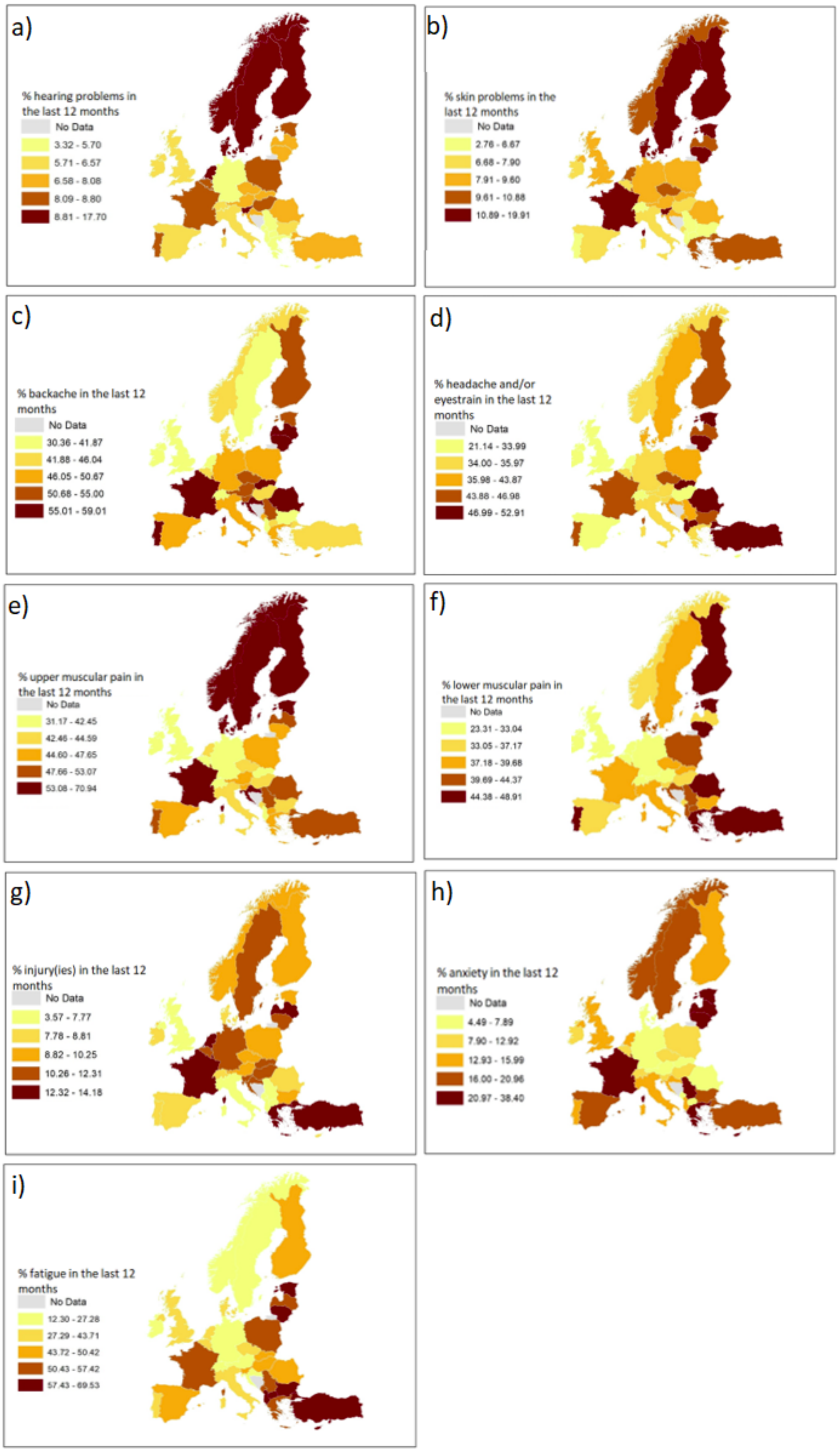


Figure 4.5: Health Outcomes in the Last 12 Months, by Country, Quantiles. a) Hearing Problems; b) Skin Problems; c) Backache; d) Headache and/or Eyestrain; e) Upper Muscular Pain f) Lower Muscular Pain; g) Injury(ies); h) Anxiety; i) Fatigue (Boundary data: [Eurostat, 2020a])

4.4. Data: British Household Panel Survey (BHPS)

In order to explore subnational variations in health outcomes, as well as to examine the research questions using a longitudinal dataset rather than a repeated cross-sectional one, the BHPS was employed. The data was obtained from the UK Data Service [University of Essex, 2018]. This allows for a more detailed examination of the influence of the temporal aspects of the worksome, as individuals are followed through all the waves of the study. The BHPS is a panel study following a nationally representative sample of individuals over 18 waves, which were taken over 18 years between 1991 and 2008 (see Figure 4.6 for the BHPS data by wave). This matches the EWCS waves, which are between 1991 and 2015. The BHPS was funded by The Economic and Social Research Council (ESRC) in the United Kingdom and was undertaken by the ESRC UK Longitudinal Studies Centre and the Institute for Social and Economic Research (ISER) at the University of Essex [Taylor et al., 2018]. The first wave started in 1991, and the initial sample was 5,500 households consisting of 10,300 individuals, using a stratified clustered designed based on postcodes [Taylor et al., 2018]. For the first part of sampling, primary sampling units (PSUs) were made of 250 postcode sectors, each containing approximately 2,500 addresses. After excluding non-residential addresses, approximately 33 addresses were selected per PSU, with a range of 21-36 per PSU. Further samples from Scotland and Wales of 1,500 samples were added in 1999, and 2,000 Northern Irish households were added in 2001 [Taylor et al., 2018]. Individuals who move out of households or change households were followed and re-interviewed in successive waves of the survey. Core questions were repeated in each wave, allowing for a longitudinal analytical approach to this data, as opposed to the repeated cross-sectional design of the EWCS.

The waves combined into a single dataset following the guidance in Taylor et al. [2018].

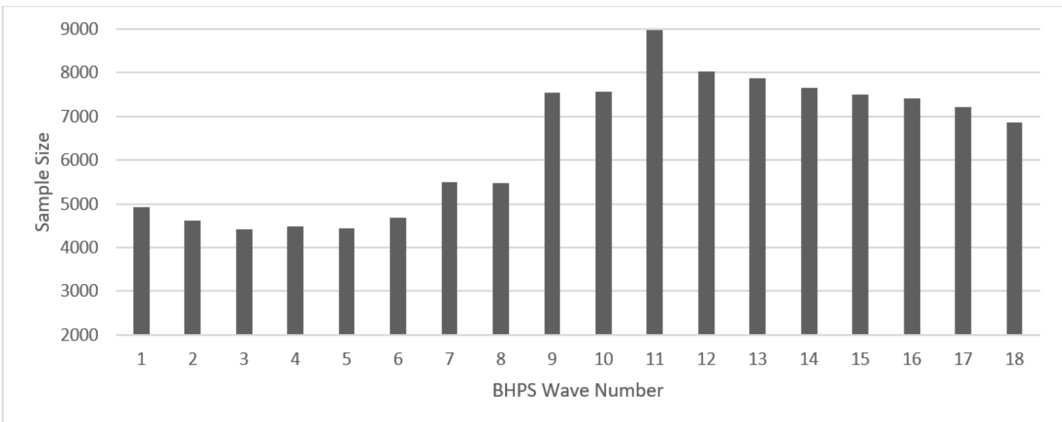


Figure 4.6: BHPS Data by Wave

4.4.1. BHPS Data Structure and Variables

The data were adjusted to match the parameters of the EWCS data, so that the analysis would be easily comparable. In doing so, the observations were limited to those between 15 and 65 years old, which is the sampling frame of the EWCS [Eurofound, 2007, 2011; Paoli, 1992, 1997; Paoli and Merllié, 2001]. This means that observations of individuals through time are excluded when the individual is under 15, or over 65, but those in between are included. Other exclusions were due to missingness in explanatory variables. One variable with a particularly large group of missing data is *job satisfaction with overall pay*. Largely, the missing data for this variable was comprised of a single category, 'inapplicable,' meaning the respondent was likely not in employment at the time of the questionnaire. The second largest missing category was 'proxy,' meaning the questions were answered on behalf of the individual in question, using a shorter questionnaire [Taylor et al., 2018]. As the population of interest is the employed in particular [see 1.1], the missing observations were thus excluded. Table 4.8 shows the number of observations per wave for the data with exclusions, giving a total n of 114,426. Each observation represents a wave-observation of a particular individual at that timepoint. After exclusions, the minimum number of observations per individual is 1, and the maximum 18. Individuals have an average of 5.92 wave-observations within them, with a standard deviation of 4.97 wave-observations.

Table 4.8: Exclusions from the BHPS Data.

Exclusion		**n**
	238,996 (total initial sample)	
Full Exclusion	**Cases removed**	**Cases remaining**
Under 15s	9	238,987
Over 65s	41,036	197,951
	Exclusions due to Missingness	
No Sex	2,094	195,857
No Job Hours	768	195,089
No job satisfaction	76,426	118,663
No job satisfaction with overall pay	208	118,455
No pay	3,284	115,171
Missing Region	745	114,426
	Total n:	**114,426**

Within the BHPS data it is possible to obtain high level geocoding. The highest subnational level is the Government Office Regions (GOR), which, in England, include 9 areas along with the other constituent nations of the United Kingdom as wholes. Figure 4.7 shows the sample per GOR.

The covariates selected for the BHPS analysis were demographics and working conditions which reflected the variables chosen for the EWCS analysis. Sex, age, and education were chosen as demographic variables. 47.8% of the sample was male, and 52.2% was female. The mean age is 37.67 (standard deviation 12.20), and the median age is 37, which indicates that age is normally distributed through the sample. As for education, to match the EWCS analysis, the variable was dichotomised. The *no tertiary education* category included the following categories: HND/HNC Teaching, A level, O level, CSE, none of these. The tertiary education

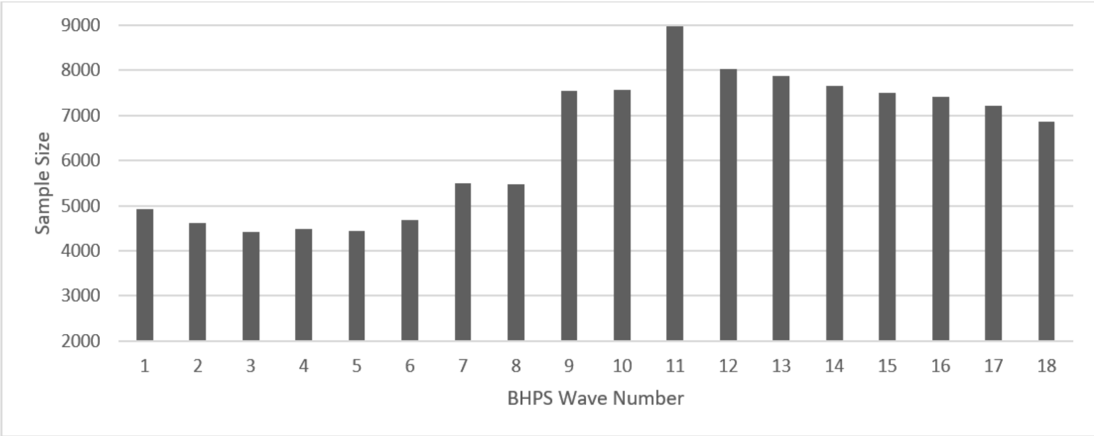


Figure 4.7: BHPS Data by Government Office Region

category included higher degree, and first degree. 83.7% of the sample had education up to tertiary, and 16.3% did. This was done following the structuring of the education variable in the EWCS analysis (section 4.3).

As for working conditions, 86.7% did not mention working flexitime, while 13.3% did. This variable was chosen to match the working time arrangements variable in the EWCS analysis. The mean job hours per week, which is the same as the hours variable in the EWCS analysis, were 33.22, with a standard deviation of 11.74. Mean gross monthly pay, which was not included in the EWCS analysis because of the variety of economies in the sample as well as problems in the data itself, was £1359, with a standard deviation of £1104. Two satisfaction variables were also included, and were reduced from seven categories to five, to match the coding of the satisfaction variable in the EWCS data. The first satisfaction variable was job satisfaction with total pay, which was chosen to match the appropriate pay variable in the EWCS. It is described in table 4.9. The second is job satisfaction overall, which matches the satisfaction with working conditions variable in the EWCS and is described in table 4.10. These variables were chosen following the same arguments as the corresponding EWCS variables.

Table 4.9: Job Satisfaction with Total Pay

Job Satisfaction with Total Pay	Frequency	Percent
Not Satisfied	4,563	3.99
Not very satisfied	21,238	18.56
Neither Satisfied/dissatisfied	9,630	8.42
Satisfied	67,668	59.14
Very Satisfied	11,327	9.90

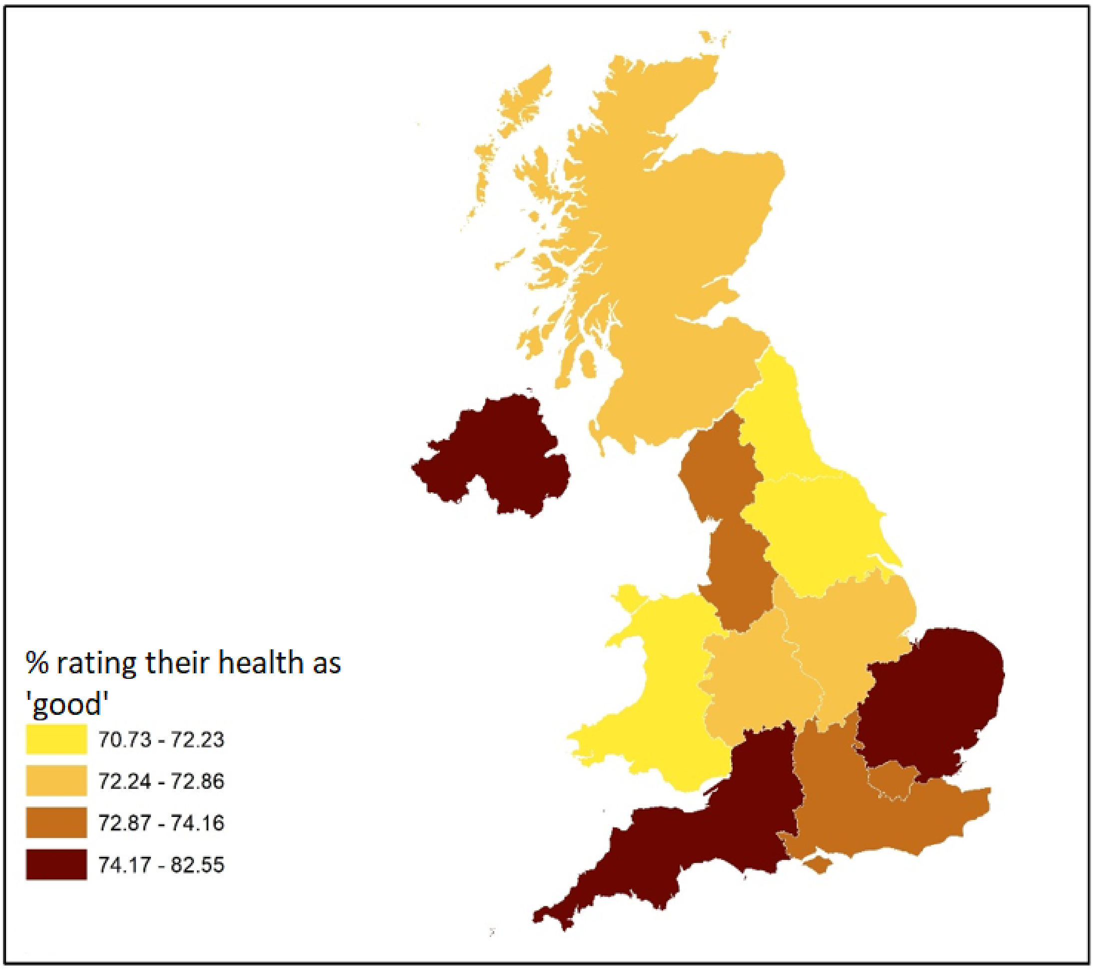
There were three outcome variables chosen from the BHPS data. These were chosen in order to empirically test the worksome framework with a number of health outcomes. They were health in the last 12 months (health status), health problems: arms, legs, hands, etc. (i.e., problems with the limbs or muscles), and health problems: anxiety/depression(anxiety/depression). These all match to EWCS variables. Health status was

Table 4.10: Job Satisfaction Overall

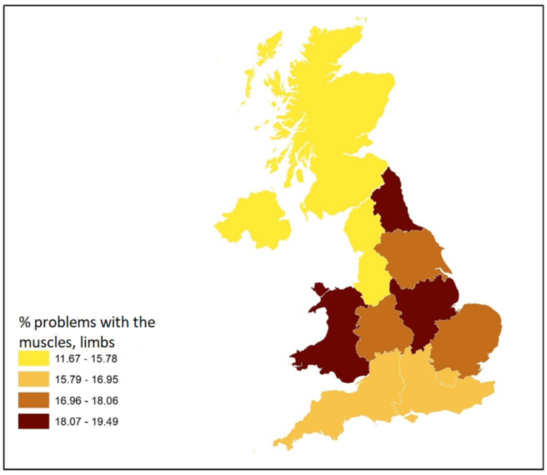
Job satisfaction overall	Frequency	Percent
Not Satisfied	1,703	1.49
Not very satisfied	10,364	9.06
Neither Satisfied/dissatisfied	8,682	7.59
Satisfied	77,952	68.12
Very Satisfied	15,725	13.74

dichotomised, so *excellent*, *very* good, and *good* health were classified as *good*, and *fair* and *poor* health were classified as *poor*. This is a common approach in epidemiology, and it has been shown to be empirically justifiable [Manor et al., 2000]. The two specific health problems were either *mentioned* or *not mentioned*. The health status variable matches the work-health effect, phrased as ‘does your work affect your health?’ The problems with the limbs or muscles variable matches the upper and lower muscular issue outcomes in the EWCS data. Finally, the anxiety/depression variable matches the anxiety/depression variable in the EWCS.

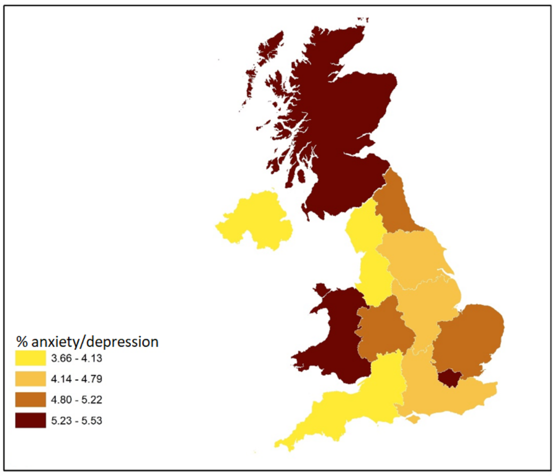
Figures 4.8a-4.8c show the geographical distribution of the outcomes in the GORs, or regions of the UK. For health status (Figure 4.8a) it appears that good health is concentrated in the south of the country and Northern Ireland but, on the whole, most people report good health (the lowest proportion of good health is around 70%). For problems with the limbs or muscles (Figure 4.8b). the concentration of reports appears to be in Wales, the East Midlands, and North East, with neighbouring regions also having a higher proportion of mentions. For anxiety/depression (Figure 4.8c), there appear to be more reports in Scotland, London and Wales, with fewer reports in the South West, North West and Northern Ireland. This indicates that, for the BHPS analysis too, geographies should be included in the modelling strategy.



(a) Health Status, Quantiles, boundary data [ONS, 2019; OS, 2020]



(b) Problems with the Limbs or Muscles, Quantiles, boundary data [ONS, 2019; OS, 2020]



(c) Problems relating to Anxiety/Depression, Quantiles, boundary data [ONS, 2019; OS, 2020]

Figure 4.8: Health outcomes in the BHPS data

4.5. Methods of Analysis

The outcome variables for all datasets are binary and categorical response variables, and as such, logistic regression is the appropriate modelling approach. Logistic regression is a transformation of the linear regression model in order to achieve a better model fit for dichotomous outcomes (Equation 4.1).

The logistic regression model can be expressed similarly to the linear regression model [Armitage et al., 2002]:

$$\begin{gathered} \text{Logit}\,(p_i) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_i X_i + e \\ p_i = \text{pr}\,\{Y_i = 1\} \end{gathered} \tag{4.1}$$

The parameters of the equation are e, the random error; β_i, the regression coefficients relating to the covariates X_i. Logit refers to the natural log transformation of p_i (the probability) to the logged odds that Y_i, the outcome, will be equal to 1 [Armitage et al., 2002].

Linear regression is not appropriate for a dichotomous outcome, as a linear regression has no upper or lower limit. Given 'yes' and 'no,' as it is not possible to have something be more than yes or less than no, therefore a modification of the linear model is required. Furthermore, "[t]he linear relationship still understates the actual relationships in the middle and overstates the relationship at the extremes" [Pampel, 2000, pg7]. Logistic regression also allows for the Bernoulli distribution inherent in the outcome variable (as it can only have two values). This would otherwise break the normality and heteroskedasticity assumptions of linear regression. The coefficients of a logistic regression are calculated as logged odds ratios: the odds create the lower limit (since all odds are positive) and logging them creates the upper limit (since unlikely events have odds between 0 and 1 with negative logarithms, and likely events have odds above 1 with positive logarithms). This constrains the shape of the outcome function [Pampel, 2000], making the predicted probability of the outcome well-behaved. Odds ratios can be generated from the log odds, which are easier to interpret substantively, as they represent the increased (or decreased) odds of an outcome happening. Therefore, the data for both the EWCS and BHPS datasets will be modelled using single level logistic regression models first in Chapters 5 and 6.

While logistic regression allows for a nonlinear relationship between the probabilities of the outcomes and the covariates, it still assumes that observations are independent. This assumption is violated by the nature of the datasets being used: in the EWCS data people are surveyed in countries in years and classified by occupation types. In the BHPS data, individuals are surveyed at the wave time-points, who work in occupations, and live within particular regions. Clearly, in neither dataset are the observations fully independent of one another, as the data are hierarchical and structured. To mitigate this issue, multilevel logistic regression models (MLR) can be used. MLRs consider the impact of the statistical dependency a given person may be subject to based on their membership in a higher level (e.g., living in a country or in a particular time, working in a particular occupation, Merlo et al. [2006]). Equations 4.2

and 4.3 show the two- and three-level logistic regression equations respectively [Armitage et al., 2002]. The parameters are similar to those in Equation 4.1: u_j is the level 2 random part of the model, and $e_i j$ is the level 1 random part of the model. β_m are the regression coefficients relating to the covariates X_i. Logit refers to the natural log transformation of p_i (the probability) to the logged odds that Y_i, the outcome, will be equal to 1, i.e., it will occur. For Equation 4.3, the only difference is the addition of the v_k term, i.e., the level 3 random part of the model. Further terms can be added to add subsequent levels to the model.

$$\begin{gathered} \text{Logit}\,(p_{ij}) = \beta_0 + \beta_1 X_{1ij} + \beta_2 X_{2j} + \ldots + \beta_m X_{mij} + u_j + e_{ij} \\ p_i = \text{pr}\{Y_i = 1\} \end{gathered} \tag{4.2}$$

$$\begin{gathered} \text{Logit }\left(p_{\text{ijk}}\right) = \beta_0 + \beta_1 X_{1ijk} + \beta_2 X2_{ijk} + \ldots + \beta_m X_{mijk} + v_k + u_{jk} + e_{ijk} \\ p_i = pr\{Y_i = 1\} \end{gathered} \tag{4.3}$$

A multilevel model is statistically, theoretically, and substantively desirable for the structure of the data. Further, it helps approximate the structural elements of the worksome, which are presented in Chapter 3. Estimation is improved, and MLRs allow for the quantification of the relative importance of higher-level structures like occupation or country, which may be difficult to model in a single level model [Larsen and Merlo, 2005]. This difficulty could occur through poorer estimation due to an increased amount of dummy parameters, and those parameters could be collinear. Furthermore, referring back to the research questions and objectives, in order to truly understand the impact and variation of geographies, time, and occupation type on a given individual response ('my work affects my health'), a multilevel structure allows for the simultaneous modelling of both random and fixed effects, and heterogeneity between levels can be modelled explicitly [Deeming and Jones, 2015; Duncan and Jones, 2000]. Each level can be assessed separately or in relation to one another.

Null models only including the constant (β_0), known as variance component models, are employed initially for several reasons: First, they allow for the discovery of where residual variance lies in the data. Second, they can help determine whether multilevel models can produce better models than single level ones. Third, variance components models can also determine the structure of future multilevel models. Seven model structures were tested using variance components models on the EWCS data to determine which was most appropriate for the data. The variance-partitioning coefficient (VPC), which in this case is the same as the intraclass correlation coefficient, or ICC (see equation 4.4), and the median odds ratio (MOR, see equation 4.5) were calculated for each model [Merlo et al., 2006]. For Equation 4.4, the VPC, 3.29 represents the individual variance. For the MOR in Equation 4.5, V_A is the area level variance, and 0.6745 represents the $75th$ centile of the cumulative distribution function of the normal distribution, with a mean of 0, and a variance of one.

$$VPC = \frac{V_A}{(V_A + 3.29)} \tag{4.4}$$

$$MOR = \exp\left[\sqrt{(2 \times V_A) \times 0.6745}\right] \tag{4.5}$$

The latent variable approach to VPC accommodates some of the technical difficulties of the logistic model, assuming that the propensity for having a given health outcome is a ”continuous latent variable underlying [the] binary response” [Merlo et al., 2006, pg292]. The VPC is not directly comparable between models, as in the logistic case it doesn’t inform about between-cluster variation, and is difficult to juxtapose with the fixed effects, which are reported in terms of odds ratios [Larsen and Merlo, 2005]. The MOR, though, is, as it is reported as an odds ratio, therefore in the same ‘unit’ as the fixed model coefficients [Merlo et al., 2006]. The MOR is the increased risk, on average, resulting from changing between a lower to a higher risk group, such as a country, if the two countries in question are chosen randomly from a distribution of the estimated variance at that level, and is expressed on the odds ratio scale Merlo et al. [2006]. An MOR of close to 1 implies that there is little change in the odds of moving between groups, i.e. less variation between groups. An MOR of less than one would therefore indicate a reduction in the odds, and therefore the risk of moving between low and high risk groups. This is important as it answers one of the research questions (RQ5), whether occupational differences between types are more important, or those within. The most appropriate structure will be chosen based on the VPC and MOR empirically, and theoretically by following the worksome framework.

After the structure has been determined, the occupational categories will be examined using 60 single level logistic regression models using a Markov Chain Monte Carlo (MCMC) Bayesian framework [Browne, 2019]. There are 12 health outcomes for 5 classification systems, described in Chapter 6. In terms of the specifics of MCMC estimation we followed the good-practice recommendation of Draper [2008]. Thus, we use likelihood approach to estimate an initial model, specify default priors to impose as little information as possible on the estimates, a burn-in of 500 simulations to get away from these initial (potentially poor) estimates, and a monitoring chain of some further 5000 simulations to characterise the parameter estimates and calculate the Deviance Information Criterion (DIC, equation 4.6). The DIC is a measure of predictive accuracy. In Equation 4.6, $\bar{D}$ is the deviance, a measure of model fit, and pD is the effective number of parameters, a measure of the complexity of a model [Spiegelhalter et al., 2002].

$$DIC = \bar{D} + pD \tag{4.6}$$

This allows for the most accurate model to be chosen regardless of the number of parameters (or categories in this case), as the DIC penalises model complexity. The DIC is an ideal procedure for comparing models with different specifications involving different classifications. The DIC can be compared within the same health measures, but not between health measures, i.e., the DIC for the NS-SEC for skin problems cannot be compared to the DIC for backache for the ISCO 1-digit system.

Having determined the appropriate model structure with the variance components models, and the appropriate covariates with the single level models, multilevel models of the EWCS and BHPS data will be analysed. The occupational categories determined using the DIC will be placed at the second level of the specified multilevel structure. The covariates determined in the single-level modelling stage will be included and the models assessed in multilevel form using the DIC. Finally, the models will be repeated for each health outcome in each dataset.

There will be five results chapters: the single level logistic regression models for each dataset, examined for reasons of parsimony; the variance components chapter, which examines which model structure might be the most appropriate, and, finally, the multilevel logistic regression models for each dataset, which allow for the examination of the clustering in the data. Firstly, the single level logistic regression models for each dataset will be examined in separate chapters.

Chapter 5

Results: EWCS Single Level Logistic Regression Models

5.1. Introduction

This chapter looks to meet research objectives 1 and 2 and their respective research questions, RQ1 and RQ2: to identify and confirm the relationship between work and health (RO1), and determine which specific working conditions underlie this relationship (RO2). As [Box, 1976, pg792] wrote, a scientist "should seek an economical description" of what is being modelled, and so emphasised the statistical principle of parsimony. And so, in the interest of parsimony, single level models for each of the outcomes have been generated and their results presented in this chapter. Simpler models are also easier to understand and implement, so if they answer the research questions as well as the multilevel ones, it is therefore more appropriate to use these models. The models were implemented in Stata versions 14 and 15 using the logit command. The results are presented as odds ratios, interpreted as the increased (or decreased) odds of the occurrence of an outcome. The outcomes and covariates can be seen in table 1. The covariates were added one by one to the models in the order presented in table 5.1, resulting in 11 models for each outcome, including the null model (intercept only). The outcomes are binary, either as *yes/no* or *mentioned/not mentioned*, and were self-declared by the individual in the survey. There are 175,206 total observations in the model. The final models will be discussed and presented here. The full set of intermediate models can be found in Appendix A.

Table 5.1: Outcomes and Covariates for all Models

Outcomes	Covariates
• Work-effect on health • In the last 12 months... – Skin problems – Hearing problems – Backache – Lower Muscular Pain – Upper Muscular Pain (inclusive of shoulders, neck, and/or upper limbs) – Anxiety – Fatigue – Headache and/or Eyestrain – Injury(ies)	• Sex (ref:male) • Age (15-65) • Has tertiary education (ref: no tertiary education) • Nights worked per month • Works shifts (ref: no) • Hours per week worked • Working time arrangement (ref: set by company, coded as 1) – Choice between several fixed schedules (2) – Adaptable within limits (3) – Entirely self-determined (4) • Skill-demand match (ref: they match, coded as 2) – Demands too low (1) – Demands too high (3) • Paid appropriately (ref: neither agree nor disagree, coded as 1) – Disagree (0) – Agree (2) • Satisfaction with working conditions (ref: very satisfied, coded as 4) – Not at all satisfied (1) – Not very satisfied (2) – Satisfied (3)

5.2. Correlations

Correlation analysis provides an initial means to explore associations and relationships between the variables in the data. Correlations of 0 indicate no relationship, and as the correlation coefficient approaches +1 or -1, the strength of the relationship increases [Gogtay and Thatte, 2017]. Correlation coefficients of around +/- 0.5 are considered reasonably strong evidence of an association [Gogtay and Thatte, 2017]. Correlations between the variables were examined, in order to check for multicollinearity, and to preliminarily examine the relationships between the variables (see table 5.2). Multicollinearity is the phenomenon when some of the covariates are highly correlated, which can lead to large standard errors and uninterpretable regression coefficients [Armitage et al., 2002]. Checking the correlation matrix is a common method to detect multicollinearity [Armitage et al., 2002].

Only three variables had correlations above 0.2 or below -0.2, ordered here from most to least correlated: appropriate pay with satisfaction with working conditions (0.398); nights worked per month with shift work (0.266); and weekly hours and sex (-0.240). None of the correlations appear sufficiently strong to cause multicollinearity, and the subsequent logistic regression models specified well. The correlations also make sense substantively. Whether a job pays appropriately likely has an impact on whether any given individual is satisfied with a job; night work tends to be structured as shift work. As discussed in the literature review 2, women tend to work more flexibly due to their multiple social, productive, and reproductive roles; this is also reflected on the higher correlation with shift work (i.e., women tend to work more shifts than men), and by women's relative lack of control in time arrangements. Following this exploratory analysis, the variables are unlikely to be collinear, and therefore single-level logistic regression models were calculated. The results of these models are discussed in the subsequent sections for each outcome variable in the EWCS data.

Table 5.2: Correlations between Covariates. Correlations which are greater than 0.2 are coloured in light blue and those less than -0.2 are coloured in light red

	Sex	Age	Tertiary Education	Nights	Shifts	Weekly Hours	Time Arrangement	Skill-Duty Match	Appropriate Pay	Satisfaction with Conditions
Sex	1									
Age	0.007	1								
Tertiary Education	0.090	-0.001	1							
Nights	-0.111	-0.036	-0.045	1						
Shifts	0.022	-0.068	-0.086	0.267	1					
Weekly Hours	-0.24	-0.006	-0.048	0.179	0.029	1				
Time Arrangement	-0.07	0.095	0.073	-0.01	-0.19	0.1	1			
Skill-Duty Match	0.023	-0.021	0.026	-0.011	-0.001	-0.009	-0.013	1		
Appropriate Pay	-0.06	-0.02	0.093	-0.043	-0.075	-0.047	0.087	0.02	1	
Satisfaction with Conditions	0.024	0.015	0.119	-0.06	-0.089	-0.092	0.088	0.031	0.398	1

5.3. Model Results

The following sections present the results of the single level logistic regression models, organised by outcome.

5.3.1. The Work-Health Effect

The work-health effect, which was when respondents were asked whether they thought their work affected their health, is taken here to be a measure of self-rated health associated with work. Table 5.3 shows the final model for this outcome. It would appear from the table that the majority of the odds ratios (ORs) indicate a small effect size, with some odds ratios below 1, namely the effect of being female rather than male (OR 0.924, 95% Confidence Interval (CI): 0.899-0.950), the *choice between several fixed working schedules* rather than a standard arrangement (OR 0.951, CI: 0.901-1.004), and *agreeing* that the job is paid appropriately rather than *neither agreeing nor disagreeing* (OR 0.982, CI 0.948-1.018). It is worth noting that the only statistically significant effect amongst the three is sex. However, the *agree* effect with respect to appropriate pay follows the expected direction, particularly considering the effort-reward imbalance model [Siegrist, 1996]. This is particularly relative to the other measured effect *disagree*, which is statistically significant, both in relation to agreeing nor disagreeing that one is paid appropriately. The same holds for the variable identifying working time arrangements. Indeed, a properly fitted model should have some insignificant variables; to exclude variables based solely on their statistical significance would produce a similar result to a stepwise regression, a technique that very often engenders overfitting and poorly specified models [Babyak, 2004]. Further, even if a variable is not statistically significant, it may still have substantive significance, especially if it is part of a dummy variable, and, again referring to [Box, 1976, pg792], science should not just involve 'fall[ing] in love with [their] model," but iteratively developing theory and practice together.

Demographic variables are patterned in a way one might expect, given the literature where older, female individuals appear to be more impacted [Ala-Mursula, 2004; Braveman et al., 2005; Geyer et al., 2006]. Being older has a small but significant effect on whether work affects health with a very narrow confidence interval: an OR of 1.014 with a confidence interval of 1.013-1.016. Having a tertiary education (e.g., a Bachelor's degree or above) appears to have increased odds of reporting that work affects health (OR 1.087, CI: 1.057-1.118).

Factors relating to the duration of work time are also in line with the literature. In terms of the amount of time worked, factors generally suggest a dose-response relationship: more work means that a respondent's work will likely affect their health. The effect of number of nights worked is small, but significantly associated with the work-health effect (OR 1.027, CI: 1.024-1.031). Further, the cumulative effect of working five nights is substantial: in this case the OR would increase to 5.135. In terms of weekly hours worked, the effect is again small, likely as the unit of measure is hours, but it does have a very tight confidence interval: OR 1.011, CI 1.01-1.012. For every hour worked per week, there is a 1.1% increase in the likelihood of work affecting health.

In terms of work configuration, results are more mixed. The effect of working shifts is 1.293 (CI 1.248-1.340), so someone working shifts is 29.3% more likely to report that their work affects their health. As for working time arrangements, relative to those *set by the company*, the effect of *choosing between several schedules* is slightly negative, but since the confidence interval crosses 1, this effect is not statistically significant (OR 0.951, CI 0.901-1.004). The other two schemes (*adaptable* and *self-determined* schedules) have a slightly increased and similar effect size on reporting that their work affects their health: *adaptable within limits* has an OR of 1.057 (CI 1.018-1.098) and *entirely self-determined* has an OR of 1.056 (CI 1.015-1.098), suggesting that increased flexibility rather than a particular scheme may have an effect on health.

In terms of the skill-demand match, having *too low* or *too high* demands appears to both cause an increase in the work-health effect, but *high demands* have a much higher effect: an odds ratio of 1.471 (CI: 1.412-1.533), whereas the effect of *low demands* is much smaller: 1.081 (CI: 1.049-1.114). This suggests that the match between skills and demand is important, but it is more damaging to health to have a job whose demands seriously outpace one's skills.

As for being paid appropriately, it is relatively unsurprising that those who *disagree* that they are paid appropriately have an increased effect of their work affecting their health of 57.4% (OR 1.574, CI 1.518-1.632), relative to those who *neither agree nor disagree*. In addition, those who *agree* that they are paid appropriately have no significant increase in work-health effect (OR 0.982, CI 0.948-1.018) Finally, those who are *not at all satisfied* with their working conditions are much more likely to report that their work affects their health (OR 5.531, CI: 5.076-6.026), though the confidence interval is fairly wide for this variable, though it narrows as the reference category is approached (a difference of almost 1 for *not at all satisfied* to a difference of around 0.1 for *satisfied*).

It would seem, then, that perceived health status and work's impact on it, with respect to demographic and working conditions is as the literature argued: lower control and higher flexibility, with less compensation can impact on the health of individuals in these occupations.

Table 5.3: Final Single Level Logistic Regression Model for the Work-Health Effect

Y: Work-health effect	OR	95% CI		p
Intercept	0.122	0.113	0.133	0.000
Sex (ref: male)	0.924	0.899	0.950	0.000
Age	1.014	1.013	1.016	0.000
Has Tertiary Education (ref: no tertiary)	1.087	1.057	1.118	0.000
Nights worked per month	1.027	1.024	1.031	0.000
Works shifts (ref: no)	1.293	1.248	1.340	0.000
Hours per week worked	1.011	1.010	1.012	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.951	0.901	1.004	0.068
Adaptable within limits	1.057	1.018	1.098	0.004
Entirely self-determined	1.056	1.015	1.098	0.006
Skill-demand match (ref: they match)				
Demands too low	1.081	1.049	1.114	0.000
Demands too high	1.471	1.412	1.533	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.574	1.518	1.632	0.000
Agree	0.982	0.948	1.018	0.321
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	5.531	5.076	6.026	0.000
Not very satisfied	2.959	2.823	3.101	0.000
Satisfied	1.298	1.255	1.343	0.000
Log Likelihood:		-63007.68		

5.3.2. Skin Problems

As for reporting skin problems in the last 12 months, several of the variables were not statistically significant. Table 5.4 reports the final model for skin problems. Tertiary education was negative, but not significant (OR 0.960, CI 0.914-1.008). Hours worked per week was not significant, and further, its effect was an OR of 1, which indicates no effect on skin problems (OR 1.000, CI 0.999-1.002). The time arrangement dummy for *choice between several fixed schedules* was also not significant, and its confidence interval was fairly wide (OR 1.076, CI 0.982-1.179); the dummy for *entirely self-determined* was also on the borderline for statistical significance, with an OR similar to the *fixed schedule choice* (OR 1.072, CI 1.000-1.148), but its confidence interval not quite crossing 1. Finally, *agreement* with appropriate pay (relative to *neither agreeing nor disagreeing*) had an OR of 1.003, but a confidence interval of 0.939-1.071, and a p value of 0.931, perhaps indicating that having appropriate pay has very little to do with reporting skin problems in the last 12 months, though not having it may do: an OR for *disagree* of 1.453 (CI 1.364-1.548) is one of the strongest effect sizes in the model.

Skin problems appear to be more prevalent among female workers rather than male (OR 1.298, CI 1.238-1.362), and decrease in older people with each year of age (OR 0.995, CI 0.993-0.997). This may be due to women working in specific occupations that may be more likely to influence skin problems, and single level analysis does not account for this. Working nights has a small but significant effect (OR 1.015, CI 1.010-1.021), and working shifts has a larger effect (OR 1.158, CI 1.092-1.227). Flexible working time arrangements, like *adaptable within limits*, show an increased effect on skin problems, with the *limited flexible scheme* having a larger effect (OR 1.335, CI 1.254-1.422). Again, the skill-demand match follows a similar pattern to the work-health effect, with both showing an increase in skin problems, but the effect of *higher* demands being larger than that of *lower* ones (an OR of 1.395, CI 1.304-1.492 for higher demands to an OR of 1.140, CI 1.084-1.200 for lower demands). The importance of having a job where your skillset matches its demands seems clear. Being *satisfied* with the working conditions also remains important, with those who are *not at all satisfied* having much higher likelihood of having skin problems than those who are *very satisfied*, and this follows a linear pattern (with increasing satisfaction, the OR of having skin problems decreases). It appears that stressful conditions increase the likelihood of reporting skin problems, and it is not necessarily dependent on education or hours worked, meaning that it may transcend occupation types and be more an issue of imbalance between risk and reward, so it is worth investigating the impact of occupations directly with multilevel models.

Table 5.4: Final Single Level Logistic Regression Model for Skin Problems in the last 12 months

Y: Skin problems	OR	95% CI		p
Intercept	0.046	0.040	0.053	0.000
Sex (ref: male)	1.298	1.238	1.362	0.000
Age	0.995	0.993	0.997	0.000
Has Tertiary Education (ref: no tertiary)	0.96	0.914	1.008	0.098
Nights worked per month	1.015	1.010	1.021	0.000
Works shifts (ref: no)	1.158	1.092	1.227	0.000
Hours per week worked	1.000	0.999	1.002	0.675
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.076	0.982	1.179	0.114
Adaptable within limits	1.335	1.254	1.422	0.000
Entirely self-determined	1.072	1.000	1.148	0.05
Skill-demand match (ref: they match)				
Demands too low	1.14	1.084	1.200	0.000
Demands too high	1.395	1.305	1.492	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.453	1.364	1.548	0.000
Agree	1.003	0.939	1.071	0.931
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	3.179	2.855	3.540	0.000
Not very satisfied	2.11	1.949	2.285	0.000
Satisfied	1.278	1.197	1.364	0.000
Log Likelihood		-27674.20		

5.3.3. Hearing Problems

Hearing problems in the last 12 months have a different pattern (see table 5.11). Women are much less likely than men to report hearing problems, and the effect is quite large (OR 0.578, CI 0.548-0.610), and older people are slightly more likely to report hearing problems (OR 1.034, CI 1.032-1.036). It is possible that men are more likely to work in jobs with loud environments, such as primary or manufacturing industries, but this is not accounted for in single level analysis.

Those without tertiary education are also more likely to report hearing problems (OR 0.852, CI 0.806-0.901). It appears that there may be some structural factors at play: perhaps the types of jobs that older men who did not attend tertiary education hold are more likely to contribute to hearing problems. Nights continues to hold a small but significant effect (OR 1.018, CI: 1.012-1.024), and it should be considered too that someone could work up to 31 nights per month. Working shifts also appears to influence an increase in hearing problems (OR 1.245, CI 1.67-1.327). Hours worked per week effectively has no effect, with an OR of 0.998, and a confidence interval of 0.996-1.000, making the variable not statistically significant.

Working time arrangements appear to follow a slightly different pattern. While the *choice between several fixed schedules* dummy remains statistically insignificant, those individuals with that characteristic, and those who *self-determine their working time* (which is statistically significant) show a negative relationship with hearing problems: the OR for the *choice of fixed schedule* is 0.921 (CI 0.828-1.024), and that of the *self-determined* workers is 0.814 (CI 0.753-0.879). It seems with hearing problems that some degree of choice or other in working time arrangements is relevant, though those whose schedules are *adaptable within limits* have higher odds of hearing problems (OR 1.114, CI 1.037-1.195). In terms of the skill-demand match, the ORs follow a similar arrangement to those for other outcomes, though the demands being *too low* are not statistically significant (OR 1.043, CI 0.985-1.104). Those who identify as having *demands too high* are 40.9% more likely to report hearing problems. Those *disagreeing* that they were paid appropriately have higher odds of hearing problems (OR 1.412, CI 1.316-1.515) than those who *neither agreed nor disagreed*, but those who *agreed* they were paid appropriately also had slightly higher odds of hearing problems (OR 1.062, CI 0.988-1.141), but this was not statistically significant. It is possible that these are working conditions characteristic of jobs with exposures that may engender hearing problems, like those with loud environments, which will be accounted for in the multilevel models in Chapter 8. Finally, those who are less than *very satisfied* with their working conditions all have higher odds of hearing problems, though these odds are lower than the same variable for other outcomes (*not at all satisfied*: OR 2.673, CI 2.367-3.019; *not very satisfied*: OR 1.879, CI 1.719-2.054; *satisfied* 1.277, CI 1.189-1.372).

5.3.4. Backache

Table 5.6 shows the model for backache in the last 12 months. The first apparent effect, or perhaps lack thereof, is that of working time arrangements. While a small effect is nonetheless still important, the confidence intervals for each dummy overlap 1 by a large margin, and the p values are all above 0.40, so it may be that working time arrangements have very little to do with the odds of reporting backache in the last 12 months. Women have higher odds of reporting backache than men (OR 1.190, CI 1.159-1.223), and older people also show higher odds, with a small, but importantly significant effect, with a narrow confidence interval (OR 1.020, CI 1.019-1.021). It is possible that the types of occupations that women and older have are more likely to be ergonomically compromised or to have strain on the back. Having a tertiary education reduced the odds of reporting backache (OR 0.724, CI 0.704-0.744), which may reflect the

Table 5.5: Final Single Level Logistic Regression Model for Hearing Problems in the last 12 months

Y: Hearing problems	OR	95% CI		p
Intercept	0.013	0.011	0.016	0.000
Sex (ref: male)	0.578	0.548	0.610	0.000
Age	1.034	1.032	1.036	0.000
Has Tertiary Education (ref: no tertiary)	0.852	0.806	0.901	0.000
Nights worked per month	1.018	1.012	1.024	0.000
Works shifts (ref: no)	1.245	1.167	1.327	0.000
Hours per week worked	0.998	0.996	1.000	0.111
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.921	0.828	1.024	0.129
Adaptable within limits	1.114	1.037	1.195	0.003
Entirely self-determined	0.814	0.753	0.879	0.000
Skill-demand match (ref: they match)				
Demands too low	1.043	0.985	1.104	0.147
Demands too high	1.409	1.308	1.519	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.412	1.316	1.515	0.000
Agree	1.062	0.988	1.141	0.102
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	2.673	2.367	3.019	0.000
Not very satisfied	1.879	1.719	2.054	0.000
Satisfied	1.277	1.189	1.372	0.000
Log Likelihood		-23480.672		

types of employment those with tertiary education take and have access to, though this model cannot speak to that. Nights worked per month also had a small but significant effect (OR 1.010, CI 1.006-1.013), and hours worked per week had an even smaller but still significant effect (OR 1.006, CI 1.005-1.007). Working shifts also, as in the majority of outcome models, has a significant effect (OR 1.136, CI 1.098-1.176). The skill-demand match difference does not appear to hold as much here, as the effect sizes are much closer (*too low* OR: 1.029, CI 0.999-1.059; *too high* OR 1.094, CI 1.050-1.139). Being paid appropriately appears to have a larger effect size, with those *disagreeing* that they are paid appropriately being 33% more likely to report backache than those that *neither agree or disagree*, and those that *agree* they are paid appropriately have lower odds of reporting backache (OR 0.930, CI 0.899-0.962). Perhaps the tradeoff between risk and reward is more pertinent for backache. Satisfaction with working conditions follows a similar pattern to the other outcomes, with increasing satisfaction leading to decreased odds of reporting backache, though the confidence intervals are much narrower than in other models, such as the work-health effect, for example.

Table 5.6: Final Single Level Logistic Regression Model for Backache in the last 12 months

Y: Backache	OR	95% CI		p
Intercept	0.133	0.123	0.144	0.000
Sex (ref: male)	1.190	1.159	1.223	0.000
Age	1.020	1.019	1.021	0.000
Has Tertiary Education (ref: no tertiary)	0.724	0.704	0.744	0.000
Nights worked per month	1.010	1.006	1.013	0.000
Works shifts (ref: no)	1.136	1.098	1.176	0.000
Hours per week worked	1.006	1.005	1.007	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.020	0.969	1.074	0.453
Adaptable within limits	0.996	0.960	1.033	0.812
Entirely self-determined	1.024	0.986	1.064	0.218
Skill-demand match (ref: they match)				
Demands too low	1.029	0.999	1.059	0.000
Demands too high	1.094	1.050	1.139	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.330	1.284	1.378	0.000
Agree	0.930	0.899	0.962	0.000
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	3.595	3.326	3.885	0.000
Not very satisfied	2.786	2.660	2.918	0.000
Satisfied	1.611	1.558	1.666	0.000
Log Likelihood		-66012.507		

5.3.5. Lower Muscular Pain

Table 5.7 reports the muscular pain in the lower limbs, i.e., lower muscular pain, reported in the last 12 months model. Women have higher odds of reporting lower muscular pain than men (OR 1.1156, CI 1.124-1.190), and age still has a small but significant effect with a tight confidence interval (OR 1.020, CI 1.019-1.021). Having tertiary education reduces the odds of reporting lower muscular pain by around 44% (OR 0.663, CI 0.644-0.683). This is possibly due to occupational differences in those with and those without tertiary education, which are not included in this model. Nights per month and hours worked per week continue to have small but significant effects (ORs 1.011, CI 1.008-1.015; 1.007, CI 1.005-1.008). Shift work has a slightly larger effect, with an OR of 1.202 (CI 1.1160-1.246). Working time arrangements, relative to fixed time set by the company, appear to either show a slight decrease in odds (*choice between several fixed schedules* OR 0.918, CI 0.868-0.971; *adaptable within limits* OR 0.927, CI 0.891-0.965), or an increase in odds in *those with self-determined time arrangements* (OR 1.083, CI 1.040-1.127). This is possibly due to those with flexible schedules working in jobs with tasks that are less risky in terms of lower muscular pain, though time arrangement was not significant for backache, and for upper muscular pain (table 5.8), the opposite effect was found. Skill-demand match with demands which are *too high* are not statistically significant, with a p of 0.905, and a relatively wide confidence interval around the OR of 1.003 (CI: 0.960-1.048). *Low demand* also shows a slight increase in odds, with an OR of 1.068 (CI 1.036-1.101). *Agreeing* that one is paid appropriately shows a 13% decrease in the odds of reporting lower muscular pain relative to those that *neither agree nor disagree*, and those who *disagree* show an increase in the odds of reporting lower muscular pain (OR 1.341, CI 1.292-1.391). Finally, satisfaction with working conditions follows the expected pattern, found by Virtanen et al. [2003], with those *not at all satisfied* having odds of 4.150 (CI 3.839-4.487), those *not very satisfied* having odds of 2.827 (2.693-2.968), and those who are *satisfied* having odds of 1.589 (CI 1.530-1.649), of course relative to those who are *very satisfied*. It is possible that lower muscular pain (and to some extent, the other two 'muscular' outcomes, backache and upper muscular pain) is less dependent on the social exposures or working conditions than on the tasks themselves in particular occupations, and therefore occupation must be included in the multilevel models.

Table 5.7: Final Single Level Logistic Regression Model for Lower Muscular Pain in the last 12 months

Y: Lower Muscular Pain	**OR**	**95% CI**		**p**
Intercept	0.079	0.072	0.086	0.000
Sex (ref: male)	1.156	1.124	1.190	0.000
Age	1.023	1.022	1.025	0.000
Has Tertiary Education (ref: no tertiary)	0.663	0.644	0.683	0.000
Nights worked per month	1.011	1.008	1.015	0.000
Works shifts (ref: no)	1.202	1.160	1.246	0.000
Hours per week worked	1.007	1.005	1.008	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.918	0.868	0.971	0.003
Adaptable within limits	0.927	0.891	0.965	0.000
Entirely self-determined	1.083	1.040	1.127	0.000
Skill-demand match (ref: they match)				
Demands too low	1.068	1.036	1.101	0.000
Demands too high	1.003	0.960	1.048	0.905
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.341	1.292	1.391	0.000
Agree	0.870	0.839	0.903	0.000
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	4.150	3.839	4.487	0.000
Not very satisfied	2.827	2.693	2.968	0.000
Satisfied	1.589	1.530	1.649	0.000
Log Likelihood		-60063.632		

5.3.6. Upper Muscular Pain

Table 5.8 shows the final single level logistic regression model for muscular pains in shoulder, neck, and/or upper limbs, i.e., upper muscular pain, in the last 12 months. Women show higher odds of reporting upper muscular pain (OR 1.292, CI 1.257-1.327), and older people have a significant but small effect (OR (1.021, 1.020-1.022). Having completed some form of university means that an individual has lower odds of reporting upper muscular pain (OR 0.788, CI 0.767-0.810). Nights worked per month shows a small increase in odds, as does hours per week worked (odds of 1.008 and 1.007 respectively, with CIs of 1.004-1.011 and 1.005-1.008 respectively). While small, these effects are nonetheless substantively important. Shift work shows an increase in odds of reporting upper muscular pain as well, with an OR of 1.109 (CI 1.071-1.147). Working time arrangements have some effect, but more with respect to the more flexible arrangements. *Having a choice between several fixed schedules* is not statistically significant, with an OR of 1.003 (CI 0.952-1.057), with a p value of 0.908. Due to its wide confidence interval, this small effect is likely to be mostly irrelevant. However, having working time arrangements that are *adaptable within limits* and *those which are entirely self-determined* show an increase in odds (1.176, CI 1.134-1.220 and 1.070, CI 1.030-1.111 respectively), meaning those in more flexible situations are more likely to report upper muscular pain. For skill-demand match, there is a smaller gap between *high* and *low* demand individuals, with those with *higher* demands relative to those whose *skills and demands match* having slightly higher odds (1.095, CI 1.052-1.141) than those with *lower demands* (OR 1.039, CI 1.10-1.070), though it should be noted that their confidence intervals overlap slightly. Perhaps, then, having a mismatch is the more relevant characteristic, rather than whether this mismatch is more or less demanding. Being paid appropriately again follows a similar pattern, with those who *disagree* relative to those who *neither disagree or agree* having much higher odds (1.412, CI 1.363-1.463) than those who *agree*, who show a decrease in odds (OR 0.956, CI 0.924-0.989). Being satisfied with the working conditions in one's job again shows its importance, with those who are *not at all satisfied* being much more likely to report upper muscular pain (OR 3.637, CI 3.365-3.931) than those who were *not very satisfied* (OR 2.611, CI 2.493-2.734) and those who were satisfied (OR 1.572, CI 1.520-1.626), relative to those who were *very satisfied.* It is worth pausing here to reflect on the three 'muscular' types of health outcome: backache, lower muscular pain, and upper muscular pain. They follow similar patterns in their covariates, so it could be there is something unaccounted for in the analysis, most likely clusters in the data, i.e. occupational differences which are not accounted for solely by demogrpahic or working conditions, or other structural concerns.

Table 5.8: Final Single Level Logistic Regression Model for Upper Muscular Pain in the last 12 months

Y: Upper Muscular Pain	OR	95% CI		p
Intercept	0.111	0.102	0.120	0.000
Sex (ref: male)	1.292	1.257	1.327	0.000
Age	1.021	1.020	1.022	0.000
Has Tertiary Education (ref: no tertiary)	0.788	0.767	0.810	0.000
Nights worked per month	1.008	1.004	1.011	0.000
Works shifts (ref: no)	1.109	1.071	1.147	0.000
Hours per week worked	1.007	1.005	1.008	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.003	0.952	1.057	0.908
Adaptable within limits	1.176	1.134	1.220	0.000
Entirely self-determined	1.070	1.030	1.111	0.001
Skill-demand match (ref: they match)				
Demands too low	1.039	1.010	1.070	0.009
Demands too high	1.095	1.052	1.141	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.412	1.363	1.463	0.000
Agree	0.956	0.924	0.989	0.009
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	3.637	3.365	3.931	0.000
Not very satisfied	2.611	2.493	2.734	0.000
Satisfied	1.572	1.520	1.626	0.000
Log Likelihood		-65903.885		

5.3.7. Anxiety

Table 9 shows the final single level logistic regression model of anxiety in the last 12 months. Women are 40.9% more likely to report anxiety in the last 12 months than men, and older people tend to have slightly higher odds of anxiety (OR 1.011, CI 1.009-1.012). Those with tertiary education show a similar OR to women, with an OR of 1.402 (CI 1.348-1.458), showing a pattern opposite to the 'muscular' outcomes. It seems possible then, that those with tertiary education are clustered in occupations that provoke anxiety. Hours worked per week and nights worked per month remain constant in their pattern, with ORs of 1.005 (CI 1.003-1.006) and 1.021 (CI 1.016-1.025) respectively. The effect of shift work has become statistically insignificant, as its confidence interval crosses 1 (OR 1.040, CI 0.990-1.092). Working time arrangements show a small increase in OR between *adaptable within limits* and *entirely self-determined* (ORs 1.132, CI 1.074-1.193 to 1.172, CI 1.110-1.237), though the confidence intervals do overlap, which may mean, again, that it is the increase in flexibility on a whole that increases the odds of anxiety, rather than the form of flexibility. Those with a *choice between several fixed schedules* do not show a significant change in odds, though it shows a small decrease in odds, the confidence intervals overlap 1 (OR 0.955, CI 0.884-1.032). For the skill-demand match, the pattern of the non-muscular outcomes returns, with both showing an increase in odds, but the *lower demands'* increase being smaller relative to the *higher demands* (OR 1.043, CI 1.00-1.088 to 1.435, CI 1.359-1.515 respectively). More demanding jobs increase the prevalence of anxiety. Being paid inappropriately also appears to increase the odds of anxiety (OR 1.510, CI 1.434-1.589), which, substantively makes sense, as financial insecurity has been shown to increase anxiety (see Chapter 2). Being paid appropriately does not appear to have a significant effect. Satisfaction with working conditions appears to follow the same pattern, but the confidence intervals have widened relative to the 'muscular' outcomes.

Table 5.9: Final Single Level Logistic Regression Model for Anxiety in the last 12 months

Y: Anxiety	OR	95% CI		p
Intercept	0.025	0.022	0.028	0.000
Sex (ref: male)	1.409	1.355	1.465	0.000
Age	1.011	1.009	1.012	0.000
Has Tertiary Education (ref: no tertiary)	1.402	1.348	1.458	0.000
Nights worked per month	1.021	1.016	1.025	0.000
Works shifts (ref: no)	1.040	0.990	1.092	0.118
Hours per week worked	1.005	1.003	1.006	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.955	0.884	1.032	0.242
Adaptable within limits	1.132	1.074	1.193	0.000
Entirely self-determined	1.172	1.110	1.237	0.000
Skill-demand match (ref: they match)				
Demands too low	1.043	1.000	1.088	0.050
Demands too high	1.435	1.359	1.515	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.510	1.434	1.589	0.000
Agree	0.996	0.944	1.050	0.880
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	5.438	4.974	5.946	0.000
Not very satisfied	3.033	2.840	3.239	0.000
Satisfied	1.523	1.442	1.608	0.000
Log Likelihood		-37695.197		

5.3.8. Fatigue

The final single level logistic regression model of fatigue in the last 12 months is shown on table 5.10. Women have higher odds of reporting fatigue in the last 12 months than men (OR 1.338, CI 1.302-1.376), and age, nights worked per month, and hours worked per week continue to have small but significant effects. Having a tertiary education also has a small but significant effect on fatigue (OR 1.089, CI 1.059-1.120), as with shift work (OR 1.076, CI 1.039-1.114). Fatigue does not appear to have a particularly strong pattern with respect to the covariates. Time arrangement shows that having some choice is better than having *entirely self-determined* working time, perhaps indicating that those who have more control may fatigue themselves more easily (OR 1.037, CI 0.998-1.079). Those with a *choice between several fixed schedules* and those with a time arrangement that is *adaptable within limits* both show decreased and very similar odds of reporting fatigue (OR 0.896, CI 0.850-0.946 and 0.899, CI 0.865-0.933 respectively). Perhaps some structure is necessary to avoid fatigue. Those with *low demands* in terms of skill-demand match show a small and statistically insignificant effect (OR 1.008, CI 0.979-1.038), but those with *high demands* show an increased OR of 1.133 (1.087-1.180). Being paid appropriately follows the pattern theorised by Siegrist [1996]: *disagreeing* one is paid appropriately leads to increased odds of reporting fatigue (OR 1.380, CI 1.331-1.430), whereas *agreeing* one is being paid appropriately leads to a slight decrease in odds of reporting fatigue (OR 0.912, CI 0.881-0.944). Being *not at all satisfied* with working conditions shows very high odds of reporting fatigue (4.960, CI 4.581-5.369), similarly for being *not very satisfied* (OR 3.384, CI 3.227-3.546), and finally being *satisfied* shows increased odds (OR 1.716, CI 1.657-1.777) relative to being *very satisfied* with working conditions. Examining fatigue in the context of geography and occupation may be more effective in pulling out the patterning in the covariates.

Table 5.10: Final Single Level Logistic Regression Model for Fatigue in the last 12 months

Y: Fatigue	OR	95% CI		p
Intercept	0.108	0.100	0.118	0.000
Sex (ref: male)	1.338	1.302	1.376	0.000
Age	1.006	1.004	1.007	0.000
Has Tertiary Education (ref: no tertiary)	1.089	1.059	1.120	0.000
Nights worked per month	1.017	1.013	1.020	0.000
Works shifts (ref: no)	1.076	1.039	1.114	0.000
Hours per week worked	1.016	1.015	1.017	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.896	0.850	0.946	0.000
Adaptable within limits	0.899	0.865	0.933	0.000
Entirely self-determined	1.037	0.998	1.079	0.064
Skill-demand match (ref: they match)				
Demands too low	1.008	0.979	1.038	0.604
Demands too high	1.133	1.087	1.180	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.380	1.331	1.430	0.000
Agree	0.912	0.881	0.944	0.000
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	4.960	4.581	5.369	0.000
Not very satisfied	3.383	3.227	3.546	0.000
Satisfied	1.716	1.657	1.777	0.000
Log Likelihood		-64066.166		

5.3.9. Headache and/or Eyestrain

Table 5.11 shows the final single level logistic regression model for headache and/or eyestrain in the last 12 months. Women show higher odds than men for headache and/or eyestrain (OR 1.687, CI 1.641-1.734). Age, nights worked per month, and hours worked per week show very similar small but significant effects to other models (ORs 1.003, CI 1.001-1.004; 1.008, CI 1.005-1.012; 1.010, CI 1.009-1.011 respectively). Having tertiary education has an increased odds of headache and/or eyestrain (OR 1.171, CI 1.139-1.204), perhaps due to the types of jobs taken by those with university education, which may involve more computer work. The effect of shift work is so small as to be insignificant, as the confidence interval overlaps 1 (OR 1.033, CI 0.998-1.070). Working time arrangements show similarly small effect sizes, with only *adaptable within limits* confidence intervals not overlapping 1 (OR 1.043, CI 1.004-1.082). Having demands which are *too low* relative to one's skill is also statistically insignificant, with a p value of 0.882, and an effect size very, very close to 1 (OR 0.998, CI 0.969-1.028). Having *high* demands, though, shows increased odds (1.234, CI 1.185-1.285), as with *disagreeing* one is being paid appropriately (OR 1.275, CI 1.230-1.322). *Agreeing* one is being paid appropriately appears to have little effect on headache and/or eyestrain, with an OR of 0.969 (CI 0.935-1.003). Indeed, even satisfaction with working conditions does not show as large effect sizes as the other outcomes, though the effect sizes are still quite large, and significant, perhaps indicating there is not something captured with this model, or that headache and/or eyestrain are difficult to model. Accounting for occupation and other group factors may improve the model.

Table 5.11: Final Single Level Logistic Regression Model for Headache and/or Eyestrain in the last 12 months

Y: Headache and/or Eyestrain	**OR**	**95% CI**		**p**
Intercept	0.143	0.132	0.155	0.000
Sex (ref: male)	1.687	1.641	1.734	0.000
Age	1.003	1.001	1.004	0.000
Has Tertiary Education (ref: no tertiary)	1.171	1.139	1.204	0.000
Nights worked per month	1.008	1.005	1.012	0.000
Works shifts (ref: no)	1.033	0.998	1.070	0.068
Hours per week worked	1.010	1.009	1.011	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.016	0.964	1.072	0.545
Adaptable within limits	1.043	1.004	1.082	0.028
Entirely self-determined	0.964	0.927	1.002	0.064
Skill-demand match (ref: they match)				
Demands too low	0.998	0.969	1.028	0.882
Demands too high	1.234	1.185	1.285	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.275	1.230	1.322	0.000
Agree	0.969	0.935	1.003	0.077
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	2.866	2.657	3.091	0.000
Not very satisfied	2.212	2.111	2.318	0.000
Satisfied	1.424	1.376	1.474	0.000
Log Likelihood		-64045.915		

5.3.10. Injury(ies)

Table 5.12 shows the final single level logistic regression model for injury(ies) in the last 12 months, the final health outcome. Women have much lower odds of reporting injury(ies) than men (OR 0.522, CI 0.498-0.548), and older people also have slightly lower odds (0.992, CI 0.990-0.993). Those with tertiary education also have decreased odds of injury(ies) (OR 0.673, CI 0.640-0.708); these characteristics indicate perhaps a certain type of person who is prone to injury, and there may be structural factors explaining why this is so, that we cannot capture adequately with a single level model. It is also possible that particular occupations may be more injury-prone than others, and those groups that are more likely to be injured cluster in those occupations. Nights per month and hours per week continue to have a small but significant increase in odds. Working shifts increases the odds of reporting injury(ies) with an OR of 1.191 (CI 1.126-1.260). Working time arrangements appear to follow no clear pattern, with the *choice between several fixed schedules* and entirely self-determined arrangements having small and statistically insignificant effects due to their confidence intervals crossing 1, whereas those with time arrangements that are *adaptable within limits* have slightly increased odds of reporting injury(ies) (OR 1.103, CI 1.033-1.177). The skill-demand match variable follows a similar pattern to the other outcomes, but the odds are closer together, though the confidence intervals do not overlap. Those with *lower* demands have increased odds of 1.133 (CI 1.078-1.191) relative to those whose demands and skills match, whereas those with *higher* demands have odds of 1.251 (CI 1.168-1.339). *Disagreeing* one is being paid appropriately has increased odds of injury(ies) (OR 1.322, CI 1.244-1.404), versus *agreeing* one is being paid appropriately, the confidence interval of which crosses 1, meaning it is insignificant (OR 0.948, CI 0.891-1.009). Like headache and/or eyestrain, the satisfaction with working conditions follows a similar pattern to all of the other outcomes, but the effect size is much smaller than in the other models, in some cases, half of what the ORs are.

Table 5.12: Final Single Level Logistic Regression Model for Injury(ies) in the last 12 months

Y: Injury(ies)	OR	95% CI		p
Intercept	0.143	0.132	0.155	0.000
Sex (ref: male)	0.522	0.498	0.548	0.000
Age	0.992	0.990	0.993	0.000
Has Tertiary Education (ref: no tertiary)	0.673	0.640	0.708	0.000
Nights worked per month	1.012	1.006	1.017	0.000
Works shifts (ref: no)	1.191	1.126	1.260	0.068
Hours per week worked	1.004	1.002	1.006	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.082	0.989	1.184	0.087
Adaptable within limits	1.103	1.033	1.177	0.004
Entirely self-determined	1.060	0.993	1.131	0.079
Skill-demand match (ref: they match)				
Demands too low	1.133	1.078	1.191	0.000
Demands too high	1.251	1.168	1.339	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.322	1.244	1.404	0.000
Agree	0.948	0.891	1.009	0.095
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	2.987	2.686	3.320	0.000
Not very satisfied	2.088	1.931	2.259	0.000
Satisfied	1.273	1.193	1.358	0.000
Log Likelihood		-28408.503		

5.4. Conclusions

These models appear to perform reasonably well with most effects being statistically significant, having narrow confidence intervals. They show patterns relative to outcome types, i.e. ‘muscular’ outcomes differ from those more related to mental health. Models around muscular health outcomes tend to skew male, older, and generally the effect of education is to decrease the odds of the outcome; satisfaction, while still important, has a smaller magnitude of effect than on the mental health-related outcomes, such as anxiety. They tend towards the opposite (female, with tertiary education). This means that certain working conditions relate more to specific outcomes than others, meaning it is important to examine the outcomes individually.

The models are fairly parsimonious; the relationships between the covariates and the outcomes essentially show that working conditions and arrangements thought of to be negative, such as working nights or shifts, have an impact on reporting of the various health outcomes. Indeed, the models reinforce the notion that flexible working conditions are of detriment to an individual’s health (see Chapter 2). However, some aspects of the relationship between working conditions and health are not captured, namely the structural aspects of the data, be it the country from which the individual hails, the year they answered the survey, or, most importantly, the occupation in which they work. People with particular demographic characteristics, such as men, may cluster in particular occupations, and this should be accounted for in the models. Further, without this information, the models do not fit into the worksome framework, as they only examine the individual as independent of all other individuals, and of the other geocontextual factors as unimportant.

Even from a data-driven standpoint, multilevel analysis is necessary, as the data are clustered. However, these single-level models provide part of the groundwork for multilevel models. Examining them first permits the possibility of simpler models being the most appropriate, which is desirable as they are easier to interpret and reproduce ([Box, 1976]. Multilevel models allow for the capture all of this information, and the examination of the variation between and within these clusters without compromising the logistic regression structure. The following chapter describes the British Household Panel Survey (BHPS) single-level logistic regression models, conducted in the same manner as the models in this chapter. This will be followed by Chapter 7, which lays the other part of the groundwork for the multilevel models, by determining what structure the random part, or the levels of the multilevel, should take.

Chapter 6

Results: BHPS Single Level Logistic Regression Models

6.1. Introduction

Following on from Chapter 5, single level logistic regression models were generated for the outcomes from the British Household Panel Survey (BHPS) data. Chapter 5 revealed patterns relative to outcome types, i.e. that certain working conditions relate more to specific outcomes than others. The approach used to answer research objectives 1 and 2, and research questions 1 and 2 was based on an international dataset which was useful for national level comparisons, but which did not allow the exploration of individual level differences. In this chapter that issue is addressed by using the BHPS data, which is a national panel survey with 18 waves. Specifically,the corresponding working conditions variables and health outcomes are explored in the BHPS data using single level logistic regression models, implemented in the same way as the EWCS models (see Chapter 5). In short, the covariates were added one by one to the models, producing the final models presented in tables 6.3-6.5, and the intermediate models can be found in Appendix B. There were 115,171 total observations. The purpose of this chapter is also to determine whether simpler single-level multivariate logistic regression models will suffice to explain how working conditions might affect health, and whether they can demonstrate the influence of the various scales discussed in the worksome.

Three outcomes were examined: health status in the last 12 months (dichotomised to *poor/good*), health problems in the arms, legs, hands (etc.), i.e., muscular or limb problems, and health problems relating to anxiety/depression. The latter two are operationalised as a binary outcome (*mentioned/not mentioned*). Both the BHPS and EWCS data use the mentioned/not mentioned dichotomy for specific health outcomes. Health status, in this case (self-declared) was chosen as it is a powerful measure of global health, as argued in the literature review (Chapter 2). The two specific health problem outcomes relating to health conditions were examined as they cover both physical and mental health and correspond to outcomes examined in the EWCS dataset. Specifically, the health problems in the limbs corresponds to the muscular pain related outcomes in the EWCS. The EWCS dataset has more muscular pain outcomes, for example, separating backache from upper body and lower body muscular pain. The BHPS anxiety/depression outcome corresponds to the EWCS anxiety one. They will be discussed in turn, and in the conclusion, then related to one another and the EWCS models. Eight covariates were also selected to correspond to variables used in the EWCS analysis (as discussed in Chapter 4). All of the variables can be seen in table 6.1 below.

Table 6.1: Outcomes and Covariates for all Models

Outcomes	**Covariates**
• Health status in the last 12 months • In the last 12 months... – Health problems in the arms, legs, hands (etc.), i.e., problems with the muscles or limbs – Health problems relating to anxiety/depression	• Sex (ref:male) • Age (15-65) • Has tertiary education (ref: no tertiary education) • Gross monthly pay (GBP) • Job hours per week • Works flexitime (ref: Not mentioned) • Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied, coded as 3) – Not satisfied (1) – Not very satisfied (2) – Satisfied (4) – Very Satisfied (5) • Job satisfaction: Overall (ref: Neither satisfied nor dissatisfied, coded as 3) – Not satisfied (1) – Not very satisfied (2) – Satisfied (4) – Very Satisfied (5)

6.2. Correlations

As before, correlation analysis provides the means to explore the relationships between the variables in the data. Before the models were analysed, the correlations between the variables were examined to check for multicollinearity, and to preliminarily examine the relationships between the variables (see table 6.2). Examining the correlation matrix is a common way to check for multicollinearity [Armitage et al., 2002]. No correlation pair was higher than 0.43. Monthly gross pay was correlated most strongly (0.401) with job hours per week, which is unsurprising: it shows that the more hours you work, the more pay you will receive. It is further correlated with having tertiary education (0.31), and negatively correlated with female sex (-0.31). Sex is also negatively correlated with job hours per week (-0.39), which indicates a potential relationship between sex, job hours per week, and monthly gross pay. As revealed in Chapter 5, this could reflect women's higher levels of flexible and part-time working, due to their multiple social roles. Overall job satisfaction was also correlated with the 'total pay' dimension of job satisfaction (0.42). However, as no correlation is high, the variables are unlikely to be collinear. Of note, monthly gross pay and job satisfaction with total pay are not very correlated (0.13), meaning that these variables may not be totally related.

Table 6.2: Correlations between Covariates. Correlations which are greater than 0.2 are coloured in light blue and those less than -0.2 are coloured in light red

	Sex	Age	Tertiary Education	Job Hours per Week	Works Flexitime	Job satisfaction: overall	Job satisfaction: total pay	Monthly gross pay
Sex	1							
Age	0.0011	1						
Tertiary Education	-0.0151	-0.0139	1					
Job hours per week	-0.3857	0.0101	0.0599	1				
Works flexitime	0.0264	0.0127	0.0565	-0.0128	1			
Job satisfaction: overall	0.0896	0.0282	-0.0423	-0.0975	0.0063	1		
Job satisfaction: total pay	0.0458	0.0424	0.0308	-0.0750	0.0189	0.4203	1	
Monthly gross pay	-0.3074	0.1598	0.3126	0.4041	0.0402	-0.0341	0.1297	1

6.3. Model Results

The following sections present the results of the single level logistic regression models, organised by outcome.

6.3.1. Health Status

Health status in the last 12 months, which was dichotomised to poor (*fair/poor*, 0) or good (*good/very good/excellent*, 1), is a measure of self-rated health. Unlike the previous EWCS data, the measure in the BHPS is not necessarily directly associated with their actual work: the EWCS respondents were asked whether they thought their work affected their health (see Chapter 4 for a description of this data, and Chapter 5 for the single level models analogous to these). Table 6.3 shows the results for the final model, which includes all the covariates. Most of the effect sizes are close to 1, which indicates a small effect size. These include sex, age, gross monthly pay, job hours per week, and flexitime. Women are less likely than men to report good health (OR 0.921, CI 0.894-0.949). Older people also are less likely to report good health, year on year (OR 0.991, CI 0.990-0.992). Interestingly, gross monthly pay shows an OR of 1.00016 (CI 1.000141-1.000178). This effect appears small as it is per single British pound: for every pound increase in gross monthly pay, there is a 0.016% increase in the odds of reporting good health. For the mean gross monthly pay of £1150, this is therefore an 18.4% increase in the odds. This even held through the models before accounting for satisfaction with total pay. Job hours per week shows that for each hour increase in time worked, there is a 0.3% decrease in the odds of reporting good health – a small, but significant effect. The effect of working flexitime is inconclusive, as the OR has a confidence interval overlapping one, meaning the effect is not statistically significant at this confidence level.

Individuals with higher levels of education (as identified by the presence of tertiary education) are 23.7% more likely to report good health than those who do not have tertiary education. Being *not satisfied* or *not very satisfied* with the total pay from your job relative to being *neither satisfied nor dissatisfied* showed a decrease in reporting good health (11.4% and 2.9% respectively), though the *not very satisfied* category was not statistically significant (OR 0.971, CI 0.920-1.024, p 0.278). As might be expected, being *satisfied* and *very satisfied* increased the odds of reporting good health by 8.7% and 13.5% respectively, evidenced by Chapter 5, and Virtanen et al. [2003]. Finally, overall job satisfaction followed a similar pattern, but with stronger effects than satisfaction with total pay. *Not satisfied* and *not very satisfied* showed decreases in the odds relative to neither satisfied nor dissatisfied by 21.6% and 13.5% respectively. Being *satisfied* or *very satisfied* with your job overall showed increases in the odds of reporting good health of 37.5 and 52.7% respectively.

Table 6.3: Final Single Level Logistic Regression Model for Health Status. Gross monthly pay is reported with a larger number of significant digits than the other covariates due to its small effect size.

Y: Health status in the last 12 months	OR	95% CI		p
Intercept	2.683	2.464	2.922	0.000
Sex (ref: male)	0.921	0.894	0.949	0.000
Age	0.991	0.990	0.992	0.000
Has Tertiary Education (ref: no tertiary)	1.237	1.187	1.289	0.000
Gross monthly pay (GBP)	1.00016	1.000141	1.000178	0.000
Job hours per week	0.997	0.995	0.998	0.000
Works flexitime (ref: Not mentioned)	0.971	0.934	1.010	0.146
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)				
Not satisfied	0.886	0.820	0.958	0.002
Not very satisfied	0.971	0.920	1.024	0.278
Satisfied	1.087	1.035	1.141	0.001
Very Satisfied	1.135	1.062	1.214	0.000
Job satisfaction: Overall (ref: Neither satisfied nor dissatisfied)				
Not satisfied	0.784	0.702	0.875	0.000
Not very satisfied	0.865	0.814	0.920	0.321
Satisfied	1.375	1.308	1.445	0.000
Very Satisfied	1.527	1.434	1.626	0.000
Log Likelihood		-65143.5		

Compared to the EWCS data, specifically the work-health effect, a dichotomised outcome of 'does your work affect your health?', similar patterns can be observed in the coefficients of the covariates which correspond. It should be noted that these particular outcomes in the BHPS and EWCS data have opposing codings, in that *good* health here in the BHPS is coded as 1, and *yes*, i.e., 'my work affects my health' is coded as 1 in the EWCS. Older people, for example are more likely to report their work affects their health in the EWCS analysis and are less likely to report good health in the BHPS analysis. Job hours per week show a similar pattern to age, as does working in flexible time arrangements, though in the EWCS data it is a categorical variable with several arrangement types. As for satisfaction with pay in the BHPS, its patterning matches that of the 'appropriate pay' variable in the EWCS, in that those less satisfied or who disagree that they are paid appropriately report either poorer health, or that their work affects their health. Overall satisfaction for both shows the same pattern. This means that, on the whole, the patterns of how the demographic and working conditions covariates match between the EWCS and BHPS analysis, and therefore similar conclusions around the research questions can be drawn. Namely, that work, and its conditions do affect health, and this varies by working condition, meeting research objectives 1 and 2, and answering research questions 1 and 2.

6.3.2. Specific health problems with the limbs or muscles

The second outcome of interest from the BHPS are health problems which related to muscular or other issues often found in the arms, legs, hands, and so on. In the survey respondents either *mentioned* (1) or *did not mention* (0) this outcome. Table 6.4 shows the model results. Women relative to men (OR 1.082, CI 1.044-1.122) and older people (OR 1.051, CI 1.049-1.052) were more likely to mention muscular problems. Having a tertiary education decreased the odds of reporting muscular problems by 19.7%. Again, gross monthly pay had a small effect, due to it being per single British pound, showing a slight decrease (0.016%) in the odds of reporting muscular problems. The effect of job hours per week was small (a 0.1% increase in the odds for each additional hour worked), and further, statistically insignificant (p 0.085). Working flexitime increased the odds of mentioning a muscular problem by 5.6%, though, without accounting for occupation, it may be difficult to know potential causes or causal direction for this effect.

Satisfaction with total pay showed a similar pattern to health status, in that those who are more satisfied tend to be healthier – those who were *satisfied* or *very satisfied* tended to have lower odds of mentioning a muscular problem relative to those who were *neither satisfied nor dissatisfied*. Conversely, those who were *not satisfied* or *not very satisfied* showed increases in the odds, though only the strongest sentiment categories (*not satisfied* and *very satisfied*) had statistically significant effects. Overall, the effects of job satisfaction were all significant, and showed the same pattern as the health status results, with stronger effects. Relative to those who were *neither satisfied or dissatisfied*, those who were *satisfied* or *very satisfied* showed a 19.2% and 22.1% decrease in the odds of reporting muscular problems, and those who were *not very satisfied* or *not satisfied* showed an 11.6% and 42.9% increase in the odds of mentioning muscular problems.

Table 6.4: Final Single Level Logistic Regression Model for Health Problems with the Limbs or Muscles. Gross monthly pay is reported with a larger number of significant digits than the other covariates due to its small effect size.

Y: Health problems with the limbs or muscles	OR	95% CI		p
Intercept	0.033	0.030	0.037	0
Sex (ref: male)	1.082	1.044	1.122	0
Age	1.051	1.049	1.052	0
Has Tertiary Education (no tertiary)	0.803	0.764	0.844	0
Gross monthly pay (GBP)	0.999919	0.999898	0.999939	0
Job hours per week	1.001	1.000	1.003	0.085
Works flexitime (ref: Not mentioned)	1.056	1.008	1.106	0.023
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)				
Not satisfied	1.161	1.056	1.275	0.002
Not very satisfied	1.065	0.997	1.137	0.062
Satisfied	0.941	0.886	0.999	0.046
Very Satisfied	0.944	0.871	1.023	0.162
Job satisfaction: Overall (ref: Neither satisfied nor dissatisfied)				
Not satisfied	1.429	1.256	1.625	0
Not very satisfied	1.116	1.035	1.203	0.004
Satisfied	0.859	0.808	0.913	0
Very Satisfied	0.779	0.721	0.841	0
Log Likelihood		-48810.1		

The analogous EWCS outcomes are lower muscular pain (LM) and upper muscular pain (UM), where the variables are also coded as *not mentioned* (0) and *mentioned* (1). The effect of sex was larger in the EWCS analysis (OR LM 1.156, CI 1.124-1.190; OR UM 1.292, CI 1.257-1.327) compared to the BHPS analysis (OR 1.082, CI 1.044-1.122). It is possible that the unaccounted for variation within or between the scales, i.e., the occupation, geography, or time levels, could account for why the EWCS data show a larger effect than the BHPS, as the EWCS data covers a diverse range of European countries. The effect of having tertiary education rather than not was similar for both, showing a decrease in the odds of reporting muscular issues in both the BHPS and EWCS analyses. Both the BHPS and EWCS analysis showed a slight increase in the odds of reporting muscular problems with increasing hours per week worked. Satisfaction with total pay (and its analogous variable 'appropriate pay' in the EWCS) and satisfaction overall both showed a decrease in the odds of reporting muscular problems with increasing satisfaction.

6.3.3. Specific health problems: anxiety or depression

The final outcome of interest from the BHPS is the reporting of anxiety and depression as health problems, which are operationalised as *not mentioned* (0) or *mentioned* (1). Table 6.5 shows the results of the final model. Overall women are far more likely to mention anxiety or depression than men: have an 125% increase in odds (OR 2.250, CI 2.106-2.404). Older people's odds of mentioning anxiety or depression increase by 1.7% for each additional year. Unlike the previous two outcomes, health status and muscular health problems, the presence of tertiary education was not significant in the case of anxiety and depression. Gross monthly pay has a small effect size, due to being per single British pound, with a 0.01% decrease in the odds of reporting anxiety/depression. Job hours per week worked decreases the odds of reporting anxiety or depression, and though the confidence interval is reasonably narrow and does not overlap 1, the p-value implies that the effect is not statistically significant.

As for satisfaction with total pay, only one of the categories is statistically significant – *not being satisfied* with your total pay increases your likelihood of mental health problems related to anxiety or depression (OR 1.215, CI 1.046-1.411). Relative to *neither satisfied nor dissatisfied*, being *satisfied* or *very satisfied* with total pay have no strong relationship with health problems due to anxiety or depression. Overall job satisfaction does have an apparent and statistically significant pattern across the satisfaction levels – as overall job satisfaction decreases the odds of reporting anxiety and depression increases. Relative to being *neither satisfied nor dissatisfied*, being *not satisfied* or *not very satisfied* means a 122.8% and 56.3% increase in the odds of mentioning anxiety or depression respectively. Being *satisfied* or *very satisfied* with the job overall shows a 33.5% and 48.4% decrease in the odds respectively.

The analogous EWCS outcome is the reporting of anxiety, coded as *not mentioned* (0) and *mentioned* (1). Sex, i.e. being a woman rather than a man, has a much larger effect in the BHPS data, with a difference in ORs of 0.841. This could be due to some UK-specific characteristic of work itself or working conditions that could lead to more women reporting anxiety/depression. This could be accounted for by including the scales and domains argued for by the worksome, so including occupation, geography, and time in the model through a multilevel structure could account for this difference between the two. Age, working flexitime, and the two satisfaction variables all had similar effect sizes to their analogous EWCS covariates. Having tertiary education rather than not has a larger effect size in the EWCS analysis, and it is

Table 6.5: Final Single Level Logistic Regression Model for Health Problems relating to Anxiety/Depression. Gross monthly pay is reported with a larger number of significant digits than the other covariates due to its small effect size.

Y: Health problems anxiety/depression	**OR**	**95% CI**		**p**
Intercept	0.028	0.023	0.034	0.000
Sex (ref: male)	2.250	2.106	2.404	0.000
Age	1.017	1.015	1.019	0.000
Has Tertiary Education (ref: no tertiary)	1.059	0.975	1.149	0.172
Gross monthly pay (GBP)	0.999868	0.999826	0.99991	0.000
Job hours per week	0.994	0.991	0.997	0.000
Works flexitime (ref: Not mentioned)	1.100	1.017	1.189	0.017
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)				
Not satisfied	1.215	1.046	1.411	0.011
Not very satisfied	1.107	0.989	1.239	0.076
Satisfied	1.013	0.912	1.125	0.816
Very Satisfied	1.063	0.924	1.222	0.394
Job satisfaction: Overall (ref: Neither satisfied nor dissatisfied)				
Not satisfied	2.228	1.870	2.655	0.000
Not very satisfied	1.563	1.392	1.754	0.000
Satisfied	0.665	0.601	0.736	0.000
Very Satisfied	0.516	0.452	0.589	0.000
Log Likelihood		-21118.7		

not statistically significant in the BHPS one. Job hours per week showed a decrease in the odds of reporting anxiety/depression in the BHPS analysis, but showed an increase in the odds in the EWCS one. The effect size is small, but similar to the difference in sex, it may be accounted for with the multilevel models.

6.4. Conclusions

This section examined single-level multivariate logistic regression models to estimate the impact of demographic information and working conditions variables, such as overall job satisfaction, on self-rated health status, as well as two mental and physical health outcomes. The findings from these models are largely consistent with one another in terms of the direction of effect for each of the variables, with few exceptions. They are also largely consistent with the EWCS models detailed in Chapter 5. Overall, they show a gendered pattern, where women tend to be less healthy. While age shows smaller effect sizes, it tends to show poorer health and increased reporting of both muscular health problems and anxiety/depression. Having tertiary education appears a bit more unclear, especially for anxiety and depression. Gross monthly pay has a small effect for all of the models, partly due to being scaled on a single GBP. These two dimensions are often used as a proxy for class, and it was found by Geyer et al. [2006] that they show strong independent effects on health. This likely means that further exploration of the data via multilevel models is required to account for the structure of the data. Specifically, the data contains repeated measures of individuals, in times, in places; ignoring this structure is likely to ignore the influences of those scales substantively, and theoretically, does not fit in with the conceptualisation of the worksome. Furthermore, as the observations in the data are time-points within individuals, the standard errors may be underestimated due to within-individual temporal autocorrelation, i.e. non-independent observations over time.

In addition, it is likely that the occupational components of the relationship are not well captured just by individual level working conditions but also require a multilevel structure. For example, having a tertiary education decreased the odds of reporting muscular problems. However, tertiary education also increased the odds of reporting anxiety or depression (though statistically insignificant), which signals there may be an occupation-specific component related to educational attainment's impact on health. Accounting for the structure of the data with multilevel models may help improve the confidence bounds and shrink the estimate, especially for tertiary education, which is likely unevenly distributed through the occupation types. Moreover, geography should also be accounted for – there are region-specific differences in the distribution of occupations in England, and therefore they are important to model. The single level models provide a base for the multilevel models, which will capture more information about the relationship between working conditions, health, occupation, and geography. The following chapter will chart out the necessary multilevel structure for the data.

Chapter 7

Variance Components Models

[1]

7.1. Introduction

There is a relationship between work and health, as the previous chapters have confirmed, and this holds through a variety of health outcomes and working conditions. However, although single level models produce useful results, one of their underlying assumptions is independence of observations, which therefore may not be most appropriate approach given the datasets in question. In the European Working Conditions Survey (EWCS), people work in specific occupations in particular countries with particular welfare regimes existing at particular points in time. Similarly, in the British Household Panel Survey (BHPS) data, wave-observations (i.e., time points) are clustered in individuals, who work in specific occupations, in particular UK regions. As a result, the single level models cannot capture the context or structure of interactions between people, who, by nature, are not independent of one another. Single level models assume a ‘universal,’ constant relationship between certain working conditions and health outcomes; it is not possible to account for differences between countries or time points [Duncan and Jones, 2000]. In this case, multilevel models are appropriate because of the hierarchy present in the data and the commonalities shared between those within countries, occupations, time periods, and welfare regimes. Multilevel models are also appropriate theoretically, in the sense that they can mirror the interactive scales within the worksome.

In essence, the EWCS and BHPS data are nested and clustered. They are nested in that, for example, occupations and individuals exist within countries. They are clustered, in that individuals live in specific countries in specific times. According to [Hox, 2010, p3], ignoring clustering in the data may produce misleading significance tests that can lead to ’spurious’ conclusions. Both random and fixed effects can be modelled simultaneously, allowing for the effects of these to be examined separately [Deeming and Jones, 2015]. Heterogeneity between

[1]The final section of this chapter on the differences between occupational classification systems has already been published in *Social Science and Medicine* Eyles et al. [2019]

levels in the models can be described explicitly [Duncan and Jones, 2000]. This chapter will test whether multilevel models are empirically necessary using the EWCS data, and then determine which structure is most appropriate for creating the final models. As the single level results were broadly similar between Chapters 5 and 6, the BHPS data were not used in the exploratory variance components models.

The EWCS dataset contains individuals classified into a number of groups. First, as the data are repeated cross-sectional, individuals are in survey years: 1991, 1995, 2000, 2005, 2010, and 2015. The years 2000 and 2001 were combined as they are part of the same survey wave, and they are mutually exclusive, i.e., data were collected as part of the same initiative in 2000 or 2001. In total there are 36 countries, although not all countries were surveyed in every year. Some were added in later waves either as they became EU member candidates, EU members, or EEA members. Individuals were not asked what their specific workplace was, but rather what occupation they worked in, so therefore occupation will be examined in its place. For exploratory modelling, the countries have been classified into six welfare regimes adapted from [Bambra, 2007], see table 4.1). Further, country-year and welfare-regime-year variables were also created. In essence, these represent a specific survey year in a specific country or welfare regime: spatio-temporal context. This was done to examine whether it may be better to examine them together as welfare regimes rather than separately due to sample size, though each country in the end had sufficient observations and statistical significance. According to Clarke [2008], who used Monte Carlo simulations to test group size for sparse data, reliable multilevel estimation is possible with five observations per group

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7.2. Examining Geography and Time

Seven multilevel logistic regression models were created as variance components models, which are null models that reveal at which level the variance lies in the data, and additionally, whether a multilevel structure may produce a better model than the single level approach. Table 7.1 shows the structure of the seven models which have been produced using MLwiN 3.01. Models 1, 2, 4, 5, and 7 are two-level models. A two-level model has a less complicated structure, which is simpler, therefore computationally less resource intensive, and further, is substantively easier to interpret. Models 3 and 6 are three-level models, used to determine where the variance lies with respect to country-years and welfare-regime years. Occupation was deemed substantively important, and therefore the final models with covariates will include it as the level directly above the individual. In all the variance components models, the individual is at the first level and the outcome variable is the binary 'Does your work effect your health?' which is answered by yes or no (No: 60.8%).

Table 7.2 shows the results of all seven models. There are also caterpillar plots, i.e., ranked residual plots (see figures 7.1-7.9) with confidence intervals, to examine the degree of clustering in the data. The variance partitioning coefficient (VPC), also known as the intraclass correlation

Table 7.1: Model Structure, with number of units in parentheses.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**
Level 3			Country (36)			Welfare Regime (6)	
Level 2	Country (36)	Year (6)	Year (154)	Country-Year (154)	Welfare Regime (6)	Year (32)	Welfare Regime-Year (32)
Level 1	Individual (175206)						

(ICC) for each higher level is shown, as well as the median odds ratio (MOR). The MOR is shown as the VPC is not directly comparable for logistic multilevel models, where as the MOR is [Merlo et al., 2006]. The MOR is the increased risk, on average, of arriving to a higher risk group from a lower risk one, when the two areas are randomly selected from the distribution of the estimated variance at that level [Merlo et al., 2006].

Table 7.2: Variance Components Model Results

	M1	S.E.	M2	S.E.	M3	S.E.	M4	S.E.	M5	S.E.	M6	S.E.	M7	S.E.
Cons (Fixed Part)	-0.141	0.06	-0.117	0.152	-0.133	0.061	-0.137	0.047	-0.104	0.147	-0.086	0.143	-0.106	0.096
Random Part														
Country Variance	0.129	0.031			0.064	0.031								
Year Var Variance			0.138	0.081	0.266	0.035					0.211	0.059		
Country Year Variance							0.332	0.039						
Welfare Regime Variance									0.13	0.076	0.082	0.072		
Welfare Regime Year Variance													0.295	0.074
VPC lvl 2	0.038		0.04		0.075		0.092		0.038		0.06		0.082	
MOR lvl2	1.409		1.425		1.636		1.733		1.4105		1.548		1.679	
VPC lvl 3					0.019						0.024			
MOR lvl 3					1.272						1.314			

Model 1 reveals that there is a strong geographic component to the data through country-level clustering. The country-level residuals are well-dispersed around the zero line, (see figure 7.1). The VPC is 3.8%, and the between-country variance is 0.129 (se 0.031). The MOR is 1.409. Model 2 examines the year level, where clustering also appears to occur. The between-year variance is 0.138 (se 0.081), and the VPC is 4%. The MOR is 1.425, meaning moving between certain years can increase the likelihood of reporting that work effects health.

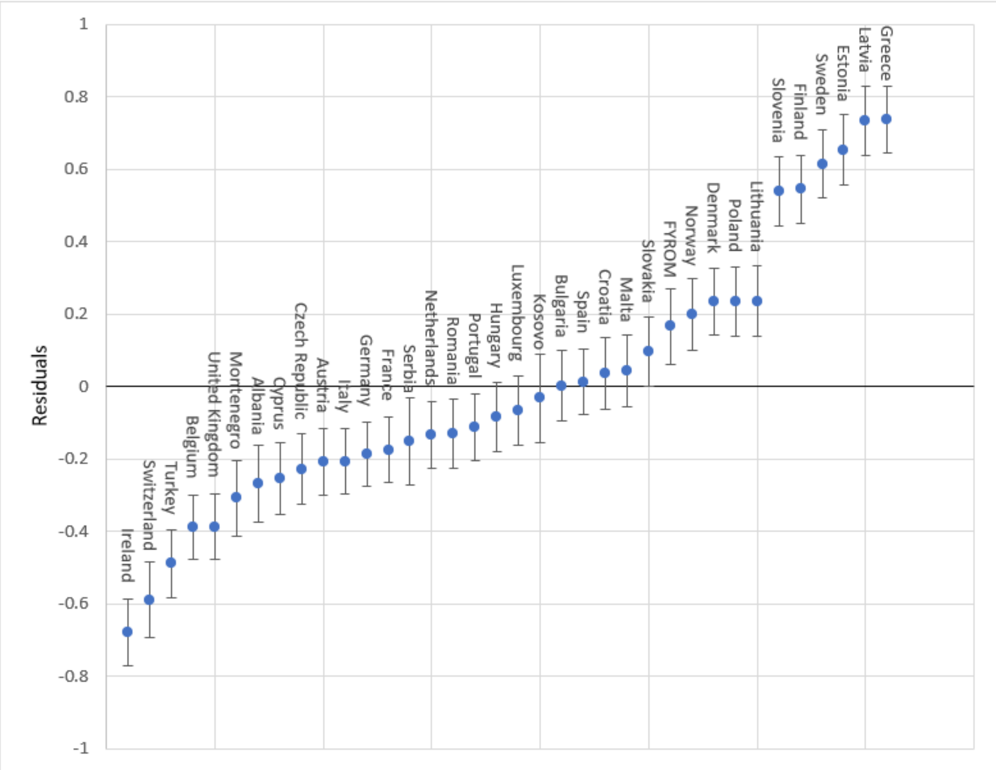

Figure 7.1: Ranked Residuals for Model 1, country

The year-level residuals for model 2 (see figure 7.2), which are reasonably well-dispersed around the zero line, though the standard errors overlap in several cases, also show clustering, though perhaps with some noisiness. This could be due to the country-level clustering indicated in model 1, thereby indicating that both countries and years should be included in the multilevel structure.

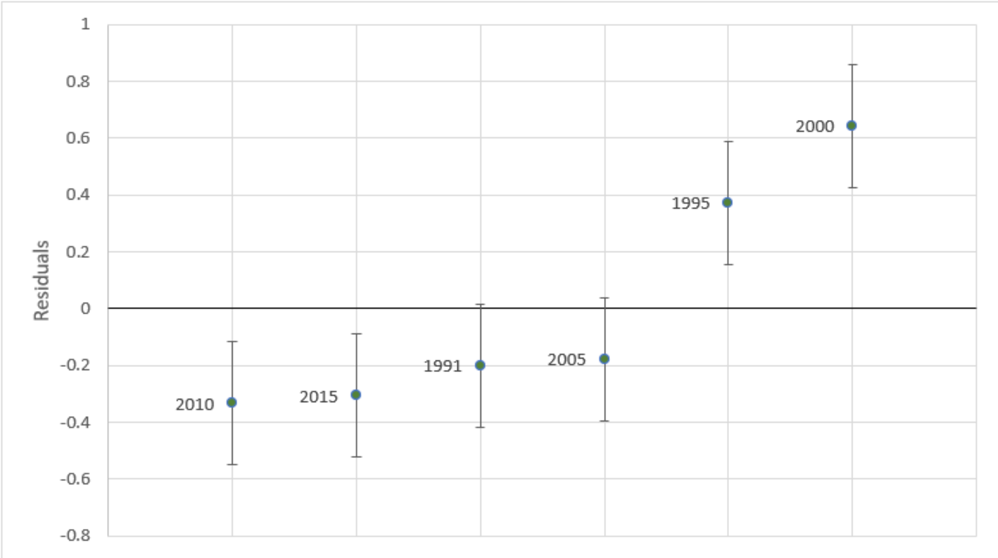

Figure 7.2: Ranked Residuals for Model 2, year

Model 3 shows how country-years are comprised in terms of the division of variance. The between-country variance itself appears to drop when years are included at level 2, at 0.064 (se 0.031), with a high standard error; the between-year variance rises compared to model 2 to 0.266 (se 0.035). Years appear to soak up more of the variance than countries in this respect. The VPC for year (level 2) is 7.5% and for countries (level 3), it is 1.9%. The MOR for years is 1.636 and for countries it is 1.272. Moving between years therefore appears to be riskier than moving between countries, i.e., there is less comparability over time than over places. Figure 7.3 shows the level 2 ranked residuals for year, effectively country-year in this case. Clustering is shown with well-dispersed residuals. The ranked residuals for country (figure 7.4, level 3), compared with those in figure 7.1, for example, show a decrease in the intensity of country-level clustering, with the residuals both closer together, and the standard error bars overlapping for a majority of the countries, meaning the variance of time has been properly accounted for.

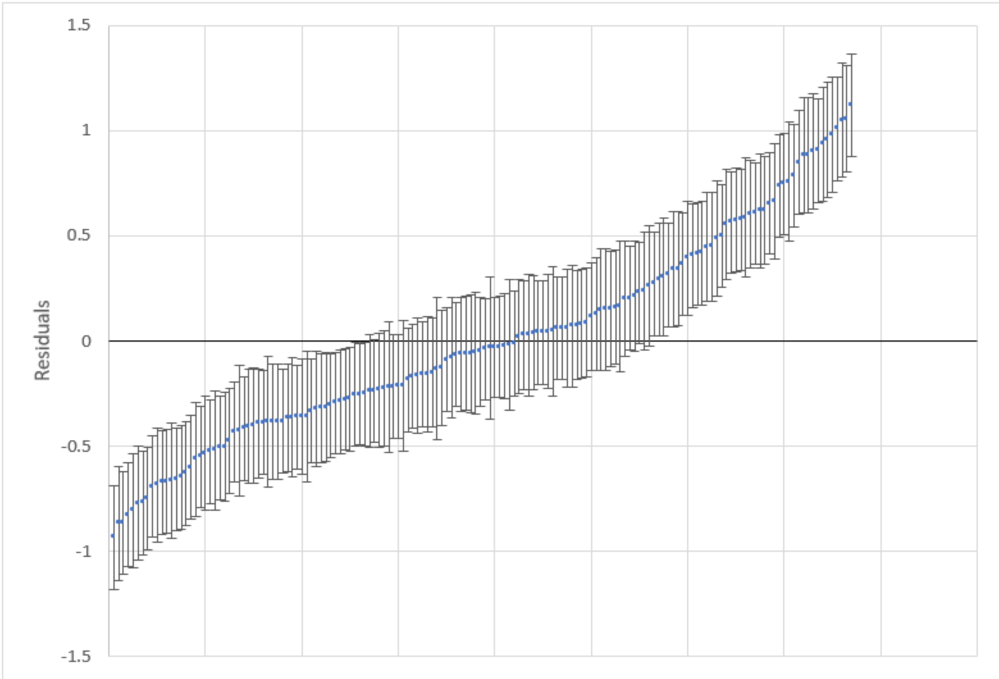

Figure 7.3: Ranked Residuals for Model 3, level 2, country-years

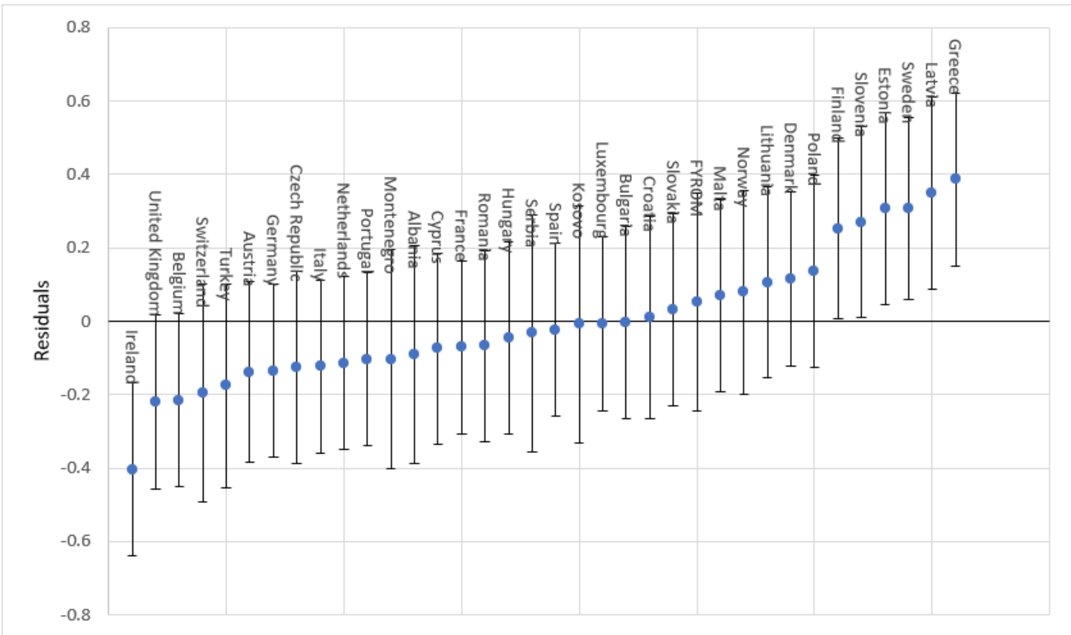

Figure 7.4: Ranked Residuals for Model 3, level 3, country

Models 3 and 4 are country-year models, with the primary difference being that model 3 is a three-level model with country at level 3 and year at level 2, and model 4 is a two-level model with country-years (a single variable) at level 2. The between country-year variance is 0.332 (se 0.039). The VPC is 9.2%, with a MOR of 1.733. The standard errors in the 2-level model are lower than those in model 3, implying that this model is a more parsimonious execution of the country-year than the 3-level version. The ranked residuals for country-years in model 4 (see figure 7.5 show clustering due to the dispersal of the residuals around the zero line, with reasonably small standard errors (especially compared to figure 7.3). However, it is substantively desirable to examine the effect of country and the effect of year separately, so proceeding with geography and time as separate levels appears to be the way forward. A large number of groups, though, may not be preferable in terms of describing the results and contextualising them, and welfare regimes are commonly used in similar research, so the possibility was explored [Kim et al., 2012; Virtanen et al., 2005a].

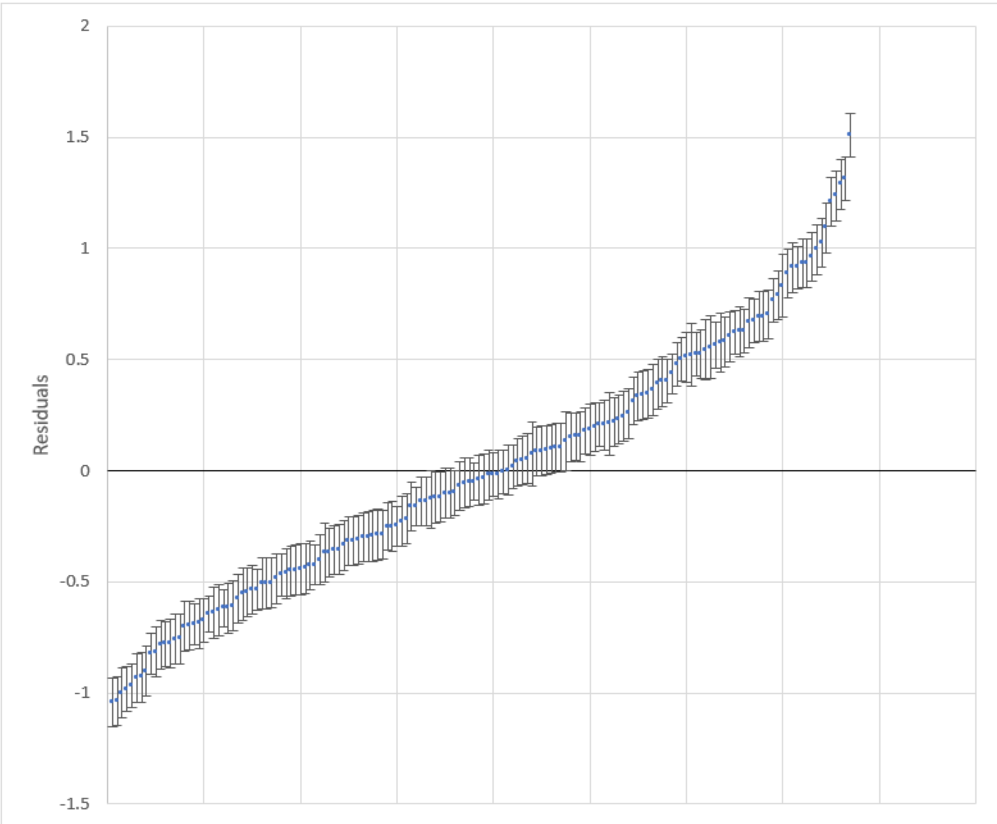

Figure 7.5: Ranked Residuals for Model 4, country-years

Model 5 is a two-level model using welfare regimes as level 2. The VPC is 3.8% and the MOR is 1.410, with a between welfare-regime variance of 0.13 (se 0.076). There is clustering evident in figure 7.6 though the standard errors do overlap in some places. This clustering, then, may be less relevant than that of country or country-years. This could be due to the fact that not all welfare regimes exist in the data across all years. By including years into the next set of models, this issue can be further examined.

Models 6 and 7 are analogous to models 3 and 4, in that they are welfare-regime years in 3- and 2- level form. For model 6, the third level between welfare-regime variance has dropped compared to model 5, to 0.082 (se 0.072), with a high standard error. The between-

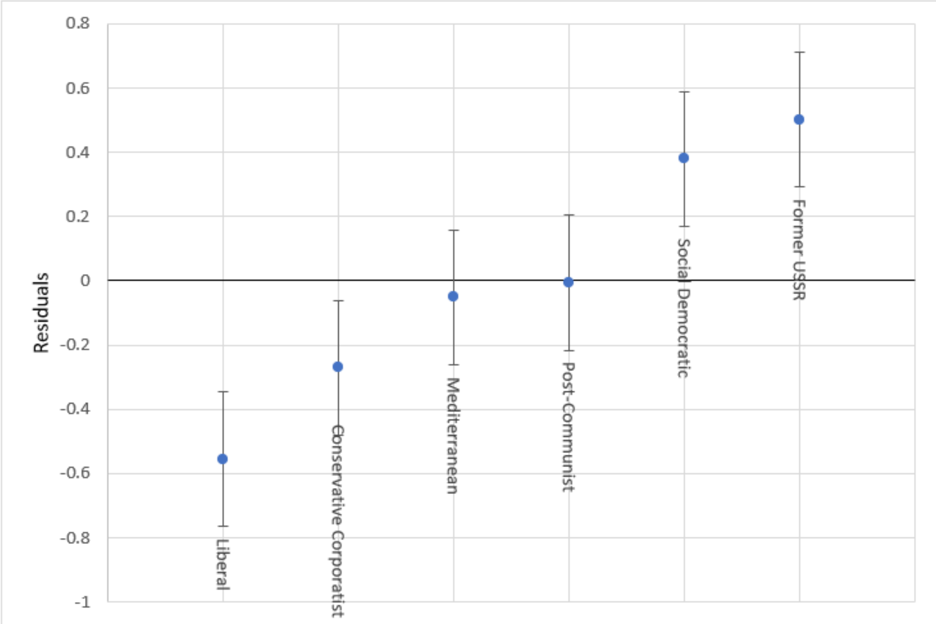

Figure 7.6: Ranked Residuals for Model 5, welfare regime

year (effectively welfare-regime year) variance is 0.211 (se 0.059). The VPC for welfare regime is 2.4% with an MOR of 1.314. For year (level 2), the VPC is 6.0%, with an MOR of 1.548. Figure 7.8 shows the ranked residuals for level 2, year (essentially welfare-regime year), which are well distributed, with overlaps in the middle of the ranks, showing clustering at that level. The welfare regime ranked residuals (figure **??**, level 3), are also distributed around 0, but like in model 3, the higher level has large, overlapping standard errors.

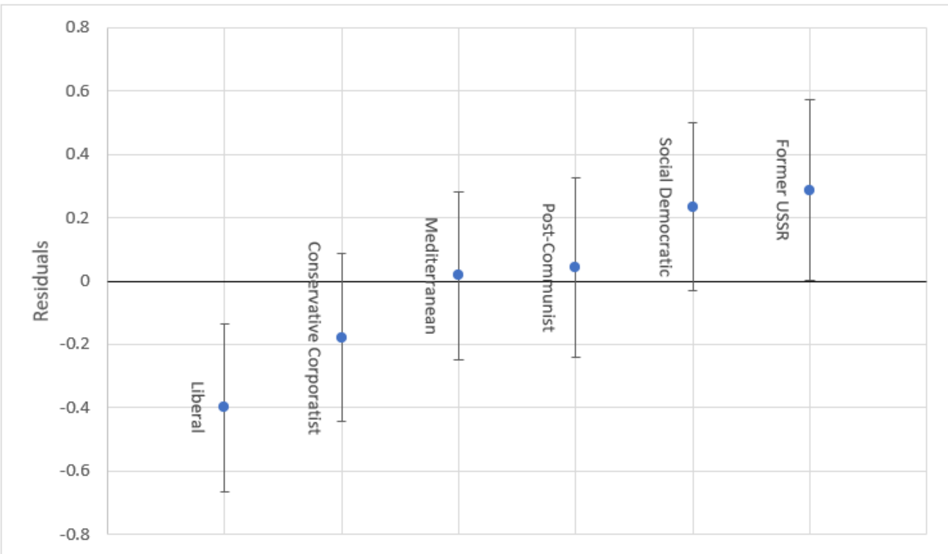

Figure 7.7: Ranked Residuals for Model 6, level 2, welfare regime-year

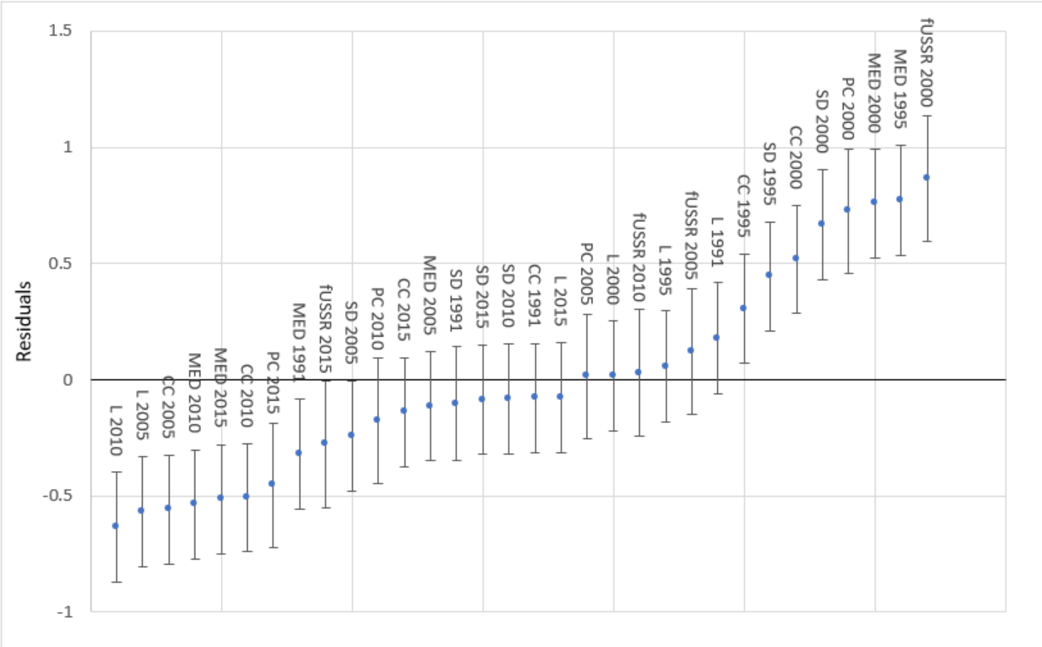

Figure 7.8: Ranked Residuals for Model 6, level 2, welfare regime

Model 7 is the 2-level version of model 6, combining welfare regimes and years to create a single variable. The between welfare-regime-year variance is 0.295 (se 0.074). The VPC is 8.2%, and the MOR is 1.679. These values are slightly lower than those for country-year, meaning that country-years are more variable than welfare-regime years, which may be expected, as the welfare regimes encompass a lot of the variation between countries. The standard errors for model 7 are lower compared to model 6, indicating a better fit for the 2-level model, similar to models 3 and 4. Figure 7.9 shows the ranked residuals for welfare-regime years, which are well-distributed around the 0 line, with small standard errors, showing clustering at the welfare-regime-year level.

So what structure should be used for the analysis? Substantively, as discussed in the context of the country-year models, it will provide more information to analyse geography and year separately. Welfare regimes may provide more parsimonious models, however, they may not account well for local between, and indeed, within, country differences. Macintyre et al. [2003] warns too of looking for empirical advantages over substantive or theoretical relevance: individual countries provide a more diverse set of units of analysis. The last thing to do is to bring in occupational categories, which are included for theoretically important reasons, described in Chapter 3. Ideally, we would have people in workplaces, however, we assume here that those in the same occupational category have similar workplace experiences. The EWCS and BHPS datasets do not have individuals in workplaces, only in occupations. This is something that can be teased out through multilevel modelling – is there more variation within or between occupational categories? The first thing that we need to do, though, is test which type of categories explain the health outcomes the best, which is what the next section explores.

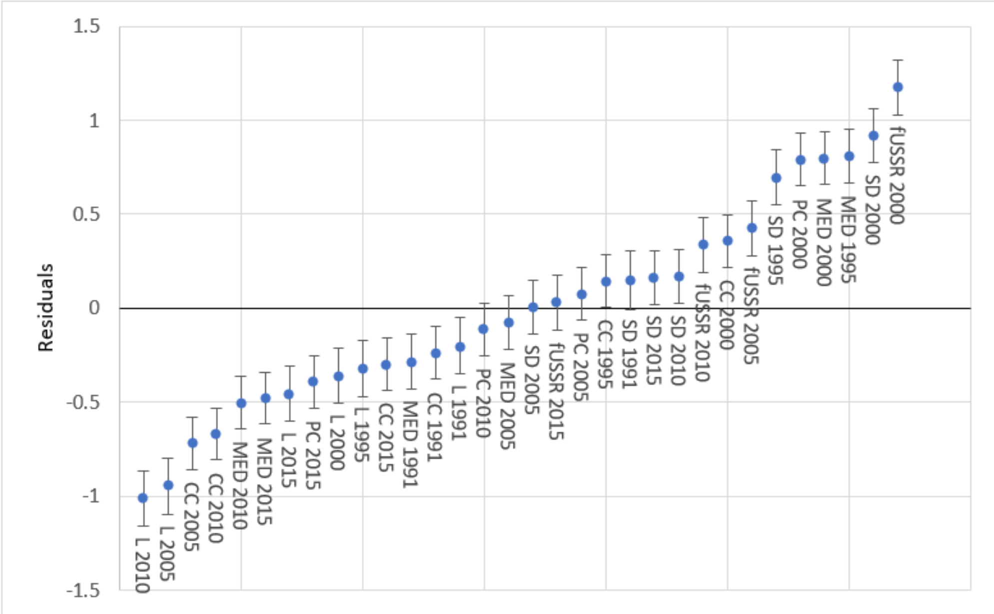

Figure 7.9: Ranked Residuals for Model 7, welfare regime-year

7.3. Which Occupational Categories Best Predict the Various Health Outcomes?

Fifty-five Logistic regression models were run using MLWiN 3.01. Separate models for each health outcome as the independent variable (n = 11) with each classification system (n = 5) as dependent variables were analysed using a Markov Chain Monte Carlo (MCMC) Bayesian framework [Browne, 2019]. This provides a Deviance Information Criterion (DIC), a measure of predictive accuracy that is the badness of fit between the observed and modelled measures penalised for model complexity [Spiegelhalter et al., 2002]. The DIC privileges model parsimony. Indeed, Box [1976] emphasises the importance of parsimony in modelling any phenomenon, due to simplicity of interpretation. Note that the DIC can be compared within the same health outcomes, but not between health outcomes, i.e., the DIC for the NS-SEC for skin problems cannot be compared to the DIC for backache for the ISCO 1-digit system.

Figure 7.10 presents only the DIC of all 55 models, by question or health measure and the classification scheme. Only the DIC for each model measure/classification pair is reported. Each outcome has the individual classification models sorted by DIC, so that the classification system with the most parsimony (lowest DIC) is on the left. The colour on the graph is consistent for each system of classification. The y-axes of the graphs are different due to the varying outcomes, as each has a difference range of DIC, but the comparison of classification systems can and should be considered within outcomes rather than between outcomes. It is not the specific value of DIC which is important, but which has the lowest DIC within an outcome.

The ISCO 2-digit schema best predicts whether an individual's work may affect their

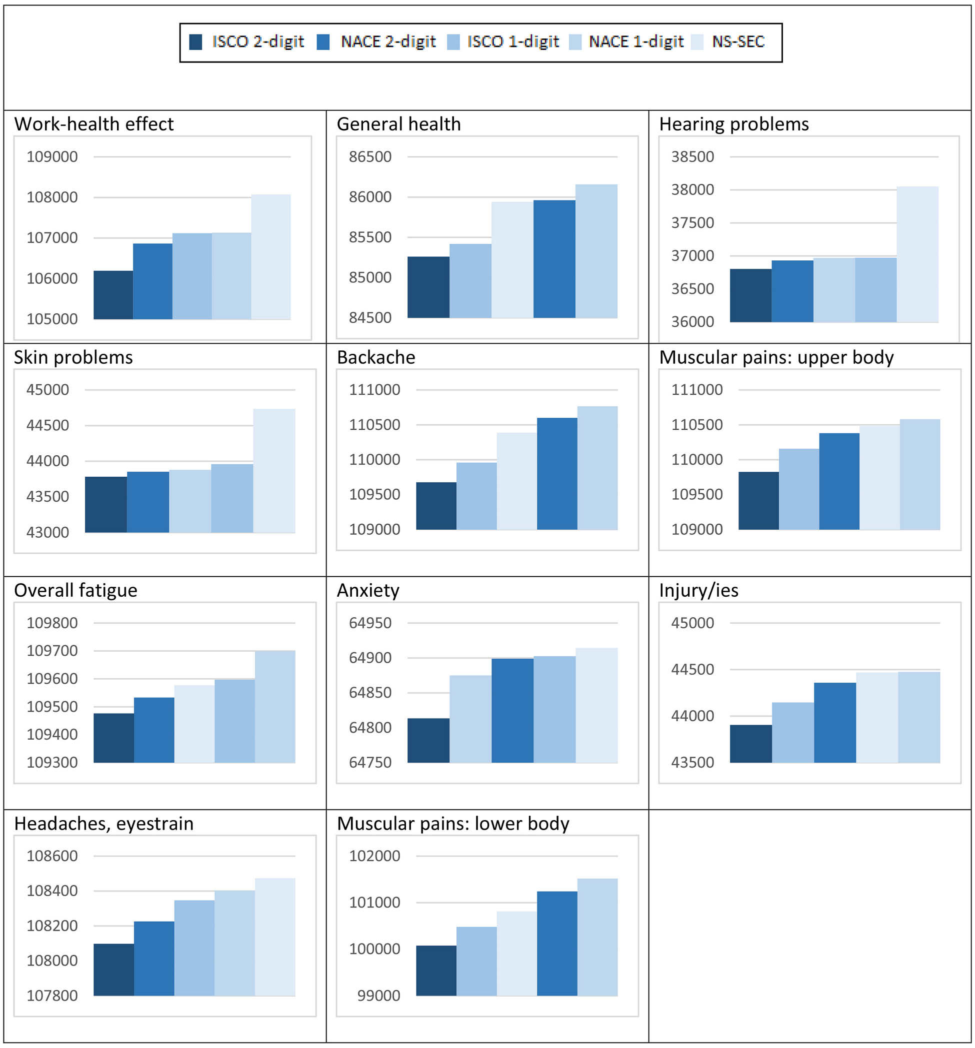

Figure 7.10: The DIC of 55 logistic regression models examining which occupational classification system works best for each health outcome. The DICs are comparable within, but not between outcomes.

health. Indeed, the ISCO 2008 2-digit classification has the highest predictive accuracy for all health outcomes across the data, not only for those questions which referred to the work-health relationship specifically. The 2-digit NACE classification outperformed the 1-digit ISCO 2008 for some outcomes, though for self-rated health, backache, lower muscular pain, upper muscular pain, and injury it was surpassed by the 1-digit ISCO. The 1-digit ISCO, therefore, did not always perform as consistently as the 2-digit version of the classification. The NS-SEC in this study borrows some predictive power from the ISCO 2-digit classification in this dataset as it is partially derived from it, and this may be why NS-SEC showed higher predictive accuracy than both the 1- and 2-digit NACE classifications for backache and lower muscular pain, as well as over the 1-digit version of the NACE for upper muscular pain and injury. The NS-SEC also had somewhat higher predictive accuracy over the 1-digit ISCO and 1-digit NACE in terms of fatigue. It seems then, that the NS-SEC may be slightly better at predicting outcomes relating to general or muscular health than the NACE. Nonetheless, the ISCO 2-digit classification remains the most empirically appropriate for predicting health outcomes in the EWCS dataset, as it had the lowest DIC for all health measures. Theoretically, this indicates that work should be considered separately from class when examining health outcomes, and reinforces the worksome (Chapter 3) as an appropriate model for enquiry into this relationship.

Empirically, the analysis in this chapter has shown that for examining the health of workers (through EWCS), occupational classifications such as the ISCO are generally the most appropriate. The more detailed 2-digit level provides better predictive accuracy, whereas the 1-digit levels may be more practical for certain analyses, particularly when sample sizes within the groups are smaller. However, some issues remain with the 1-digit ISCO when it comes to predictive accuracy for certain health measures, where it is outperformed by the NACE 2-digit classification. In some cases, the NS-SEC did not have the least predictive accuracy compared to the other systems, primarily the NACE. One reason for this could be that the SOC2010, used to derive the NS-SEC, in the case of this data, was derived itself from the ISCO 2008 2-digit version, and therefore could have borrowed some statistical power from that system. Another could be that the NACE is a classification of industries or economic activities rather than occupations and may not be completely suited to this sort of analysis. The NACE, though, is formed so as not to distinguish by the ownership, legality, modes of operation, or formality of economic activities [Eurostat, 2020b]. This may be nonetheless helpful, as the EMCONET. [2007] research agenda includes non-standard forms of work beyond precarious or flexible work, including informal work and slavery. The worksome too allows for non-standard forms of work. The ISCO, for example, does not necessarily have provisions for these, so in those cases, the NACE may be more appropriate depending on the nature of the work. The ISCO 2008 2-digit version nonetheless does allow for the vast majority of occupations to be classified as it does not discriminate by conditions, so therefore flexible and modern working conditions can be accounted for as long as they are acknowledged explicitly in the study.

7.4. Conclusions

Multilevel models are necessary due to the nested, clustered structure of the EWCS and BHPS data, and due to the relationships, which we are interested in: the linkage between working conditions and health outcomes. Furthermore, the single level models did not appear to capture all relevant information (Chapters 5 and 6). It is worth pausing for a moment and disregarding the dataset itself. In doing so we can return to the theoretical framework of the worksome (Chapter 3). This has a strong focus on the interactions of the between and within various contexts and/or scales (in other words on nested or clustered contextual structures). The multilevel model structure can be used to empirically demonstrate the existence and usefulness of the worksome. In this chapter, the MOR was used to compare variance components models generated, to see which structure has the most clustering in terms of the increased risk, in order to lay the structure for answering research questions and objectives around geographic, temporal, and occupational variation (Chapter 1.2). This chapter also compared occupational classifications and their predictive accuracy for the specific health outcomes in the EWCS data, in order to select the most appropriate for this structure. This was done using only the EWCS data, as the BHPS data in the single level models (Chapter 6) largely followed the same patterns in their results.

For the overall structure, It is apparent that the country-years are the most distinct. Welfare-regime years follow closely in terms of MOR and VPC, however, countries are of more substantive interest. Furthermore, welfare regimes are missing in particular years, as many of the post-Communist countries joined the EU, and therefore the survey, in later waves. Finally, the separate effects of both country and year are of interest, as time represents the life-course approach in the worksome, and countries one of the geocontextual scales. Models 3 and 6 allow for the partitioning of the variance between years and countries and years and welfare-regimes specifically. In these models it becomes apparent that time (as measured here using years) must be included as time appears to account for some of the variability. Moreover, there is greater variability in terms of time than places. Ultimately, this leads to the identification of country-years, as the most computationally appropriate way of capturing the most residual variance than using countries or years alone or welfare-regimes (and welfare-regime years). As occupation was always an important theoretical element of the model, only the classification system was examined, and the 2 digit ISCO-08 performed better than the others in terms of accuracy in predicting health outcomes. Therefore, the final model structure will be individuals in occupations, measured by the 2 digit ISCO-08, in years in countries.

Chapter 8

Results: EWCS Multilevel Logistic Regression Models

8.1. Introduction

This chapter presents the results of the multilevel models. The structure of these models was first determined by the analogous single level models presented in Chapter 5. Due to the hierarchical structure of the data, there was some unexplained information in the single level models. Since the variance components models indicate significant heterogeneity between hierarchies, it is reasonable to investigate a full multilevel logistic model specification. As discussed before, accuracy can change significantly when data structure is accounted for, so there are compelling substantive reasons for taking this approach. Furthermore, there are theoretically compelling reasons, as the worksome encourages the explicit inclusion of these scales and domains, such as occupation or geography. Therefore, the modelling strategy for the multilevel models was broadly similar to that of the single level models in Chapters 5 and 9. The same covariates were used in the multilevel models as the single level models, and the same outcomes were used (10 covariates plus one intercept, 10 outcomes; see table 5.1). 110 four level Bayesian logistic regression models were ran using the *runmlwin* command [Leckie and Charlton, 2013] in Stata 14 and 15. The covariates were added one by one. Bayesian models provide credible intervals rather than confidence intervals, and account for prior evidence. The prior values for the Bayesian models were generated as multilevel logistic regression models with the same structure, estimated using iterative generalized least squares (IGLS). Table 8.1 presents the group structure of the multilevel models. The data are suitable for multilevel analysis following Clarke [2008] who suggested that at least 5 observations per group was required for reliable estimation. This structure is supported by the variance components analysis of the data (see Chapter 7). As discussed, country and year are separated here for substantive purposes. Welfare regimes were not chosen, as the effects of the individual countries themselves are of interest as they show local variation more effectively. It allows for the examination of the random effect of country and year separately, and is more intuitively understandable separately than, for example, making

Table 8.1: Group Structure

Group	Number of groups	Observations per group: Minimum	Mean	Maximum
Country	36	826	2,859.80	6840
Year	3	26,195	34,317	38,568
Occupation (ISCO-88 2 digit)	28	316	3,676.80	10,446
Individual		102,951		

comparisons between, for example, Belgium in 2005 and Ireland in 2015.

Table 8.2 shows the direction of the effect of the odds ratios for all the final models for all outcomes. The outcomes include the work-health effect, and then problems in the last 12 months with: the skin, hearing, backache, lower muscular pain, upper muscular pain, anxiety, fatigue, headache and eyestrain and injury(ies). Similar patterns can be seen as the single level models (Chapter 5), though the multilevel structure allows for the examination of the structures which individuals relate to and exist in. It was apparent that most of the variation was at the first level, or the level of individuals, however, in the multilevel structure most of the variation was found at the country level, with occupation not far behind. The final model structure was the preferable model for all of the outcomes, having a lower deviance information criterion (DIC, see Chapters 4, 6) than all previous models. The DIC is a Bayesian measure of predictive accuracy, penalised for model complexity. Tables 8.3-8.12 show the final models for all of the outcomes, presented as mean odds ratios. The intermediate models can be found in Appendix 3.

Table 8.2: Direction of Effect for Each Final Model. A: Work-health effect; B: Skin; C: Hearing; D: Backache; E: Lower Muscular Pain; F: Upper Muscular Pain; G: Anxiety; H: Fatigue; I: Headache and Eyestrain; J: Injury(ies). Light red represents a decrease in the likelihood of the outcome and light blue represents an increase in the likelihood

	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**
Intercept	-	-	-	-	-	-	-	-	-	-
Sex (ref: male)	-	+	-	+	+	+	+	+	+	-
Age	+	-	+	+	+	+	+	+	+	-
Has Tertiary Education (ref: up to secondary)	+	-	-	-	-	-	+	+	+	-
Nights worked per month	+	+	+	+	+	+	+	+	+	+
Works shifts (ref: no)	+	+	+	+	+	+	+	+	+	+
Hours per week worked	+	+	+	+	+	+	+	+	+	+
Working time arrangement (ref: set by company)										
Choice between several fixed schedules	-	+	-	+	-	+	+	+	+	+
Adaptable within limits	+	+	+	+	+	+	+	+	+	+
Entirely self-determined	+	+	+	+	+	+	+	+	+	+
Skill-demand match (ref: they match)										
Demands too low	+	+	+	+	+	+	+	+	+	+
Demands too high	+	+	+	+	+	+	+	+	+	+
Paid appropriately (ref: Neither agree nor disagree)										
Disagree	+	+	+	+	+	+	+	+	+	+
Agree	-	-	-	+	-	-	-	-	-	-
Satisfaction with working conditions (ref: Very Satisfied)										
Not at all satisfied	+	+	+	+	+	+	+	+	+	+
Not very satisfied	+	+	+	+	+	+	+	+	+	+
Satisfied	+	+	+	+	+	+	+	+	+	+
Random Part										
MOR Country Level	+	+	+	+	+	+	+	+	+	+
MOR Year Level	-	+	+	+	+	+	+	+	+	-
MOR Occupation Level	+	+	+	-	+	+	-	-	-	+

8.2. Model Results

The following sections present the results of the multilevel logistic regression models, organised by outcome.

8.2.1. The Work-Health Effect

The work-health effect model has almost exactly the same coefficients as the single level model (see table 8.3). Women have lower odds of reporting their work affects their health than men (OR 0.924, CI 0.899-0.950). Older people have slightly raised odds of having their work affecting their health (OR 1.014, CI 1.013-1.016), as well as people with tertiary education (OR 1.087 CI 1.057-1.118). Nights per month (OR 1.027, CI 1.024-1.031) and hours per week worked (OR 1.011, CI 1.010-1.012) both have small positive effects on the odds. Working shifts relative to not working shifts has increased odds of the work health effect (OR 1.293, CI 1.248-1.340). Working time arrangements show that a *choice between several fixed schedules* relative to being *set one by the company* has a slightly negative effect on the odds (OR 0.951, CI 0.901-1.004), whereas the two categories which are more flexible (*adaptable within limits* and *entirely self-determined*) have coefficients which are almost exactly the same, only off by 0.001, showing an increase in the odds of reporting that work affects health. It seems that flexibility itself is the driver of this covariate, with respect to the more flexible categories. *High* demands cause an increase in odds, and same with *low* demands, both relative to *matching* skills and demands (ORs 1.081 CI 1.049-1.114 (low); 1.471 CI 1.412-1.533). A respondent who *agrees* that they are paid appropriately relative to *neither agreeing nor disagreeing* appears to have a negative effect on the odds (0.982, CI 0.938-1.018), though the credible interval indicates that perhaps this is less certain than the positive effect of *disagreeing* that you are paid appropriately (OR 1.574, CI 1.518-1.632). Satisfaction with working conditions shows that the odds ratio increases with a lack of satisfaction relative to being very satisfied.

As indicated earlier, these effects follow the single level model very closely, and as it is more parsimonious, it could be a better model. However, the random part of the model reveals what the single level model cannot: the partitioning of the variance between levels in the hierarchy, and therefore the scales of the worksome. Countries show the most variation (variance 0.183), with an MOR of 1.210, meaning that the differences between countries are highly relevant, similar to the odds ratio for working shifts (1.293, CI 1.248-1.340). They account for 4.8% of the variation. This means that the effect of geography is important with respect to reporting that work affects health, The MOR of years (variance 0.078) has reduced odds – 0.863, and years account for only 0.8% of the variation in the data. Finally, occupations slightly vary (variance 0.087), with an MOR of 1.049, similar to the effect of working nights (OR 1.027, CI 1.024-1.031) or having tertiary education (OR 1.087, CI 1.057-1.118), accounting for 2.7% of the variation. Therefore some occupations affect health more than others. It can be inferred that 91.7% of the total variation in the work-health effect is attributable to the individual level.

Table 8.3: Final Multilevel Logistic Regression Model for the Work-Health Effect

	OR	95% CI		p
Intercept	0.122	0.113	0.133	0.000
Sex (ref: male)	0.924	0.899	0.950	0.000
Age	1.014	1.013	1.016	0.000
Has Tertiary Education (ref: no tertiary)	1.087	1.057	1.118	0.000
Nights worked per month	1.027	1.024	1.031	0.000
Works shifts (ref: no)	1.293	1.248	1.340	0.000
Hours per week worked	1.011	1.010	1.012	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.951	0.901	1.004	0.068
Adaptable within limits	1.057	1.018	1.098	0.004
Entirely self-determined	1.056	1.015	1.098	0.006
Skill-demand match (ref: they match)				
Demands too low	1.081	1.049	1.114	0.000
Demands too high	1.471	1.412	1.533	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.574	1.518	1.632	0.000
Agree	0.982	0.948	1.018	0.321
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	5.531	5.076	6.026	0.000
Not very satisfied	2.959	2.823	3.101	0.000
Satisfied	1.298	1.255	1.343	0.000
DIC	121032.97			
pD	79.63			
Random Part	**Mean**	**95% CI**		**SD**
Country variance	0.171	0.106	0.273	0.044
Year variance	0.030	0.002	0.169	0.186
Occupation variance (ISCO 88 2 digit)	0.097	0.056	0.167	0.029
MOR Country Level	1.210			
ICC Country Level	0.048			
MOR Year Level	0.863			
ICC Year Level	0.008			
MOR Occupation Level	1.049			
ICC Occupation Level	0.027			

8.2.2. Skin Problems

Table 8.4 shows the final model for skin problems in the last twelve months. In this model, the coefficients do differ from the single level model. The effect of sex is larger than in the work-health effect model (OR 1.426, CI 1.348-1.505), so women are more likely to report skin problems than men. Older people are less likely to report skin problems (OR 0.993, CI 0.932-0.995), as are those without tertiary education, and the credible interval overlaps 1, which means this effect is less certain (OR 0.990, CI 0.932-1.049). Nights worked per month and hours worked per week have small but significant effects on the likelihood to report skin problems. Working shifts has a reasonable positive effect on the odds ratio for skin problems (OR 1.143, CI 1.069-1.214). Working time arrangements demonstrate that being *adaptable within certain limits* (OR 1.192, CI 1.112-1.275), has a stronger effect than having a *choice between fixed schedules* or being *entirely self-determined*. It seems that flexibility induces the reporting of skin problems, regardless of scheme. Skill-demand match shows that both *too low* (OR 1.176, CI 1.118-1.240) and *too high* demands increase the odds of skin problems, but the effect of *high* demands is larger (OR 1.365, CI 1.274-1.457). *Disagreeing* that pay is appropriate relative to *neither agreeing or disagreeing* has a positive effect on the odds of skin problems (OR 1.373, CI 1.291-1.458), while the credible interval of the effect of *agreeing* crosses 1, leaving uncertainty around its direction. Increasing dissatisfaction with working conditions increases the odds of skin problems as well. The random part of the model demonstrates again that countries account for 5% of the variation, with an MOR of 1.235, similar to the effect of being *satisfied* with working conditions (relative to being *very satisfied*). Years account for 2.1% of the variation in skin problems, however, the MOR is 1.001, so moving between years, i.e., through time has very little effect on the risk of reporting skin problems. Occupations account for 2.4% of the variation, and its MOR is 1.023, so the between-occupation risk is similar to the effect of working nights. The individual level accounts for 90.5% of the variation.

Table 8.4: Final Multilevel Logistic Regression Model for Skin Problems in the last 12 months

	OR	95% CI		p
Intercept	0.036	0.025	0.046	0.000
Sex (ref: male)	1.426	1.348	1.505	0.000
Age	0.993	0.991	0.995	0.000
Has Tertiary Education (ref: no tertiary)	0.990	0.932	1.049	0.376
Nights worked per month	1.015	1.010	1.021	0.000
Works shifts (ref: no)	1.143	1.069	1.214	0.000
Hours per week worked	1.003	1.002	1.005	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.051	0.954	1.153	0.149
Adaptable within limits	1.192	1.112	1.275	0.000
Entirely self-determined	1.081	0.999	1.164	0.026
Skill-demand match (ref: they match)				
Demands too low	1.176	1.118	1.240	0.000
Demands too high	1.365	1.274	1.457	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.373	1.291	1.458	0.000
Agree	0.977	0.912	1.045	0.243
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	3.480	3.117	3.851	0.000
Not very satisfied	2.234	2.062	2.413	0.000
Satisfied	1.300	1.221	1.391	0.000
DIC	54086.01			
pD	77.26			
Random Part	**Mean**	**95% CI**		**SD**
Country variance	0.183	0.108	0.299	0.049
Year variance	0.078	0.001	0.544	0.327
Occupation variance (ISCO 88 2 digit)	0.087	0.047	0.153	0.027
MOR Country Level	1.235			
ICC Country Level	0.050			
MOR Year Level	1.001			
ICC Year Level	0.021			
MOR Occupation Level	1.023			
ICC Occupation Level	0.024			

8.2.3. Hearing Problems

Table 8.11 shows the final model for hearing problems. It does differ from the single level version. The effect of being a woman shows a reduced odds of hearing problems relative to being a man (OR 0.738, CI 0.694-0.782). Older people have an increased odds of hearing problems, and those with tertiary education have a reduced odds of hearing problems (OR 0.851, CI 0.790-0.916). Nights worked per month has a small but significant effect (OR 1.019, CI 1.013-1.025). Working shifts increases the odds of hearing problems (OR 1.305, CI 1.215-1.396). Hours per week worked has very little effect if at all on hearing problems. The working time arrangements also have an unclear effect, relative to standard arrangements: the *choice between several fixed schedules* and *adaptable within limits* dummies both have wider credible intervals that cross over 1; the effect of *self-determined* time arrangement has a narrower credible interval that does not cross 1, and reduces the odds of hearing problems (OR 0.910, CI 0.831-0.991). It seems that flexibility is less relevant when it comes to hearing problems. The skill-demand match faces a similar issue: demands being *too high* (OR 1.407, CI 1.299-1.514) increases the odds of hearing problems, but *too low* demands are not significant. *Agreeing* that pay is appropriate relative to *neither agreeing or disagreeing* also has an unclear effect (OR 1.033, CI 0.955-1.114), whereas *disagreeing* that one is paid appropriately has a larger, significant effect on the odds of hearing problems (OR 1.348, CI 1.250-1.461). The magnitude of the effect of satisfaction with working conditions is smaller than the other models, but it follows the same pattern (the more satisfied you are, the lower the odds of hearing problems).

For the random part of the model, occupations and countries account for almost equal amounts of the variation (5.0% and 5.1% respectively). The MOR of countries is 1.253, and for occupations is 1.247, which are close to the effect of working shifts. This means that the between-country and between-occupation effects are similar, so the differences between these are what is important. Years account for less variation at 2.7%, with an MOR of 1.062, which is close to the effect of age. 87.2% of the variation is at the individual level, suggesting that variation is reasonably systematic.

Table 8.5: Final Multilevel Logistic Regression Model for Hearing Problems in the last 12 months

	OR	95% CI		p
Intercept	0.010	0.008	0.012	0.000
Sex (ref: male)	0.738	0.694	0.782	0.000
Age	1.033	1.031	1.036	0.000
Has Tertiary Education (ref: up to secondary)	0.851	0.790	0.916	0.000
Nights worked per month	1.019	1.013	1.025	0.000
Works shifts (ref: no)	1.305	1.215	1.396	0.000
Hours per week worked	1.001	0.999	1.003	0.144
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.958	0.857	1.071	0.215
Adaptable within limits	1.010	0.943	1.091	0.406
Entirely self-determined	0.910	0.831	0.991	0.016
Skill-demand match (ref: they match)				
Demands too low	1.058	0.996	1.122	0.037
Demands too high	1.407	1.299	1.514	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.348	1.250	1.461	0.000
Agree	1.033	0.955	1.114	0.206
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	2.932	2.567	3.318	0.000
Not very satisfied	2.028	1.848	2.225	0.000
Satisfied	1.302	1.209	1.398	0.000
DIC	45116.03			
pD	78.410			
Random Part	**Mean**	**95% CI**		**SD**
Country variance	0.192	0.114	0.318	0.053
Year variance	0.103	0.008	0.493	0.457
Occupation variance (ISCO 88 2 digit)	0.189	0.105	0.330	0.058
MOR Country Level	1.253			
ICC Country Level	0.051			
MOR Year Level	1.062			
ICC Year Level	0.027			
MOR Occupation Level	1.247			
ICC Occupation Level	0.05			

8.2.4. Backache

Table 8.6 shows the final model for backache in the last twelve months. Women are more likely to report backache than men (OR 1.373, CI 1.332-1.416), as are older people (OR 1.019, CI 1.017-1.020). Having tertiary education decreases the odds of reporting backache (OR 0.835, CI 0.808-0.865). Nights worked per month (OR 1.012, CI 1.008-1.016) and hours per week worked (OR 1.007, CI 1.006-1.009) have small but significant effects on the odds of backache. Working shifts also increases the odds of backache (OR 1.105, CI 1.063-1.148). In terms of working time arrangement, all of the confidence intervals of the dummy variables overlap, and the effect sizes are not particularly different, ranging from ORs of 1.064-1.079, in increasing independence. It may be that flexibility is relevant to backache, but it is unclear what sort of effect the differing categories have. The skill-demand match shows that *high* demand increases the odds more than *low* demand, but both increase the odds relative to *matching* skills and demands. *Agreeing* one is paid appropriately reduces the odds of backache (OR 0.909, CI 0.879-0.939), whereas *disagreeing* increases the odds of backache relative to *neither agreeing nor disagreeing* (OR 1.317, CI 1.273-1.363). Satisfaction with working conditions, as in all of the models, is the largest group of effects.

For backache, years account for the most variation in the outcome, at 17%, with an MOR of 2.225, meaning between-year, or, moving through time, is increasingly risky, of similar magnitude to being *not very satisfied* with working conditions (OR 2.810, CI 2.674-2.958). As the data are repeated cross-sectional, this means that in the years the data have been collected that there must have been changes over time in relation to backache. Countries account for 2.4% of the variation, and the MOR of 1.053 is roughly equivalent to the effect of having demands which are *too low* (1.066, CI 1.034-1.097). Occupations have very little effect, accounting for 1.8% of the variation and having a reduction in odds with respect to the MOR of 0.998, which is fairly close to 1. This means that there is little variation between occupations, and that perhaps within-occupation characteristics may be more relevant for backache. Individual variation accounts for 78.8% of the outcome variance, which indicates that systematic factors may come into play far more for backache.

Table 8.6: Final Multilevel Logistic Regression Model for Backache in the last 12 months

	OR	95% CI		p
Intercept	0.141	0.116	0.165	0.000
Sex (ref: male)	1.373	1.332	1.416	0.000
Age	1.019	1.017	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.835	0.808	0.865	0.000
Nights worked per month	1.012	1.008	1.016	0.000
Works shifts (ref: no)	1.105	1.063	1.148	0.000
Hours per week worked	1.007	1.006	1.009	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.063	1.007	1.121	0.013
Adaptable within limits	1.073	1.032	1.118	0.000
Entirely self-determined	1.079	1.033	1.124	0.000
Skill-demand match (ref: they match)				
Demands too low	1.066	1.034	1.097	0.000
Demands too high	1.120	1.073	1.163	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.317	1.273	1.363	0.000
Agree	0.909	0.879	0.939	0.000
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	3.791	3.500	4.090	0.000
Not very satisfied	2.810	2.674	2.958	0.000
Satisfied	1.572	1.520	1.627	0.000
DIC	126822.580			
pD	79.300			
Random Part	**Mean**	**95% CI**		**SD**
Country variance	0.099	0.060	0.160	0.026
Year variance	0.712	0.072	3.274	4.171
Occupation variance (ISCO 88 2 digit)	0.077	0.043	0.134	0.024
MOR Country Level	1.053			
ICC Country Level	0.024			
MOR Year Level	2.225			
ICC Year Level	0.170			
MOR Occupation Level	0.998			
ICC Occupation Level	0.018			

8.2.5. Lower Muscular Pain

Table 8.7 shows the final model for muscular pains in the lower limbs in the last 12 months. Being female increases the odds of reporting lower limb pain relative to being male (OR 1.318, CI 1.272-1.361), as does being older (OR 1.024, CI 1.023-1.026), and less educated (tertiary education OR 0.831, CI 0.773-0.0831). Nights worked per month and hours per week worked both have a small but significant increase in the odds of lower limb pain. Working shifts also produces increased odds of reporting muscular pain in the lower limbs (OR 1.162, CI 1.118-1.205). Working time arrangements are largely unclear: the direction of the effect is uncertain, and, indeed, there is no clear pattern to the results as the credible intervals also overlap each other. The skill-demand match shows that having demands which are *too low* produce slightly higher odds, though, again, the credible intervals of the two categories overlap, so there is some uncertainty. *Agreeing* one is being paid appropriately reduces the odds of reporting lower limb pain (OR 0.866, CI 0.834-0.901), and *disagreeing* one is being paid appropriately, following what was found in Section 5.7, increases the odds (OR 1.297, CI 1.252-1.348), both relative to *neither agreeing nor disagreeing* that one is paid appropriately. Satisfaction with working conditions follows the same pattern as the other models, but follows more similarly the models for backache and upper muscular pain.

The random part of the model shows that countries only account for 2.0% of the variation, and, their MOR is 0.987, similar to the effect of having tertiary education. Years account for 2.4% of the variation, and have an MOR of 1.024, similar to the effect of monthly nights worked (OR 1.013, CI 1.010-1.017). Occupations account for slightly more variation at 3.3%, with an MOR of 1.096, roughly similar to the effect of having demands which are *too low* relative to one's skill (OR 1.094, CI 1.060-1.131). It would appear then that the impact of all of the clusters are relatively small in comparison to some of the fixed effects covariates, but nonetheless must be included due to the structure of the data, and the theoretical requirements of the worksome.

Table 8.7: Final Multilevel Logistic Regression Model for Lower Muscular Pain in the last 12 months

	OR	**95% CI**		**p**
Intercept	0.066	0.055	0.076	0.000
Sex (ref: male)	1.318	1.272	1.361	0.000
Age	1.024	1.023	1.026	0.000
Has Tertiary Education (ref: no tertiary)	0.801	0.773	0.831	0.000
Nights worked per month	1.013	1.010	1.017	0.000
Works shifts (ref: no)	1.162	1.118	1.205	0.000
Hours per week worked	1.006	1.005	1.007	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.981	0.925	1.040	0.266
Adaptable within limits	1.011	0.971	1.055	0.303
Entirely self-determined	1.043	0.997	1.090	0.031
Skill-demand match (ref: they match)				
Demands too low	1.094	1.060	1.131	0.000
Demands too high	1.076	1.026	1.125	0.002
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.297	1.252	1.348	0.000
Agree	0.866	0.834	0.901	0.000
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	3.804	3.517	4.129	0.000
Not very satisfied	2.628	2.502	2.758	0.000
Satisfied	1.532	1.475	1.591	0.000
DIC	117034.840			
pD	78.880			
Random Part	**Mean**	**95% CI**		**SD**
Country variance	0.072	0.044	0.117	0.019
Year variance	0.087	0.008	0.457	0.291
Occupation variance (ISCO 88 2 digit)	0.118	0.066	0.205	0.037
MOR Country Level	0.987			
ICC Country Level	0.020			
MOR Year Level	1.024			
ICC Year Level	0.024			
MOR Occupation Level	1.096			
ICC Occupation Level	0.033			

8.2.6. Upper Muscular Pain

Table 8.8 shows the final model for muscular pains in the shoulders, neck, and/or upper limbs in the last 12 months. Being female rather than male increases the odds of reporting upper muscular pain (OR 1.555, CI 1.509-1.606), as well as being older, though the effect of age is fairly small (OR 1.020, CI 1.018-1.021). Having tertiary education decreases the odds of reporting upper muscular pain (OR 0.868, CI 0.838-0.896). Nights worked per month and hours worked per week have similar effect sizes: nights have an OR of 1.010 (CI 1.006-1.014), and hours per week have an OR of 1.008 (CI 1.007-1.010). Working shifts increases the odds of reporting upper muscular pain (OR 1.106, CI 1.064-1.146). Working time arrangements have one insignificant dummy, the *choice between fixed schedules*. Those whose arrangements are *adaptable within limits* have a higher OR than those whose hours are *entirely self-determined* (OR 1.132, CI 1087-1.182 vs OR 1.060, CI 1.017-1.105) have higher odds of reporting upper muscular pain, reinforcing flexibility as a driver of health problems or outcomes. The skill-demand match shows that not having a match in general increases the odds, but, having demands which are *too high* increases the odds a fair bit more than having demands which are *too low* (OR 1.156, CI 1.106-1.208 vs OR 1.094, CI 1.062-1.129). *Agreeing* one is being paid appropriately reduces the odds of reporting upper muscular pain (OR 0.897, CI 0.867-0.930), whereas *disagreeing* that one is paid appropriately increases them (OR 1.356, CI 1.307-1.408). Satisfaction with working conditions follows a similar pattern to other 'muscular' (backache and lower muscular pain) outcomes, with increased odds for all categories relative to very satisfied in descending order.

As for the random part of the model, years account for the most variation (12.9%), with an MOR of 1.871, meaning that the difference between years is quite important. Countries account for the next most variation, accounting for 3.2% of variation, with an MOR of 1.118, similar to the effect of those whose time arrangements are *adaptable within limits*. Occupations account for 2.3% of the variation, with an MOR of 1.038, similar to the effect of those whose time arrangements are *entirely self-determined*. The between-country and between-occupation effects show that those differences are highly relevant. Individual level variation accounts for 81.6% of the variation.

Table 8.8: Final Multilevel Logistic Regression Model for Upper Muscular Pain in the last 12 months

	OR	**95% CI**		**p**
Intercept	0.082	0.065	0.121	0.000
Sex (ref: male)	1.555	1.509	1.606	0.000
Age	1.020	1.018	1.021	0.000
Has Tertiary Education (ref: no tertiary)	0.868	0.838	0.896	0.000
Nights worked per month	1.010	1.006	1.014	0.000
Works shifts (ref: no)	1.106	1.064	1.146	0.000
Hours per week worked	1.008	1.007	1.010	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.030	0.972	1.086	0.165
Adaptable within limits	1.132	1.087	1.182	0.000
Entirely self-determined	1.060	1.017	1.105	0.004
Skill-demand match (ref: they match)				
Demands too low	1.094	1.062	1.129	0.000
Demands too high	1.156	1.106	1.208	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.356	1.307	1.408	0.000
Agree	0.897	0.867	0.930	0.000
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	3.851	3.521	4.175	0.000
Not very satisfied	2.725	2.591	2.864	0.000
Satisfied	1.580	1.522	1.636	0.000
DIC	125730.400			
pD	79.790			
Random Part	**Mean**	**95% CI**		**SD**
Country variance	0.128	0.077	0.210	0.034
Year variance	0.520	0.058	2.515	1.284
Occupation variance (ISCO 88 2 digit)	0.093	0.053	0.165	0.030
MOR Country Level	1.118			
ICC Country Level	0.032			
MOR Year Level	1.871			
ICC Year Level	0.129			
MOR Occupation Level	1.038			
ICC Occupation Level	0.023			

8.2.7. Anxiety

Table 8.9 shows the final model for anxiety in the last 12 months. Women relative to men have higher odds of reporting anxiety in 12 months (OR 1.407, CI 1.340-1.472), as do older people (OR 1.017, CI 1.008-1.012). Those with tertiary education also have increased odds of reporting anxiety (OR 1.137, CI 1.083-1.192). Nights worked per month have increased odds (OR 1.019 CI 1.014-1.024) and hours per week have slightly increased odds of reporting anxiety (OR 1.006 CI 1.004-1.008). Working shifts has an increased odds of reporting anxiety (OR 1.086, CI 1.032-1.142). Working time arrangements appear to have similar effects for two of the categories: *adaptable within limits* and *entirely self-determined* time arrangements have nearly identical effect sizes with overlapping credible intervals (OR 1.204, CI 1.137-1.271 and OR 1.207, CI 1.135-1.281 respectively). This indicates that it may be flexibility itself rather than the type of flexibility that impacts on anxiety. The choice between *several fixed schedules category* does not have a significant effect. The skill-demand match had an effect relative to matching. Demands which were *too low* had slightly increased odds of reporting anxiety (OR 1.066, CI 1.019-1.116), whereas demands being *too high* had a larger effect (OR 1.522, CI 1.422-1.613). Higher demands relative to skill appear to engender anxiety. *Disagreeing* one is being paid appropriately had a similarly sized effect on the odds (OR 1.496, CI 1.365-1.516), whereas *agreeing* one is being paid appropriately had a decrease in the odds relative to *neither agreeing nor disagreeing* that one is paid appropriately (OR 0.929, CI 0.877-0.980). The risk-reward trade-off appears to be highly relevant in the case of anxiety. Finally, the effect of satisfaction with working conditions has a similar pattern to the other outcomes, but the effect of being *not at all satisfied* has a much higher order of magnitude (OR 6.448, CI 5.879-7.096) compared to the other effects.

As for the random part of the model, countries account for 11.3% of the variation, with an MOR of 1.763. This means that the differences between countries are relevant to anxiety, so perhaps there are some regulatory differences that may account for this. Years account for the next largest amount of variation at 7.8%, with an MOR of 1.501, similar to the effect of working a job with demands *too high* relative to an individual's skills. Finally, occupations account for almost none of the variation in the model (0.6%), with a very low variance (0.023), and an MOR which shows decreasing odds of reporting anxiety from one occupation to another. Individual level variation accounts for 80.3% of variation.

Table 8.9: Final Multilevel Logistic Regression Model for Anxiety in the last 12 months

	OR	**95% CI**		**p**
Intercept	0.018	0.013	0.023	0.000
Sex (ref: male)	1.407	1.340	1.472	0.000
Age	1.010	1.008	1.012	0.000
Has Tertiary Education (ref: no tertiary)	1.137	1.083	1.192	0.000
Nights worked per month	1.019	1.014	1.024	0.000
Works shifts (ref: no)	1.086	1.032	1.142	0.001
Hours per week worked	1.006	1.004	1.008	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.020	0.940	1.106	0.325
Adaptable within limits	1.204	1.137	1.271	0.000
Entirely self-determined	1.207	1.135	1.281	0.000
Skill-demand match (ref: they match)				
Demands too low	1.066	1.019	1.116	0.002
Demands too high	1.522	1.442	1.613	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.436	1.365	1.516	0.000
Agree	0.929	0.877	0.980	0.004
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	6.448	5.879	7.096	0.000
Not very satisfied	3.335	3.089	3.567	0.000
Satisfied	1.591	1.499	1.684	0.000
DIC	70921.180			
pD	75.720			
Random Part	**Mean**	**95% CI**		**SD**
Country variance	0.465	0.289	0.752	0.121
Year variance	0.320	0.026	1.687	1.095
Occupation variance (ISCO 88 2 digit)	0.023	0.011	0.045	0.009
MOR Country Level	1.769			
ICC Country Level	0.113			
MOR Year Level	1.501			
ICC Year Level	0.078			
MOR Occupation Level	0.837			

8.2.8. Fatigue

Table 8.10 shows the final model for fatigue in the last 12 months. Women have increased odds of reporting fatigue relative to men (OR 1.447, CI 1.400-1.496), as well as older people, though the effect is small (OR 1.007, CI 1.005-1.008). Those with a tertiary education also have increased odds of fatigue (OR 1.026, CI 0.991-1.061), though its credible interval crosses 1 and therefore may not be significant. Nights worked per month has a similar effect size (OR 1.023, CI 1.019-1.027). Hours per week worked also has a relatively small but important effect on the odds of reporting fatigue (OR 1.013, CI 1.012-1.014). Working shifts as opposed to not produces increased odds of fatigue (OR 1.115, CI 1.072-1.158). Working time arrangements all showed increased odds relative to fixed schedules, though the credible interval for a *choice between several fixed schedules* overlapped 1.Relative to *fixed schedules*, both *adaptable within limits* and *entirely self-determined* working time arrangements had increased odds of reporting fatigue. As for the skill-demand match, relative to matching skills and demand, both *too low* and *too high* demands have increased odds of reporting fatigue, though demands which are too high have a higher odds ratio (OR 1.227, CI 1.173-1.281). *Agreeing* one is being paid appropriately decreases the odds of reporting fatigue (OR 0.908, CI 0.874-0.943), and *disagreeing* one is being paid appropriately increases the odds of reporting fatigue (OR 1.389, CI 1.340-1.444). The satisfaction with working conditions categories all had increased odds relative to being *very satisfied* and these odds increased with dissatisfaction.

As for the random part of the model, countries and years both accounted for similar amounts of the variation (10.2% and 10.0% respectively), with MORs of 1.692 and 1.673 respectively, similar to the effect size of being *satisfied* with working conditions relative to being *very satisfied*. The differences between countries and years are therefore highly relevant for fatigue, which may be indicative of changing policy with respect to working conditions that may impact on fatigue. Occupations, similar to anxiety, were not very variable (variance: 0.013), accounting for 0.3% of variation, with an MOR showing decreased odds of reporting fatigue (0.794). Individual variance then accounts for only 79.5% of variation.

Table 8.10: Final Multilevel Logistic Regression Model for Fatigue in the last 12 months

	OR	95% CI		p
Intercept	0.087	0.067	0.109	0.000
Sex (ref: male)	1.447	1.400	1.496	0.000
Age	1.007	1.005	1.008	0.000
Has Tertiary Education (ref: no tertiary)	1.026	0.991	1.061	0.081
Nights worked per month	1.023	1.019	1.027	0.000
Works shifts (ref: no)	1.115	1.072	1.158	0.000
Hours per week worked	1.013	1.012	1.014	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.044	0.988	1.103	0.062
Adaptable within limits	1.183	1.135	1.237	0.000
Entirely self-determined	1.083	1.036	1.130	0.000
Skill-demand match (ref: they match)				
Demands too low	1.044	1.013	1.076	0.004
Demands too high	1.227	1.173	1.281	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.389	1.340	1.444	0.000
Agree	0.908	0.874	0.943	0.000
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	4.758	4.353	5.183	0.000
Not very satisfied	3.192	3.036	3.362	0.000
Satisfied	1.634	1.571	1.689	0.000
DIC	119064.450			
pD	76.590			
Random Part	**Mean**	**95% CI**		**SD**
Country variance	0.423	0.262	0.687	0.109
Year variance	0.413	0.046	1.814	1.361
Occupation variance (ISCO 88 2 digit)	0.013	0.007	0.024	0.004
MOR Country Level	1.692			
ICC Country Level	0.102			
MOR Year Level	1.673			
ICC Year Level	0.100			
MOR Occupation Level	0.794			
ICC Occupation Level	0.003			

8.2.9. Headache and/or Eyestrain

Table 8.11 shows the final model for headache and eyestrain in the last 12 months. Women have a much higher odds of reporting headache and/or eye problems than men (OR 1.741, CI 1.689-1.801), an effect larger than all of the other covariates bar two: the *not very satisfied* (OR 2.230, CI 2.117-2.344) and *not at all satisfied* (OR 3.048, CI 2.811-3.299) categories for satisfaction with working conditions relative to *very satisfied*. This could be due to within-occupation related differences in the tasks men and women are assigned, as occupation is accounted for in the model. The effect of age is very small – the credible interval does not cross 1, but it includes it, and it is very narrow (OR 1.001, CI 1.000-1.002). Having a tertiary education rather than not increases the odds of reporting headache and eyestrain (OR 1.073, CI 1.036-1.111). Nights worked per month has a small but significant effect (OR 1.015, CI 1,011-1,019), and working shifts rather than not also shows an increase in the odds (OR 1.055, CI 1.015-1.094). Hours per week worked also has a small effect, but with a very narrow credible interval (OR 1.008, CI 1.007-1.009). The patterning of working time arrangements is somewhat unclear: *entirely self-determined* arrangements have a credible interval overlapping 1, as does a choice between *several fixed schedules*, though its interval is narrower. *Adaptable within limits* shows an increase in odds (OR 1.099, CI 1.053-1.144). It seems that flexibility in time arrangements is less relevant to headache and/or eyestrain. Skill-demand match shows that a lack of match in either direction increases the odds of headache and/or eyestrain, though the effect of *high* demands is, following the other outcomes, higher (OR 1.255, CI 1.19-1.309; OR of *low* demand 1.049, CI 1.01-1.081). *Agreeing* one is being paid appropriately shows a decrease in the odds of reporting headache and/or eyestrain (OR 0.945, CI 0.911-0.979), while *disagreeing* one is being paid appropriately increases the odds by a fair bit (OR 1.303, CI 1.253-1.354). Satisfaction with working conditions follows the same patterning as the other EWCS outcomes: with increasing satisfaction, there are lower odds of reporting headache and/or eyestrain.

The random part of the model shows that years are the most variable, accounting for 24.6% of variation, with an MOR of 2.987, close in effect to being *not at all satisfied* with working conditions. This may be related to changes over time in technologies used at work. Countries account for 2.0% of variation and have an MOR of 1.030, similar to the effect of working shifts. Between country differences therefore are relevant, but the impact of them is smaller than the other two clusters. Occupations account for only 0.4% of the variation, and have an MOR that shows a decrease in risk, of 0.822. 73% of variation lies at the individual level.

Table 8.11: Final Multilevel Logistic Regression Model for Headache and/or Eyestrain in the last 12 months

	OR	**95% CI**		**p**
Intercept	0.164	0.122	0.250	0.000
Sex (ref: male)	1.741	1.689	1.801	0.000
Age	1.001	1.000	1.002	0.023
Has Tertiary Education (ref: up to secondary)	1.073	1.036	1.111	0.000
Nights worked per month	1.015	1.011	1.019	0.000
Works shifts (ref: no)	1.055	1.015	1.094	0.007
Hours per week worked	1.008	1.007	1.009	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.057	0.998	1.115	0.029
Adaptable within limits	1.099	1.053	1.144	0.000
Entirely self-determined	1.016	0.972	1.058	0.243
Skill-demand match (ref: they match)				
Demands too low	1.049	1.018	1.081	0.000
Demands too high	1.255	1.198	1.309	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.303	1.253	1.354	0.000
Agree	0.945	0.911	0.979	0.002
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	3.048	2.811	3.299	0.000
Not very satisfied	2.230	2.117	2.344	0.000
Satisfied	1.394	1.340	1.450	0.000
DIC	121791.64			
pD	76.85			
Random Part	**Mean**	**95% CI**		**SD**
Country variance	0.090	0.054	0.147	0.024
Year variance	1.107	0.100	5.143	9.319
Occupation variance (ISCO 88 2 digit)	0.019	0.010	0.035	0.006
MOR Country Level	1.030			
ICC Country Level	0.020			
MOR Year Level	2.987			
ICC Year Level	0.246			
MOR Occupation Level	0.822			

8.2.10. Injury(ies)

Table 8.12 shows the final model for injury(ies) in the last 12 months. Women were less likely to report injury(ies) than men (OR 0.624, CI 0.590-0.658). Older people also have decreased odds of reporting injury (OR 0.991, CI 0.989-0.992), as well as those with tertiary education (OR 0.800, CI 0.753-0.850). This is perhaps due to differences in the work itself performed by these groups within the occupations. Nights worked per month (OR 1.013, CI 1.007-1.018) and hours per week worked (OR 1.007, CI 1.005-1.009) had relatively small but significant effects. Working shifts rather than not creates an increase in the odds of reporting injury(ies) (OR 1.220, CI 1.144-1.296). Perhaps there is some aspect of shift work that relates to injury(ies) - unfavourable shifts may lead to a higher rate of injury(ies) perhaps due to fatigue. Some of the working time arrangement categories have credible intervals overlapping 1, but the patterning of it overall shows that a *choice between several fixed schedules* and *entirely self-determined* arrangements have increased odds which are lower than *adaptable within limits* (OR 1.092, CI 1.018-1.166). Flexibility remains relevant then to reporting injury(ies). As for the skill-demand match, the magnitude of difference between demands being *too low* and *too high* is lower than for other outcomes, though *higher* demands still have a higher odds ratio (OR 1.235, CI 1.151-1.317; low demand OR 1.144, CI 1.088-1.207). As injury(ies) as an event are unexpected, and usually accidental, it makes sense that the magnitude of difference between them is lower. *Agreeing* one is being paid appropriately reduces the odds of reporting injury(ies) slightly (OR 0.935, CI 0.873-0.997), whereas *disagreeing* one is being paid appropriately increases the odds ratio similar to working shifts (OR 1.266, CI 1.192-1.343). Satisfaction with working conditions followed a similar pattern to the other outcomes (relative to *very satisfied*), the odds of reporting injury(ies) increased), however the magnitude of difference between the categories is reduced. This suggests that injury(ies) have an element of randomness to them that is not necessarily tied to working conditions.

As for the random part of the model, countries and occupations account for 5.0% and 4.7% of the variation, and years 1.2%. The MOR for countries is 1.238, similar to the effect of working shifts or being paid inappropriately. The MOR for years is 0.903, similar to the effect of age. The MOR for occupations is 1.213, again, similar to the MOR for countries. This means that between occupation differences are more relevant to injury(ies) than those within, which means injury(ies) cluster in particular occupations. The individual level accounts for 89.1% of the variation.

Table 8.12: Final Multilevel Logistic Regression Model for Injury(ies) in the last 12 months

	OR	**95% CI**		**p**
Intercept	0.077	0.062	0.094	0.000
Sex (ref: male)	0.624	0.590	0.658	0.000
Age	0.991	0.989	0.992	0.000
Has Tertiary Education (ref: up to secondary)	0.800	0.753	0.850	0.000
Nights worked per month	1.013	1.007	1.018	0.000
Works shifts (ref: no)	1.220	1.144	1.296	0.000
Hours per week worked	1.007	1.005	1.009	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.085	0.990	1.183	0.037
Adaptable within limits	1.092	1.018	1.166	0.006
Entirely self-determined	1.064	0.986	1.140	0.058
Skill-demand match (ref: they match)				
Demands too low	1.144	1.088	1.207	0.000
Demands too high	1.235	1.151	1.317	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.266	1.192	1.343	0.000
Agree	0.935	0.873	0.997	0.021
Satisfaction with working conditions (ref: Very Satisfied)				
Not at all satisfied	2.960	2.652	3.311	0.000
Not very satisfied	2.066	1.899	2.257	0.000
Satisfied	1.231	1.147	1.316	0.000
DIC	54884.77			
pD	78.43			
Random Part	**Mean**	**95% CI**		**SD**
Country variance	0.184	0.112	0.301	0.049
Year variance	0.042	0.004	0.203	0.165
Occupation variance (ISCO 88 2 digit)	0.172	0.096	0.301	0.056
MOR Country Level	1.238			
ICC Country Level	0.050			
MOR Year Level	0.903			
ICC Year Level	0.012			
MOR Occupation Level	1.213			
ICC Occupation Level	0.047			

8.3. Conclusions

For all outcomes the intercept showed that the average person in the data was less than likely to report them. Sex, age, having tertiary education, the choice between several fixed schedules, being paid appropriately, and the MORs for year and occupation all show, for some outcomes, a decrease in the odds of reporting them. This can be seen in table 8.2.

All other variables for all other outcomes showed an increase in the odds of reporting them. Women and older people are more vulnerable, and those without tertiary education are more likely to report physical outcomes, whereas for non-muscular health outcomes (anxiety, fatigue, headache/eyestrain, and the work-health effect), those with tertiary education are more likely to report them. Working non-standard types of hours, i.e., at night, or shiftwork, or working a larger number of hours per week also show an increase in the odds for all outcomes. Time arrangement types appear to show that more flexibility tends to cause an increase in the odds of reporting outcomes relative to fixed company hours. Having a job where your skills and the demands of the job do not match properly, whether it is less or more demanding all showed an increase in the odds of reporting the outcomes, though sometimes the difference between the two ORs was larger or smaller. Satisfaction with working conditions followed the pattern that might be expected for all outcomes following what was found in the single level models in Chapter 5, in that, relative to being very satisfied, all other categories had higher odds, and in the case of 'not very satisfied,' extremely high odds relative to the other variables.

In conclusion, the patterning of the covariates reinforces the conclusions drawn from the single level models (Chapter 5). However, the random parts of the multilevel models are necessary, as it can be seen that scales of exposure and the contexts of these exposures, as well as the variation between and within them, are relevant to all of the health outcomes. The following chapter will examine similar models using longitudinal data, the British Household Panel Survey.

Chapter 9

Results: BHPS Multilevel Logistic Regression Models

9.1. Introduction

Carrying forward from the EWCS models in the previous chapter, examining the same type of model on a different, finer-grained dataset was a logical continuation, in order to explore the research objectives and questions at a subnational level, using longitudinal data, and to confirm the conclusions drawn from that analysis. Furthermore, it emphasises reproducibility, in that, similar conclusions are drawn about the BHPS analysis as in the EWCS analysis. This is important to reinforce empirically the worksome and its emphasis on the scales and domains of exposure. This chapter details the multilevel models analysing the British Household Panel Survey (BHPS) data. The rationale for using multilevel models here is similar to that for the EWCS models. The structure of the groups and models is described, followed by the models for each outcome. The models examine self-rated health status, and two specific health problems - problems with arms legs hands etc.., i.e., problems with the muscles or limbs, and anxiety/depression. The models were implemented as four level Bayesian logistic regression models, specified using the runmlwin command (Leckie and Charlton 2013) in Stata 15. The same covariates were used in the multilevel models as the single level models as reported in Chapter 6 (see table 6.1). The modelling strategy and rationale is further elaborated on in Chapter 4.

Table 9.1: Group Structure

		Observations per group		
Group	**Number of groups**	**Minimum**	**Mean**	**Maximum**
Region	13	1	8,859.30	18905
Occupation	116	1	992.9	6536
Individual	19508	1	5.9	18
Observations		115,171		

Table 9.1 presents the group structure of the multilevel models. The lowest level are the observations, which nest into individuals, who in turn are nested in ISCO-classified occupations, which are finally nested in regions. There are a sufficient number of observations per group, even at the individual level (see table 9.1). This is supported by Clarke [2008], who concluded through a simulation study that 5 observations per group was enough for reliable analysis. This structure is supported empirically by the exploratory variance components analysis of the EWCS data, where the ISCO classification was found to be the most appropriate for examining working conditions and health (Chapter 7, also [Eyles et al., 2019]). Furthermore, this structure is theoretically supported by the worksome, as the influence of each domain (e.g., geography) can be examined separately.

Table 9.2 shows a summary of the direction of effect for each of the model covariates for each outcome: firstly for self-rated health status, secondly health problems with arms, legs, and hands, or muscular and limb problems, and thirdly, health problems relating to anxiety and depression. The outcomes follow similar patterns to the single level models (Chapter 6), though some of the covariates that were not statistically significant in the simpler models became significant in the multilevel ones. It was apparent that most of the variation was at level 2, the individual level, for all outcomes, meaning individuals themselves vary more over time than occupations or regions. The final models were preferable to the previous models, as they had a lower deviance information criterion (DIC, see chapters 4, 7), a Bayesian measure of predictive accuracy which is penalised for model complexity (pD, shown in the results tables 9.3-9.5). The models will be discussed first on their own, and then in relation to one another in the conclusion.

Table 9.2: Direction of Effect for each Final Model. Light red represents a decrease in the likelihood of the outcome and light blue represents an increase in the likelihood. Grey represents an OR of 1

	Health Status (0 - fair, poor; 1 - good, very good, excellent)	**Health problems with muscles or limbs (0- not mentioned; 1- mentioned)**	**Health problems anxiety/depression (0- not mentioned; 1- mentioned)**
Intercept	+	-	-
Sex (ref: male)	-	+	+
Age	-	+	+
Has Tertiary Education (ref: up to secondary)	+	-	-
Gross monthly pay (GBP)	+	-	-
Job hours per week	+	1	-
Works flexitime (ref: Not mentioned)	-	+	+
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)			
Not satisfied	-	+	-
Not very satisfied	-	+	-
Satisfied	+	-	-
Very Satisfied	+	-	-
Job satisfaction: Overall (ref: Neither satisfied nor dissatisfied)			
Not satisfied	-	+	+
Not very satisfied	-	-	+
Satisfied	+	-	+
Very Satisfied	+	-	-
Random Part			
MOR Region Level	-	+	-
MOR Occupation Level	-	-	-
MOR Individual Level	+	+	+

9.2. Model Results

The following sections present the results of the multilevel logistic regression models, organised by outcome. The overall results of all models will be compared to the analogous EWCS models from Chapter 8 in section 9.3, the conclusions.

9.2.1. Health Status

Health status in the last 12 months was dichotomised to poor (*fair/poo0* as 0) or good (*good/very good/excellent* as 1) and was used as a measure of self-rated health. It is a strong, well-validated measure of actual health status (see Chapter 2). This section will describe the Bayesian multilevel logistic regression model of this outcome. Table 9.3 shows the final model, which includes all covariates. Female respondents are less likely to report good health than men (OR 0.873, CI 0.822-0.928). Age has a small effect, where older people are more likely to report poor health for each additional year (OR 0.988, CI 0.986-0.990). Those with a tertiary education relative to those who do not are 37.5% more likely to report good health.

Moving on to the variables specifically related to work, pay has an incredibly small effect in the model, due to being per single British Pound, with an OR of 1.000136 (CI 1.000112-1.000165), reflecting the similar finding in the single level BHPS models (see Chapter 6). For every single GBP pay increases, the odds of reporting good health increases by 0.013%. This was true even in models where job satisfaction with total pay was excluded. Job hours per week has a very small effect (OR 0.997, CI 0.995-0.999), where the more hours you work, the more likely you are to report poor health. Working flexitime, which was not statistically significant in the single level model, is significant in the multilevel one (OR 0.921, CI 0.878-0.970), showing the importance of including the group structure in the models. Those working flexitime appear to be less likely to report good health, which reinforces what was found in the literature review (Chapter 2). As discussed above, ignoring the heterogeneity among groups has obscured this effect in the single-level case, but the multilevel model adequately accounts for this. This is of substantive importance, since flexitime is one element of the new flexible employment regime, which can vary by occupation and does vary over time as was described in the literature review.

Overall job satisfaction followed a similar pattern to the single level models in Chapter 6: relative to being *neither satisfied nor dissatisfied*, those *satisfied* with their jobs showed a higher odds of reporting good health, with 31.2% and 51.9% increases for *satisfied* and *very satisfied*, and 15.4% and 23.8% decreases in the odds of reporting good health for *not very satisfied* and *not satisfied*. Satisfaction with total pay showed a similar pattern, but with smaller effects (OR *not satisfied* 0.908, CI 0.820-0.999; OR *not very satisfied* 0.949, CI 0.888-1.006; OR *satisfied* 1.036, CI 0.976-1.090; OR *very satisfied* 1.124, CI 1.033-1.212). It seems, as in the EWCS models, that satisfaction is one of the most important elements of working conditions with respect to health.

The random part of the model also is of interest. Like the EWCS multilevel models in Chapter 8, much of the variation is attributable to the individual level (level 2), with an intraclass correlation (ICC) of 31.2%. By comparison UK regions (level 4 in the model) have a substantially smaller ICC (1.3%) and occupations (level 3) only 0.1%. It can be inferred that 67.4% of the variation is attributable to the observations within an individual over time. Indeed, individuals show the most variance (1.521), compared to variances of 0.063 and 0.007 for regions and occupations respectively. The median odds ratios (MORs) provide further detail in this analysis. Moving randomly between individuals gives us an increase in the odds of reporting good health (MOR 3.860), whereas moving randomly between occupations (MOR 0.758) or regions (MOR 0.962) shows a decrease in the odds of reporting good health. This means that differences between individuals are more risky than those between different occupations or regions, though there is likely to still be variation within those occupations and regions. Aronsson and Blom [2010] discuss the difficulty of examining good health rather than illness, but health status is a self-reported measure and does not ask specifically about illness. Further, Idler and Benyamini [1997] argue that self-reported health status is a robust measure of overall healthiness, which varies little even when the question obtaining it is asked differently.

Table 9.3: Final Multilevel Logistic Regression Model for Health Status. Gross monthly pay is reported with a larger number of significant digits than the other covariates due to its small effect size.

	OR	**95% CI**		**p**
Intercept	4.473	3.774	5.34	0.000
Sex (ref: male)	0.873	0.822	0.928	0.000
Age	0.988	0.986	0.990	0.000
Has Tertiary Education (ref: no tertiary)	1.375	1.281	1.478	0.000
Gross monthly pay (GBP)	1.000136	1.000112	1.000165	0.000
Job hours per week	0.997	0.995	0.999	0.002
Works flexitime (ref: Not mentioned)	0.921	0.878	0.97	0.000
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)				
Not satisfied	0.908	0.82	0.999	0.023
Not very satisfied	0.949	0.888	1.006	0.037
Satisfied	1.036	0.976	1.09	0.109
Very Satisfied	1.124	1.033	1.212	0.003
Job satisfaction: Overall (ref: Neither satisfied nor dissatisfied)				
Not satisfied	0.762	0.663	0.866	0.000
Not very satisfied	0.846	0.788	0.91	0.000
Satisfied	1.312	1.243	1.391	0.000
Very Satisfied	1.519	1.413	1.64	0.000
DIC	115327.03			
pD	9139.56			
Random Part	**Mean**	**95% CI**		**SD**
Region Variance	0.063	0.025	0.146	0.032
Occupation Variance	0.007	0.003	0.013	0.003
Individual Variance	1.521	1.453	1.593	0.035
Region MOR	0.962			
Region ICC	0.013			
Occupation MOR	0.758			
Occupation ICC	0.001			
Individual MOR	3.86			
Individual ICC	0.312			

9.2.2. Specific Health Problems with the Limbs or Muscles

Health problems relating to muscular issues found in arms, legs, hands, and so forth, was the second outcome of interest. In the survey respondents either mentioned (1) or did not mention (0) these problems. Table 9.4 shows the final Bayesian multilevel logistic regression model, which includes all covariates. Women are more likely to report these sorts of muscular problems than men (OR 1.148, CI 1.020-1.268). As age increases, so do the odds of reporting muscular (OR 1.094, CI 1.090-1.098). Having tertiary education, as opposed to having up to secondary education reduces the odds of mentioning muscular or limb health problems by 31.5%.

As with the muscular health single level model, and with the health status model above, pay has a small effect, as it is per single British pound (OR 0.9999331, CI 0.9998996- 0.9999654). Job hours per week also had no effect, but the reported credible interval is wider (CI 0.997-1.002) and was statistically insignificant (p 0.405). For those individuals working flexitime there is a slightly increased odds of reporting these health problems compared to individuals not working flexitime (OR 1.064, CI 0.985-1.146) though the p value falls just short of the 95% credible threshold (p 0.052). Satisfaction with total pay only had statistically significant effects for the *satisfied* and *very satisfied* categories, with a 7.8% and 11% reduction in the odds of reporting these problems respectively, meaning that perhaps the relationship between effort and reward is stronger when reward is larger than effort. As for overall job satisfaction, it followed a gradient relative to *neither satisfied nor dissatisfied*, with being *not satisfied* and *not very satisfied* increasing the odds of reporting problems with muscles or limbs by 42.5% and 10.8% respectively. Being *satisfied* or *very satisfied* in the job overall was associated with an 8.1 and 21% reduction in the odds of reporting these problems respectively.

The random part of this health problems model performs similarly to the health status model. Most variance is attributable to the individual level (variance 5.897) with an ICC of 62.3%. The region level (variance 0.284) ICC is 3%, and the occupation ICC is 0, meaning that most occupational variation is within rather than between occupations (occupational variance 0.002). This means that 34.7% of the variation lies between the observations of each individual. This is again reflected in the MORs, which substantively express the odds of reporting a given outcome when moving randomly between groups. For individuals, an increase in the odds of reporting muscular or limb health problems is shown with a MOR of 20.916. Relative to all other effects in the model, this is by far the largest, which suggests that individual-level heterogeneity dominates the observed effects. Regions also show an increase in the odds with an MOR of 1.433, similar to the effect of overall job satisfaction being ‘not satisfied.’ Finally, the occupation MOR of 0.722 shows a decrease in the odds of reporting these health problems when moving randomly between different occupations.

Table 9.4: Final Multilevel Logistic Regression Model for Health Problems with the Limbs or Muscles. Gross monthly pay is reported with a larger number of significant digits than the other covariates due to its small effect size.

	OR	**95% CI**		**p**
Intercept	0.003	0.002	0.006	0.000
Sex (ref: male)	1.148	1.020	1.268	0.013
Age	1.094	1.090	1.098	0.000
Has Tertiary Education (ref: up to secondary)	0.685	0.602	0.782	0.000
Gross monthly pay (GBP)	0.9999331	0.9998996	0.9999654	0.000
Job hours per week	1.000	0.997	1.002	0.405
Works flexitime (ref: Not mentioned)	1.064	0.985	1.146	0.052
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)				
Not satisfied	1.004	0.870	1.156	0.493
Not very satisfied	1.004	0.915	1.102	0.485
Satisfied	0.922	0.838	1.012	0.044
Very Satisfied	0.890	0.784	1.001	0.026
Job satisfaction: Overall (ref: Neither satisfied nor dissatisfied)				
Not satisfied	1.425	1.158	1.724	0.000
Not very satisfied	1.108	0.994	1.228	0.033
Satisfied	0.919	0.840	1.002	0.026
Very Satisfied	0.790	0.696	0.878	0.000
DIC	66879.79			
pD	8331.99			
Random Part	**Mean**	**95% CI**		**SD**
Region Variance	0.284	0.033	1.485	0.42
Occupation Variance	0.002	0	0.008	0.002
Individual Variance	5.897	5.602	6.2	0.158
Region MOR	1.433			
Region ICC	0.030			
Occupation MOR	0.722			
Occupation ICC	0.000			
Individual MOR	20.916			
Individual ICC	0.623			

9.2.3. Specific Health Problems relating to Anxiety/Depression

The final outcome of interest from the BHPS data is self-reported health problems relating to anxiety/depression. In the survey, respondents either *mentioned* (1) or did *not mention* (0) experience of anxiety and/or depression. Table 9.5 shows the final model, which includes all covariates. The largest covariate effect by far in the model is the effect of being female, with women being 280% more likely to report anxiety and depression than men (OR 3.802, CI 3.192-4.479). Being older also increases the odds of reporting anxiety/depression by 3.6% for each additional year of age. Having tertiary education is not statistically significant, with a credible interval overlapping 1 (OR 0.959, CI 0.797-1.147). Gross monthly pay (scaled to single GBP) had no significant effect, and unlike the other models, and the corresponding single level model for the same outcome, the effect is not statistically significant to the 95% credible level (p 0.089).

Job hours per week slightly decrease the odds of reporting anxiety/depression, with a 0.5% reduction in the odds for every extra hour worked per week. This is perhaps due to the social aspects of the work environment, or an increase in time spend productively. Working flexitime is associated with a 10.3% increase in the odds of reporting anxiety and depression, though the credible interval overlaps 1 (CI 0.976-1.231) and therefore it is not a significant contributor to the outcome. The pattern for job satisfaction with total pay is somewhat unclear. The only statistically significant odds ratio is for *not satisfied* which indicates an increase in anxiety and/or depression (OR 1.211, CI 0.978-1.497) while the other categories all show an increase but with confidence intervals overlapping zero. As for overall job satisfaction, being *not satisfied* or *not very satisfied* relative to being *neither satisfied nor dissatisfied* are associated with 138.1% and 67.6% increases in the odds of reporting anxiety/depression. Being *satisfied* or *very satisfied* were associated with 27.6% and 39.9% decreases in the odds of reporting anxiety or depression.

The clusters also have an interesting pattern. Individuals (variance 7.508) account for the most variance, with an ICC of 69.2%, followed by regions (variance 0.029) at 0.3%, and occupations (variance 0.015) at 0.1%. Therefore around 30.4% of the variance lies at the level of the observations within the individuals, i.e., the same person at different time points. The MOR at the individual level is 32.500, which means the ‘riskiness’ of randomly changing between individuals is very high. The MORs for region and occupation are of similar size, showing a decrease in the odds of reporting anxiety/depression moving randomly between groups (MOR 0.857 and 0.804 respectively).

Table 9.5: Final Multilevel Logistic Regression Model relating to Anxiety/Depression. Gross monthly pay is reported with a larger number of significant digits than the other covariates due to its small effect size.

	OR	95% CI		p
Intercept	0.001	0.001	0.001	0.000
Sex (ref: male)	3.802	3.192	4.479	0.000
Age	1.036	1.031	1.041	0.000
Has Tertiary Education (ref: up to secondary)	0.959	0.797	1.147	0.321
Gross monthly pay (GBP)	0.999957	0.9998932	1.000016	0.089
Job hours per week	0.995	0.991	0.999	0.004
Works flexitime (ref: Not mentioned)	1.103	0.976	1.231	0.051
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)				
Not satisfied	1.211	0.978	1.497	0.040
Not very satisfied	1.104	0.943	1.317	0.127
Satisfied	1.106	0.960	1.29	0.115
Very Satisfied	1.035	0.848	1.272	0.406
Job satisfaction: Overall (ref: Neither satisfied nor dissatisfied)				
Not satisfied	2.381	1.846	3.089	0.000
Not very satisfied	1.676	1.445	1.943	0.000
Satisfied	0.724	0.630	0.818	0.000
Very Satisfied	0.601	0.505	0.706	0.000
DIC	28442.9			
pD	4217.76			
Random Part	**Mean**	**95% CI**		**SD**
Region Variance	0.029	0.004	0.09	0.023
Occupation Variance	0.015	0.002	0.037	0.009
Individual Variance	7.508	6.866	8.134	0.326
Region MOR	0.857			
Region ICC	0.003			
Occupation MOR	0.804			
Occupation ICC	0.001			
Individual MOR	32.500			
Individual ICC	0.692			

9.3. Conclusions

This chapter described the BHPS Bayesian multilevel logistic regression models, which examined self-rated health status, and two specific health problems. The two specific health problems were problems with the muscles or limbs and anxiety/depression. The final models presented in this chapter had the best fit measured using to the DIC, which is a penalised Bayesian measure of predictive accuracy. The patterning of the effects was similar to many of the EWCS models in Chapter 8 (see table 8.2 for the EWCS data, and 9.2 for the BHPS data), and as such provides a confirmatory analysis to reinforce the worksome. Through multilevel models, the structures and scales of the relationships between working conditions, demographic variables, and a set of health outcomes can be explored.

Women are more likely to report poor health than men, as well more likely to report both health problems. The same pattern applies with age: for every year increase in age, for health status there is a 1.2% increase in the odds of reporting poor health, 9.4% increase in the odds of reporting health problems with the limbs, and a 3.6% increase in the odds of reporting anxiety/depression. Having a tertiary education increases the odds of reporting good health status and decreases the odds of reporting both health problems.

An effect that carried through from the single level BHPS models was that gross monthly pay, in units of a single GBP, has a small effect on the health outcomes. This is a potentially important result as Geyer et al. [2006] indicated its importance in understanding health and employment outcomes. It is also important to note that these results held even in the initial models without the covariates controlling for other characteristics (see Appendix D for intermediate models). This finding also has important implications for the analysis with the EWCS data as gross pay is not available within that dataset and, based on the previous literature that could be considered a serious limitation. The findings here point to it being a less serious omission. Ultimately, perhaps this means that after accounting for working conditions, pay is relatively unimportant. Job hours per week had a small effect for health status and anxiety/depression: the more job hours worked, the higher the odds of reporting good general health, however, the lower the odds of reporting anxiety/depression.

Another important finding is about working flexitime. Working flexitime rather than not shows an increase in the odds of reporting poor health, muscular or limb health problems, and anxiety/depression. This demonstrates the negative effects described in the literature of flexible employment. Flexible employment is characterised by insecurity and uncertainty, due to the erosion or removal of labour rights and unions. Working conditions become less favourable and more tenuous, with changing expectations of, for example, more work in fewer hours [McNamara et al., 2011]. As for satisfaction with total pay, there was no consistent pattern for anxiety/depression, and effects were statistically insignificant. For health problems relating to muscles or limbs, dissatisfaction with total pay increased the odds of reporting problems relative to being *neither satisfied nor dissatisfied*. Similarly, for health status, dissatisfaction led to higher odds of reporting poor general health. As for overall job satisfaction, similar patterns were found for all three outcomes. Being in one of the two satisfied categories relative to being *neither satisfied nor dissatisfied* showed higher odds of not reporting health problems with the limbs or anxiety and depression, and higher odds of reporting good general health.

Finally, looking at the MORs for the random part of the model, the individual level for each outcome showed that a large part of the risk was contained at this level, especially with the large size of the MOR. MORs are advantageous as they are directly comparable to the model ORs, and for the individual level, for example, for anxiety/depression, the MOR for individuals was almost 10 times higher than then next largest OR, which was for sex. The occupation level MORs showed a decrease in risk moving between the differing occupations, which means a large part of the occupation-level risk is within rather than between occupations. This may be due to unobserved occupation-related covariates, and, in theory, in the worksome, occupation acts as a stand-in for workplace. Therefore, it could be that within-workplace variation is responsible for this effect. For example, tasks could be assigned differently based on gender, even within the same occupation in the same workplace. This was seen in the ‘anxiety’ outcome for the

EWCS data, where occupation showed the same direction of effect for its MOR (other outcomes from the EWCS data showing a decrease in the odds of the occupation MOR were backache, fatigue, and headache/eyestrain). As for the region level MOR, it showed decreases in the odds for health status and anxiety/depression, but an increase in the odds for health problems with the limbs. Therefore, it is likely that the differences between geographies are important for muscular health problems, but the differences within geographies are more important for general health and anxiety/depression. As argued in the worksome chapter (Chapter 3), the domains at differing scales relating to time in an individual and otherwise, individuals within occupations, and those occupations contextualised within geographies are important with respect to the results. The multilevel models have shown both in this chapter, and the previous one with the EWCS data, that the worksome is not only theoretically important but also empirically relevant. The multilevel models reveal more about the impact of the working conditions on the outcomes, with more precise estimates that truly account for the differing scales and levels in the data, and, indeed, the existence of those scales in reality.

This chapter presented the results of three Bayesian multilevel logistic regression models analysed on the BHPS data. The most important working condition with respect to all outcomes is overall job satisfaction, mirroring what was found in the EWCS multilevel analysis (Chapter 8). Most of the variation lies between individuals. The following chapter will further situate both the results from this chapter about the BHPS and the results about the EWCS into the context of the worksome and literature review.

Chapter 10

Discussion

10.1. Introduction

This thesis has explored the relationship between work and health. This chapter will summarize the empirical work, both alone and in relation to the worksome. In general, employment conditions that would be expected to negatively impact health – for example being paid badly, or being very dissatisfied, or having a job which does not match your skills – do indeed show negative impacts on health, although there is some substantial variation with respect to different health outcomes, seen especially in the EWCS analysis, and reinforced by the BHPS one. This is particularly apparent in the multilevel analysis chapters, which include a modelling structure that is both substantively (the data are clustered) and theoretically (the worksome framework) informed. The multilevel structure allows for the explicit modelling of the scales of the worksome. Whilst the analytical chapters have explored a set of national and international work-related health outcomes, what they did not do is put the work into a wider context or discuss the outcomes in detail in relation to the literature review, the worksome framework, and each other. For the majority of the models, both those using the European Working Conditions Survey (EWCS) and those deploying the British Household Panel Survey (BHPS), the relationships found tend to be as expected. That is to say, that working conditions considered poor are, in general, bad for your health.

The multilevel models give apparently similar overall results to the single level models for both datasets (Chapters 5, 6), and for the work-health effect from EWCS (i.e., a measure of self-rated health associated with work), and even the coefficients of the fixed part of the multilevel model are virtually identical to the single level model. For the BHPS dataset, this also held for most models, but some effects gained statistical significance. So, a natural question arises:

Multilevel models are more complex, and therefore difficult to interpret, so why are the multilevel models more appropriate for both datasets, if a simple model may do?

This could be for several reasons. The first reason is related to the requirements of statistical analysis in that the structure of the data violates some of the assumptions of single level regression analysis. In other words, the observations are not independent of one another but clustered geographically, temporally and within occupations. In the BHPS data, there are also observations clustered in individuals, i.e., time in individuals. The importance of these clusterings cannot be ignored, and is reflected in the results, particularly in the variance components models (see Chapter 7) where the structure of the models is determined, as well as in the random effects of the final multilevel models in Chapters 8 and 9. Further, multilevel models allow for the understanding of the effect of these clusters in the data.

The second reason refers back to the worksome chapter and the framework that it proposed. The worksome includes a variety of domains and scales (see figure 10.1), and proposes that exposures (i.e., working conditions) along the social-physical gradient and interactions within and between these domains are highly relevant to health outcomes along the life course. In order to incorporate the crucial element of geographical and temporal scales and domains, a multilevel structure, or an approximation of the structural domains of the worksome, should be included in any modelling strategy, to facilitate the examination of both the individual and contextual effects both within and between scales [Kim et al., 2012]. The worksome structure also allows for the integration of a variety of explanatory variables, and for the efficient planning of multilevel analysis.

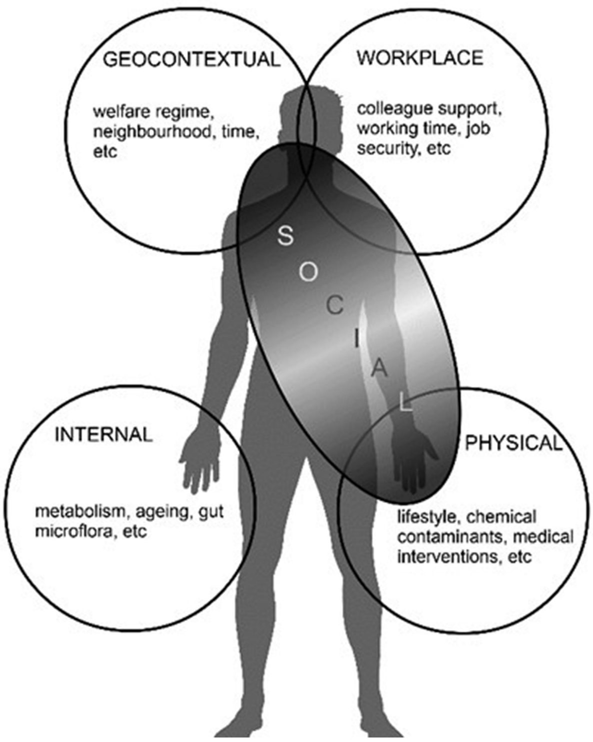

Figure 10.1: The worksome, published in [Eyles et al., 2019]

Finally, multilevel models can capture the heterogeneity of working conditions and arrangements (primarily through the 'occupation' level), through their partitioning of the variance. While there are scenarios in which a single level model may be preferable due to the structure of the data, i.e., in a study of a single workplace at a single point in time, the vast majority of the time a multilevel structure better approximates the data. People do not live in a vacuum – they live through time, in places, and work in workplaces, and the worksome framework promotes the capture of these rich context in which lives are lived. In doing so, it may be possible to provide a better understanding of how work (or employment) influences health and explore the heterogeneity in work outcomes observed: any work may be good for health compared to unemployment, but not all work is good work.

10.2. Overview of the Analysis

A selection of working conditions was chosen to represent the heterogeneous aspects of the contemporary employment landscape. Sex, age, and education were included as demographic variables to be controlled for, reflecting common practice within the literature and most population-level studies [Kirkwood and Sterne, 2002]. Covariates about specific working conditions were also included that related to working time, skills and demand, pay, and job satisfaction. The random part of the model provided the structural context to these working conditions. Looking at the coefficients in more detail across the outcomes in the EWCS analysis, it is instructive to group them together when they follow similar patterns. The first group consisting of anxiety, fatigue, and headache/eyestrain and all appear to be similar to the 'muscular' conditions, such as backache, upper muscular pain, and lower muscular pain. Although the second group of injury(ies), skin problems, and hearing problems also seem to be similar to the 'muscular' conditions, there are some notable differences, such as women being less likely to report skin problems and injury(ies) than men. As for the BHPS outcomes, i.e. health status, health problems with the limbs or muscles, and anxiety/depression, they largely followed the same pattern as the EWCS variables for the fixed effects, and any differences will be discussed in the sections below.

10.2.1. Demographic Variables

Demographic variables were included as they are highly relevant to the individual in question, and, in the case of age and sex, can be relevant to the 'internal' domain of the worksome, as well as an individual's interactions with others and with their context across the life course. The first group and 'muscular' conditions in the EWCS are characterised by, in general, women having increased odds of reporting those outcomes than men. This could reflect women's distinct social roles, which may put an increased burden on their health and levels of stress [Ala-Mursula, 2004]. However, injury(ies) and hearing problems affect men more than women, which may be due to unmodeled differences in job roles within occupations, which may be gendered. For instance, a male worker in a factory may have the same 'occupation,' as a female counterpart but perhaps work in a more dangerous or louder part of the factory. Men and women may cluster in different sorts of occupation. For example, Barbulescu and Bidwell [2012] found that men and women tend to apply for different types of jobs based on perceived gender roles, which influence whether they identify with particular occupations. This is why including the multilevel part of the model is important, to account, in part, for these structural differences. The BHPS analysis, similar to the EWCS analysis, showed that women tended to have lower odds of reporting good health, and higher odds of reporting the two health problem outcomes, which were muscular problems with the limbs and anxiety/depression.

Older people, for all EWCS outcomes apart from injury(ies) and skin problems, have an increased likelihood of reporting these health outcomes, although for most all this effect size was fairly small, but significant (as the credible interval around the odds ratios were very narrow). This pattern carries through to the BHPS analysis, where older people were more likely to report both muscular problems with the limbs, and anxiety/depression, as well as less likely to report good health status. Older people tend to report more health problems and have poorer health than younger people in general, so this pattern is as expected [McMurdo, 2000].

Having a tertiary education rather than not in the EWCS analysis had a protective effect for the ‘muscular’ outcomes as well as for hearing problems, injury(ies), and skin problems, even when occupation is accounted for in the model. This pattern also holds for the BHPS analysis, where those with tertiary education have higher odds of reporting good health status, and fewer reported muscular problems with the limbs. For the work-health effect (i.e., ‘Does your work effect your health?’), anxiety, fatigue, and headache/eyestrain, in the EWCS, having a tertiary education rather than not actually increases the likelihood of reporting these outcomes. This indicates that there is something particular to these health issues related to educational attainment. This is especially true for anxiety. Perhaps this is to do with the types of work associated with having a tertiary education, or perhaps the job market for those with a higher education is less secure, with more flexible employment terms. However, in the BHPS analysis, those who had tertiary education were less likely to report anxiety/depression, though the effect size was not statistically significant.

10.2.2. Time-related Working Conditions

Working nights, shift work, and hours worked per week were included in the EWCS analysis as they were theorised and empirically indicated to be related to the health of those working [Bambra et al., 2008a; Erren et al., 2008; Kleiner and Pavalko, 2013]. Within the BHPS analysis it was only possible to include working hours as the other variables were unavailable. Working time arrangements were included, despite being related to the working time variables, because they are a proxy for a person’s sense of control or security in work. This was expected to be especially true as employment becomes increasingly flexible, with ambiguous benefits to workers [Benach et al., 2014; Peck, 1996; Standing, 2011]. However, this work makes it apparent that, contrary to the literature, worker control over working time (or lack thereof) had no systematic effect on health. In the EWCS analysis, working time arrangements were represented by a time arrangement variable which several types of arrangement, oriented towards the level of control a given individual had. In the BHPS analysis the information was less detailed than in the EWCS, and as a result the concept was represented by whether an individual worked flexitime. Time-related variables also represent well the social-physical gradient of exposure in the worksome, as they are both physical (working time is physical presence at the workplace) but also social (working time and arrangements are socially mediated, and often controlled by the workplace).

The number of nights worked per month has a similar effect across all EWCS outcomes: working at night, and working increasing numbers of nights, is not good for health outcomes; the odds of reporting all of them are raised. Working at night has been found to increase the risk of breast cancer in Danish women aged 30-54 [Hansen, 2001]. Wong et al. [2011] found that the injury rate for night shift workers did not decline compared to other workplace injuries over a 10-year period. Working at night, or working shifts causes disruptions to the circadian rhythm, which can affect health negatively [Erren et al., 2008]. Working shifts compared to more regular patterns of work increases the likelihood of reporting negatively for all outcomes, with the lowest effect being that of headache/eyestrain. It seems that working shifts has no health promoting behaviour for any of the outcomes, and it is likely due to the constant disruption of the circadian rhythms of those working such patterns [Knutsson, 2003].

Hours worked per week consistently increased the likelihood for reporting all EWCS outcomes. Similar to age, the effect was very small, likely due to the number of potential hours that could be worked in any given week. This is most likely to be dependent on working arrangements, such as whether a self-employed person considers all of their time 'work time,' or those who work many shifts across a given week. The ORs for hours worked per week all had narrow credible intervals, suggesting that the effect is significant. For the BHPS analysis, job hours per week followed the same pattern, whereby the effect sizes were fairly small, with more hours worked making the odds of reporting good health status lower, and the odds of reporting anxiety/depression higher. This is possibly due to the upper limit of hours that can be worked per week, which is often dependent on working time arrangements.

Working time arrangements are measured in the EWCS through four categories. The reference category was that *schedules were fixed by the company*. Relative to this category, almost all of the more flexible options showed an increase in the odds of reporting the outcomes, other than the *choice between several fixed schedules,* which showed a decrease in the odds for the work-health effect, hearing, and lower muscular pain. For the BHPS analysis, the binary variable of working flexitime (either it being mentioned or not) was found to increase the odds of reporting muscular problems with the limbs and anxiety/depression, and decrease the odds of reporting good health. It seems that flexibility, as theorised in the literature review (Chapter 2), both constrains and liberates labour; as Ross [2009] discusses, the capitalism of today seeks to actively decompose working conditions and employment, as it allows for more profits, it erodes labour's control over working practices, and normalises insecure conditions which become endemic to the labour market [Bardasi and Francesconi, 2004; Bourdieu, 1998; Canaan, 1999]. The increasing demands on labour can obscure the effects of working conditions, as insecurities are experienced even by those in standard working arrangements [Scott-Marshall and Tompa, 2011].

10.2.3. Skill-Demand Match

The skill-demand match in the EWCS analysis, for example, reflects the job-demand control model developed by Karasek and Theorell [1990]. Whether or not the skills one has attained can meet the demands of a job is important, as well as being able to develop those skills [D'Souza et al., 2003]. The reference category here was that skills and demands of a job *match*; they could either have demands which are *too low*, or demands which are *too high*. It is important to an individual to be able to control outcomes which are important to them. Having demands which do not match skills increased the odds of reporting all outcomes, for both low and high demand jobs. However, the effect is larger when demands are larger. This is reasonable: higher demands may include a higher pace of work, whereas lower demands may engender a sense of ennui or a lack of fulfilment.

10.2.4. Pay-related Covariates

The trade-off between compensation and risk is also key within the worksome and builds on the effort-reward imbalance model by Siegrist [1996]. Being paid appropriately was selected for the EWCS analysis for several reasons. Firstly, the EWCS contains data from many different countries within which there are a wide variety of different national pay structures and levels. Thus, whether or not pay is appropriate within the national context represents a better measure of the material well-being aspect of income rather than reporting a monetary income itself. It is also important to note that the EWCS data do not capture income well across waves, and it is difficult to reconcile the individual income variables. Secondly, being paid appropriately also reflects feelings of acceptance of working conditions and feelings of control and self-efficacy, which the literature has shown are important for individual well-being and health [Bourdieu, 1998; Canaan, 1999; Peck, 1996; Ross, 2009]. Indeed, the effort-reward imbalance model of the work-health relationship is based on the trade-off between compensation, usually pay, and the risks taken in a given occupation [Siegrist, 1996]. The feeling of being paid appropriately then, implies a certain protective effect, which is also indicative of a sense of security.

Being paid appropriately is a useful measure as it can proxy insecurity, and whether or not other less satisfactory working conditions may become tolerable. In the BHPS analysis, this was measured using satisfaction with overall pay. For the EWCS analysis, *agreeing* that one is paid appropriately (relative to *neither agreeing nor disagreeing*) reduces the likelihood of reporting any of the outcomes. Backache is the only outcome which does not follow the trend for being paid appropriately in the EWCS. Perhaps backache can occur regardless of the level of pay, due to ergonomics or other workplace conditions that aren't. Similarly, in the BHPS analysis, anxiety/depression do not show a clear pattern relative to being *neither satisfied nor dissatisfied* with pay, though many of the effects are statistically insignificant. Indeed, *disagreeing* that one is paid appropriately in the EWCS relative to *neither agreeing nor disagreeing*, shows an increase in all of the health outcomes. Similar patterns are seen for satisfaction in the BHPS data: being *satisfied* with total pay shows higher odds of reporting good health status, and lower odds of reporting muscular problems with the limbs. Being paid badly demonstrates a certain insecurity; most people have a rough idea of what pay a given occupation may realistically command. If a disconnect occurs, similarly to the skill-demand match variable, then negative health effects can occur. Pay appropriateness also is a way of measuring the material well-being and income generated by work, especially for the EWCS, given the large differences between wages in European countries (400 euros in Portugal is much different to 400 euros in Finland, for example). Monthly gross pay was considered in the BHPS analysis, as the BHPS data are solely taken in the UK, but (like hours worked) the effect size was very small for all outcomes, in part due to the scale (per British pound).

Recall that in the BHPS analysis, two pay-related variables were chosen. When using the BHPS, the international component of the analysis was omitted – the differences in the economies and therefore the wages between the states making up the UK were less of a concern than in the EWCS dataset. As such, the other pay variable used was monthly gross pay (in pounds, GBP). The gross monthly pay variable had very little (on the magnitude of 4 decimal places) effect, due to the scale (per British pound). However, job satisfaction with total pay had reasonably clear effects for health status (being more satisfied led to better reported health) and problems with the limbs (being more satisfied led to less report of these health problems). However, it was unclear for anxiety/depression, where most of the effects were statistically insignificant, and while a pattern was somewhat apparent, with those less satisfied being more likely to report this outcome, all the satisfaction covariates showed an increase in the odds of reporting anxiety/depression. This indicates that anxiety/depression may be related to more than just satisfaction, but perhaps other social exposures at the workplace or in other domains. These variables measure the disconnections between expected reward and expected risk [Siegrist, 1996].

10.2.5. Satisfaction with Working Conditions

Satisfaction with working conditions was included in the analysis more as a control variable, similar to the demographic ones, to examine if the other relationships found in the model held when it was included. It encompasses the workplace domain of the worksome, in that it is a measure of an individual's sentiment about all exposures or conditions of their occupation. The relationships of the other working conditions and demographic variables do hold, though the odds ratios for satisfaction are much larger than all of the other coefficients, for most all the models, both single and multilevel, for all of the outcomes. This was also true for the similar variable in the BHPS analysis, overall job satisfaction. Insecurity can lead to reduced satisfaction [Richter et al., 2013], and thereby increase the risk of negative health effects, but insecurity itself is also linked to negative health effects. The very large odds ratios relative to the other effects found in all of the outcomes in both studies confirms that the models are indeed accounting for the confounding effect of satisfaction. While satisfaction may appear to have a large influence, it is "not a direct measure of health status" [Benavides et al., 2000](Benavides et al 2000), and the other aspects of working conditions are nonetheless important despite their smaller effect sizes.

Together, the set of variables measure the context of an individual, but it is the multilevel models which best account for and measure the influence of these contexts.

10.2.6. Why Multilevel Models?

The multilevel analyses allowed insight into the worksome framework at multiple scales. These differences are important and reveal how different health outcomes vary across Europe, and within regions. The multilevel models allow for the explicit inclusion of geography, time, and occupational structures. This is crucial for approximating the domains and scales within the worksome. Multilevel models account for the influences of these elements deliberately and allow for the examination of how much each domain or scale of a particular domain varies, and whether it varies more within each individual group, or between groups. This has consequences for policy: by more accurately specifying not only which working conditions impact health, but at which scale they vary most, policymakers can better target their interventions.

The EU is varied and diverse in terms of regulatory and welfare regime, labour markets, and workplace practices and cultures. Especially for the EWCS data, accounting for country specific geography is therefore very important. The median odds ratios (MORs) provide a way of measuring the effect of a given level of the model hierarchy and are therefore a useful tool in accounting for and understanding risk of an outcome between or within clusters. MORs above 1 can be interpreted as the increased risk in the outcome when moving randomly between groups. MORs close to 1 can be interpreted as little change in those odds when moving randomly between groups. MORs below 1 indicate a reduction in the odds of the outcome when moving randomly between groups. In all EWCS models, bar the upper muscular pain outcome, the median odds ratio for the country level is above 1, meaning that a fair amount of the risk of the outcomes in question is consistently to be found between countries at the geographic level, even when including time and occupation. As noted above, the BHPS is restricted to a single national setting – at least in terms of the regulatory framework for employment – and it would be expected that there is less variation within a country but between regions and states (e.g. Scotland vs England) than between nations. Indeed, the models demonstrate this to be the case – the regional MOR is below 1, which indicates a reduction in risk when moving randomly between regions, as opposed to moving between times within individuals.

To look more specifically at the health outcomes, for the EWCS, all of the levels have at least one MOR for one outcome showing a reduction in the odds when moving randomly between groups, i.e., an MOR below 1. For countries, this is just for lower muscular pain, so the risk of moving from one cluster to another is reduced by around 13%. This also could mean that more variability exists within the country level than between the different countries. For all other outcomes, the MORs shows an increase in risk moving between countries. The MORs for anxiety and fatigue are particularly high. This could indicate that countries vary a fair amount from one another; perhaps some countries' regulatory and labour market contexts engender more fatigue and anxiety than others. The work-health effect, injury, skin problems, and hearing problems all have similar MORs, around the effect size of working shifts rather than not for most of those outcomes. Upper muscular pain has a slightly lower MOR relative to those outcomes, as well as backache and headache/eyestrain, but the risk is still increased when moving between any given country to another random country.

For region, the corresponding geographic level in the BHPS analysis, the MORs for general health status and anxiety/depression were below 1, meaning moving randomly between regions shows a reduction in the odds of these outcomes. This makes sense, as the regulatory regime and policy environment around employment should be largely consistent within the UK (see section 2.6). The opposite is true for the muscular problems with the limbs, which showed an increase in the odds, meaning the differences between regions are of importance. As occupations were accounted for, this is not necessarily due to a difference in the distribution of occupations between the regions, but perhaps to unaccounted for region-level characteristics. Therefore, as the geographies for both the EWCS and BHPS analyses are highly relevant, the worksome framework, specifically the geocontextual domain, is conceptually reinforced.

The other levels for the EWCS analysis, survey years and occupation, show much more heterogeneity with respect to the different outcomes in terms of how they vary, especially occupation. For the BHPS analysis, the other levels are occupation, and the individual, with observations at the wave timepoints as the lowest level. In the BHPS analysis, most of the variation was concentrated at the individual level, i.e., the differences within individuals between time was most pertinent. Nonetheless, the empirical part of the work reinforces the theoretical, i.e., the worksome: geography, scales, and contexts matter, and so taking a life course approach to examine health outcomes over time is appropriate.

Within the nation states in the EWCS analysis, observations were nested by years. Within the worksome framework we would expect the year effects to be relatively stable – certainly there would be less variation temporally than there was nationally, and we observed a variety of patterns in its MORs. The work-health effect, i.e., whether one's work effects one's health, and injury show a decreased risk moving between years. Skin problems show practically no cluster effect. Hearing problems and lower muscular pain have very small effect sizes for their MORs, whereas backache, headache/eyestrain, and upper muscular pain have very large MORs, meaning risk increases between years, especially for headache/eyestrain. This could be reflective of changes to working practices and conditions over time, such as the increasing expectation of flexibility discussed in the literature review, or perhaps due to the increase in the use of technology at work. Anxiety and fatigue have reasonably large MORs, similar to those for the country level, meaning the risk around time and the risk with respect to geographies is very similar for those outcomes.

The effect of occupation is varied as well in the EWCS analysis. The work-health effect, i.e., whether one's work affects one's health, skin problems, upper muscular pain, and lower muscular pain all have similar effect sizes for their MORs: for example, if someone changes occupations, the risk of reporting these outcomes is increased, but it is not as risky as it is for other outcomes. Hearing problems and injury show the largest difference between occupations.

These problems cluster in particular occupations, given the variety of working practices, safety schemes, and how variable conditions that may cause these are (factory versus office work, for example). Finally, backache, anxiety, fatigue, and headache/eyestrain all show decreased odds, meaning that they vary more within particular occupations than between them.

The BHPS occupation level MORs for all outcomes showed a decrease in risk between occupations as well, therefore a substantial part of the occupation-level risk lies within occupational groups rather than between them. Perhaps the differences between occupations are less important as to whether someone may report those outcomes than the conditions within the particular occupation or workplace themselves. There also could be omitted occupation-level factors, such as workplace-specific organisational regimes or the social environment and relationships between colleagues and managers. Perhaps the commonality in these may also be less related to specific work environments or practices and more so other lifestyle factors (neighbourhood perhaps), which are not necessarily available in the datasets used, but nonetheless included in the worksome framework.

Finally, the individual level was the lowest level in the EWCS analysis and the second level in the BHPS analysis. The lowest level in the BHPS analysis were observations at the various waves within individuals. A large part of the risk was contained at the individual level for both the EWCS and BHPS analysis. In the case of the EWCS, for many of the outcomes the individual level accounts for around 90% or more of the variance. For the BHPS, the individuals themselves accounted for 31.2% of the variance for health status, and then 62.3% and 69.2% for muscular problems with the limbs and anxiety/depression respectively. Interestingly, this indicates that for general health, the differences over time for individuals account for the most variation, so within individual, between time differences are most relevant. This shows the importance of the passage of time, or, the life course, to an individual's general health and how it may vary. However, for the specific health outcomes, the difference between individuals in and of themselves, rather than the differences within individuals between different time points, are more important. This indicates that the conditions under which people live, and importantly to this thesis, work, are highly relevant to specific health outcomes. The variety of different occupations, and importantly, workplaces, and whether or not their conditions are more similar within or between them is also not always clear, so the worksome allows for this to be accounted for.

10.3. Contextualising the Results

But what does this mean, substantively? In general, the models all show that irregular working patterns (e.g., at night or shifts) or working excessively (e.g., hours per week) impact health negatively. This is something intuitive, but to discover a consistent empirical effect that remains no matter what outcome or dataset is being examined is important. This indicates, too, that the results are likely to be less biased, especially in terms of reverse causality. This is particularly so for the BHPS, as it followed individuals over time, and, as Martikainen and Valkonen [1999] found, the 'healthy worker effect' wore off with increasing duration of follow-up. As Marmot and Bell [2016] note, what lies beyond the immediate causes of poor health must be understood. Therefore, what is also apparent is that with increasing uncertainty about conditions or security come increases in the likelihood of negative health impacts, and this persists and may even accumulate over time. For example, while flexible working arrangements may seem to allow a given person to plan their life more freely, this is actually accompanied by an increase in the odds of reporting some sort of ill health. Flexible conditions of work may suit some, and benefit some, but overall it undermines stable working conditions for all. Having set hours is more certain, and flexible arrangements are not always without constraint [Daykin, 1999]; [Peck, 1996, pg23-24] cites "a fragile balance between control and consent." Control and certainty seem to come hand in hand. These conditions are also not always a choice, in the sense that for some, only a limited range of occupations are available, and thus cannot necessarily be modified at an individual level.

The results of the analyses presented here indicate that labour policy change is required to reduce insecurity and uncertainty for workers; the practices around flexible work appear to lack consistency. The social determinants of health, like work and working conditions, and, further, health inequalities, are after all, considered to be modifiable [Dahlgren and Whitehead, 2006; Wilkinson, 2005]. It is the role of policy to reform or replace structures and law in welfare states [Eikemo and Bambra, 2008]. Work and its conditions have changed over time, and across geographies, and while social and health inequalities persist across these contexts, variations in the slope of the gradients of these inequalities implies that policy and can reduce them [Marmot et al., 2008].

For example, policymakers should approach the issue of flexible work cautiously, as some aspects of it are desirable, such as the ability to set working hours around other pursuits in life. The moves to zero-hour contracts provide security in some circumstances but can also introduce instability and uncertainty in others [Koumenta and Williams, 2019]. However, overall, well executed flexibility can assist with the goal of creating a framework for working that both enables firms to be more mobile, but also engenders a sense of certainty within workers. Individuals should feel that outcomes which are important to them are to some extent in their control, even if in reality determining contextual factors may not be [Kawachi, 2002; Niedhammer et al., 2004; Siegrist and Marmot, 2004]. The effect of working nights or shifts can, to some extent, be mediated by the idea of having control, or indeed being paid appropriately for the work undertaken. Pay schemes even within the same occupation can differ, depending on employee status, tenure, and other characteristics, which is why accounting for both differing working conditions and contexts is important [Connelly et al., 2016].

The empirical results also reinforce the worksome framework (see figure 10.1). The worksome framework includes several domains and scales which link together to examine the impacts of exposures, or working conditions, along the social-physical gradient. The geocontextual domain includes several scales, of which the workplace was pulled out into its own explicit domain to emphasise its importance in determining the health of individuals. The social determinants of health sit in these domains [Eyles et al., 2019; Wild, 2012], and allow for the examination of the health inequalities they may engender. Further, the life course approach, which highlights time as highly important underlies the entire worksome framework. Health inequalities have been shown to persist over time [Corna, 2013], and researching them using the worksome will allow for the unpacking of the less immediate causes of poor health [Marmot and Bell, 2016] or negative health outcomes.

It is apparent from the random part of the models that scales of exposure and contexts (both geographic, occupational, and temporal) are highly relevant to the health outcomes, and therefore the individual. This is important with respect to country differences, but also relevant to the characteristics within any given geography, as was shown for region in the BHPS analysis. The analysis demonstrated that the relationship between health and work are dependent on the scale at which the analysis takes place, and the country level relationship is not necessarily replicated at lower spatial scales. For example, the temporal scale is more important for the specific health outcomes and conditions of the BHPS analysis, but less so for the general health status outcome.

The social-physical aspects of exposure were explored well in the EWCS models, through measures like working at night, or time arrangements [Dembe et al., 2005; Kivimäki et al., 2015]. Working time is an intangible sort of exposure that exists within the grey area of the physical-social gradient. Occupation was used in the models as a proxy for workplace as both sets of data were at a national or regional level, and therefore individuals were not grouped into workplaces. The assumption was therefore made that those within the same occupation may have similar roles and workplaces; further that they have perhaps some impact on the conditions therein. Both individual and context effects can be analysed through the worksome due to its multifacetedness, despite individual employment experiences (and even contexts) being heterogeneous and in some respects difficult to measure. The complexities of the relationships between the geocontextual and its varying scales and social determinants of health, as well as time, with their influence on the individual are made easier to understand through the worksome framework. The worksome redirects how the relationships between occupation and health are understood, with its emphasis on the interactions between and within all of these elements. Occupation is therefore a social determinant of health in its own right, and is worth examining, as discussed in Chapter 3. The worksome was developed to provide a transferable, reproducible theoretical framework that will remain consistent over time, as advocated by Kim and colleagues (2012), to allow for and develop better linkages between disparate research projects into work and health.

It must be recalled, however, that having a job – working – in general has a protective health effect compared to being unemployed [Dodu, 2005; Smith, 1985]. This study has made it clearer which aspects of work are of detriment to health and which promote it. Feelings of control over one's own destiny, a secure, certain position, and constraints which feel appropriate seem to be key to the work-health relationship. The potential impact of work on the individual is substantial as for most adults a very large proportion of their time there, hence the emphasis of the worksome on a life course approach. It is rarely, though increasingly, studied as a wider determinant of health. Historically it has been examined in and of itself (occupational health), with a focus on physical exposures, rather than in a wider context. Geography and time are important too, as discussed. For some occupations, individuals vary more within them than between differing occupations, and the system of classification is important. Occupations should be examined in and of themselves rather than as (poor) proxies of social class, using a system which imposes a set of social values on them, limiting the transferability between contexts. In essence, while occupations may be distributed unequally in society, unlike social class, the divisions themselves between particular types of occupation are not a constructed hierarchy that may indeed reinforce social inequalities. Further, occupation is a more stable measure than social class, which changes significantly over time [Corna, 2013; Liberatos et al., 1988]. This is because social class is based in what has social value at the time of its creation, as well as, in some cases, the class divisions themselves are based on creating a smooth mortality gradient, as Scott [2002] argues. As many social class measures are based on occupational ones, survey data often will have data items for both. The theoretical and empirical parts of this work have shown that survey data can be used under the worksome paradigm to expand knowledge around the linkages between working conditions and contextual conditions at different scales and health [Brunekreef, 2013].

The current work has addressed some of Kim et al. [2012] arguments that empirical studies around work and health are inconsistent and lack a reasonable framework for interpretation which can understand differing contexts and realities at different levels. Through the worksome, a framework has been provided, and the empirical portion of the research in this thesis both augments and advances the worksome, using a variety of contextual and individual-level variables. The next and final chapter will orient this thesis in the context of the research questions and objectives and make suggestions for future directions for research.

Chapter 11

Conclusions and Future Directions

11.1. Revisiting the Rationale and Context

This thesis has examined the widening gap in health inequalities, specifically relating to occupation, a social determinant of health. While occupation has been studied extensively, especially with respect to unemployment [Bartley and Ferrie, 2001], Kim et al. [2012] claimed that there was a lack of clear-cut results with respect to the employment-health relationship, due to several factors, including what Kauskamp et al. [2013] describe as heterogeneity in research, often due to context, differing measures, or sample composition. This can be mitigated with what [Kim et al., 2012, pg100] describe as ”a sound interpretative framework that is capable of facilitating an understanding of different social and employment realities.” Indeed, the overall aim of this thesis was to examine working conditions and their relationship with health, and to develop a theoretical framework which will allow the unification of disparate research in this area.

The worksome was developed with this overarching aim in mind: uniting disparate research into work and health under a readily understandable framework. The worksome was developed out of the exposome, a life-course [Ben-Shlomo and Kuh, 2002] approach to examining exposure developed by Wild [2005, 2012]. The worksome was seen as necessary as the exposome itself does little to account for social determinants of health [Wild, 2012]. Work is also relevant to how the public lives even away from the workplace [Kleiner and Pavalko, 2013]. Most people work for at least part of their lives. In the UK, for example, around 88.7% of individuals 16-74 are employed [ONS, 2011], and work as an aspect of life persists through the majority of the life course, and accounts for a large proportion of time. Work is important not only for material subsistence, but also holds a key place in the social-cultural fabric of most societies [Bambra, 2011; Payne, 1999; Peck, 1996]. Sustained employment is essential in most communities [van der Noordt et al., 2014]. While there have been several models proposed of work and health, such as Siegrist [1996]’s effort-reward imbalance model, or Karasek and Theorell [1990]’s job-demand control model, the labour market, the workplace, and geographical contexts are changing so quickly, that they may no longer be entirely applicable [Richter et al., 2013]. The worksome allows for shifting contexts and interactions between them, as well as for a variety of exposure types on the social-physical gradient.

Recent attention has been paid to specific rather than general conditions in the workplace ([Siegrist et al., 2010], for research on general working conditions [Benach et al., 2002; Braveman et al., 2005; Cheng et al., 2000; Lewchuk et al., 2003; Siegrist, 1996]. A fair amount of work on health outcomes relating to work focuses chiefly on exposure to physical hazards ([Arif and Delclos, 2012]. 'Social' working conditions can also be operationalised as exposures, such as working time [Dembe et al., 2005; Kivimäki et al., 2015]. Working time is both a social and a physical exposure; the time worked itself is physical, but how that time is arranged is social. Indeed, [Kleiner and Pavalko, 2013, pg985] argue that "[w]ork time poses a unique challenge, theoretically and methodologically, because it can potentially channel several health-relevant mechanisms." This complexity is captured through the social-physical gradient of exposure described in the worksome. Tangible and intangible exposures are both important, and while most tangible exposures are characterised in the risk literature as involuntary [Smith, 2013], intangible exposures may appear to be taken voluntarily, and social or financial constraints may make them involuntary. This is likely because the distribution of occupations and the conditions therein throughout society is irregular, and often across various axes, such as gender, age, and education [Benach et al., 2012]. Therefore, occupational specificity is important; research often focuses on one particular occupation type, or one particular geography, but rarely manages to compare health outcomes and working conditions across a variety of occupations and industries. This is in part due to a dearth of data that allows for these types of questions to be posed, but also perhaps a general focus in the research environment on finer grained questions.

The worksome consists of a wide array of exposures and pathways that are shaped by and contribute to social inequalities in health. A physical-social gradient will feature in the worksome. Changes in working conditions may originate in one industry or occupational type and spread to other fields, so addressing the temporal element is important [Benach et al., 2014]. The concept of the worksome will be expanded on through the theoretical framework and reinforced with empirical analysis of survey data. This therefore provides the 'sound interpretive framework' that Kim et al. [2012] called for. The framework was supported by the empirical part of this thesis, using the European Working Conditions Survey (EWCS) and the British Household Panel Survey (BHPS). The EWCS is a repeated cross-sectional sample and was taken over 25 years in a series of waves. Since each country took a sample, individuals can be grouped by time, country, and occupation. There is also information on specific health outcomes, and many questions were asked on specific working conditions. This allows for the empirical models to provide a broad, international picture of the relationships between work and health. The BHPS was chosen as it is a longitudinal panel survey, taken over 18 years in the United Kingdom, at around the same time as the EWCS. Observations at the wave time-points are grouped into individuals, who are grouped in occupations and regions. There are a few health outcomes which carry through all waves, and a set of analogous working condition and demographic variables chosen to match the EWCS data. The same analytic approach was chosen for both datasets, so that their results would be easily comparable. Logistic regression was chosen as the outcome variables were binary. As the individuals in the sample were clustered in groups, a multilevel approach was taken. First, single level models were run, in order to examine whether simpler models were appropriate, despite the data being clustered, and the worksome theoretical framework emphasising the importance of accounting for the structure of the scales at which exposures occur. While the coefficients for the multilevel models were broadly similar to those in the single level models, the random parts of the multilevel models answer many of the research questions and objectives.

11.2. A Review of the Research Questions and Objectives

Here the research questions and objectives will be reviewed, primarily in the context of the chapter structure.

11.2.1. Research Objectives

1. **Investigate and confirm the relationship between work and health**

Establishing the relationship between work and health in the EWCS and BHPS datasets was important to proceeding with the rest of the thesis. The literature review (Chapter 2) provided background information on the relationship between work and health and described gaps in the current research. The data and methods chapter (Chapter 4) described the outcomes and selected working conditions, providing the rationale for the logistic regression models presented in Chapters 5-9. The discussion (Chapter 10) situated the results in the literature. The relationship between work and health was therefore confirmed in the context of those in work: certain working conditions increased the odds of the set of health outcomes.

2. **Determine which specific working conditions underlie this relationship**

As the relationship between work and health was established, it was crucial to expand on the work described in the literature review (Chapter 2), much of which went into detail on specific working conditions, and forward a broader picture of the relationship between work and health. The data and methods chapter (Chapter 4) provided descriptive statistics and graphics about the specific working conditions within the EWCS dataset. The single level models (Chapter 5,6) showed that the specific working conditions did have a relationship with a variety of health outcomes in both datasets, and discussed the correlations between those conditions. The multilevel models (Chapters 8,9) extended the single level models, and while in some cases had very similar coefficients, were nonetheless necessary due to objective 3, and research questions 3-6, which emphasised the importance of describing the relevance and effect of these clusters. The discussion (Chapter 10) located the results about specific working conditions in the context of the literature and of the theoretical framework, the worksome.

3. **Examine and explore the geographies of these relationships**

The relationships between work and health did vary geographically, as was proposed. The literature review (Chapter 2) provided a view of a variety of conclusions drawn from work around the world. The variance components chapter (Chapter 7) explicitly explored the geographies of the work-health relationship, and even described the countries in terms of welfare regimes. The multilevel chapters (Chapter 8,9) spotlighted the geographies of the relationship not only between work and health, but on the specific working conditions and various health outcomes. In the EWCS analysis in Chapter 8, for outcomes grouped as 'muscular' geography mattered far less than for, for example, anxiety or fatigue. In the latter, geography accounted for more than 10% of variation, as opposed to under 3% for 'muscular' outcomes. In the BHPS analysis in Chapter 9, regional geography accounted for far less of the variation across all outcomes, often less than 1%. The discussion (Chapter 10) positioned the geographical parts of the multilevel model both in the context of the research landscape, but also as an empirical reinforcement of the worksome framework.

4. **Develop a transferable conceptual framework, the 'worksome,' and apply it to the empirical examples**

The worksome framework was largely developed in Chapter 3, large parts of which were taken from a paper previously published in *Social Science and Medicine* [Eyles et al., 2019]. The framework was designed to be transferable to many different research contexts, and to allow for the linkages of disparate research into health and work, the main aim of this thesis. The multilevel models (Chapters 8,9) empirically augmented the worksome, particularly through the random part of the models, which shows that for all outcomes, scale and group clustering were highly relevant. The discussion (Chapter 10) focused on linking the empirical part of the thesis to the theoretical framework both via the results and via the information provided in the literature review (Chapter 2).

11.2.2. Specific Research Questions

1. **What is the relationship between work and health?**

It has been well established that working is generally better for one's health than not [Bambra, 2010; Norstrom and Gronqvist, 2015; Smith, 1985]. The relationships examined in this thesis between working conditions and health showed those conditions had an impact on all of the health outcomes (see Chapters 5,6), reinforcing the literature (see Chapter 2). The discussion (Chapter 10) expanded on the results and explained these relationships.

2. **Which specific working conditions impact on this relationship? How do they vary across individuals (i.e. by gender, age, and so on)?**

The literature review (Chapter 2) discussed which conditions have been examined already, and to some extent how they vary across individuals. The data and methods chapter (Chapter 4) described the EWCS and BHPS datasets and the selected working conditions, as well as the rationale for selecting those variables. The single level and multilevel model chapters (Chapters 5 and 6, then Chapters 8 and 9) analysed the specific working conditions in the context of a series of health outcomes across two datasets, finding that most conditions thought to be detrimental to health, such as shift work, or working nights, increased the likelihood of reporting those health outcomes. The discussion (Chapter 10) situated these results within the context of the research environment.

3. **What is the impact of geography - in this case varying EU countries and UK regions? Does this vary by time?**

Geography indeed showed an impact on health outcomes, even in models accounting for working conditions (Chapters 7,8,9). Even in graphs of the proportion reporting various health outcomes, geographic differences were apparent (Chapter 4). Time also had an effect, though for certain health outcomes, specifically the work-health effect and injury(ies), it showed a decrease in the likelihood of reporting them, measured by the median odds ratio (MOR, see Chapter 8). Chapter 9 showed that there is more variation within regions in the UK rather than between them, however, so it is possible that international differences are more important than subnational ones with respect to working conditions and health. The discussion (Chapter 10) further elaborates on the impact of geography.

4. **How do responses change over time, and is this related to geography?**

The literature review (Chapter 2) discussed how employment has become increasingly precarious through time, and that industries have become geographically dispersed over time [Benach et al., 2014]. Despite the occurrence of delocalisation [Bourdieu, 1998], the impact of time nonetheless has varied geographically (Chapters 7-9). Chapter 9 showed that general health in the BHPS survey varied the most across individuals through time. The discussion (Chapter 10) described how the outcomes varied over time and through geographies in detail. This research question is closely related to research question 3.

5. **How might the impact on health vary across occupation types?**

- Do individuals vary more within the same occupation type or between occupation types?
- What is the geography and temporality of this?
- Does the system of occupational classification matter (e.g. either the Nomenclature of Economic Activities (NACE) or the International Standard Classification of Occupations (ISCO)?

The literature review identified a gap in the research (Chapter 2): most research focuses on specific occupations (often due to data constraints) or does not include occupation as a unit of analysis in any capacity. The parts of the variance components chapter (Chapter 7) taken from the paper in *Social Science and Medicine* [Eyles et al., 2019] showed that the system of classification is important, and a system using just occupational rather than industrial or class classifications is preferable for examining health outcomes. This was theoretically reinforced in Chapter 10. Occupations vary across countries (Chapter 8), and sometimes the differences are more within occupation than without, given the MORs below 1 for backache, anxiety, fatigue, and headache/eyestrain. As for the BHPS analysis (Chapter 9), between-occupation variation was small, meaning the differences within occupations were more important at the UK subnational level.

6. **What is the relationship between work, working conditions, and specific health outcomes such as backache or anxiety? Does this vary by occupation type, geography, and/or time?**

Specific health outcomes had varying relationships with working conditions. The literature review discussed this in some detail (Chapter 2), and the single level models (Chapter 5) showed that the relationships differed by outcome, though some can be grouped together by the patterns in those relationships, such as the 'muscular' health outcomes. The multilevel models (Chapters 8,9), while the coefficients were similar to the single level models, showed that these outcomes and their relationships to working conditions vary across occupation, geography, and time. Some effects became statistically significant in the multilevel models. The discussion (Chapter 10) situated these results within the theoretical framework, i.e. the worksome, and within the literature.

11.3. Strengths and Limitations

There are many strengths to this work. The EWCS data themselves are well validated and collected through an EU initiative, the European Foundation for the Improvement of Living and Working Conditions (Chapter 4), with sufficient information to perform an analysis including contexts and scales. The BHPS data, similarly, are robust and commonly used to answer a variety of research questions (Chapter 4). As similar empirical effects were found in both sets of models, it is unlikely that the effects occurred due to chance. The methods used are appropriate to the data and to the theoretical aims of the research, namely empirically reinforcing the worksome framework. Crucially, multilevel models approximate the scale aspect of the worksome. This approach also is strong as concepts are operationalised discretely and unambiguously in a language that a lay or policymaking audience can understand. Risk is quantified in terms of odds ratios, which are commonly understood, and a quantitative approach is also preferable for policymakers.

One limitation is that the fluid or interactive nature of scale was not explored via cross-classified models, as they would not work with the structure of the data. Further, both the

EWCS and BHPS data are not grouped by workplace due to how the sample was taken (a random national sample), so occupation was used to approximate it. Individual conditions were examined due to the heterogeneity of results around status and employment contract types [Bardasi and Francesconi, 2004; McNamara et al., 2011; Scott-Marshall and Tompa, 2011]. There was also missingness in both the EWCS and BHPS data. In the EWCS data, this appeared to be largely at random, but in the BHPS data, it is possible that particular time points in given individuals were excluded when they were unemployed. This may lead to bias, and though this study's population of interest was the employed, episodes of unemployment may nonetheless be relevant. Furthermore, the EWCS data were repeated cross-sectional rather than longitudinal, so a true life-course approach could not be taken. This limitation was mitigated by analysing the BHPS data. Reverse causation may also occur, in that it is possible that individuals working atypical jobs are already unhealthy, and the characteristics of those jobs may not necessarily lead to negative health impacts [Bardasi and Francesconi, 2004; Carpenter, 1987; Muntaner et al., 2010; Payne, 1999]. Further, wellbeing or health promoting characteristics were not necessarily easy to examine as the survey focused on negative health impacts. And, as indicated by Clougherty et al. [2010] it may be difficult to see what health-promoting aspects work may have, apart from income or material benefit. Work is a large part of life, and the worksome, like the exposome, prioritises a life course approach. This matters because the presence of good health is not just the absence of poor health.

Another limitation to this thesis is its purely quantitative approach. Taking the worksome as a holistic framework, it requires further engagement with a host of approaches to elicit a better understanding. For instance, a mixed methods approach, and, indeed, qualitative work would help reinforce and build on the worksome framework, especially the idea of the levels and interactions between scales, something which is difficult to capture with quantitative data. This PhD establishes the worksome framework as a concept by conducting an initial quantitative investigation to explore major issues relating to work and health. As a PhD funded via the Advanced Quantitative Methods (AQM) route of the ESRC SWDTP, qualitative work was precluded but there are clear benefits to undertaking such research in future. A mixed methods study would likely examine the scales and how they interact, potentially by interviewing individuals within workplaces, and linking this to research on relationships between firms within and between industries, and across jurisdictional geographies. It would also explore the meaning of work in the context of everyday life.

11.4. Directions for Future Research

Future research could further reinforce the worksome concept. Including lifestyle factors or neighbourhood variables, for example, which exist outside of the workplace, may be worth pursuing, in order to account for information that was unavailable in the analysis conducted in this thesis. Cross-classified and more complex multilevel model structures could also be pursued. Data with objective measures of health or that in other, non-European geographies could be used to reproduce this work and further it by employing the worksome framework in other contexts.

If possible, future work should examine specific workplaces rather than occupation types, but it is difficult to do this as the data may not exist, or it may be too expensive to be practicable to collect sufficient data.

Both qualitative and quantitative forms of research are key to forming a better picture of the work-health relationship. Within the quantitative approaches, this thesis employed multilevel models to approximate the proposed domains and interactions between them [Hox, 2010]. For qualitative research, which this thesis did not undertake, the effects people have on systems and scales and how they are affected by them could be elucidated through interviews, or participatory work where the participants guide the research journey.

11.5. Final Conclusions

[Kim et al., 2012, pg100] argued that there was a dearth of 'precise conclusions' on the relationships between working conditions and health, mentioning

"some inconsistent results in the majority of empirical studies, the lack of a sound interpretative framework that is capable of facilitating an understanding of different social and employment realities; and limited contextual and labour market-related variables that interact with individual employment situations."

This thesis aimed to, and has provided a theoretical framework in the worksome, which is capable of uniting the disparate research on work and health, and further, it has empirically reinforced this framework by examining working conditions and their relationships with health using two robust datasets: a repeated cross-sectional European dataset and a longitudinal British panel survey.

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Appendices

Appendix A

EWCS Single Level Intermediate Models

Table A.1: Intermediate Models for the Work-Health Effect

Model 0

Parameter	OR	95% CI		p
Intercept	0.669	0.660	0.677	0.000
Log Likelihood	-67568.038			

Model 1

Parameter	OR	95% CI		p
Intercept	0.716	0.704	0.729	0.000
Sex (ref: male)	0.870	0.848	0.892	0.000
Log Likelihood	-67509.846			

Model 2

Parameter	OR	95% CI		p
Intercept	0.446	0.425	0.469	0.000
Sex (ref: male)	0.868	0.847	0.891	0.000
Age	1.012	1.010	1.013	0.000
Log Likelihood	-67297.545			

Model 3

Parameter	OR	95% CI		p
Intercept	0.455	0.433	0.478	0.000
Sex (ref: male)	0.872	0.850	0.895	0.000
Age	1.011	1.010	1.013	0.000
Has Tertiary Education (ref: no tertiary)	0.947	0.923	0.973	0.000
Log Likelihood	-67289.396			

Model 4

Parameter	OR	95% CI		p
Intercept	0.407	0.387	0.428	0.000
Sex (ref: male)	0.906	0.883	0.929	0.000

Age	1.012	1.011	1.013	0.000
Has Tertiary Education (ref: no tertiary)	0.960	0.935	0.986	0.002
Nights worked per month	1.045	1.042	1.049	0.000
Log Likelihood	-66930.412			
	Model 5			
Parameter	OR	95% CI		p
Intercept	0.376	0.387	0.396	0.000
Sex (ref: male)	0.892	0.883	0.915	0.000
Age	1.013	1.012	1.014	0.000
Has Tertiary Education (ref: no tertiary)	0.980	0.954	1.006	0.130
Nights worked per month	1.036	1.033	1.040	0.000
Works shifts (ref: no)	1.366	1.321	1.412	0.000
Log Likelihood	-66760.985			
	Model 6			
Parameter	OR	95% CI		p
Intercept	0.213	0.387	0.228	0.000
Sex (ref: male)	0.962	0.937	0.988	0.005
Age	1.013	1.012	1.014	0.000
Has Tertiary Education (ref: no tertiary)	0.989	0.963	1.015	0.397
Nights worked per month	1.030	1.026	1.033	0.000
Works shifts (ref: no)	1.374	1.330	1.421	0.000
Hours per week worked	1.014	1.013	1.015	0.000
Log Likelihood	-66443.060			
	Model 7			
Parameter	OR	95% CI		p
Intercept	0.217	0.203	0.233	0.000
Sex (ref: male)	0.963	0.937	0.989	0.005
Age	1.013	1.012	1.014	0.000
Has Tertiary Education (ref: no tertiary)	0.994	0.968	1.021	0.657
Nights worked per month	1.030	1.026	1.033	0.000
Works shifts (ref: no)	1.376	1.330	1.423	0.000
Hours per week worked	1.013	1.012	1.015	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.885	0.840	0.932	0.000
Adaptable within limits	0.956	0.922	0.992	0.016
Entirely self-determined	0.987	0.951	1.025	0.492
Log Likelihood	-66430.737			
	Model 8			
Parameter	OR	95% CI		p
Intercept	0.192	0.179	0.206	0.000
Sex (ref: male)	0.966	0.941	0.992	0.011
Age	1.014	1.013	1.015	0.000
Has Tertiary Education (ref: no tertiary)	0.970	0.944	0.996	0.250
Nights worked per month	1.030	1.026	1.033	0.000
Works shifts (ref: no)	1.377	1.331	1.425	0.000

Hours per week worked	1.013	1.012	1.015	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.881	0.837	0.929	0.000
Adaptable within limits	0.950	0.916	0.985	0.006
Entirely self-determined	0.985	0.949	1.023	0.430
Skill-demand match (ref: they match)				
Demands too low	1.151	1.119	1.184	0.000
Demands too high	1.500	1.441	1.561	0.000
Log Likelihood	-66222.831			

Model 9

Parameter	OR	95% CI		p
Intercept	0.178	0.165	0.192	0.000
Sex (ref: male)	0.908	0.883	0.933	0.011
Age	1.013	1.012	1.014	0.000
Has Tertiary Education (ref: no tertiary)	1.025	0.997	1.053	0.081
Nights worked per month	1.028	1.024	1.032	0.000
Works shifts (ref: no)	1.329	1.284	1.376	0.000
Hours per week worked	1.012	1.011	1.013	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.921	0.874	0.972	0.002
Adaptable within limits	1.013	0.976	1.051	0.500
Entirely self-determined	1.038	1.000	1.079	0.053
Skill-demand match (ref: they match)				
Demands too low	1.116	1.084	1.149	0.000
Demands too high	1.466	1.407	1.526	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.946	1.879	2.015	0.000
Agree	0.860	0.832	0.890	0.000
Log Likelihood	-64690.230			

Table A.2: Intermediate Models for Skin Problems in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.086	0.084	0.088	0.000
Log Likelihood	-28540.357			

Model 1

Parameter	OR	95% CI		p
Intercept	0.076	0.074	0.079	0.000
Sex (ref: male)	1.268	1.212	1.327	0.000
Log Likelihood	-28487.565			

Model 2

Parameter	OR	95% CI		p
Intercept	0.097	0.089	0.105	0.000
Sex (ref: male)	1.270	1.213	1.329	0.000

Age	0.994	0.992	0.996	0.000
Log Likelihood	-28470.435			
	Model 3			
Parameter	OR	95% CI		p
Intercept	0.100	0.092	0.109	0.000
Sex (ref: male)	1.281	1.224	1.341	0.000
Age	0.994	0.992	0.996	0.000
Has Tertiary Education (ref: no tertiary)	0.902	0.860	0.946	0.000
Log Likelihood	-28461.215			
	Model 4			
Parameter	OR	95% CI		p
Intercept	0.094	0.086	0.102	0.000
Sex (ref: male)	1.311	1.253	1.373	0.000
Age	0.994	0.993	0.996	0.000
Has Tertiary Education (ref: no tertiary)	0.909	0.867	0.953	0.000
Nights worked per month	1.024	1.019	1.030	0.000
Log Likelihood	-28421.626			
	Model 5			
Parameter	OR	95% CI		p
Intercept	0.089	0.082	0.098	0.000
Sex (ref: male)	1.300	1.242	1.362	0.000
Age	0.995	0.993	0.997	0.000
Has Tertiary Education (ref: no tertiary)	0.921	0.878	0.965	0.001
Nights worked per month	1.020	1.014	1.025	0.000
Works shifts (ref: no)	1.204	1.138	1.273	0.000
Log Likelihood	-28400.969			
	Model 6			
Parameter	OR	95% CI		p
Intercept	0.078	0.070	0.088	0.000
Sex (ref: male)	1.323	1.262	1.387	0.000
Age	0.995	0.993	0.997	0.000
Has Tertiary Education (ref: no tertiary)	0.922	0.880	0.967	0.001
Nights worked per month	1.018	1.013	1.024	0.000
Works shifts (ref: no)	1.205	1.139	1.274	0.000
Hours per week worked	1.003	1.001	1.005	0.001
Log Likelihood	-28395.409			
	Model 7			
Parameter	OR	95% CI		p
Intercept	0.076	0.067	0.085	0.000
Sex (ref: male)	1.327	1.265	1.391	0.000
Age	0.995	0.993	0.997	0.000
Has Tertiary Education (ref: no tertiary)	0.903	0.861	0.948	0.000
Nights worked per month	1.019	1.013	1.024	0.000
Works shifts (ref: no)	1.230	1.161	1.302	0.000
Hours per week worked	1.003	1.001	1.005	0.000

Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.008	0.921	1.104	0.861
Adaptable within limits	1.225	1.152	1.303	0.000
Entirely self-determined	1.019	0.952	1.091	0.582
Log Likelihood	-28374.655			

	Model 8			
Parameter	OR	95% CI		p
Intercept	0.066	0.059	0.075	0.000
Sex (ref: male)	1.334	1.272	1.398	0.000
Age	0.996	0.994	0.997	0.000
Has Tertiary Education (ref: no tertiary)	0.881	0.840	0.925	0.000
Nights worked per month	1.018	1.013	1.024	0.000
Works shifts (ref: no)	1.229	1.161	1.302	0.000
Hours per week worked	1.003	1.001	1.005	0.001
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.006	0.919	1.102	0.889
Adaptable within limits	1.219	1.146	1.297	0.000
Entirely self-determined	1.015	0.948	1.087	0.663
Skill-demand match (ref: they match)				
Demands too low	1.208	1.148	1.270	0.000
Demands too high	1.435	1.343	1.534	0.000
Log Likelihood	-28310.032			

	Model 9			
Parameter	OR	95% CI		p
Intercept	0.062	0.054	0.070	0.000
Sex (ref: male)	1.273	1.214	1.335	0.000
Age	0.994	0.992	0.996	0.000
Has Tertiary Education (ref: no tertiary)	0.917	0.874	0.963	0.001
Nights worked per month	1.017	1.011	1.022	0.000
Works shifts (ref: no)	1.186	1.120	1.256	0.000
Hours per week worked	1.002	1.000	1.004	0.036
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.046	0.955	1.145	0.334
Adaptable within limits	1.284	1.207	1.367	0.000
Entirely self-determined	1.060	0.990	1.136	0.094
Skill-demand match (ref: they match)				
Demands too low	1.175	1.117	1.236	0.000
Demands too high	1.398	1.307	1.494	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.720	1.618	1.829	0.000
Agree	0.906	0.850	0.966	0.003
Log Likelihood	-27982.407			

Table A.3: Intermediate Models for Hearing Problems in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.069	0.067	0.071	0.000
Log Likelihood	-24611.591			

Model 1

Parameter	OR	95% CI		p
Intercept	0.087	0.085	0.090	0.000
Sex (ref: male)	0.586	0.557	0.617	0.000
Log Likelihood	-24396.807			

Model 2

Parameter	OR	95% CI		p
Intercept	0.023	0.021	0.026	0.000
Sex (ref: male)	0.584	0.554	0.614	0.000
Age	1.031	1.029	1.033	0.000
Log Likelihood	-24012.829			

Model 3

Parameter	OR	95% CI		p
Intercept	0.025	0.023	0.028	0.000
Sex (ref: male)	0.594	0.564	0.625	0.000
Age	1.031	1.029	1.033	0.000
Has Tertiary Education (ref: no tertiary)	0.795	0.753	0.838	0.000
Log Likelihood	-23976.757			

Model 4

Parameter	OR	95% CI		p
Intercept	0.023	0.021	0.026	0.000
Sex (ref: male)	0.608	0.577	0.640	0.000
Age	1.032	1.029	1.034	0.000
Has Tertiary Education (ref: no tertiary)	0.803	0.761	0.847	0.000
Nights worked per month	1.026	1.021	1.031	0.000
Log Likelihood	-23936.341			

Model 5

Parameter	OR	95% CI		p
Intercept	0.021	0.019	0.024	0.000
Sex (ref: male)	0.600	0.569	0.632	0.000
Age	1.032	1.030	1.035	0.000
Has Tertiary Education (ref: no tertiary)	0.820	0.777	0.865	0.000
Nights worked per month	1.019	1.013	1.025	0.000
Works shifts (ref: no)	1.343	1.262	1.428	0.000
Log Likelihood	-23894.245			

Model 6

Parameter	OR	95% CI		p
Intercept	0.022	0.019	0.025	0.000
Sex (ref: male)	0.599	0.568	0.631	0.000
Age	1.032	1.030	1.035	0.000
Has Tertiary Education (ref: no tertiary)	0.819	0.776	0.865	0.000

Nights worked per month	1.019	1.013	1.025	0.000
Works shifts (ref: no)	1.342	1.262	1.428	0.000
Hours per week worked	1.000	0.998	1.002	0.738
Log Likelihood	-23894.189			
	Model 7			
Parameter	OR	95% CI		p
Intercept	0.021	0.019	0.025	0.000
Sex (ref: male)	0.595	0.564	0.628	0.000
Age	1.033	1.031	1.035	0.000
Has Tertiary Education (ref: no tertiary)	0.814	0.770	0.859	0.000
Nights worked per month	1.020	1.014	1.026	0.000
Works shifts (ref: no)	1.307	1.226	1.393	0.000
Hours per week worked	1.001	0.998	1.003	0.579
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.878	0.790	0.976	0.016
Adaptable within limits	1.046	0.975	1.122	0.210
Entirely self-determined	0.786	0.728	0.848	0.000
Log Likelihood	-23868.312			
	Model 8			
Parameter	OR	95% CI		p
Intercept	0.019	0.017	0.022	0.000
Sex (ref: male)	0.596	0.565	0.629	0.000
Age	1.034	1.031	1.036	0.000
Has Tertiary Education (ref: no tertiary)	0.795	0.752	0.840	0.000
Nights worked per month	1.020	1.014	1.026	0.000
Works shifts (ref: no)	1.305	1.224	1.391	0.000
Hours per week worked	1.001	0.998	1.003	0.624
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.873	0.786	0.971	0.012
Adaptable within limits	1.038	0.967	1.113	0.303
Entirely self-determined	0.785	0.728	0.848	0.000
Skill-demand match (ref: they match)				
Demands too low	1.089	1.029	1.152	0.003
Demands too high	1.444	1.341	1.556	0.000
Log Likelihood	-23823.793			
	Model 9			
Parameter	OR	95% CI		p
Intercept	0.017	0.015	0.020	0.000
Sex (ref: male)	0.571	0.541	0.602	0.011
Age	1.033	1.031	1.036	0.000
Has Tertiary Education (ref: no tertiary)	1.019	0.777	0.868	0.000
Nights worked per month	1.019	1.013	1.025	0.000
Works shifts (ref: no)	1.270	1.192	1.354	0.000
Hours per week worked	1.000	0.997	1.002	0.686
Working time arrangement (ref: set by company)				

Choice between several fixed schedules	0.903	0.812	1.004	0.060
Adaptable within limits	1.082	1.008	1.161	0.030
Entirely self-determined	0.807	0.747	0.871	0.000
Skill-demand match (ref: they match)				
Demands too low	1.064	1.005	1.126	0.000
Demands too high	1.412	1.311	1.521	0.393
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.613	1.507	1.728	0.000
Agree	0.970	0.904	1.040	0.000
Log Likelihood	-23646.673			

Table A.4: Intermediate Models for Backache in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.687	0.679	0.696	0.000
Log Likelihood	-69581.688			

Model 1

Parameter	OR	95% CI		p
Intercept	0.653	0.642	0.665	0.000
Sex (ref: male)	1.106	1.079	1.134	0.000
Log Likelihood	-69550.124			

Model 3

Parameter	OR	95% CI		p
Intercept	0.353	0.336	0.371	0.000
Sex (ref: male)	1.147	1.118	1.176	0.000
Age	1.018	1.017	1.019	0.000
Has Tertiary Education (ref: no tertiary)	0.651	0.634	0.668	0.000

Model 4

Parameter	OR	95% CI		p
Intercept	0.335	0.318	0.352	0.000
Sex (ref: male)	1.169	1.140	1.199	0.000
Age	1.019	1.018	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.655	0.638	0.672	0.000
Nights worked per month	1.022	1.019	1.026	0.000
Log Likelihood	-68396.405			

Model 5

Parameter	OR	95% CI		p
Intercept	0.318	0.302	0.335	0.000
Sex (ref: male)	1.158	1.129	1.188	0.000
Age	1.019	1.018	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.663	0.646	0.681	0.000
Nights worked per month	1.017	1.013	1.020	0.000
Works shifts (ref: no)	1.224	1.185	1.265	0.000
Log Likelihood	-68323.324			

Model 6

Parameter	OR	95% CI		p
Intercept	0.022	0.019	0.025	0.000
Sex (ref: male)	0.599	0.568	0.631	0.000
Age	1.032	1.030	1.035	0.000
Has Tertiary Education (ref: no tertiary)	0.819	0.776	0.865	0.000
Nights worked per month	1.019	1.013	1.025	0.000
Works shifts (ref: no)	1.342	1.262	1.428	0.000
Hours per week worked	1.000	0.998	1.002	0.738
Log Likelihood	-68185.965			

Model 7

Parameter	OR	95% CI		p
Intercept	0.225	0.210	0.240	0.000
Sex (ref: male)	1.215	1.183	1.247	0.000
Age	1.019	1.018	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.672	0.654	0.690	0.000
Nights worked per month	1.012	1.009	1.016	0.000
Works shifts (ref: no)	1.212	1.172	1.253	0.000
Hours per week worked	1.009	1.008	1.010	0.000
Working time arrangement (ref: set by company)	0.225	0.210	0.240	0.000
Choice between several fixed schedules	1.215	1.183	1.247	0.000
Adaptable within limits	1.019	1.018	1.020	0.000
Entirely self-determined	0.672	0.654	0.690	0.000
Log Likelihood	-68170.552			

Model 8

Parameter	OR	95% CI		p
Intercept	0.215	0.201	0.231	0.000
Sex (ref: male)	1.217	1.185	1.249	0.000
Age	1.020	1.018	1.021	0.000
Has Tertiary Education (ref: no tertiary)	0.667	0.649	0.685	0.000
Nights worked per month	1.012	1.009	1.016	0.000
Works shifts (ref: no)	1.212	1.172	1.253	0.000
Hours per week worked	1.009	1.008	1.010	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.958	0.910	1.008	0.097
Adaptable within limits	0.908	0.876	0.941	0.000
Entirely self-determined	0.946	0.912	0.982	0.003
Skill-demand match (ref: they match)				
Demands too low	1.073	1.043	1.104	0.000
Demands too high	1.116	1.072	1.161	0.000
Log Likelihood	-68149.488			

Model 9

Parameter	OR	95% CI		p
Intercept	0.219	0.203	0.235	0.000
Sex (ref: male)	1.164	1.134	1.196	0.000

Age	1.019	1.018	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.694	0.675	0.713	0.000
Nights worked per month	1.011	1.007	1.014	0.000
Works shifts (ref: no)	1.174	1.135	1.215	0.000
Hours per week worked	1.008	1.007	1.009	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.994	0.945	1.047	0.826
Adaptable within limits	0.957	0.923	0.993	0.018
Entirely self-determined	0.985	0.949	1.023	0.443
Skill-demand match (ref: they match)				
Demands too low	1.046	1.017	1.077	0.002
Demands too high	1.091	1.048	1.135	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.552	1.500	1.605	0.000
Agree	0.806	0.780	0.833	0.000
Log Likelihood	-67181.389			

Table A.5: Intermediate Models for Lower Muscular Pain in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.462	0.456	0.468	0.000
Log Likelihood	-64212.197			

Model 1

Parameter	OR	95% CI		p
Intercept	0.448	0.440	0.457	0.000
Sex (ref: male)	1.060	1.032	1.088	0.000
Log Likelihood	-64202.858			

Model 2

Parameter	OR	95% CI		p
Intercept	0.186	0.177	0.196	0.000
Sex (ref: male)	1.058	1.030	1.086	0.000
Age	1.021	1.020	1.022	0.000
Log Likelihood	-63550.322			

Model 3

Parameter	OR	95% CI		p
Intercept	0.220	0.209	0.232	0.000
Sex (ref: male)	1.107	1.078	1.137	0.000
Age	1.021	1.020	1.022	0.000
Has Tertiary Education (ref: no tertiary)	0.582	0.565	0.598	0.000
Log Likelihood	-62829.401			

Model 4

Parameter	OR	95% CI		p
Intercept	0.206	0.195	0.217	0.000
Sex (ref: male)	1.133	1.103	1.164	0.000

Age	1.022	1.021	1.023	0.000
Has Tertiary Education (ref: no tertiary)	0.586	0.569	0.602	0.000
Nights worked per month	1.026	1.023	1.029	0.000
Log Likelihood	-62712.932			
	Model 5			
Parameter	OR	95% CI		p
Intercept	0.193	0.182	0.203	0.000
Sex (ref: male)	1.120	1.090	1.151	0.000
Age	1.022	1.021	1.023	0.000
Has Tertiary Education (ref: no tertiary)	0.595	0.578	0.612	0.000
Nights worked per month	1.019	1.016	1.023	0.000
Works shifts (ref: no)	1.285	1.242	1.330	0.000
Log Likelihood	-62610.193			
	Model 6			
Parameter	OR	95% CI		p
Intercept	0.126	0.117	0.136	0.000
Sex (ref: male)	1.186	1.153	1.219	0.000
Age	1.022	1.021	1.024	0.000
Has Tertiary Education (ref: no tertiary)	0.598	0.581	0.615	0.001
Nights worked per month	1.014	1.011	1.018	0.000
Works shifts (ref: no)	1.291	1.248	1.336	0.000
Hours per week worked	1.010	1.009	1.011	0.000
Log Likelihood	-62448.301			
	Model 7			
Parameter	OR	95% CI		p
Intercept	0.132	0.123	0.142	0.000
Sex (ref: male)	1.186	1.153	1.220	0.000
Age	1.023	1.021	1.024	0.000
Has Tertiary Education (ref: no tertiary)	0.609	0.592	0.627	0.000
Nights worked per month	1.014	1.010	1.017	0.000
Works shifts (ref: no)	1.284	1.239	1.329	0.000
Hours per week worked	1.010	1.009	1.011	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.857	0.811	0.905	0.000
Adaptable within limits	0.837	0.805	0.870	0.000
Entirely self-determined	1.003	0.964	1.042	0.897
Log Likelihood	-62394.827			
	Model 8			
Parameter	OR	95% CI		p
Intercept	0.126	0.117	0.136	0.000
Sex (ref: male)	1.189	1.157	1.223	0.000
Age	1.023	1.021	1.024	0.000
Has Tertiary Education (ref: no tertiary)	0.606	0.589	0.624	0.000
Nights worked per month	1.014	1.010	1.017	0.000
Works shifts (ref: no)	1.283	1.239	1.329	0.000

Hours per week worked	1.010	1.009	1.011	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.857	0.812	0.906	0.000
Adaptable within limits	0.838	0.806	0.871	0.000
Entirely self-determined	0.998	0.960	1.038	0.935
Skill-demand match (ref: they match)				
Demands too low	1.121	1.088	1.155	0.000
Demands too high	1.030	0.987	1.075	0.179
Log Likelihood	-62366.481			

	Model 9			
Parameter	OR	95% CI		p
Intercept	0.131	0.121	0.141	0.000
Sex (ref: male)	1.129	1.098	1.162	0.000
Age	1.022	1.021	1.023	0.000
Has Tertiary Education (ref: no tertiary)	0.634	0.616	0.653	0.000
Nights worked per month	1.012	1.009	1.016	0.000
Works shifts (ref: no)	1.240	1.197	1.285	0.000
Hours per week worked	1.008	1.007	1.009	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.894	0.846	0.945	0.000
Adaptable within limits	0.889	0.855	0.925	0.000
Entirely self-determined	1.047	1.006	1.089	0.023
Skill-demand match (ref: they match)				
Demands too low	1.091	1.058	1.124	0.000
Demands too high	1.003	0.960	1.047	0.897
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.594	1.538	1.651	0.000
Agree	0.753	0.727	0.781	0.000
Log Likelihood	-61240.108			

Table A.6: Intermediate Models for Upper Muscular Pain in the last 12 months

Model 0				
Parameter	OR	95% CI		p
Intercept	0.669	0.661	0.678	0.000
Log Likelihood	-69328.211			

	Model 1			
Parameter	OR	95% CI		p
Intercept	0.610	0.599	0.621	0.000
Sex (ref: male)	1.202	1.172	1.232	0.000
Log Likelihood	-69224.050			

	Model 2			
Parameter	OR	95% CI		p
Intercept	0.275	0.262	0.289	0.000
Sex (ref: male)	1.201	1.171	1.231	0.000

Age	1.019	1.018	1.020	0.000
Log Likelihood	-68620.548			
	Model 3			
Parameter	OR	95% CI		p
Intercept	0.306	0.291	0.321	0.000
Sex (ref: male)	1.236	1.205	1.268	0.000
Age	1.019	1.018	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.721	0.703	0.740	0.000
Log Likelihood	-68320.444			
	Model 4			
Parameter	OR	95% CI		p
Intercept	0.292	0.277	0.307	0.000
Sex (ref: male)	1.257	1.225	1.289	0.000
Age	1.020	1.019	1.021	0.000
Has Tertiary Education (ref: no tertiary)	0.725	0.706	0.744	0.000
Nights worked per month	1.019	1.016	1.022	0.000
Log Likelihood	-68253.608			
	Model 5			
Parameter	OR	95% CI		p
Intercept	0.281	0.267	0.295	0.000
Sex (ref: male)	1.248	1.216	1.280	0.000
Age	1.020	1.019	1.021	0.000
Has Tertiary Education (ref: no tertiary)	0.732	0.713	0.752	0.000
Nights worked per month	1.015	1.011	1.018	0.000
Works shifts (ref: no)	1.170	1.132	1.209	0.000
Log Likelihood	-68323.324			
	Model 6			
Parameter	OR	95% CI		p
Intercept	0.191	0.178	0.204	0.000
Sex (ref: male)	1.315	1.281	1.350	0.000
Age	1.020	1.019	1.021	0.000
Has Tertiary Education (ref: no tertiary)	0.736	0.717	0.756	0.001
Nights worked per month	1.010	1.007	1.014	0.000
Works shifts (ref: no)	1.174	1.136	1.213	0.000
Hours per week worked	1.009	1.008	1.010	0.000
Log Likelihood	-68058.731			
	Model 7			
Parameter	OR	95% CI		p
Intercept	0.190	0.177	0.203	0.000
Sex (ref: male)	1.316	1.282	1.352	0.000
Age	1.020	1.019	1.021	0.000
Has Tertiary Education (ref: no tertiary)	0.731	0.712	0.751	0.000
Nights worked per month	1.010	1.007	1.014	0.000
Works shifts (ref: no)	1.183	1.144	1.223	0.000
Hours per week worked	1.009	1.008	1.010	0.000

Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.942	0.895	0.992	0.023
Adaptable within limits	1.069	1.031	1.107	0.000
Entirely self-determined	0.990	0.954	1.028	0.603
Log Likelihood	-68047.495			

	Model 8			
Parameter	OR	95% CI		p
Intercept	0.181	0.169	0.194	0.000
Sex (ref: male)	1.319	1.285	1.355	0.000
Age	1.020	1.019	1.021	0.000
Has Tertiary Education (ref: no tertiary)	0.725	0.706	0.745	0.000
Nights worked per month	1.010	1.007	1.014	0.000
Works shifts (ref: no)	1.183	1.143	1.223	0.000
Hours per week worked	1.009	1.008	1.010	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.942	0.895	0.991	0.022
Adaptable within limits	1.067	1.030	1.106	0.000
Entirely self-determined	0.988	0.952	1.025	0.525
Skill-demand match (ref: they match)				
Demands too low	1.086	1.055	1.117	0.000
Demands too high	1.121	1.077	1.166	0.000
Log Likelihood	-68022.130			

	Model 9			
Parameter	OR	95% CI		p
Intercept	0.178	0.165	0.191	0.000
Sex (ref: male)	1.263	1.229	1.297	0.000
Age	1.020	1.019	1.021	0.000
Has Tertiary Education (ref: no tertiary)	0.755	0.735	0.776	0.000
Nights worked per month	1.008	1.005	1.012	0.000
Works shifts (ref: no)	1.144	1.106	1.183	0.000
Hours per week worked	1.008	1.007	1.009	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.979	0.929	1.031	0.415
Adaptable within limits	1.129	1.089	1.171	0.000
Entirely self-determined	1.031	0.993	1.070	0.109
Skill-demand match (ref: they match)				
Demands too low	1.057	1.027	1.088	0.000
Demands too high	1.093	1.050	1.138	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.639	1.584	1.696	0.000
Agree	0.835	0.807	0.863	0.000
Log Likelihood	-66978.575			

Table A.7: Intermediate Models for Anxiety in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.151	0.148	0.153	0.000
Log Likelihood	-39971.158			

Model 1

Parameter	OR	95% CI		p
Intercept	0.128	0.125	0.132	0.000
Sex (ref: male)	1.353	1.305	1.404	0.000
Log Likelihood	-39837.967			

Model 2

Parameter	OR	95% CI		p
Intercept	0.088	0.082	0.095	0.000
Sex (ref: male)	1.352	1.304	1.403	0.000
Age	1.009	1.007	1.011	0.000
Log Likelihood	-39775.057			

Model 3

Parameter	OR	95% CI		p
Intercept	0.082	0.076	0.088	0.000
Sex (ref: male)	1.329	1.282	1.379	0.000
Age	1.009	1.008	1.011	0.000
Has Tertiary Education (ref: no tertiary)	1.224	1.180	1.270	0.000
Log Likelihood	-39717.800			

Model 4

Parameter	OR	95% CI		p
Intercept	0.075	0.070	0.081	0.000
Sex (ref: male)	1.370	1.320	1.421	0.000
Age	1.010	1.008	1.011	0.000
Has Tertiary Education (ref: no tertiary)	1.238	1.193	1.284	0.000
Nights worked per month	1.032	1.027	1.036	0.000
Log Likelihood	-39617.461			

Model 5

Parameter	OR	95% CI		p
Intercept	0.073	0.068	0.079	0.000
Sex (ref: male)	1.364	1.314	1.415	0.000
Age	1.010	1.008	1.011	0.000
Has Tertiary Education (ref: no tertiary)	1.246	1.201	1.293	0.000
Nights worked per month	1.029	1.025	1.034	0.000
Works shifts (ref: no)	1.105	1.055	1.157	0.000
Log Likelihood	-39608.665			

Model 6

Parameter	OR	95% CI		p
Intercept	0.050	0.045	0.055	0.000
Sex (ref: male)	1.433	1.380	1.489	0.000
Age	1.010	1.008	1.011	0.000
Has Tertiary Education (ref: no tertiary)	1.254	1.208	1.302	0.000

Nights worked per month	1.024	1.020	1.028	0.000
Works shifts (ref: no)	1.110	1.060	1.163	0.000
Hours per week worked	1.009	1.008	1.011	0.000
Log Likelihood	-39537.236			

Model 7

Parameter	OR	95% CI		p
Intercept	0.051	0.046	0.056	0.000
Sex (ref: male)	1.440	1.386	1.495	0.000
Age	1.010	1.008	1.011	0.000
Has Tertiary Education (ref: no tertiary)	1.256	1.209	1.304	0.000
Nights worked per month	1.024	1.019	1.028	0.000
Works shifts (ref: no)	1.132	1.080	1.187	0.000
Hours per week worked	1.009	1.007	1.010	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.881	0.816	0.950	0.001
Adaptable within limits	1.012	0.961	1.065	0.657
Entirely self-determined	1.078	1.023	1.137	0.005
Log Likelihood	-39526.494			

Model 8

Parameter	OR	95% CI		p
Intercept	0.045	0.041	0.050	0.000
Sex (ref: male)	1.445	1.391	1.501	0.000
Age	1.010	1.009	1.012	0.000
Has Tertiary Education (ref: no tertiary)	1.224	1.179	1.272	0.000
Nights worked per month	1.024	1.019	1.028	0.000
Works shifts (ref: no)	1.132	1.080	1.187	0.000
Hours per week worked	1.009	1.007	1.010	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.877	0.813	0.947	0.001
Adaptable within limits	1.005	0.955	1.058	0.840
Entirely self-determined	1.078	1.022	1.136	0.005
Skill-demand match (ref: they match)				
Demands too low	1.123	1.078	1.170	0.000
Demands too high	1.480	1.404	1.561	0.000
Log Likelihood	-39425.229			

Model 9

Parameter	OR	95% CI		p
Intercept	0.042	0.038	0.047	0.000
Sex (ref: male)	1.363	1.312	1.417	0.000
Age	1.009	1.008	1.011	0.000
Has Tertiary Education (ref: no tertiary)	1.298	1.249	1.348	0.000
Nights worked per month	1.022	1.017	1.026	0.000
Works shifts (ref: no)	1.081	1.031	1.134	0.001
Hours per week worked	1.007	1.005	1.009	0.000
Working time arrangement (ref: set by company)				

Choice between several fixed schedules	0.918	0.850	0.991	0.029
Adaptable within limits	1.073	1.019	1.130	0.008
Entirely self-determined	1.141	1.082	1.203	0.000
Skill-demand match (ref: they match)				
Demands too low	1.086	1.042	1.132	0.000
Demands too high	1.435	1.360	1.514	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.897	1.806	1.993	0.000
Agree	0.854	0.811	0.899	0.000
Log Likelihood	-38661.953			

Table A.8: Intermediate Models for Fatigue in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.602	0.594	0.609	0.000
Log Likelihood	-68146.475			
	Model 1			
Parameter	OR	95% CI		p
Intercept	0.551	0.542	0.561	0.000
Sex (ref: male)	1.189	1.160	1.220	0.000
Log Likelihood	-68055.896			
	Model 2			
Parameter	OR	95% CI		p
Intercept	0.462	0.440	0.485	0.000
Sex (ref: male)	1.189	1.159	1.219	0.000
Age	1.004	1.003	1.005	0.000
Log Likelihood	-68026.166			
	Model 3			
Parameter	OR	95% CI		p
Intercept	0.474	0.451	0.498	0.000
Sex (ref: male)	1.197	1.167	1.227	0.000
Age	1.004	1.003	1.005	0.000
Has Tertiary Education (ref: no tertiary)	0.926	0.902	0.951	0.000
Log Likelihood	-68009.567			
	Model 4			
Parameter	OR	95% CI		p
Intercept	0.437	0.416	0.460	0.000
Sex (ref: male)	1.232	1.201	1.264	0.000
Age	1.005	1.004	1.006	0.000
Has Tertiary Education (ref: no tertiary)	0.935	0.911	0.960	0.000
Nights worked per month	1.033	1.030	1.036	0.000
Log Likelihood	-67810.752			
	Model 5			
Parameter	OR	95% CI		p

Intercept	0.420	0.400	0.442	0.000
Sex (ref: male)	1.223	1.192	1.254	0.000
Age	1.005	1.004	1.006	0.000
Has Tertiary Education (ref: no tertiary)	0.945	0.920	0.970	0.000
Nights worked per month	1.029	1.025	1.032	0.000
Works shifts (ref: no)	1.172	1.134	1.211	0.000
Log Likelihood	-67766.280			

	Model 6			
Parameter	OR	95% CI		p
Intercept	0.190	0.177	0.204	0.000
Sex (ref: male)	1.363	1.327	1.400	0.000
Age	1.005	1.004	1.006	0.000
Has Tertiary Education (ref: no tertiary)	0.956	0.931	0.982	0.001
Nights worked per month	1.019	1.016	1.023	0.000
Works shifts (ref: no)	1.182	1.143	1.221	0.000
Hours per week worked	1.019	1.018	1.020	0.000
Log Likelihood	-67144.302			

	Model 7			
Parameter	OR	95% CI		p
Intercept	0.200	0.186	0.214	0.000
Sex (ref: male)	1.360	1.325	1.397	0.000
Age	1.005	1.004	1.006	0.000
Has Tertiary Education (ref: no tertiary)	0.977	0.951	1.004	0.090
Nights worked per month	1.019	1.016	1.023	0.000
Works shifts (ref: no)	1.163	1.125	1.203	0.000
Hours per week worked	1.019	1.018	1.020	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.838	0.795	0.882	0.000
Adaptable within limits	0.812	0.783	0.843	0.000
Entirely self-determined	0.946	0.912	0.982	0.004
Log Likelihood	-67068.038			

	Model 8			
Parameter	OR	95% CI		p
Intercept	0.190	0.177	0.204	0.000
Sex (ref: male)	1.363	1.327	1.400	0.000
Age	1.006	1.005	1.007	0.000
Has Tertiary Education (ref: no tertiary)	0.968	0.942	0.994	0.018
Nights worked per month	1.019	1.016	1.023	0.000
Works shifts (ref: no)	1.163	1.125	1.203	0.000
Hours per week worked	1.019	1.018	1.020	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.837	0.794	0.881	0.000
Adaptable within limits	0.810	0.781	0.841	0.000
Entirely self-determined	0.945	0.910	0.981	0.003
Skill-demand match (ref: they match)				

Demands too low	1.064	1.034	1.095	0.000
Demands too high	1.159	1.114	1.206	0.000
Log Likelihood	-67038.726			

Model 9

Parameter	OR	95% CI		p
Intercept	0.194	0.180	0.209	0.000
Sex (ref: male)	1.297	1.263	1.333	0.000
Age	1.005	1.004	1.006	0.000
Has Tertiary Education (ref: no tertiary)	1.023	0.995	1.051	0.107
Nights worked per month	1.017	1.014	1.021	0.000
Works shifts (ref: no)	1.120	1.082	1.159	0.000
Hours per week worked	1.018	1.017	1.019	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.871	0.826	0.918	0.000
Adaptable within limits	0.860	0.829	0.893	0.000
Entirely self-determined	0.994	0.957	1.032	0.745
Skill-demand match (ref: they match)				
Demands too low	1.033	1.003	1.063	0.028
Demands too high	1.130	1.085	1.176	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.668	1.612	1.726	0.000
Agree	0.773	0.747	0.799	0.000
Log Likelihood	-65731.661			

Table A.9: Intermediate Models for Headache and/or Eyestrain in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.528	0.521	0.534	0.000
Log Likelihood	-66355.226			

Model 1

Parameter	OR	95% CI		p
Intercept	0.416	0.408	0.424	0.000
Sex (ref: male)	1.586	1.545	1.627	0.000
Log Likelihood	-65742.131			

Model 2

Parameter	OR	95% CI		p
Intercept	0.389	0.370	0.409	0.000
Sex (ref: male)	1.585	1.545	1.627	0.000
Age	1.002	1.001	1.003	0.004
Log Likelihood	-65738.087			

Model 3

Parameter	OR	95% CI		p
Intercept	0.379	0.360	0.399	0.000
Sex (ref: male)	1.576	1.535	1.617	0.000

Age	1.002	1.001	1.003	0.004
Has Tertiary Education (ref: no tertiary)	1.074	1.046	1.103	0.000
Log Likelihood	-65724.152			

Model 4

Parameter	OR	95% CI		p
Intercept	0.362	0.344	0.381	0.000
Sex (ref: male)	1.602	1.561	1.645	0.000
Age	1.002	1.001	1.003	0.001
Has Tertiary Education (ref: no tertiary)	1.080	1.052	1.110	0.000
Nights worked per month	1.019	1.016	1.022	0.000
Log Likelihood	-65661.669			

Model 5

Parameter	OR	95% CI		p
Intercept	0.353	0.335	0.372	0.000
Sex (ref: male)	1.595	1.554	1.638	0.000
Age	1.002	1.001	1.003	0.000
Has Tertiary Education (ref: no tertiary)	1.087	1.059	1.117	0.000
Nights worked per month	1.016	1.013	1.020	0.000
Works shifts (ref: no)	1.103	1.067	1.141	0.000
Log Likelihood	-65645.389			

Model 6

Parameter	OR	95% CI		p
Intercept	0.217	0.202	0.232	0.000
Sex (ref: male)	1.707	1.662	1.754	0.000
Age	1.002	1.001	1.003	0.000
Has Tertiary Education (ref: no tertiary)	1.096	1.067	1.125	0.000
Nights worked per month	1.010	1.007	1.014	0.000
Works shifts (ref: no)	1.108	1.071	1.146	0.000
Hours per week worked	1.012	1.011	1.013	0.000
Log Likelihood	-65410.801			

Model 7

Parameter	OR	95% CI		p
Intercept	0.217	0.202	0.233	0.000
Sex (ref: male)	1.702	1.656	1.748	0.000
Age	1.002	1.001	1.003	0.000
Has Tertiary Education (ref: no tertiary)	1.097	1.068	1.127	0.000
Nights worked per month	1.010	1.007	1.014	0.000
Works shifts (ref: no)	1.092	1.055	1.130	0.000
Hours per week worked	1.012	1.011	1.013	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.969	0.919	1.020	0.230
Adaptable within limits	0.973	0.938	1.009	0.145
Entirely self-determined	0.907	0.873	0.943	0.000
Log Likelihood	-65398.174			

	Model 8			
Parameter	OR	95% CI		p
Intercept	0.206	0.192	0.221	0.000
Sex (ref: male)	1.704	1.659	1.751	0.000
Age	1.003	1.002	1.004	0.000
Has Tertiary Education (ref: no tertiary)	1.083	1.054	1.113	0.000
Nights worked per month	1.010	1.007	1.014	0.000
Works shifts (ref: no)	1.092	1.055	1.130	0.000
Hours per week worked	1.012	1.011	1.013	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.967	0.918	1.018	0.202
Adaptable within limits	0.969	0.934	1.005	0.094
Entirely self-determined	0.907	0.873	0.943	0.000
Skill-demand match (ref: they match)				
Demands too low	1.036	1.006	1.067	0.017
Demands too high	1.254	1.204	1.305	0.000
Log Likelihood	-65337.685			

	Model 9			
Parameter	OR	95% CI		p
Intercept	0.206	0.191	0.222	0.000
Sex (ref: male)	1.651	1.606	1.696	0.000
Age	1.002	1.001	1.003	0.000
Has Tertiary Education (ref: no tertiary)	1.123	1.093	1.155	0.000
Nights worked per month	1.009	1.006	1.013	0.000
Works shifts (ref: no)	1.062	1.026	1.099	0.001
Hours per week worked	1.011	1.010	1.012	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.995	0.944	1.049	0.857
Adaptable within limits	1.010	0.974	1.048	0.587
Entirely self-determined	0.938	0.902	0.975	0.001
Skill-demand match (ref: they match)				
Demands too low	1.015	0.985	1.045	0.336
Demands too high	1.231	1.182	1.282	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.453	1.403	1.505	0.000
Agree	0.868	0.839	0.898	0.000
Log Likelihood	-64758.298			

Table A.10: Intermediate Models for Injury(ies) in the last 12 months

Model 0				
Parameter	OR	95% CI		p
Intercept	0.093	0.091	0.095	0.000
Log Likelihood	-29861.541			

	Model 1			

Parameter	OR	95% CI		p
Intercept	0.125	0.122	0.129	0.000
Sex (ref: male)	0.492	0.470	0.515	0.000
Log Likelihood	-29383.568			

Model 2

Parameter	OR	95% CI		p
Intercept	0.185	0.171	0.201	0.000
Sex (ref: male)	0.493	0.471	0.516	0.000
Age	0.990	0.989	0.992	0.000
Log Likelihood	-29334.056			

Model 3

Parameter	OR	95% CI		p
Intercept	0.212	0.195	0.230	0.000
Sex (ref: male)	0.512	0.489	0.537	0.000
Age	0.991	0.989	0.993	0.000
Has Tertiary Education (ref: no tertiary)	0.612	0.582	0.643	0.000
Log Likelihood	-29133.249			

Model 4

Parameter	OR	95% CI		p
Intercept	0.200	0.184	0.217	0.000
Sex (ref: male)	0.524	0.500	0.548	0.000
Age	0.991	0.989	0.993	0.000
Has Tertiary Education (ref: no tertiary)	0.617	0.587	0.648	0.000
Nights worked per month	1.023	1.018	1.028	0.000
Log Likelihood	-29091.440			

Model 5

Parameter	OR	95% CI		p
Intercept	0.189	0.174	0.205	0.000
Sex (ref: male)	0.518	0.494	0.543	0.000
Age	0.991	0.990	0.993	0.000
Has Tertiary Education (ref: no tertiary)	0.626	0.596	0.658	0.000
Nights worked per month	1.018	1.013	1.023	0.000
Works shifts (ref: no)	1.238	1.172	1.307	0.000
Log Likelihood	-29062.645			

Model 6

Parameter	OR	95% CI		p
Intercept	0.141	0.126	0.158	0.000
Sex (ref: male)	0.539	0.514	0.565	0.000
Age	0.991	0.989	0.993	0.000
Has Tertiary Education (ref: no tertiary)	0.630	0.600	0.662	0.000
Nights worked per month	1.014	1.009	1.019	0.000
Works shifts (ref: no)	1.247	1.181	1.317	0.000
Hours per week worked	1.007	1.005	1.009	0.000
Log Likelihood	-29031.824			

	Model 7			
Parameter	OR	95% CI		p
Intercept	0.141	0.126	0.158	0.000
Sex (ref: male)	0.539	0.514	0.565	0.000
Age	0.991	0.989	0.993	0.000
Has Tertiary Education (ref: no tertiary)	0.629	0.598	0.662	0.000
Nights worked per month	1.014	1.009	1.019	0.000
Works shifts (ref: no)	1.251	1.183	1.322	0.000
Hours per week worked	1.007	1.005	1.009	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.019	0.932	1.114	0.677
Adaptable within limits	1.014	0.951	1.082	0.664
Entirely self-determined	1.016	0.953	1.083	0.628
Log Likelihood	-29031.597			

	Model 8			
Parameter	OR	95% CI		p
Intercept	0.127	0.113	0.142	0.000
Sex (ref: male)	0.541	0.516	0.567	0.000
Age	0.992	0.990	0.994	0.000
Has Tertiary Education (ref: no tertiary)	0.618	0.588	0.650	0.000
Nights worked per month	1.014	1.009	1.019	0.000
Works shifts (ref: no)	1.249	1.181	1.321	0.000
Hours per week worked	1.007	1.005	1.009	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.967	1.018	0.931	0.702
Adaptable within limits	0.969	1.010	0.946	0.764
Entirely self-determined	0.907	1.011	0.948	0.742
Skill-demand match (ref: they match)				
Demands too low	1.190	1.133	1.250	0.000
Demands too high	1.278	1.195	1.367	0.000
Log Likelihood	-28993.317			

	Model 9			
Parameter	OR	95% CI		p
Intercept	0.124	0.110	0.141	0.000
Sex (ref: male)	0.516	0.492	0.541	0.000
Age	0.991	0.989	0.993	0.000
Has Tertiary Education (ref: no tertiary)	0.645	0.613	0.678	0.000
Nights worked per month	1.012	1.007	1.018	0.000
Works shifts (ref: no)	1.215	1.148	1.285	0.001
Hours per week worked	1.006	1.004	1.008	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.056	0.965	1.155	0.238
Adaptable within limits	1.063	0.996	1.135	0.065
Entirely self-determined	1.049	0.984	1.119	0.146
Skill-demand match (ref: they match)				

Demands too low	1.162	1.106	1.221	0.000
Demands too high	1.252	1.170	1.340	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.565	1.476	1.659	0.000
Agree	0.853	0.803	0.907	0.000
Log Likelihood	-28706.716			

Appendix B

BHPS Single Level Intermediate Models

Table B.1: Intermediate Models for Health Status

Model 0				
	OR	95% CI		p
Intercept	2.832	2.795	2.869	0.000
Log Likelihood		-66118.007		
	Model 1			
	OR	95% CI		p
Intercept	3.015	2.957	3.074	0.000
Sex (ref: male)	0.888	0.894	0.949	0.000
Log Likelihood		-66079.092		
	Model 2			
	OR	95% CI		p
Intercept	3.811	3.642	3.988	0.000
Sex (ref: male)	0.888	0.865	0.912	0.000
Age	0.994	0.993	0.995	0.000
Log Likelihood		-66015.778		
	Model 3			
	OR	95% CI		p
Intercept	3.591	3.431	3.759	0.000
Sex (ref: male)	0.891	0.868	0.915	0.000
Age	0.994	0.993	0.995	0.000
Has Tertiary Education (ref: no tertiary)	1.401	1.349	1.455	0.000
Log Likelihood		-65857.233		
	Model 4			
	OR	95% CI		p
Intercept	3.058	2.914	3.210	0.000
Sex (ref: male)	0.987	0.959	1.015	0.351

Age	0.992	0.991	0.993	0.000
Has Tertiary Education (ref: no tertiary)	1.219	1.171	1.270	0.000
Gross monthly pay (GBP)	1.000156	1.00014	1.000173	0.000
Log Likelihood		-65668.783		

	Model 5			
	OR	95% CI		p
Intercept	3.637	3.410	3.880	0.000
Sex (ref: male)	0.955	0.927	0.984	0.002
Age	0.992	0.991	0.993	0.000
Has Tertiary Education (ref: no tertiary)	1.201	1.153	1.251	0.000
Gross monthly pay (GBP)	1.000185	1.000167	1.000204	0.000
Job hours per week	0.995	0.993	0.996	0.000
Log Likelihood		-65636.614		

	Model 6			
	OR	95% CI		p
Intercept	3.647	3.418	3.891	0.000
Sex (ref: male)	0.956	0.928	0.984	0.003
Age	0.992	0.991	0.993	0.000
Has Tertiary Education (ref: no tertiary)	1.202	1.154	1.252	0.000
Gross monthly pay (GBP)	1.000186	1.000168	1.000204	0.000
Job hours per week	0.995	0.993	0.996	0.000
Works flexitime (ref: Not mentioned)	0.976	0.938	1.015	0.218
Log Likelihood		-65635.859		

	Model 7			
	OR	95% CI		p
Intercept	3.304	0.910	0.965	0.000
Sex (ref: male)	0.937	0.991	0.993	0.000
Age	0.992	0.99	0.992	0.000
Has Tertiary Education (ref: no tertiary)	1.223	1.174	1.274	0.000
Gross monthly pay (GBP)	1.000149	1.000131	1.000167	0.000
Job hours per week	0.996	0.995	0.998	0.000
Works flexitime (ref: Not mentioned)	0.973	0.936	1.012	0.168
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)				
Not satisfied	0.764	0.709	0.824	0.000
Not very satisfied	0.919	0.872	0.969	0.002
Satisfied	1.183	1.127	1.241	0.000
Very Satisfied	1.311	1.231	1.396	0.000
Log Likelihood		-65435.446		

Table B.2: Intermediate Models for Health Problems with the Limbs or Muscles

Model 0

	OR	95% CI		p
Intercept	0.199	0.196	0.202	0.000
Log Likelihood		-51767.204		

	Model 1			
	OR	95% CI		p
Intercept	0.189	0.185	0.193	0.000
Sex (ref: male)	1.102	1.068	1.137	0.000
Log Likelihood		-51748.576		
	Model 2			
	OR	95% CI		p
Intercept	0.027	0.026	0.029	0.000
Sex (ref: male)	1.108	1.073	1.144	0.000
Age	1.049	1.048	1.051	0.000
Log Likelihood		-49112.354		
	Model 3			
	OR	95% CI		p
Intercept	0.029	0.027	0.031	0.000
Sex (ref: male)	1.103	1.068	1.139	0.000
Age	1.049	1.048	1.050	0.000
Has Tertiary Education (ref: no tertiary)	0.748	0.714	0.784	0.000
Log Likelihood		-49034.168		
	Model 4			
	OR	95% CI		p
Intercept	0.032	0.030	0.035	0.000
Sex (ref: male)	1.037	1.001	1.073	0.041
Age	1.050	1.048	1.051	0.000
Has Tertiary Education (ref: no tertiary)	0.812	0.773	0.853	0.000
Gross monthly pay (GBP)	0.999914	0.9998955	0.9999324	0.000
Log Likelihood		-48989.043		
	Model 5			
	OR	95% CI		p
Intercept	0.029	0.027	0.032	0.000
Sex (ref: male)	1.058	1.020	1.096	0.002
Age	1.050	1.049	1.051	0.000
Has Tertiary Education (ref: no tertiary)	0.820	0.780	0.861	0.000
Gross monthly pay (GBP)	0.9999001	0.99988	0.9999201	0.000
Job hours per week	1.003	1.001	1.005	0.000
Log Likelihood		-48982.202		
	Model 6			
	OR	95% CI		p
Intercept	0.029	0.027	0.032	0.000
Sex (ref: male)	1.056	1.019	1.095	0.003
Age	1.050	1.049	1.051	0.000
Has Tertiary Education (ref: no tertiary)	0.818	0.778	0.860	0.000
Gross monthly pay (GBP)	0.999899	0.9998789	0.9999191	0.000
Job hours per week	1.003	1.001	1.005	0.000
Works flexitime (ref: Not mentioned)	1.052	1.005	1.103	0.031

Log Likelihood		-48979.903		

Model 7

	OR	95% CI		p
Intercept	0.030	0.028	0.034	0.000
Sex (ref: male)	1.072	1.034	1.112	0.000
Age	1.050	1.049	1.052	0.000
Has Tertiary Education (ref: no tertiary)	0.809	0.770	0.850	0.000
Gross monthly pay (GBP)	0.9999247	0.9999046	0.9999449	0.000
Job hours per week	1.002	1.000	1.003	0.040
Works flexitime (ref: Not mentioned)	1.055	1.007	1.105	0.024
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)				
Not satisfied	1.302	1.188	1.426	0.000
Not very satisfied	1.103	1.033	1.177	0.003
Satisfied	0.898	0.846	0.952	0.000
Very Satisfied	0.858	0.795	0.925	0.000
Log Likelihood		-48894.029		

Table B.3: Intermediate Models for Health Problems relating to Anxiety/Depression

Model 0

	OR	95% CI		p
Intercept	0.050	0.049	0.052	0.000
Log Likelihood		-22095.716		

Model 1

	OR	95% CI		p
Intercept	0.029	0.028	0.031	0.000
Sex (ref: male)	2.417	2.277	2.566	0.000
Log Likelihood		-21636.989		

Model 2

	OR	95% CI		p
Intercept	0.017	0.015	0.018	0.000
Sex (ref: male)	2.420	2.279	2.569	0.000
Age	1.015	1.012	1.017	0.000
Log Likelihood		-21555.888		

Model 3

	OR	95% CI		p
Intercept	0.017	0.015	0.019	0.000
Sex (ref: male)	2.419	2.278	2.568	0.000
Age	1.015	1.012	1.017	0.000
Has Tertiary Education (ref: no tertiary)	0.968	0.898	1.043	0.391
Log Likelihood		-21555.518		

Model 4

	OR	95% CI		p
Intercept	0.021	0.018	0.023	0.000

Sex (ref: male)	2.159	2.024	2.301	0.000
Age	1.016	1.014	1.018	0.000
Has Tertiary Education (ref: no tertiary)	1.128	1.040	1.224	0.004
Gross monthly pay (GBP)	0.9998258	0.9997888	0.9998627	0.000
Log Likelihood		-21508.502		
	Model 5			
	OR	95% CI		p
Intercept	0.022	0.019	0.025	0.000
Sex (ref: male)	2.130	1.995	2.275	0.000
Age	1.016	1.014	1.018	0.000
Has Tertiary Education (ref: no tertiary)	1.119	1.031	1.214	0.007
Gross monthly pay (GBP)	0.9998426	0.9998016	0.9998836	0
Job hours per week	0.998	0.995	1.000	0.076
Log Likelihood		-21506.935		
	Model 6			
	OR	95% CI		p
Intercept	0.022	0.019	0.025	0.000
Sex (ref: male)	2.125	1.990	2.269	0.000
Age	1.016	1.014	1.018	0.000
Has Tertiary Education (ref: no tertiary)	1.116	1.029	1.211	0.008
Gross monthly pay (GBP)	0.9998399	0.9997987	0.999881	0
Job hours per week	0.998	0.995	1.000	0.083
Works flexitime (ref: Not mentioned)	1.094	1.012	1.182	0.024
Log Likelihood		-21504.427		
	Model 7			
	OR	95% CI		p
Intercept	0.023	0.019	0.027	0.000
Sex (ref: male)	2.178	2.040	2.327	0.000
Age	1.016	1.014	1.018	0.000
Has Tertiary Education (ref: no tertiary)	1.089	1.004	1.182	0.041
Gross monthly pay (GBP)	0.9998932	0.9998523	0.999934	0
Job hours per week	0.995	0.992	0.997	0.000
Works flexitime (ref: Not mentioned)	1.100	1.017	1.189	0.017
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)				
Not satisfied	1.705	1.477	1.969	0.000
Not very satisfied	1.249	1.118	1.396	0.000
Satisfied	0.878	0.793	0.973	0.013
Very Satisfied	0.811	0.711	0.925	0.002
Log Likelihood		-21406.552		

Appendix C

EWCS Multilevel Intermediate Models

Table C.1: Intermediate Models for Health Status

Model 0				
Parameter	OR	95% CI		p
Intercept	0.699	0.585	0.865	0.000
DIC		128846.000		
pD		64.350		
Random part	Mean	95% CI		SD
Country variance	0.164	0.100	0.260	0.042
Year variance	0.023	0.002	0.108	0.093
Occupation variance (ISCO 88 2 digit)	0.144	0.080	0.251	0.045
MOR Country Level	1.196			
ICC Country Level	0.045			
MOR Year Level	0.834			
ICC Year Level	0.006			
MOR Occupation Level	1.153			
ICC Occupation Level	0.040			
	Model 1			
Parameter	OR	95% CI		p
Intercept	0.813	0.652	1.030	0.032
Sex (ref: male)	1.013	0.985	1.042	0.187
DIC		128845.910		
pD		64.830		
Random part	Mean	95% CI		SD
Country variance	0.165	0.103	0.263	0.042
Year variance	0.028	0.002	0.143	0.086
Occupation variance (ISCO 88 2 digit)	0.140	0.079	0.244	0.043
MOR Country Level	1.197			
ICC Country Level	0.045			
MOR Year Level	0.855			
ICC Year Level	0.008			
MOR Occupation Level	1.145			

ICC Occupation Level	0.039			
	Model 2			
Parameter	OR	95% CI		p
Intercept	0.515	0.437	0.597	0.000
Sex (ref: male)	1.013	0.982	1.042	0.194
Age	1.010	1.009	1.011	0.000
DIC		128562.490		
pD		66.020		
Random part	Mean	95% CI		SD
Country variance	0.164	0.102	0.269	0.043
Year variance	0.026	0.002	0.121	0.131
Occupation variance (ISCO 88 2 digit)	0.133	0.076	0.229	0.040
MOR Country Level	1.196			
ICC Country Level	0.045			
MOR Year Level	0.847			
ICC Year Level	0.007			
MOR Occupation Level	1.131			
ICC Occupation Level	0.037			
	Model 3			
Parameter	OR	95% CI		p
Intercept	0.481	0.418	0.543	0.000
Sex (ref: male)	1.013	0.983	1.044	0.214
Age	1.010	1.009	1.011	0.000
Has Tertiary Education (ref: no tertiary)	1.013	0.980	1.047	0.220
DIC		128563.700		
pD		66.920		
Random Part	Mean	95% CI		SD
Country variance	0.162	0.101	0.257	0.040
Year variance	0.029	0.002	0.158	0.093
Occupation variance (ISCO 88 2 digit)	0.135	0.077	0.237	0.041
MOR Country Level	1.191			
ICC Country Level	0.045			
MOR Year Level	0.857			
ICC Year Level	0.008			
MOR Occupation Level	1.134			
ICC Occupation Level	0.037			
	Model 4			
Parameter	OR	95% CI		p
Intercept	0.407	0.387	0.428	0.000
Sex (ref: male)	0.906	0.883	0.929	0.000
Age	1.012	1.011	1.013	0.000
Has Tertiary Education (ref: no tertiary)	0.960	0.935	0.986	0.002
Nights worked per month	1.045	1.042	1.049	0.000
DIC		127968.670		
pD		68.460		

Random Part	Mean	95% CI		SD
Country variance	0.165	0.103	0.264	0.042
Year variance	0.027	0.002	0.138	0.115
Occupation variance (ISCO 88 2 digit)	0.133	0.075	0.230	0.040
MOR Country Level	1.198			
ICC Country Level	0.046			
MOR Year Level	0.852			
ICC Year Level	0.008			
MOR Occupation Level	1.130			
ICC Occupation Level	0.037			
	Model 5			
Parameter	OR	95% CI		p
Intercept	0.376	0.387	0.396	0.000
Sex (ref: male)	0.892	0.883	0.915	0.000
Age	1.013	1.012	1.014	0.000
Has Tertiary Education (ref: no tertiary)	0.980	0.954	1.006	0.130
Nights worked per month	1.036	1.033	1.040	0.000
Works shifts (ref: no)	1.366	1.321	1.412	0.000
DIC		127783.040		
pD		69.080		
Random Part	Mean	95% CI		SD
Country variance	0.158	0.098	0.256	0.041
Year variance	0.033	0.002	0.189	0.190
Occupation variance (ISCO 88 2 digit)	0.128	0.073	0.221	0.038
MOR Country Level	1.183			
ICC Country Level	0.044			
MOR Year Level	0.872			
ICC Year Level	0.009			
MOR Occupation Level	1.120			
ICC Occupation Level	0.036			
	Model 6			
Parameter	OR	95% CI		p
Intercept	0.213	0.387	0.228	0.000
Sex (ref: male)	0.962	0.937	0.988	0.005
Age	1.013	1.012	1.014	0.000
Has Tertiary Education (ref: no tertiary)	0.989	0.963	1.015	0.397
Nights worked per month	1.030	1.026	1.033	0.000
Works shifts (ref: no)	1.374	1.330	1.421	0.000
Hours per week worked	1.014	1.013	1.015	0.000
DIC		127252.690		
pD		70.030		
Random Part	Mean	95% CI		SD
Country variance	0.157	0.096	0.251	0.041
Year variance	0.023	0.002	0.109	0.124
Occupation variance (ISCO 88 2 digit)	0.131	0.074	0.228	0.040
MOR Country Level	1.181			

ICC Country Level	0.044			
MOR Year Level	0.837			
ICC Year Level	0.006			
MOR Occupation Level	1.126			
ICC Occupation Level	0.037			

	Model 7			
Parameter	OR	95% CI		p
Intercept	0.217	0.203	0.233	0.000
Sex (ref: male)	0.963	0.937	0.989	0.005
Age	1.013	1.012	1.014	0.000
Has Tertiary Education (ref: no tertiary)	0.994	0.968	1.021	0.657
Nights worked per month	1.030	1.026	1.033	0.000
Works shifts (ref: no)	1.376	1.330	1.423	0.000
Hours per week worked	1.013	1.012	1.015	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.885	0.840	0.932	0.000
Adaptable within limits	0.956	0.922	0.992	0.016
Entirely self-determined	0.987	0.951	1.025	0.492
DIC		127256.040		
pD		72.650		
Random part	Mean	95% CI		SD
Country variance	0.159	0.097	0.254	0.041
Year variance	0.019	0.002	0.090	0.062
Occupation variance (ISCO 88 2 digit)	0.133	0.076	0.228	0.040
MOR Country Level	1.185			
ICC Country Level	0.044			
MOR Year Level	0.820			
ICC Year Level	0.005			
MOR Occupation Level	1.130			
ICC Occupation Level	0.037			

	Model 8			
Parameter	OR	95% CI		p
Intercept	0.192	0.179	0.206	0.000
Sex (ref: male)	0.966	0.941	0.992	0.011
Age	1.014	1.013	1.015	0.000
Has Tertiary Education (ref: no tertiary)	0.970	0.944	0.996	0.250
Nights worked per month	1.030	1.026	1.033	0.000
Works shifts (ref: no)	1.377	1.331	1.425	0.000
Hours per week worked	1.013	1.012	1.015	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.881	0.837	0.929	0.000
Adaptable within limits	0.950	0.916	0.985	0.006
Entirely self-determined	0.985	0.949	1.023	0.430
Skill-demand match (ref: they match)				
Demands too low	1.151	1.119	1.184	0.000
Demands too high	1.500	1.441	1.561	0.000

DIC		126838.900		
pD		74.780		
Random Part	Mean	95% CI		SD
Country variance	0.155	0.096	0.246	0.039
Year variance	0.020	0.002	0.096	0.096
Occupation variance (ISCO 88 2 digit)	0.136	0.077	0.230	0.041
MOR Country Level	1.177			
ICC Country Level	0.043			
MOR Year Level	0.823			
ICC Year Level	0.006			
MOR Occupation Level	1.135			
ICC Occupation Level	0.038			
	Model 9			
Parameter	OR	95% CI		p
Intercept	0.178	0.165	0.192	0.000
Sex (ref: male)	0.908	0.883	0.933	0.011
Age	1.013	1.012	1.014	0.000
Has Tertiary Education (ref: no tertiary)	1.025	0.997	1.053	0.081
Nights worked per month	1.028	1.024	1.032	0.000
Works shifts (ref: no)	1.329	1.284	1.376	0.000
Hours per week worked	1.012	1.011	1.013	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.921	0.874	0.972	0.002
Adaptable within limits	1.013	0.976	1.051	0.500
Entirely self-determined	1.038	1.000	1.079	0.053
Skill-demand match (ref: they match)				
Demands too low	1.116	1.084	1.149	0.000
Demands too high	1.466	1.407	1.526	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.946	1.879	2.015	0.000
Agree	0.860	0.832	0.890	0.000
DIC		124309.850		
pD		76.620		
Random Part	Mean	95%CI		SD
Country variance	0.153	0.094	0.244	0.039
Year variance	0.023	0.002	0.107	0.126
Occupation variance (ISCO 88 2 digit)	0.114	0.066	0.199	0.035
MOR Country Level	1.172			
ICC Country Level	0.043			
MOR Year Level	0.837			
ICC Year Level	0.007			
MOR Occupation Level	1.088			
ICC Occupation Level	0.032			

Table C.2: Intermediate Models for Skin Problems in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.080	0.069	0.096	0.000
DIC		55743.480		
pD		60.930		
Random part	Mean	95% CI		SD
Country variance	0.151	0.090	0.246	0.040
Year variance	0.017	0.001	0.088	0.051
Occupation variance (ISCO 88 2 digit)	0.099	0.054	0.175	0.031
MOR Country Level	1.169			
ICC Country Level	0.043			
MOR Year Level	0.809			
ICC Year Level	0.005			
MOR Occupation Level	1.052			
ICC Occupation Level	0.028			

Model 1

Parameter	OR	95% CI		p
Intercept	0.066	0.055	0.083	0.000
Sex (ref: male)	1.403	1.331	1.477	0.000
DIC		55591.510		
pD		62.930		
Random part	Mean	95% CI		SD
Country variance	0.147	0.087	0.241	0.040
Year variance	0.032	0.001	0.178	0.276
Occupation variance (ISCO 88 2 digit)	0.114	0.063	0.199	0.036
MOR Country Level	1.160			
ICC Country Level	0.041			
MOR Year Level	0.870			
ICC Year Level	0.009			
MOR Occupation Level	1.088			
ICC Occupation Level	0.032			

Model 2

Parameter	OR	95% CI		p
Intercept	0.092	0.073	0.109	0.000
Sex (ref: male)	1.408	1.331	1.485	0.000
Age	0.993	0.990	0.995	0.000
DIC		55539.680		
pD		63.710		
Random part	Mean	95% CI		SD
Country variance	0.149	0.089	0.245	0.040
Year variance	0.015	0.001	0.080	0.042
Occupation variance (ISCO 88 2 digit)	0.115	0.064	0.198	0.035
MOR Country Level	1.164			
ICC Country Level	0.042			
MOR Year Level	0.801			

ICC Year Level	0.004			
MOR Occupation Level	1.090			
ICC Occupation Level	0.032			

Model 3

Parameter	OR	95% CI		p
Intercept	0.097	0.076	0.115	0.000
Sex (ref: male)	1.406	1.334	1.482	0.000
Age	0.993	0.991	0.995	0.000
Has Tertiary Education (ref: no tertiary)	0.988	0.932	1.046	0.333
DIC		55541.110		
pD		64.300		
Random Part	Mean	95% CI		SD
Country variance	0.151	0.091	0.248	0.041
Year variance	0.020	0.001	0.105	0.118
Occupation variance (ISCO 88 2 digit)	0.113	0.062	0.198	0.036
MOR Country Level	1.169			
ICC Country Level	0.042			
MOR Year Level	0.824			
ICC Year Level	0.006			
MOR Occupation Level	1.085			
ICC Occupation Level	0.032			

Model 4

Parameter	OR	95% CI		p
Intercept	0.083	0.070	0.105	0.000
Sex (ref: male)	1.445	1.370	1.527	0.000
Age	0.993	0.991	0.994	0.000
Has Tertiary Education (ref: no tertiary)	0.994	0.936	1.053	0.422
Nights worked per month	1.025	1.020	1.031	0.000
DIC		55464.120		
pD		65.240		
Random Part	Mean	95% CI		SD
Country variance	0.151	0.089	0.250	0.041
Year variance	0.016	0.001	0.081	0.080
Occupation variance (ISCO 88 2 digit)	0.114	0.062	0.204	0.037
MOR Country Level	1.168			
ICC Country Level	0.042			
MOR Year Level	0.808			
ICC Year Level	0.005			
MOR Occupation Level	1.088			
ICC Occupation Level	0.032			

Model 5

Parameter	OR	95% CI		p
Intercept	0.085	0.075	0.101	0.000
Sex (ref: male)	1.441	1.363	1.525	0.000
Age	0.993	0.992	0.995	0.000

Has Tertiary Education (ref: no tertiary)	0.995	0.937	1.052	0.432
Nights worked per month	1.021	1.016	1.027	0.000
Works shifts (ref: no)	1.199	1.126	1.272	0.000
DIC		55433.390		
pD		66.060		
Random Part	Mean	95% CI		SD
Country variance	0.151	0.091	0.244	0.040
Year variance	0.019	0.001	0.101	0.068
Occupation variance (ISCO 88 2 digit)	0.107	0.059	0.187	0.033
MOR Country Level	1.168			
ICC Country Level	0.042			
MOR Year Level	0.818			
ICC Year Level	0.005			
MOR Occupation Level	1.072			
ICC Occupation Level	0.030			

Model 6

Parameter	OR	95% CI		p
Intercept	0.067	0.057	0.078	0.000
Sex (ref: male)	1.467	1.390	1.544	0.000
Age	0.993	0.991	0.995	0.000
Has Tertiary Education (ref: no tertiary)	0.995	0.937	1.052	0.437
Nights worked per month	1.019	1.013	1.025	0.000
Works shifts (ref: no)	1.198	1.128	1.269	0.000
Hours per week worked	1.005	1.003	1.007	0.000
DIC		55410.430		
pD		67.410		
Random Part	Mean	95% CI		SD
Country variance	0.157	0.094	0.257	0.042
Year variance	0.022	0.001	0.098	0.212
Occupation variance (ISCO 88 2 digit)	0.110	0.060	0.199	0.036
MOR Country Level	1.181			
ICC Country Level	0.044			
MOR Year Level	0.832			
ICC Year Level	0.006			
MOR Occupation Level	1.079			
ICC Occupation Level	0.031			

Model 7

Parameter	OR	95% CI		p
Intercept	0.066	0.048	0.080	0.000
Sex (ref: male)	1.469	1.394	1.549	0.000
Age	0.993	0.991	0.995	0.000
Has Tertiary Education (ref: no tertiary)	0.983	0.923	1.037	0.280
Nights worked per month	1.019	1.014	1.025	0.000
Works shifts (ref: no)	1.206	1.132	1.275	0.000
Hours per week worked	1.005	1.003	1.007	0.000
Working time arrangement (ref: set by company)				

Choice between several fixed schedules	1.013	0.928	1.098	0.400
Adaptable within limits	1.138	1.066	1.213	0.001
Entirely self-determined	0.999	0.930	1.073	0.504
DIC		55399.190		
pD		69.630		
Random Part	Mean	95% CI		SD
Country variance	0.157	0.093	0.264	0.041
Year variance	0.021	0.001	0.115	0.062
Occupation variance (ISCO 88 2 digit)	0.113	0.062	0.202	0.040
MOR Country Level	1.181			
ICC Country Level	0.044			
MOR Year Level	0.827			
ICC Year Level	0.006			
MOR Occupation Level	1.085			
ICC Occupation Level	0.032			

	Model 8			
Parameter	OR	95% CI		p
Intercept	0.054	0.041	0.065	0.000
Sex (ref: male)	1.483	1.406	1.557	0.000
Age	0.994	0.992	0.996	0.000
Has Tertiary Education (ref: no tertiary)	0.970	0.916	1.031	0.151
Nights worked per month	1.019	1.013	1.025	0.000
Works shifts (ref: no)	1.207	1.138	1.279	0.000
Hours per week worked	1.005	1.003	1.007	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.012	0.917	1.106	0.396
Adaptable within limits	1.139	1.066	1.218	0.000
Entirely self-determined	0.993	0.920	1.069	0.432
Skill-demand match (ref: they match)				
Demands too low	1.242	1.178	1.313	0.000
Demands too high	1.436	1.341	1.537	0.000
DIC		55268.810		
pD		72.500		
Random Part	Mean	95% CI		SD
Country variance	0.149	0.090	0.248	0.040
Year variance	0.019	0.001	0.089	0.140
Occupation variance (ISCO 88 2 digit)	0.116	0.064	0.201	0.035
MOR Country Level	1.164			
ICC Country Level	0.042			
MOR Year Level	0.819			
ICC Year Level	0.005			
MOR Occupation Level	1.092			
ICC Occupation Level	0.032			

		Model 9			
Parameter		OR	95% CI		p
Intercept		0.051	0.041	0.065	0.000

Sex (ref: male)	1.424	1.348	1.507	0.000
Age	0.993	0.991	0.995	0.000
Has Tertiary Education (ref: no tertiary)	0.988	0.930	1.048	0.343
Nights worked per month	1.018	1.012	1.024	0.000
Works shifts (ref: no)	1.175	1.101	1.242	0.000
Hours per week worked	1.004	1.002	1.006	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.038	0.949	1.141	0.220
Adaptable within limits	1.173	1.095	1.257	0.000
Entirely self-determined	1.039	0.963	1.120	0.147
Skill-demand match (ref: they match)				
Demands too low	1.212	1.148	1.275	0.000
Demands too high	1.389	1.297	1.487	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.633	1.532	1.739	0.000
Agree	0.896	0.836	0.957	0.001
DIC		54750.130		
pD		75.140		
Random Part	Mean	95%CI		SD
Country variance	0.147	0.088	0.242	0.039
Year variance	0.016	0.001	0.086	0.063
Occupation variance (ISCO 88 2 digit)	0.103	0.056	0.184	0.033
MOR Country Level	1.160			
ICC Country Level	0.041			
MOR Year Level	0.806			
ICC Year Level	0.004			
MOR Occupation Level	1.061			
ICC Occupation Level	0.029			

Table C.3: Intermediate Models for Hearing Problems in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.067	0.050	0.085	0.000
DIC		46871.410		
pD		62.560		
Random part	Mean	95% CI		SD
Country variance	0.154	0.093	0.252	0.042
Year variance	0.077	0.007	0.369	0.227
Occupation variance (ISCO 88 2 digit)	0.293	0.167	0.503	0.088
MOR Country Level	1.174			
ICC Country Level	0.040			
MOR Year Level	0.999			
ICC Year Level	0.020			
MOR Occupation Level	1.451			
ICC Occupation Level	0.077			

Model 1

Parameter	OR	95% CI		p
Intercept	0.076	0.056	0.111	0.000
Sex (ref: male)	0.747	0.703	0.794	0.000
DIC		46785.560		
pD		62.990		
Random part	Mean	95% CI		SD
Country variance	0.158	0.093	0.258	0.043
Year variance	0.104	0.007	0.580	0.473
Occupation variance (ISCO 88 2 digit)	0.236	0.132	0.417	0.073
MOR Country Level	1.183			
ICC Country Level	0.042			
MOR Year Level	1.063			
ICC Year Level	0.027			
MOR Occupation Level	1.341			
ICC Occupation Level	0.062			

Model 2

Parameter	OR	95% CI		p
Intercept	0.019	0.014	0.025	0.000
Sex (ref: male)	0.742	0.697	0.787	0.000
Age	1.031	1.029	1.033	0.000
DIC		46073.210		
pD		63.680		
Random part	Mean	95% CI		SD
Country variance	0.145	0.087	0.238	0.039
Year variance	0.110	0.011	0.572	0.325
Occupation variance (ISCO 88 2 digit)	0.243	0.137	0.419	0.075
MOR Country Level	1.155			
ICC Country Level	0.038			
MOR Year Level	1.078			
ICC Year Level	0.029			
MOR Occupation Level	1.355			
ICC Occupation Level	0.064			

Model 3

Parameter	OR	95% CI		p
Intercept	0.019	0.016	0.025	0.000
Sex (ref: male)	0.740	0.698	0.788	0.000
Age	1.031	1.029	1.033	0.000
Has Tertiary Education (ref: no tertiary)	0.835	0.781	0.890	0.000
DIC		46048.970		
pD		64.310		
Random Part	Mean	95% CI		SD
Country variance	0.148	0.089	0.243	0.040
Year variance	0.129	0.010	0.662	0.546
Occupation variance (ISCO 88 2 digit)	0.214	0.119	0.370	0.065

MOR Country Level	1.162			
ICC Country Level	0.039			
MOR Year Level	1.120			
ICC Year Level	0.034			
MOR Occupation Level	1.297			
ICC Occupation Level	0.056			

	Model 4			
Parameter	OR	95% CI		p
Intercept	0.019	0.016	0.024	0.000
Sex (ref: male)	0.765	0.720	0.814	0.000
Age	1.031	1.029	1.034	0.000
Has Tertiary Education (ref: no tertiary)	0.836	0.781	0.893	0.000
Nights worked per month	1.029	1.024	1.036	0.000
DIC		45959.980		
pD		65.950		
Random Part	Mean	95% CI		SD
Country variance	0.151	0.090	0.243	0.040
Year variance	0.106	0.010	0.513	0.400
Occupation variance (ISCO 88 2 digit)	0.212	0.119	0.361	0.064
MOR Country Level	1.168			
ICC Country Level	0.040			
MOR Year Level	1.069			
ICC Year Level	0.028			
MOR Occupation Level	1.294			
ICC Occupation Level	0.057			

	Model 5			
Parameter	OR	95% CI		p
Intercept	0.019	0.015	0.025	0.000
Sex (ref: male)	0.759	0.713	0.807	0.000
Age	1.032	1.030	1.034	0.000
Has Tertiary Education (ref: no tertiary)	0.847	0.789	0.903	0.000
Nights worked per month	1.022	1.016	1.028	0.000
Works shifts (ref: no)	1.380	1.290	1.476	0.000
DIC		45875.480		
pD		66.870		
Random Part	Mean	95% CI		SD
Country variance	0.155	0.093	0.256	0.043
Year variance	0.121	0.011	0.566	0.699
Occupation variance (ISCO 88 2 digit)	0.207	0.117	0.356	0.063
MOR Country Level	1.176			
ICC Country Level	0.041			
MOR Year Level	1.103			
ICC Year Level	0.032			
MOR Occupation Level	1.283			
ICC Occupation Level	0.055			

Model 6				
Parameter	OR	95% CI		p
Intercept	0.039	0.024	0.061	0.000
Sex (ref: male)	0.767	0.724	0.815	0.000
Age	1.032	1.030	1.035	0.000
Has Tertiary Education (ref: no tertiary)	0.842	0.785	0.903	0.000
Nights worked per month	1.021	1.015	1.027	0.000
Works shifts (ref: no)	1.382	1.294	1.479	0.000
Hours per week worked	1.002	1.000	1.004	0.020
DIC		45871.990		
pD		67.510		
Random Part	Mean	95% CI		SD
Country variance	0.156	0.094	0.255	0.042
Year variance	2.223	0.176	11.018	9.648
Occupation variance (ISCO 88 2 digit)	0.211	0.116	0.370	0.066
MOR Country Level	1.179			
ICC Country Level	0.027			
MOR Year Level	5.556			
ICC Year Level	0.378			
MOR Occupation Level	1.291			
ICC Occupation Level	0.036			

Model 7				
Parameter	OR	95% CI		p
Intercept	0.017	0.012	0.021	0.000
Sex (ref: male)	0.765	0.720	0.811	0.000
Age	1.033	1.030	1.035	0.000
Has Tertiary Education (ref: no tertiary)	0.846	0.788	0.907	0.000
Nights worked per month	1.021	1.015	1.028	0.000
Works shifts (ref: no)	1.359	1.271	1.456	0.000
Hours per week worked	1.003	1.001	1.005	0.005
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.935	0.838	1.036	0.108
Adaptable within limits	0.981	0.909	1.059	0.313
Entirely self-determined	0.854	0.784	0.929	0.000
DIC		45863.910		
pD		70.840		
Random Part	Mean	95% CI		SD
Country variance	0.156	0.093	0.261	0.041
Year variance	0.113	0.010	0.600	0.062
Occupation variance (ISCO 88 2 digit)	0.205	0.115	0.360	0.040
MOR Country Level	1.179			
ICC Country Level	0.041			
MOR Year Level	1.086			
ICC Year Level	0.030			
MOR Occupation Level	1.280			
ICC Occupation Level	0.055			

Model 8

Parameter	OR	95% CI		p
Intercept	0.016	0.010	0.023	0.000
Sex (ref: male)	0.766	0.719	0.814	0.000
Age	1.034	1.031	1.036	0.000
Has Tertiary Education (ref: no tertiary)	0.836	0.783	0.898	0.000
Nights worked per month	1.022	1.015	1.027	0.000
Works shifts (ref: no)	1.355	1.266	1.445	0.000
Hours per week worked	1.003	1.000	1.005	0.018
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.931	0.837	1.031	0.085
Adaptable within limits	0.977	0.904	1.053	0.270
Entirely self-determined	0.849	0.781	0.918	0.000
Skill-demand match (ref: they match)				
Demands too low	1.107	1.042	1.174	0.000
Demands too high	1.472	1.366	1.586	0.000
DIC		45774.780		
pD		72.990		
Random Part	Mean	95% CI		SD
Country variance	0.153	0.092	0.250	0.041
Year variance	0.183	0.011	0.842	1.164
Occupation variance (ISCO 88 2 digit)	0.209	0.118	0.368	0.065
MOR Country Level	1.174			
ICC Country Level	0.040			
MOR Year Level	1.236			
ICC Year Level	0.048			
MOR Occupation Level	1.288			
ICC Occupation Level	0.055			

Model 9

Parameter	OR	95% CI		p
Intercept	0.010	0.007	0.013	0.000
Sex (ref: male)	0.741	0.697	0.786	0.000
Age	1.033	1.031	1.036	0.000
Has Tertiary Education (ref: no tertiary)	0.851	0.792	0.914	0.000
Nights worked per month	1.021	1.014	1.027	0.000
Works shifts (ref: no)	1.335	1.250	1.423	0.000
Hours per week worked	1.002	0.999	1.004	0.063
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.953	0.851	1.057	0.174
Adaptable within limits	1.000	0.921	1.080	0.496
Entirely self-determined	0.877	0.808	0.949	0.001
Skill-demand match (ref: they match)				
Demands too low	1.080	1.020	1.146	0.005
Demands too high	1.429	1.318	1.547	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.547	1.441	1.656	0.000

Agree	0.953	0.887	1.019	0.095
DIC		45488.230		
pD		74.220		
Random Part	Mean	95%CI		SD
Country variance	0.155	0.092	0.257	0.042
Year variance	0.456	0.013	2.299	3.057
Occupation variance (ISCO 88 2 digit)	0.206	0.114	0.359	0.063
MOR Country Level	1.176			
ICC Country Level	0.038			
MOR Year Level	1.753			
ICC Year Level	0.111			
MOR Occupation Level	1.281			
ICC Occupation Level	0.050			

Table C.4: Intermediate Models for Backache in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.465	0.326	0.731	0.000
DIC		132677.270		
pD		63.720		
Random part	Mean	95% CI		SD
Country variance	0.103	0.063	0.164	0.026
Year variance	0.866	0.061	4.697	3.126
Occupation variance (ISCO 88 2 digit)	0.131	0.075	0.222	0.039
MOR Country Level	1.061			
ICC Country Level	0.023			
MOR Year Level	2.515			
ICC Year Level	0.197			
MOR Occupation Level	1.126			
ICC Occupation Level	0.030			
	Model 1			

Parameter	OR	95% CI		p
Intercept	0.879	0.669	1.199	0.204
Sex (ref: male)	1.334	1.294	1.375	0.000
DIC		132318.140		
pD		64.630		
Random part	Mean	95% CI		SD
Country variance	0.098	0.060	0.159	0.026
Year variance	1.199	0.097	5.940	4.980
Occupation variance (ISCO 88 2 digit)	0.160	0.092	0.285	0.049
MOR Country Level	1.051			
ICC Country Level	0.021			
MOR Year Level	3.174			
ICC Year Level	0.253			
MOR Occupation Level	1.188			

ICC Occupation Level	0.034			
	Model 2			
Parameter	OR	95% CI		p
Intercept	0.323	0.267	0.392	0.000
Sex (ref: male)	1.329	1.287	1.367	0.000
Age	1.018	1.017	1.019	0.000
DIC		131365.960		
pD		66.000		
Random part	Mean	95% CI		SD
Country variance	0.096	0.059	0.152	0.024
Year variance	0.406	0.048	2.029	0.942
Occupation variance (ISCO 88 2 digit)	0.148	0.086	0.254	0.045
MOR Country Level	1.044			
ICC Country Level	0.024			
MOR Year Level	1.662			
ICC Year Level	0.103			
MOR Occupation Level	1.163			
ICC Occupation Level	0.038			
	Model 3			
Parameter	OR	95% CI		p
Intercept	0.257	0.212	0.326	0.000
Sex (ref: male)	1.331	1.292	1.369	0.000
Age	1.018	1.017	1.019	0.000
Has Tertiary Education (ref: no tertiary)	0.823	0.797	0.849	0.000
DIC		131241.600		
pD		67.070		
Random Part	Mean	95% CI		SD
Country variance	0.097	0.060	0.156	0.025
Year variance	0.367	0.044	1.737	1.038
Occupation variance (ISCO 88 2 digit)	0.116	0.067	0.198	0.034
MOR Country Level	1.047			
ICC Country Level	0.025			
MOR Year Level	1.589			
ICC Year Level	0.095			
MOR Occupation Level	1.091			
ICC Occupation Level	0.030			
	Model 4			
Parameter	OR	95% CI		p
Intercept	0.352	0.278	0.489	0.000
Sex (ref: male)	1.364	1.324	1.408	0.000
Age	1.018	1.017	1.019	0.000
Has Tertiary Education (ref: no tertiary)	0.825	0.796	0.852	0.000
Nights worked per month	1.024	1.020	1.027	0.000
DIC		131058.020		
pD		67.690		

Random Part	Mean	95% CI		SD
Country variance	0.096	0.059	0.155	0.025
Year variance	0.691	0.051	3.635	3.585
Occupation variance (ISCO 88 2 digit)	0.115	0.065	0.199	0.035
MOR Country Level	1.046			
ICC Country Level	0.023			
MOR Year Level	2.185			
ICC Year Level	0.165			
MOR Occupation Level	1.090			
ICC Occupation Level	0.027			
	Model 5			
Parameter	OR	95% CI		p
Intercept	0.297	0.252	0.359	0.000
Sex (ref: male)	1.363	1.321	1.406	0.000
Age	1.019	1.017	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.829	0.803	0.857	0.000
Nights worked per month	1.020	1.016	1.024	0.000
Works shifts (ref: no)	1.167	1.128	1.211	0.000
DIC		130989.490		
pD		69.120		
Random Part	Mean	95% CI		SD
Country variance	0.094	0.057	0.152	0.024
Year variance	0.415	0.045	1.984	1.536
Occupation variance (ISCO 88 2 digit)	0.120	0.066	0.211	0.037
MOR Country Level	1.039			
ICC Country Level	0.024			
MOR Year Level	1.677			
ICC Year Level	0.106			
MOR Occupation Level	1.100			
ICC Occupation Level	0.031			
	Model 6			
Parameter	OR	95% CI		p
Intercept	0.285	0.203	0.385	0.000
Sex (ref: male)	1.409	1.367	1.453	0.000
Age	1.018	1.017	1.019	0.000
Has Tertiary Education (ref: no tertiary)	0.824	0.798	0.851	0.000
Nights worked per month	1.016	1.012	1.019	0.000
Works shifts (ref: no)	1.166	1.126	1.208	0.000
Hours per week worked	1.009	1.008	1.010	0.000
DIC		130763.400		
pD		69.700		
Random Part	Mean	95% CI		SD
Country variance	0.093	0.057	0.151	0.024
Year variance	0.908	0.075	3.877	5.782
Occupation variance (ISCO 88 2 digit)	0.115	0.065	0.198	0.035
MOR Country Level	1.038			

ICC Country Level	0.021			
MOR Year Level	2.596			
ICC Year Level	0.206			
MOR Occupation Level	1.089			
ICC Occupation Level	0.026			
	Model 7			
Parameter	OR	95% CI		p
Intercept	0.326	0.259	0.390	0.000
Sex (ref: male)	1.410	1.368	1.454	0.000
Age	1.018	1.017	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.823	0.795	0.853	0.000
Nights worked per month	1.016	1.012	1.019	0.000
Works shifts (ref: no)	1.166	1.126	1.206	0.000
Hours per week worked	1.009	1.008	1.010	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.030	0.976	1.084	0.136
Adaptable within limits	1.032	0.994	1.072	0.060
Entirely self-determined	0.989	0.950	1.029	0.303
DIC		130764.900		
pD		72.770		
Random Part	Mean	95% CI		SD
Country variance	0.091	0.055	0.149	0.024
Year variance	1.594	0.133	7.769	8.569
Occupation variance (ISCO 88 2 digit)	0.117	0.067	0.200	0.035
MOR Country Level	1.034			
ICC Country Level	0.018			
MOR Year Level	4.022			
ICC Year Level	0.313			
MOR Occupation Level	1.095			
ICC Occupation Level	0.023			
	Model 8			
Parameter	OR	95% CI		p
Intercept	0.034	0.236	0.367	0.000
Sex (ref: male)	0.024	1.367	1.460	0.000
Age	0.001	1.018	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.014	0.791	0.846	0.000
Nights worked per month	0.002	1.012	1.019	0.000
Works shifts (ref: no)	0.021	1.127	1.210	0.000
Hours per week worked	0.001	1.007	1.010	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.028	0.974	1.084	0.160
Adaptable within limits	1.030	0.989	1.072	0.067
Entirely self-determined	0.984	0.943	1.028	0.227
Skill-demand match (ref: they match)				
Demands too low	1.107	1.076	1.139	0.000
Demands too high	1.167	1.121	1.213	0.000

DIC		130689.510		
pD		74.870		
Random Part	Mean	95% CI		SD
Country variance	0.090	0.055	0.145	0.023
Year variance	1.635	0.103	6.299	23.891
Occupation variance (ISCO 88 2 digit)	0.119	0.068	0.205	0.035
MOR Country Level	1.032			
ICC Country Level	0.018			
MOR Year Level	4.115			
ICC Year Level	0.318			
MOR Occupation Level	1.098			
ICC Occupation Level	0.023			
	Model 9			
Parameter	OR	95% CI		p
Intercept	0.379	0.296	0.521	0.000
Sex (ref: male)	1.365	1.322	1.410	0.000
Age	1.018	1.017	1.019	0.000
Has Tertiary Education (ref: no tertiary)	0.833	0.805	0.860	0.000
Nights worked per month	1.014	1.011	1.018	0.000
Works shifts (ref: no)	1.138	1.096	1.180	0.000
Hours per week worked	1.008	1.007	1.009	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.052	0.999	1.110	0.029
Adaptable within limits	1.060	1.020	1.101	0.004
Entirely self-determined	1.024	0.979	1.068	0.146
Skill-demand match (ref: they match)				
Demands too low	1.082	1.048	1.114	0.000
Demands too high	1.132	1.083	1.183	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.542	1.489	1.596	0.000
Agree	0.804	0.777	0.833	0.000
DIC		128984.380		
pD		76.770		
Random Part	Mean	95%CI		SD
Country variance	0.084	0.051	0.136	0.022
Year variance	1.924	0.181	9.261	5.902
Occupation variance (ISCO 88 2 digit)	0.100	0.057	0.171	0.031
MOR Country Level	1.016			
ICC Country Level	0.016			
MOR Year Level	4.796			
ICC Year Level	0.356			
MOR Occupation Level	1.054			
ICC Occupation Level	0.018			

Table C.5: Intermediate Models for Lower Muscular Pain in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.503	0.375	0.654	0.000
DIC		122927.060		
pD		63.790		
Random part	Mean	95% CI		SD
Country variance	0.096	0.059	0.157	0.030
Year variance	0.105	0.007	0.545	1.334
Occupation variance (ISCO 88 2 digit)	0.209	0.122	0.360	0.040
MOR Country Level	1.045			
ICC Country Level	0.026			
MOR Year Level	1.068			
ICC Year Level	0.028			
MOR Occupation Level	1.288			
ICC Occupation Level	0.056			

Model 1

Parameter	OR	95% CI		p
Intercept	0.431	0.381	0.499	0.000
Sex (ref: male)	1.290	1.247	1.332	0.000
DIC		122674.570		
pD		64.500		
Random part	Mean	95% CI		SD
Country variance	0.093	0.057	0.150	0.024
Year variance	0.129	0.007	0.585	1.223
Occupation variance (ISCO 88 2 digit)	0.231	0.132	0.392	0.067
MOR Country Level	1.038			
ICC Country Level	0.025			
MOR Year Level	1.121			
ICC Year Level	0.034			
MOR Occupation Level	1.330			
ICC Occupation Level	0.062			

Model 2

Parameter	OR	95% CI		p
Intercept	0.143	0.116	0.174	0.000
Sex (ref: male)	1.285	1.246	1.328	0.000
Age	1.023	1.022	1.025	0.000
DIC		130403.390		
pD		65.590		
Random part	Mean	95% CI		SD
Country variance	0.102	0.062	0.165	0.027
Year variance	0.049	0.005	0.247	0.184
Occupation variance (ISCO 88 2 digit)	0.229	0.128	0.395	0.069
MOR Country Level	1.060			
ICC Country Level	0.028			
MOR Year Level	0.922			

ICC Year Level	0.013			
MOR Occupation Level	1.328			
ICC Occupation Level	0.062			
	Model 3			
Parameter	OR	95% CI		p
Intercept	0.164	0.141	0.194	0.000
Sex (ref: male)	1.287	1.248	1.328	0.000
Age	1.023	1.022	1.024	0.000
Has Tertiary Education (ref: no tertiary)	0.785	0.757	0.813	0.000
DIC		121095.520		
pD		66.600		
Random Part	Mean	95% CI		SD
Country variance	0.105	0.063	0.173	0.028
Year variance	0.055	0.005	0.246	0.390
Occupation variance (ISCO 88 2 digit)	0.170	0.096	0.288	0.050
MOR Country Level	1.066			
ICC Country Level	0.029			
MOR Year Level	0.939			
ICC Year Level	0.015			
MOR Occupation Level	1.207			
ICC Occupation Level	0.047			
	Model 4			
Parameter	OR	95% CI		p
Intercept	0.168	0.135	0.195	0.000
Sex (ref: male)	1.319	1.277	1.361	0.000
Age	1.023	1.022	1.024	0.000
Has Tertiary Education (ref: no tertiary)	0.786	0.759	0.815	0.000
Nights worked per month	1.025	1.022	1.029	0.000
DIC		120899.700		
pD		67.670		
Random Part	Mean	95% CI		SD
Country variance	0.104	0.063	0.168	0.027
Year variance	0.075	0.005	0.290	1.248
Occupation variance (ISCO 88 2 digit)	0.166	0.094	0.286	0.050
MOR Country Level	1.063			
ICC Country Level	0.029			
MOR Year Level	0.994			
ICC Year Level	0.021			
MOR Occupation Level	1.201			
ICC Occupation Level	0.046			
	Model 5			
Parameter	OR	95% CI		p
Intercept	0.158	0.108	0.199	0.000
Sex (ref: male)	1.318	1.277	1.362	0.000
Age	1.024	1.022	1.025	0.000

Has Tertiary Education (ref: no tertiary)	0.791	0.762	0.820	0.000
Nights worked per month	1.020	1.017	1.024	0.000
Works shifts (ref: no)	1.223	1.180	1.266	0.000
DIC		120789.790		
pD		69.310		
Random Part	Mean	95% CI		SD
Country variance	0.102	0.062	0.164	0.026
Year variance	0.121	0.006	0.665	0.513
Occupation variance (ISCO 88 2 digit)	0.168	0.095	0.292	0.051
MOR Country Level	1.060			
ICC Country Level	0.028			
MOR Year Level	1.103			
ICC Year Level	0.033			
MOR Occupation Level	1.205			
ICC Occupation Level	0.046			

Model 6

Parameter	OR	95% CI		p
Intercept	0.117	0.103	0.137	0.000
Sex (ref: male)	1.354	1.311	1.398	0.000
Age	1.024	1.022	1.025	0.000
Has Tertiary Education (ref: no tertiary)	0.787	0.761	0.816	0.000
Nights worked per month	1.017	1.013	1.021	0.000
Works shifts (ref: no)	1.223	1.181	1.269	0.000
Hours per week worked	1.007	1.006	1.008	0.000
DIC		120657.650		
pD		70.000		
Random Part	Mean	95% CI		SD
Country variance	0.094	0.058	0.152	0.024
Year variance	0.048	0.005	0.259	0.127
Occupation variance (ISCO 88 2 digit)	0.168	0.096	0.291	0.051
MOR Country Level	1.040			
ICC Country Level	0.026			
MOR Year Level	0.920			
ICC Year Level	0.013			
MOR Occupation Level	1.205			
ICC Occupation Level	0.047			

Model 7

Parameter	OR	95% CI		p
Intercept	0.099	0.085	0.117	0.000
Sex (ref: male)	1.355	1.314	1.396	0.000
Age	1.024	1.023	1.025	0.000
Has Tertiary Education (ref: no tertiary)	0.791	0.763	0.819	0.000
Nights worked per month	1.017	1.014	1.021	0.000
Works shifts (ref: no)	1.220	1.176	1.265	0.000
Hours per week worked	1.007	1.006	1.009	0.000
Working time arrangement (ref: set by company)				

Choice between several fixed schedules	0.949	0.894	1.006	0.041
Adaptable within limits	0.971	0.932	1.013	0.089
Entirely self-determined	0.961	0.919	1.004	0.036
DIC		120658.900		
pD		73.670		
Random Part	Mean	95% CI		SD
Country variance	0.092	0.056	0.144	0.024
Year variance	0.063	0.005	0.335	0.193
Occupation variance (ISCO 88 2 digit)	0.170	0.096	0.296	0.052
MOR Country Level	1.035			
ICC Country Level	0.025			
MOR Year Level	0.963			
ICC Year Level	0.018			
MOR Occupation Level	1.208			
ICC Occupation Level	0.047			

	Model 8			
Parameter	OR	95% CI		p
Intercept	0.115	0.096	0.155	0.000
Sex (ref: male)	1.354	1.308	1.396	0.000
Age	1.024	1.023	1.025	0.000
Has Tertiary Education (ref: no tertiary)	0.781	0.754	0.810	0.000
Nights worked per month	1.017	1.013	1.021	0.000
Works shifts (ref: no)	1.218	1.172	1.263	0.000
Hours per week worked	1.007	1.006	1.008	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.949	0.897	1.003	0.032
Adaptable within limits	0.968	0.927	1.012	0.072
Entirely self-determined	0.956	0.911	0.999	0.022
Skill-demand match (ref: they match)				
Demands too low	1.136	1.102	1.169	0.000
Demands too high	1.124	1.075	1.174	0.000
DIC		120583.330		
pD		74.900		
Random Part	Mean	95% CI		SD
Country variance	0.095	0.058	0.154	0.025
Year variance	0.080	0.006	0.410	0.538
Occupation variance (ISCO 88 2 digit)	0.166	0.095	0.286	0.049
MOR Country Level	1.042			
ICC Country Level	0.026			
MOR Year Level	1.006			
ICC Year Level	0.022			
MOR Occupation Level	1.201			
ICC Occupation Level	0.046			

	Model 9			
Parameter	OR	95% CI		p
Intercept	0.119	0.095	0.143	0.000

Sex (ref: male)	1.309	1.267	1.350	0.000
Age	1.023	1.022	1.025	0.000
Has Tertiary Education (ref: no tertiary)	0.798	0.771	0.828	0.000
Nights worked per month	1.015	1.012	1.019	0.000
Works shifts (ref: no)	1.192	1.149	1.240	0.000
Hours per week worked	1.006	1.005	1.007	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.974	0.920	1.031	0.178
Adaptable within limits	1.000	0.959	1.045	0.491
Entirely self-determined	0.997	0.952	1.040	0.455
Skill-demand match (ref: they match)				
Demands too low	1.113	1.077	1.148	0.000
Demands too high	1.090	1.041	1.143	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.523	1.471	1.580	0.000
Agree	0.772	0.744	0.800	0.000
DIC		118898.860		
pD		76.320		
Random Part	Mean	95%CI		SD
Country variance	0.082	0.050	0.135	0.022
Year variance	0.119	0.007	0.620	0.533
Occupation variance (ISCO 88 2 digit)	0.145	0.081	0.252	0.045
MOR Country Level	1.012			
ICC Country Level	0.023			
MOR Year Level	1.099			
ICC Year Level	0.033			
MOR Occupation Level	1.155			
ICC Occupation Level	0.040			

Table C.6: Intermediate Models for Upper Muscular Pain in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.567	0.495	0.657	0.000
DIC		132134.700		
pD		63.700		
Random part	Mean	95% CI		SD
Country variance	0.117	0.072	0.184	0.030
Year variance	0.452	0.053	2.110	1.334
Occupation variance (ISCO 88 2 digit)	0.131	0.075	0.230	0.040
MOR Country Level	1.094			
ICC Country Level	0.029			
MOR Year Level	1.745			
ICC Year Level	0.113			
MOR Occupation Level	1.125			
ICC Occupation Level	0.033			

	Model 1			
Parameter	OR	95% CI		p
Intercept	0.551	0.436	0.667	0.000
Sex (ref: male)	1.498	1.456	1.540	0.000
DIC		131421.470		
pD		63.970		
Random part	Mean	95% CI		SD
Country variance	0.110	0.068	0.177	0.028
Year variance	0.476	0.052	2.626	1.266
Occupation variance (ISCO 88 2 digit)	0.162	0.093	0.280	0.048
MOR Country Level	1.079			
ICC Country Level	0.027			
MOR Year Level	1.790			
ICC Year Level	0.118			
MOR Occupation Level	1.192			
ICC Occupation Level	0.040			
	Model 2			
Parameter	OR	95% CI		p
Intercept	0.240	0.216	0.264	0.000
Sex (ref: male)	1.498	1.453	1.545	0.000
Age	1.019	1.018	1.020	0.000
DIC		130403.390		
pD		65.590		
Random part	Mean	95% CI		SD
Country variance	0.109	0.068	0.179	0.028
Year variance	0.387	0.046	1.771	1.475
Occupation variance (ISCO 88 2 digit)	0.156	0.090	0.267	0.046
MOR Country Level	1.076			
ICC Country Level	0.028			
MOR Year Level	1.625			
ICC Year Level	0.098			
MOR Occupation Level	1.179			
ICC Occupation Level	0.040			
	Model 3			
Parameter	OR	95% CI		p
Intercept	0.297	0.249	0.336	0.000
Sex (ref: male)	1.499	1.453	1.546	0.000
Age	1.019	1.017	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.857	0.829	0.885	0.000
DIC		130328.710		
pD		66.920		
Random Part	Mean	95% CI		SD
Country variance	0.113	0.070	0.183	0.029
Year variance	0.461	0.051	2.195	1.198
Occupation variance (ISCO 88 2 digit)	0.129	0.074	0.220	0.038
MOR Country Level	1.085			

ICC Country Level	0.028			
MOR Year Level	1.761			
ICC Year Level	0.115			
MOR Occupation Level	1.121			
ICC Occupation Level	0.032			
	Model 4			
Parameter	OR	95% CI		p
Intercept	0.266	0.227	0.317	0.000
Sex (ref: male)	1.533	1.484	1.582	0.000
Age	1.019	1.018	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.860	0.832	0.889	0.000
Nights worked per month	1.022	1.019	1.026	0.000
DIC		130168.590		
pD		67.860		
Random Part	Mean	95% CI		SD
Country variance	0.113	0.069	0.182	0.029
Year variance	0.395	0.048	2.026	1.141
Occupation variance (ISCO 88 2 digit)	0.134	0.077	0.240	0.042
MOR Country Level	1.085			
ICC Country Level	0.029			
MOR Year Level	1.640			
ICC Year Level	0.100			
MOR Occupation Level	1.132			
ICC Occupation Level	0.034			
	Model 5			
Parameter	OR	95% CI		p
Intercept	0.416	0.333	0.565	0.000
Sex (ref: male)	1.534	1.488	1.581	0.000
Age	1.019	1.018	1.021	0.000
Has Tertiary Education (ref: no tertiary)	0.864	0.835	0.891	0.000
Nights worked per month	1.019	1.015	1.022	0.000
Works shifts (ref: no)	1.164	1.123	1.208	0.000
DIC		130989.490		
pD		69.120		
Random Part	Mean	95% CI		SD
Country variance	0.112	0.068	0.181	0.029
Year variance	1.220	0.113	5.772	3.600
Occupation variance (ISCO 88 2 digit)	0.132	0.076	0.228	0.039
MOR Country Level	1.082			
ICC Country Level	0.024			
MOR Year Level	3.216			
ICC Year Level	0.257			
MOR Occupation Level	1.128			
ICC Occupation Level	0.028			
	Model 6			

Parameter	OR	95% CI		p
Intercept	0.217	0.177	0.258	0.000
Sex (ref: male)	1.593	1.547	1.639	0.000
Age	1.019	1.018	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.859	0.831	0.888	0.000
Nights worked per month	1.014	1.010	1.017	0.000
Works shifts (ref: no)	1.164	1.121	1.206	0.000
Hours per week worked	1.010	1.009	1.011	0.000
DIC		129830.720		
pD		69.360		
Random Part	Mean	95% CI		SD
Country variance	0.113	0.069	0.181	0.029
Year variance	0.737	0.083	3.591	2.020
Occupation variance (ISCO 88 2 digit)	0.129	0.074	0.225	0.040
MOR Country Level	1.084			
ICC Country Level	0.026			
MOR Year Level	2.272			
ICC Year Level	0.173			
MOR Occupation Level	1.122			
ICC Occupation Level	0.030			
	Model 7			

Parameter	OR	95% CI		p
Intercept	0.175	0.146	0.217	0.000
Sex (ref: male)	1.594	1.545	1.646	0.000
Age	1.019	1.018	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.856	0.829	0.884	0.000
Nights worked per month	1.014	1.011	1.018	0.000
Works shifts (ref: no)	1.167	1.128	1.211	0.000
Hours per week worked	1.010	1.008	1.011	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.999	0.948	1.054	0.464
Adaptable within limits	1.086	1.044	1.129	0.000
Entirely self-determined	0.972	0.933	1.012	0.078
DIC		129813.480		
pD		72.520		
Random Part	Mean	95% CI		SD
Country variance	0.111	0.069	0.178	0.028
Year variance	0.501	0.051	2.183	1.977
Occupation variance (ISCO 88 2 digit)	0.134	0.076	0.228	0.040
MOR Country Level	1.081			
ICC Country Level	0.028			
MOR Year Level	1.835			
ICC Year Level	0.124			
MOR Occupation Level	1.131			
ICC Occupation Level	0.033			
	Model 8			

Parameter	OR	95% CI		p
Intercept	0.338	0.250	0.462	0.000
Sex (ref: male)	1.599	1.547	1.651	0.000
Age	1.020	1.019	1.021	0.000
Has Tertiary Education (ref: no tertiary)	0.848	0.819	0.877	0.000
Nights worked per month	1.014	1.010	1.018	0.000
Works shifts (ref: no)	1.168	1.126	1.211	0.000
Hours per week worked	1.010	1.009	1.011	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.999	0.947	1.051	0.481
Adaptable within limits	1.085	1.046	1.129	0.000
Entirely self-determined	0.966	0.924	1.007	0.052
Skill-demand match (ref: they match)				
Demands too low	1.137	1.104	1.171	0.000
Demands too high	1.205	1.158	1.255	0.000
DIC		129698.250		
pD		75.330		
Random Part	Mean	95% CI		SD
Country variance	0.114	0.070	0.184	0.029
Year variance	2.648	0.248	12.222	10.123
Occupation variance (ISCO 88 2 digit)	0.137	0.078	0.236	0.041
MOR Country Level	1.086			
ICC Country Level	0.018			
MOR Year Level	6.737			
ICC Year Level	0.428			
MOR Occupation Level	1.139			
ICC Occupation Level	0.022			

Model 9

Parameter	OR	95% CI		p
Intercept	0.214	0.165	0.263	0.000
Sex (ref: male)	1.548	1.500	1.597	0.000
Age	1.019	1.018	1.020	0.000
Has Tertiary Education (ref: no tertiary)	0.866	0.837	0.897	0.000
Nights worked per month	1.012	1.009	1.016	0.000
Works shifts (ref: no)	1.140	1.099	1.185	0.000
Hours per week worked	1.009	1.008	1.010	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.023	0.968	1.082	0.223
Adaptable within limits	1.121	1.078	1.167	0.000
Entirely self-determined	1.009	0.967	1.050	0.340
Skill-demand match (ref: they match)				
Demands too low	1.111	1.078	1.145	0.000
Demands too high	1.169	1.121	1.218	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.583	1.526	1.637	0.000
Agree	0.796	0.770	0.823	0.000

DIC		127810.300		
pD		76.950		
Random Part	Mean	95%CI		SD
Country variance	0.111	0.068	0.178	0.028
Year variance	1.072	0.092	4.960	5.928
Occupation variance (ISCO 88 2 digit)	0.117	0.066	0.201	0.035
MOR Country Level	1.080			
ICC Country Level	0.024			
MOR Year Level	2.918			
ICC Year Level	0.234			
MOR Occupation Level	1.095			
ICC Occupation Level	0.026			

Table C.7: Intermediate Models for Anxiety in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.126	0.108	0.149	0.000
DIC		75289.500		
pD		60.070		
Random part	Mean	95% CI		SD
Country variance	0.459	0.286	0.744	0.116
Year variance	0.150	0.017	0.708	0.457
Occupation variance (ISCO 88 2 digit)	0.022	0.011	0.040	0.008
MOR Country Level	1.758			
ICC Country Level	0.117			
MOR Year Level	1.167			
ICC Year Level	0.038			
MOR Occupation Level	0.832			
ICC Occupation Level	0.006			

Model 1

Parameter	OR	95% CI		p
Intercept	0.147	0.071	0.215	0.000
Sex (ref: male)	1.355	1.299	1.412	0.000
DIC		75103.990		
pD		57.720		
Random part	Mean	95% CI		SD
Country variance	0.470	0.287	0.766	0.124
Year variance	0.501	0.021	2.779	2.262
Occupation variance (ISCO 88 2 digit)	0.010	0.004	0.020	0.004
MOR Country Level	1.778			
ICC Country Level	0.110			
MOR Year Level	1.836			
ICC Year Level	0.117			
MOR Occupation Level	0.778			
ICC Occupation Level	0.002			

Model 2				
Parameter	OR	95% CI		p
Intercept	0.091	0.067	0.128	0.000
Sex (ref: male)	1.360	1.303	1.420	0.000
Age	1.009	1.007	1.011	0.000
DIC		74998.140		
pD		57.970		
Random part	Mean	95% CI		SD
Country variance	0.454	0.282	0.721	0.114
Year variance	0.338	0.019	1.748	1.168
Occupation variance (ISCO 88 2 digit)	0.009	0.004	0.018	0.004
MOR Country Level	1.749			
ICC Country Level	0.111			
MOR Year Level	1.536			
ICC Year Level	0.083			
MOR Occupation Level	0.772			
ICC Occupation Level	0.002			

Model 3				
Parameter	OR	95% CI		p
Intercept	0.092	0.064	0.142	0.000
Sex (ref: male)	1.359	1.303	1.419	0.000
Age	1.009	1.008	1.011	0.000
Has Tertiary Education (ref: no tertiary)	1.098	1.050	1.144	0.000
DIC		74988.560		
pD		57.600		
Random Part	Mean	95% CI		SD
Country variance	0.457	0.283	0.729	0.118
Year variance	0.385	0.019	1.998	1.780
Occupation variance (ISCO 88 2 digit)	0.007	0.002	0.014	0.003
MOR Country Level	1.754			
ICC Country Level	0.110			
MOR Year Level	1.621			
ICC Year Level	0.093			
MOR Occupation Level	0.756			
ICC Occupation Level	0.002			

Model 4				
Parameter	OR	95% CI		p
Intercept	0.048	0.034	0.080	0.000
Sex (ref: male)	1.404	1.344	1.464	0.000
Age	1.010	1.008	1.011	0.000
Has Tertiary Education (ref: no tertiary)	1.112	1.063	1.161	0.000
Nights worked per month	1.031	1.026	1.035	0.000
DIC		74814.880		
pD		56.430		
Random Part	Mean	95% CI		SD

Country variance	0.454	0.283	0.730	0.116
Year variance	0.419	0.024	2.156	1.507
Occupation variance (ISCO 88 2 digit)	0.005	0.002	0.010	0.002
MOR Country Level	1.750			
ICC Country Level	0.109			
MOR Year Level	1.685			
ICC Year Level	0.101			
MOR Occupation Level	0.744			
ICC Occupation Level	0.001			
	Model 5			
Parameter	OR	95% CI		p
Intercept	0.081	0.052	0.099	0.000
Sex (ref: male)	1.398	1.339	1.456	0.000
Age	1.010	1.008	1.012	0.000
Has Tertiary Education (ref: no tertiary)	1.113	1.062	1.164	0.000
Nights worked per month	1.028	1.023	1.033	0.000
Works shifts (ref: no)	1.143	1.089	1.198	0.000
DIC		74789.010		
pD		58.510		
Random Part	Mean	95% CI		SD
Country variance	0.450	0.278	0.707	0.113
Year variance	0.368	0.022	2.176	1.001
Occupation variance (ISCO 88 2 digit)	0.006	0.002	0.012	0.003
MOR Country Level	1.742			
ICC Country Level	0.109			
MOR Year Level	1.591			
ICC Year Level	0.090			
MOR Occupation Level	0.749			
ICC Occupation Level	0.001			
	Model 6			
Parameter	OR	95% CI		p
Intercept	0.060	0.044	0.074	0.000
Sex (ref: male)	1.442	1.386	1.501	0.000
Age	1.010	1.008	1.011	0.000
Has Tertiary Education (ref: no tertiary)	1.110	1.058	1.161	0.000
Nights worked per month	1.024	1.019	1.028	0.000
Works shifts (ref: no)	1.144	1.086	1.199	0.000
Hours per week worked	1.008	1.007	1.010	0.000
DIC		74688.920		
pD		60.030		
Random Part	Mean	95% CI		SD
Country variance	0.455	0.279	0.732	0.116
Year variance	0.234	0.019	1.279	0.728
Occupation variance (ISCO 88 2 digit)	0.006	0.002	0.013	0.003
MOR Country Level	1.751			
ICC Country Level	0.114			

MOR Year Level	1.336			
ICC Year Level	0.059			
MOR Occupation Level	0.752			
ICC Occupation Level	0.001			
	Model 7			
Parameter	OR	95% CI		p
Intercept	0.048	0.039	0.056	0.000
Sex (ref: male)	1.448	1.385	1.507	0.000
Age	1.009	1.008	1.011	0.000
Has Tertiary Education (ref: no tertiary)	1.102	1.053	1.153	0.000
Nights worked per month	1.024	1.019	1.028	0.000
Works shifts (ref: no)	1.166	1.110	1.223	0.000
Hours per week worked	1.008	1.006	1.010	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.969	0.895	1.044	0.216
Adaptable within limits	1.138	1.076	1.204	0.000
Entirely self-determined	1.085	1.026	1.147	0.003
DIC		74668.310		
pD		62.990		
Random Part	Mean	95% CI		SD
Country variance	0.455	0.280	0.740	0.118
Year variance	0.153	0.015	0.645	0.942
Occupation variance (ISCO 88 2 digit)	0.006	0.002	0.013	0.003
MOR Country Level	1.752			
ICC Country Level	0.117			
MOR Year Level	1.173			
ICC Year Level	0.039			
MOR Occupation Level	0.754			
ICC Occupation Level	0.002			
	Model 8			
Parameter	OR	95% CI		p
Intercept	0.084	0.069	0.103	0.000
Sex (ref: male)	1.464	1.408	1.522	0.000
Age	1.010	1.009	1.012	0.000
Has Tertiary Education (ref: no tertiary)	1.083	1.034	1.129	0.000
Nights worked per month	1.024	1.019	1.028	0.000
Works shifts (ref: no)	1.164	1.106	1.220	0.000
Hours per week worked	1.008	1.006	1.009	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.966	0.892	1.043	0.184
Adaptable within limits	1.130	1.070	1.196	0.000
Entirely self-determined	1.083	1.019	1.148	0.008
Skill-demand match (ref: they match)				
Demands too low	1.137	1.092	1.183	0.000
Demands too high	1.620	1.535	1.706	0.000
DIC		74394.110		

pD		62.840		
Random Part	Mean	95% CI		SD
Country variance	0.477	0.293	0.759	0.123
Year variance	2.150	0.172	8.349	28.406
Occupation variance (ISCO 88 2 digit)	0.005	0.002	0.010	0.002
MOR Country Level	1.792			
ICC Country Level	0.081			
MOR Year Level	5.366			
ICC Year Level	0.363			
MOR Occupation Level	0.743			
ICC Occupation Level	0.001			

	Model 9			
Parameter	OR	95% CI		p
Intercept	0.101	0.072	0.141	0.000
Sex (ref: male)	1.396	1.340	1.459	0.000
Age	1.009	1.007	1.011	0.000
Has Tertiary Education (ref: no tertiary)	1.129	1.078	1.183	0.000
Nights worked per month	1.021	1.016	1.026	0.000
Works shifts (ref: no)	1.125	1.072	1.184	0.000
Hours per week worked	1.007	1.005	1.009	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	0.996	0.918	1.074	0.452
Adaptable within limits	1.178	1.111	1.244	0.000
Entirely self-determined	1.135	1.068	1.201	0.000
Skill-demand match (ref: they match)				
Demands too low	1.100	1.050	1.148	0.000
Demands too high	1.550	1.462	1.639	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.825	1.740	1.907	0.000
Agree	0.807	0.767	0.847	0.000
DIC		72987.960		
pD		67.970		
Random Part	Mean	95%CI		SD
Country variance	0.446	0.279	0.710	0.112
Year variance	2.796	0.198	13.205	23.167
Occupation variance (ISCO 88 2 digit)	0.007	0.003	0.015	0.003
MOR Country Level	1.734			
ICC Country Level	0.068			
MOR Year Level	7.179			
ICC Year Level	0.428			
MOR Occupation Level	0.760			
ICC Occupation Level	0.001			

Table C.8: Intermediate Models for Fatigue in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.711	0.622	0.815	0.000
DIC		125550.900		
pD		61.540		
Random part	Mean	95% CI		SD
Country variance	0.480	0.297	0.760	0.120
Year variance	0.568	0.045	2.603	2.846
Occupation variance (ISCO 88 2 digit)	0.019	0.010	0.034	0.006
MOR Country Level	1.797			
ICC Country Level	0.110			
MOR Year Level	1.959			
ICC Year Level	0.130			
MOR Occupation Level	0.819			
ICC Occupation Level	0.004			

	Model 1			
Parameter	OR	95% CI		p
Intercept	0.566	0.468	0.728	0.000
Sex (ref: male)	1.354	1.314	1.393	0.000
DIC		125168.070		
pD		63.250		
Random part	Mean	95% CI		SD
Country variance	0.478	0.301	0.761	0.120
Year variance	0.392	0.036	1.870	2.117
Occupation variance (ISCO 88 2 digit)	0.025	0.014	0.045	0.008
MOR Country Level	1.793			
ICC Country Level	0.114			
MOR Year Level	1.636			
ICC Year Level	0.094			
MOR Occupation Level	0.843			
ICC Occupation Level	0.006			

	Model 2			
Parameter	OR	95% CI		p
0 Intercept	0.443	0.347	0.509	0.000
1 Sex (ref: male)	1.351	1.310	1.391	0.000
2 Age	1.006	1.005	1.007	0.000
DIC		125068.690		
pD		65.050		
Random part	Mean	95% CI		SD
Country variance	0.487	0.304	0.776	0.125
Year variance	0.321	0.036	1.500	0.885
Occupation variance (ISCO 88 2 digit)	0.023	0.013	0.042	0.007
MOR Country Level	1.809			
ICC Country Level	0.118			
MOR Year Level	1.504			
ICC Year Level	0.078			
MOR Occupation Level	0.837			

ICC Occupation Level	0.006			
	Model 3			
Parameter	OR	95% CI		p
Intercept	0.489	0.400	0.542	0.000
Sex (ref: male)	1.354	1.311	1.395	0.000
Age	1.006	1.005	1.007	0.000
Has Tertiary Education (ref: no tertiary)	0.991	0.958	1.026	0.278
DIC		125068.410		
pD		64.820		
Random Part	Mean	95% CI		SD
Country variance	0.483	0.299	0.780	0.124
Year variance	0.492	0.049	2.185	2.500
Occupation variance (ISCO 88 2 digit)	0.023	0.012	0.040	0.007
MOR Country Level	1.803			
ICC Country Level	0.113			
MOR Year Level	1.818			
ICC Year Level	0.115			
MOR Occupation Level	0.834			
ICC Occupation Level	0.005			
	Model 4			
Parameter	OR	95% CI		p
Intercept	0.450	0.363	0.536	0.000
Sex (ref: male)	1.405	1.362	1.446	0.000
Age	1.007	1.006	1.008	0.000
Has Tertiary Education (ref: no tertiary)	0.996	0.963	1.029	0.409
Nights worked per month	1.037	1.034	1.041	0.000
DIC		124638.430		
pD		65.380		
Random Part	Mean	95% CI		SD
Country variance	0.480	0.301	0.768	0.123
Year variance	0.498	0.052	2.279	1.862
Occupation variance (ISCO 88 2 digit)	0.022	0.012	0.039	0.007
MOR Country Level	1.797			
ICC Country Level	0.112			
MOR Year Level	1.831			
ICC Year Level	0.116			
MOR Occupation Level	0.832			
ICC Occupation Level	0.005			
	Model 5			
Parameter	OR	95% CI		p
Intercept	0.289	0.214	0.365	0.000
Sex (ref: male)	1.403	1.357	1.445	0.000
Age	1.007	1.006	1.008	0.000
Has Tertiary Education (ref: no tertiary)	0.999	0.967	1.033	0.461
Nights worked per month	1.033	1.030	1.037	0.000

Works shifts (ref: no)	1.177	1.134	1.221	0.000
DIC		124566.430		
pD		67.060		
Random Part	Mean	95% CI		SD
Country variance	0.495	0.308	0.800	0.127
Year variance	0.377	0.041	1.892	1.343
Occupation variance (ISCO 88 2 digit)	0.022	0.012	0.039	0.007
MOR Country Level	1.824			
ICC Country Level	0.118			
MOR Year Level	1.607			
ICC Year Level	0.090			
MOR Occupation Level	0.832			
ICC Occupation Level	0.005			

	Model 6			
Parameter	OR	95% CI		p
Intercept	0.182	0.140	0.223	0.000
Sex (ref: male)	1.481	1.434	1.529	0.000
Age	1.007	1.006	1.008	0.000
Has Tertiary Education (ref: no tertiary)	0.996	0.963	1.028	0.403
Nights worked per month	1.027	1.023	1.030	0.000
Works shifts (ref: no)	1.178	1.137	1.221	0.000
Hours per week worked	1.014	1.013	1.015	0.000
DIC		124012.870		
pD		67.550		
Random Part	Mean	95% CI		SD
Country variance	0.457	0.284	0.741	0.118
Year variance	0.370	0.035	1.546	3.437
Occupation variance (ISCO 88 2 digit)	0.023	0.012	0.041	0.007
MOR Country Level	1.755			
ICC Country Level	0.110			
MOR Year Level	1.595			
ICC Year Level	0.089			
MOR Occupation Level	0.835			
ICC Occupation Level	0.006			

	Model 7			
Parameter	OR	95% CI		p
Intercept	0.037	0.210	0.322	0.000
Sex (ref: male)	0.024	1.437	1.530	0.000
Age	0.001	1.005	1.008	0.000
Has Tertiary Education (ref: no tertiary)	0.017	0.957	1.025	0.278
Nights worked per month	0.002	1.023	1.031	0.000
Works shifts (ref: no)	0.023	1.138	1.226	0.000
Hours per week worked	0.001	1.013	1.015	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.000	0.946	1.058	0.474
Adaptable within limits	1.128	1.084	1.172	0.000

Entirely self-determined	0.983	0.943	1.030	0.210
DIC		123978.670		
pD		70.990		
Random Part	Mean	95% CI		SD
Country variance	0.466	0.292	0.740	0.118
Year variance	0.654	0.054	3.458	2.162
Occupation variance (ISCO 88 2 digit)	0.024	0.013	0.044	0.008
MOR Country Level	1.771			
ICC Country Level	0.105			
MOR Year Level	2.117			
ICC Year Level	0.148			
MOR Occupation Level	0.840			
ICC Occupation Level	0.005			

	Model 8			
Parameter	OR	95% CI		p
Intercept	0.197	0.177	0.222	0.000
Sex (ref: male)	1.488	1.443	1.535	0.000
Age	1.007	1.006	1.009	0.000
Has Tertiary Education (ref: no tertiary)	0.981	0.948	1.015	0.141
Nights worked per month	1.027	1.023	1.030	0.000
Works shifts (ref: no)	1.185	1.142	1.228	0.000
Hours per week worked	1.014	1.013	1.015	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.004	0.947	1.057	0.472
Adaptable within limits	1.126	1.080	1.171	0.000
Entirely self-determined	0.981	0.940	1.024	0.197
Skill-demand match (ref: they match)				
Demands too low	1.092	1.060	1.126	0.000
Demands too high	1.286	1.229	1.343	0.000
DIC		123840.000		
pD		73.010		
Random Part	Mean	95% CI		SD
Country variance	0.475	0.291	0.764	0.120
Year variance	0.417	0.040	2.027	1.212
Occupation variance (ISCO 88 2 digit)	0.025	0.014	0.045	0.008
MOR Country Level	1.788			
ICC Country Level	0.113			
MOR Year Level	1.682			
ICC Year Level	0.099			
MOR Occupation Level	0.845			
ICC Occupation Level	0.006			

	Model 9			
Parameter	OR	95% CI		p
Intercept	0.198	0.159	0.247	0.000
Sex (ref: male)	1.432	1.386	1.477	0.000
Age	1.006	1.005	1.007	0.000

Has Tertiary Education (ref: no tertiary)	1.010	0.977	1.043	0.268
Nights worked per month	1.025	1.021	1.029	0.000
Works shifts (ref: no)	1.152	1.108	1.197	0.000
Hours per week worked	1.013	1.012	1.015	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.030	0.972	1.088	0.155
Adaptable within limits	1.167	1.120	1.218	0.000
Entirely self-determined	1.026	0.980	1.070	0.129
Skill-demand match (ref: they match)				
Demands too low	1.064	1.031	1.096	0.000
Demands too high	1.242	1.191	1.297	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.667	1.609	1.729	0.000
Agree	0.793	0.766	0.820	0.000
DIC		121724.470		
pD		73.660		
Random Part	Mean	95%CI		SD
Country variance	0.452	0.280	0.723	0.115
Year variance	0.482	0.042	1.963	2.802
Occupation variance (ISCO 88 2 digit)	0.018	0.009	0.032	0.006
MOR Country Level	1.745			
ICC Country Level	0.106			
MOR Year Level	1.800			
ICC Year Level	0.114			
MOR Occupation Level	0.814			
ICC Occupation Level	0.004			

Table C.9: Intermediate Models for Headache and/or Eyestrain in the last 12 months

Model 0

Parameter	OR	95% CI		p
Intercept	0.825	0.662	0.973	0.008
DIC		125985.870		
pD		61.820		
Random part	Mean	95% CI		SD
Country variance	0.125	0.078	0.200	0.031
Year variance	1.900	0.194	9.625	7.207
Occupation variance (ISCO 88 2 digit)	0.028	0.015	0.049	0.009
MOR Country Level	1.112			
ICC Country Level	0.023			
MOR Year Level	4.738			
ICC Year Level	0.356			
MOR Occupation Level	0.853			
ICC Occupation Level	0.005			

Model 1

Parameter	OR	95% CI		p

Intercept	0.388	0.288	0.516	0.000
Sex (ref: male)	1.666	1.616	1.716	0.000
DIC		124924.360		
pD		59.950		
Random part	Mean	95% CI		SD
Country variance	0.122	0.076	0.199	0.032
Year variance	0.865	0.091	4.399	3.041
Occupation variance (ISCO 88 2 digit)	0.010	0.005	0.019	0.004
MOR Country Level	1.106			
ICC Country Level	0.028			
MOR Year Level	2.514			
ICC Year Level	0.202			
MOR Occupation Level	0.780			
ICC Occupation Level	0.002			
	Model 2			
Parameter	OR	95% CI		p
Intercept	0.293	0.181	0.391	0.000
Sex (ref: male)	1.666	1.615	1.716	0.000
Age	1.001	1.000	1.002	0.047
DIC		130403.390		
pD		65.590		
Random part	Mean	95% CI		SD
Country variance	0.122	0.075	0.198	0.031
Year variance	0.879	0.089	4.289	2.400
Occupation variance (ISCO 88 2 digit)	0.010	0.005	0.019	0.004
MOR Country Level	1.106			
ICC Country Level	0.028			
MOR Year Level	2.540			
ICC Year Level	0.204			
MOR Occupation Level	0.779			
ICC Occupation Level	0.002			
	Model 3			
Parameter	OR	95% CI		p
Intercept	0.359	0.304	0.436	0.000
Sex (ref: male)	1.664	1.612	1.718	0.000
Age	1.001	1.000	1.002	0.082
Has Tertiary Education (ref: no tertiary)	1.050	1.017	1.087	0.001
DIC		124921.800		
pD		62.140		
Random Part	Mean	95% CI		SD
Country variance	0.120	0.074	0.194	0.031
Year variance	0.721	0.084	3.351	2.530
Occupation variance (ISCO 88 2 digit)	0.009	0.005	0.016	0.003
MOR Country Level	1.102			
ICC Country Level	0.029			
MOR Year Level	2.241			

ICC Year Level	0.174			
MOR Occupation Level	0.771			
ICC Occupation Level	0.002			
	Model 4			
Parameter	OR	95% CI		p
Intercept	0.318	0.243	0.387	0.000
Sex (ref: male)	1.711	1.664	1.759	0.000
Age	1.001	1.000	1.003	0.008
Has Tertiary Education (ref: no tertiary)	1.056	1.017	1.093	0.004
Nights worked per month	1.025	1.021	1.029	0.000
DIC		124729.540		
pD		63.440		
Random Part	Mean	95% CI		SD
Country variance	0.122	0.074	0.199	0.032
Year variance	0.718	0.083	3.615	2.135
Occupation variance (ISCO 88 2 digit)	0.010	0.005	0.018	0.003
MOR Country Level	1.104			
ICC Country Level	0.029			
MOR Year Level	2.236			
ICC Year Level	0.174			
MOR Occupation Level	0.775			
ICC Occupation Level	0.002			
	Model 5			
Parameter	OR	95% CI		p
Intercept	0.410	0.352	0.484	0.000
Sex (ref: male)	1.705	1.655	1.754	0.000
Age	1.001	1.000	1.003	0.006
Has Tertiary Education (ref: no tertiary)	1.055	1.022	1.089	0.000
Nights worked per month	1.023	1.019	1.026	0.000
Works shifts (ref: no)	1.105	1.064	1.146	0.000
DIC		124699.710		
pD		64.340		
Random Part	Mean	95% CI		SD
Country variance	0.121	0.074	0.196	0.032
Year variance	1.300	0.093	3.945	30.888
Occupation variance (ISCO 88 2 digit)	0.011	0.005	0.020	0.004
MOR Country Level	1.104			
ICC Country Level	0.026			
MOR Year Level	3.384			
ICC Year Level	0.275			
MOR Occupation Level	0.781			
ICC Occupation Level	0.002			
	Model 6			
Parameter	OR	95% CI		p
Intercept	0.287	0.249	0.334	0.000

Sex (ref: male)	1.763	1.705	1.818	0.000
Age	1.001	1.000	1.002	0.034
Has Tertiary Education (ref: no tertiary)	1.054	1.020	1.089	0.000
Nights worked per month	1.018	1.015	1.022	0.000
Works shifts (ref: no)	1.107	1.067	1.148	0.000
Hours per week worked	1.009	1.008	1.010	0.000
DIC		124484.950		
pD		65.900		
Random Part	Mean	95% CI		SD
Country variance	0.108	0.066	0.176	0.028
Year variance	0.928	0.103	4.609	2.455
Occupation variance (ISCO 88 2 digit)	0.011	0.006	0.020	0.004
MOR Country Level	1.075			
ICC Country Level	0.025			
MOR Year Level	2.633			
ICC Year Level	0.214			
MOR Occupation Level	0.785			
ICC Occupation Level	0.003			

	Model 8			
Parameter	OR	95% CI		p
Intercept	0.281	0.230	0.371	0.000
Sex (ref: male)	1.769	1.715	1.825	0.000
Age	1.002	1.001	1.003	0.000
Has Tertiary Education (ref: no tertiary)	1.041	1.007	1.077	0.010
Nights worked per month	1.018	1.015	1.022	0.000
Works shifts (ref: no)	1.104	1.062	1.147	0.000
Hours per week worked	1.009	1.008	1.010	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.027	0.975	1.082	0.155
Adaptable within limits	1.065	1.023	1.107	0.001
Entirely self-determined	0.947	0.906	0.988	0.006
Skill-demand match (ref: they match)				
Demands too low	1.084	1.053	1.118	0.000
Demands too high	1.299	1.245	1.354	0.000
DIC		124321.810		
pD		70.330		
Random Part	Mean	95% CI		SD
Country variance	0.112	0.068	0.182	0.029
Year variance	1.185	0.109	5.287	7.228
Occupation variance (ISCO 88 2 digit)	0.010	0.005	0.019	0.003
MOR Country Level	1.082			
ICC Country Level	0.024			
MOR Year Level	3.144			
ICC Year Level	0.258			
MOR Occupation Level	0.777			
ICC Occupation Level	0.002			

	Model 9			
Parameter	OR	95% CI		p
Intercept	0.253	0.169	0.324	0.000
Sex (ref: male)	1.726	1.670	1.786	0.000
Age	1.001	1.000	1.002	0.034
Has Tertiary Education (ref: no tertiary)	1.063	1.030	1.097	0.000
Nights worked per month	1.017	1.013	1.021	0.000
Works shifts (ref: no)	1.082	1.041	1.123	0.000
Hours per week worked	1.008	1.007	1.010	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.049	0.995	1.107	0.041
Adaptable within limits	1.091	1.046	1.138	0.000
Entirely self-determined	0.979	0.938	1.022	0.181
Skill-demand match (ref: they match)				
Demands too low	1.066	1.035	1.100	0.000
Demands too high	1.268	1.218	1.323	0.000
Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.492	1.439	1.549	0.000
Agree	0.859	0.826	0.890	0.000
DIC		123140.640		
pD		73.880		
Random Part	Mean	95%CI		SD
Country variance	0.102	0.061	0.166	0.027
Year variance	1.167	0.108	5.476	5.122
Occupation variance (ISCO 88 2 digit)	0.013	0.007	0.024	0.004
MOR Country Level	1.060			
ICC Country Level	0.022			
MOR Year Level	3.108			
ICC Year Level	0.255			
MOR Occupation Level	0.794			
ICC Occupation Level	0.003			

Table C.10: Intermediate Models for Injury(ies) in the last 12 months

Model 0				
Parameter	OR	95% CI		p
Intercept	0.097	0.069	0.126	0.000
DIC		56631.060		
pD		62.590		
Random part	Mean	95% CI		SD
Country variance	0.134	0.081	0.222	0.031
Year variance	0.127	0.008	0.738	7.207
Occupation variance (ISCO 88 2 digit)	0.337	0.192	0.587	0.009
MOR Country Level	1.133			
ICC Country Level	0.035			
MOR Year Level	1.116			

ICC Year Level	0.033			
MOR Occupation Level	1.533			
ICC Occupation Level	0.087			
	Model 1			
Parameter	OR	95% CI		p
Intercept	0.101	0.078	0.126	0.000
Sex (ref: male)	0.610	0.578	0.643	0.000
DIC		56309.700		
pD		64.030		
Random part	Mean	95% CI		SD
Country variance	0.142	0.086	0.234	0.038
Year variance	0.118	0.007	0.389	2.687
Occupation variance (ISCO 88 2 digit)	0.266	0.149	0.471	0.082
MOR Country Level	1.150			
ICC Country Level	0.037			
MOR Year Level	1.097			
ICC Year Level	0.031			
MOR Occupation Level	1.399			
ICC Occupation Level	0.070			
	Model 2			
Parameter	OR	95% CI		p
Intercept	0.159	0.132	0.195	0.000
Sex (ref: male)	0.613	0.582	0.647	0.000
Age	0.991	0.989	0.993	0.000
DIC		56222.930		
pD		65.080		
Random part	Mean	95% CI		SD
Country variance	0.146	0.086	0.242	0.040
Year variance	0.072	0.006	0.325	0.814
Occupation variance (ISCO 88 2 digit)	0.268	0.150	0.479	0.084
MOR Country Level	1.158			
ICC Country Level	0.039			
MOR Year Level	0.985			
ICC Year Level	0.019			
MOR Occupation Level	1.402			
ICC Occupation Level	0.071			
	Model 3			
Parameter	OR	95% CI		p
Intercept	0.156	0.119	0.211	0.000
Sex (ref: male)	0.613	0.580	0.648	0.000
Age	0.991	0.988	0.992	0.000
Has Tertiary Education (ref: no tertiary)	0.794	0.746	0.841	0.000
DIC		56170.930		
pD		65.590		
Random Part	Mean	95% CI		SD

Country variance	0.150	0.090	0.243	0.040
Year variance	0.096	0.007	0.503	0.464
Occupation variance (ISCO 88 2 digit)	0.219	0.123	0.374	0.067
MOR Country Level	1.165			
ICC Country Level	0.040			
MOR Year Level	1.046			
ICC Year Level	0.026			
MOR Occupation Level	1.308			
ICC Occupation Level	0.058			
	Model 4			
Parameter	OR	95% CI		p
Intercept	0.130	0.096	0.172	0.000
Sex (ref: male)	0.632	0.600	0.666	0.000
Age	0.991	0.989	0.993	0.000
Has Tertiary Education (ref: no tertiary)	0.796	0.750	0.845	0.000
Nights worked per month	1.026	1.021	1.030	0.000
DIC		56078.210		
pD		66.200		
Random Part	Mean	95% CI		SD
Country variance	0.156	0.092	0.264	0.044
Year variance	0.104	0.007	0.583	0.436
Occupation variance (ISCO 88 2 digit)	0.222	0.122	0.401	0.072
MOR Country Level	1.180			
ICC Country Level	0.041			
MOR Year Level	1.063			
ICC Year Level	0.027			
MOR Occupation Level	1.314			
ICC Occupation Level	0.059			
	Model 5			
Parameter	OR	95% CI		p
Intercept	0.114	0.080	0.166	0.000
Sex (ref: male)	0.629	0.596	0.664	0.000
Age	0.991	0.989	0.993	0.000
Has Tertiary Education (ref: no tertiary)	0.801	0.756	0.849	0.000
Nights worked per month	1.021	1.015	1.026	0.000
Works shifts (ref: no)	1.273	1.197	1.351	0.000
DIC		56019.760		
pD		67.580		
Random Part	Mean	95% CI		SD
Country variance	0.152	0.090	0.252	0.042
Year variance	0.352	0.010	1.815	2.130
Occupation variance (ISCO 88 2 digit)	0.209	0.119	0.359	0.063
MOR Country Level	1.171			
ICC Country Level	0.038			
MOR Year Level	1.561			
ICC Year Level	0.088			

MOR Occupation Level	1.289			
ICC Occupation Level	0.052			
	Model 6			
Parameter	OR	95% CI		p
Intercept	0.096	0.076	0.123	0.000
Sex (ref: male)	0.651	0.616	0.688	0.000
Age	0.991	0.989	0.992	0.000
Has Tertiary Education (ref: no tertiary)	0.798	0.752	0.847	0.000
Nights worked per month	1.016	1.010	1.021	0.000
Works shifts (ref: no)	1.274	1.201	1.348	0.000
Hours per week worked	1.009	1.007	1.011	0.000
DIC		55940.680		
pD		68.140		
Random Part	Mean	95% CI		SD
Country variance	0.162	0.096	0.265	0.044
Year variance	0.089	0.006	0.439	0.561
Occupation variance (ISCO 88 2 digit)	0.211	0.119	0.363	0.063
MOR Country Level	1.191			
ICC Country Level	0.043			
MOR Year Level	1.028			
ICC Year Level	0.024			
MOR Occupation Level	1.291			
ICC Occupation Level	0.056			
	Model 7			
Parameter	OR	95% CI		p
Intercept	0.100	0.073	0.129	0.000
Sex (ref: male)	0.649	0.615	0.684	0.000
Age	0.991	0.989	0.993	0.000
Has Tertiary Education (ref: no tertiary)	0.797	0.748	0.850	0.000
Nights worked per month	1.016	1.011	1.021	0.000
Works shifts (ref: no)	1.273	1.204	1.345	0.000
Hours per week worked	1.009	1.007	1.011	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.052	0.949	1.148	0.152
Adaptable within limits	1.053	0.979	1.132	0.085
Entirely Self-determined	0.998	0.925	1.073	0.468
DIC		55945.320		
pD		72.190		
Random Part	Mean	95% CI		SD
Country variance	0.159	0.096	0.257	0.043
Year variance	0.099	0.006	0.458	0.597
Occupation variance (ISCO 88 2 digit)	0.211	0.117	0.373	0.065
MOR Country Level	1.185			
ICC Country Level	0.042			
MOR Year Level	1.052			
ICC Year Level	0.026			

MOR Occupation Level	1.292			
ICC Occupation Level	0.056			
	Model 8			
Parameter	OR	95% CI		p
Intercept	0.090	0.073	0.115	0.000
Sex (ref: male)	0.652	0.618	0.688	0.000
Age	0.992	0.990	0.993	0.000
Has Tertiary Education (ref: no tertiary)	0.783	0.736	0.834	0.000
Nights worked per month	1.016	1.010	1.021	0.000
Works shifts (ref: no)	1.274	1.207	1.346	0.000
Hours per week worked	1.009	1.007	1.011	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.052	0.957	1.157	0.145
Adaptable within limits	1.051	0.981	1.127	0.076
Entirely self-determined	0.992	0.924	1.068	0.401
Skill-demand match (ref: they match)				
Demands too low	1.197	1.142	1.255	0.000
Demands too high	1.289	1.207	1.382	0.000
DIC		55871.250		
pD		73.750		
Random Part	Mean	95% CI		SD
Country variance	0.159	0.095	0.263	0.044
Year variance	0.070	0.006	0.372	0.233
Occupation variance (ISCO 88 2 digit)	0.216	0.122	0.381	0.067
MOR Country Level	1.186			
ICC Country Level	0.043			
MOR Year Level	0.982			
ICC Year Level	0.019			
MOR Occupation Level	1.301			
ICC Occupation Level	0.058			
	Model 9			
Parameter	OR	95% CI		p
Intercept	0.085	0.065	0.109	0.000
Sex (ref: male)	0.629	0.597	0.665	0.000
Age	0.991	0.989	0.992	0.000
Has Tertiary Education (ref: no tertiary)	0.800	0.753	0.847	0.000
Nights worked per month	1.015	1.010	1.020	0.000
Works shifts (ref: no)	1.249	1.181	1.321	0.000
Hours per week worked	1.008	1.006	1.010	0.000
Working time arrangement (ref: set by company)				
Choice between several fixed schedules	1.081	0.986	1.183	0.051
Adaptable within limits	1.083	1.013	1.158	0.009
Entirely self-determined	1.031	0.956	1.105	0.204
Skill-demand match (ref: they match)				
Demands too low	1.171	1.116	1.233	0.000
Demands too high	1.251	1.166	1.343	0.000

Paid appropriately (ref: Neither agree nor disagree)				
Disagree	1.492	1.404	1.577	0.000
Agree	0.858	0.809	0.912	0.000
DIC		55443.620		
pD		75.200		
Random Part	Mean	95%CI		SD
Country variance	0.156	0.093	0.257	0.042
Year variance	0.055	0.005	0.275	0.226
Occupation variance (ISCO 88 2 digit)	0.195	0.110	0.339	0.060
MOR Country Level	1.180			
ICC Country Level	0.042			
MOR Year Level	0.941			
ICC Year Level	0.015			
MOR Occupation Level	1.260			
ICC Occupation Level	0.053			

Appendix D

BHPS Multilevel Intermediate Models

Table D.1: Intermediate Models for Health Status

Model 0

	OR	95% CI		p
Intercept	3.783	3.290	4.229	0.000
DIC	115883.010			
pD	9366.570			
Random Part	Mean	95% CI		SD
Region Variance	0.065	0.027	0.151	0.033
Occupation Variance	0.019	0.011	0.03	0.005
Individual Variance	1.599	1.527	1.677	0.039
Region MOR	0.967			
Region ICC	0.013			
Occupation MOR	0.820			
Occupation ICC	0.004			
Individual MOR	4.032			
Individual ICC	0.322			
	Model 1			

	OR	95% CI		p
Intercept	4.121	3.696	4.655	0.000
Sex (ref: male)	0.852	0.806	0.899	0.013
DIC	115882.070			
pD	9359.290			
Random Part	Mean	95% CI		SD
Region Variance	0.065	0.027	0.153	0.034
Occupation Variance	0.018	0.01	0.03	0.005
Individual Variance	1.594	1.514	1.671	0.040
Region MOR	0.968			
Region ICC	0.013			
Occupation MOR	0.816			
Occupation ICC	0.004			
Individual MOR	4.021			

Individual ICC	0.321			
	Model 2			
	OR	95% CI		p
Intercept	6.099	5.392	7.097	0.000
Sex (ref: male)	0.851	0.802	0.903	0.000
Age	0.991	0.989	0.992	0.000
DIC	115797.180			
pD	9320.310			
Random Part	Mean	95% CI		SD
Region Variance	0.072	0.039	0.028	0.176
Occupation Variance	0.021	0.006	0.011	0.034
Individual Variance	1.590	0.036	1.152	1.661
Region MOR	0.985			
Region ICC	0.014			
Occupation MOR	0.827			
Occupation ICC	0.004			
Individual MOR	4.012			
Individual ICC	0.320			
	Model 3			
	OR	95% CI		p
Intercept	5.444	4.738	6.639	0.000
Sex (ref: male)	0.855	0.810	0.902	0.000
Age	0.991	0.989	0.993	0.000
Has Tertiary Education (ref: up to secondary)	1.471	1.372	1.575	0.000
DIC	115737.790			
pD	9287.750			
Random Part	Mean	95% CI		SD
Region Variance	0.067	0.027	0.161	0.035
Occupation Variance	0.012	0.006	0.02	0.004
Individual Variance	1.580	1.503	1.655	0.039
Region MOR	0.974			
Region ICC	0.014			
Occupation MOR	0.786			
Occupation ICC	0.002			
Individual MOR	3.990			
Individual ICC	0.319			
	Model 4			
	OR	95% CI		p
Intercept	4.778	4.099	5.607	0.000
Sex (ref: male)	0.919	0.867	0.975	0.000
Age	0.988	0.987	0.991	0.000
Has Tertiary Education (ref: up to secondary)	1.345	1.238	1.450	0.000
Gross monthly pay (GBP)	1.000132	1.000104	1.00016	0.000
DIC	115688.550			
pD	9259.860			

Random Part	Mean	95% CI		SD
Region Variance	0.065	0.026	0.153	0.034
Occupation Variance	0.007	0.002	0.013	0.003
Individual Variance	1.569	1.497	1.645	0.037
Region MOR	0.968			
Region ICC	0.013			
Occupation MOR	0.757			
Occupation ICC	0.001			
Individual MOR	3.965			
Individual ICC	0.318			
	Model 5			
	OR	95% CI		p
Intercept	5.677	4.938	6.497	0.000
Sex (ref: male)	0.893	0.843	0.943	0.000
Age	0.988	0.986	0.990	0.000
Has Tertiary Education (ref: up to secondary)	1.334	1.242	1.434	0.000
Gross monthly pay (GBP)	1.000151	1.000124	1.000178	0.000
Job hours per week	0.996	0.994	0.997	0.405
DIC	115678.01			
pD	9245.290			
Random Part	Mean	95% CI		SD
Region Variance	0.065	0.026	0.153	0.035
Occupation Variance	0.007	0.003	0.013	0.003
Individual Variance	1.563	1.495	1.642	0.038
Region MOR	0.967			
Region ICC	0.013			
Occupation MOR	0.760			
Occupation ICC	0.001			
Individual MOR	3.951			
Individual ICC	0.317			
	Model 6			
	OR	95% CI		p
Intercept	5.695	4.855	6.663	0.000
Sex (ref: male)	0.892	0.846	0.944	0.000
Age	0.988	0.986	0.989	0.000
Has Tertiary Education (ref: up to secondary)	1.341	1.244	1.443	0.000
Gross monthly pay (GBP)	1.000151	1.000124	1.000176	0.000
Job hours per week	0.995	0.994	0.997	0.000
Works flexitime (ref: Not mentioned)	0.928	0.878	0.980	0.000
DIC	115670.28			
pD	9255.820			
Random Part	Mean	95% CI		SD
Region Variance	0.067	0.027	0.156	0.035
Occupation Variance	0.007	0.002	0.013	0.003
Individual Variance	1.567	1.493	1.646	0.038
Region MOR	0.972			

Region ICC	0.014			
Occupation MOR	0.758			
Occupation ICC	0.001			
Individual MOR	3.962			
Individual ICC	0.318			

	Model 7			
	OR	95% CI		p
Intercept	5.270	4.272	6.633	0.000
Sex (ref: male)	0.879	0.820	0.932	0.000
Age	0.988	0.986	0.990	0.000
Has Tertiary Education (ref: up to secondary)	1.358	1.262	1.457	0.000
Gross monthly pay (GBP)	1.000127	1.000101	1.000154	0.000
Job hours per week	0.997	0.995	0.999	0.000
Works flexitime (ref: Not mentioned)	0.925	0.882	0.971	0.001
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)				
Not satisfied	0.796	0.724	0.874	0.000
Not very satisfied	0.905	0.850	0.961	0.000
Satisfied	1.114	1.053	1.174	0.000
Very Satisfied	1.297	1.197	1.398	0.000
DIC	115585.600			
pD	9188.89			
Random Part	Mean	95% CI		SD
Region Variance	0.070	0.279	0.161	0.036
Occupation Variance	0.007	0.003	0.012	0.002
Individual Variance	1.539	1.474	1.611	0.036
Region MOR	0.980			
Region ICC	0.014			
Occupation MOR	0.757			
Occupation ICC	0.001			
Individual MOR	3.898			
Individual ICC	0.314			

Table D.2: Intermediate Models for Health Problems with the Limbs or Muscles

Model 0				
	OR	95% CI		p
Intercept	0.048	0.042	0.057	0.000
DIC	69028.630			
pD	8898.240			
Random Part	Mean	95% CI		SD
Region Variance	0.083	0.029	0.212	0.048
Occupation Variance	0.016	0.007	0.308	0.006
Individual Variance	6.397	6.064	6.745	0.178
Region MOR	1.013			
Region ICC	0.008			
Occupation MOR	0.807			

Occupation ICC	0.002			
Individual MOR	24.119			
Individual ICC	0.654			
	Model 1			
	OR	95% CI		p
Intercept	0.042	0.033	0.052	0.000
Sex (ref: male)	1.225	1.114	1.346	0.000
DIC	68979.890			
pD	8884.190			
Random Part	Mean	95% CI		SD
Region Variance	0.089	0.032	0.153	0.053
Occupation Variance	0.018	0.009	0.033	0.006
Individual Variance	6.421	6.052	6.801	0.189
Region MOR	1.029			
Region ICC	0.009			
Occupation MOR	0.816			
Occupation ICC	0.002			
Individual MOR	24.284			
Individual ICC	0.654			
	Model 2			
	OR	95% CI		p
Intercept	0.002	0.001	0.002	0.000
Sex (ref: male)	1.180	1.068	1.298	0.000
Age	1.092	1.089	1.097	0.000
DIC	66916.100			
pD	8353.050			
Random Part	Mean	95% CI		SD
Region Variance	0.121	0.039	0.372	0.095
Occupation Variance	0.004	0.001	0.011	0.003
Individual Variance	5.993	5.676	6.303	0.165
Region MOR	1.102			
Region ICC	0.013			
Occupation MOR	0.740			
Occupation ICC	4.535E-04			
Individual MOR	21.504			
Individual ICC	0.637			
	Model 3			
	OR	95% CI		p
Intercept	0.002	0.001	0.003	0.001
Sex (ref: male)	1.171	1.064	1.301	0.000
Age	1.091	1.088	1.094	0.000
Has Tertiary Education (ref: up to secondary)	0.653	0.576	0.739	0.000
DIC	66931.460			
pD	8342.800			
Random Part	Mean	95% CI		SD

Region Variance	0.127	0.096	0.037	0.377
Occupation Variance	0.003	0.003	0.001	0.011
Individual Variance	5.927	0.156	5.623	6.239
Region MOR	1.117			
Region ICC	0.733			
Occupation MOR	0.014			
Occupation ICC	3.673E-04			
Individual MOR	21.099			
Individual ICC	0.634			
	Model 4			
	OR	95% CI		p
Intercept	0.002	0.001	0.002	0.000
Sex (ref: male)	1.122	1.022	1.228	0.013
Age	1.094	1.090	1.098	0.000
Has Tertiary Education (ref: up to secondary)	0.709	0.630	0.810	0.000
Gross monthly pay (GBP)	0.9999238	0.9998892	0.9999594	0.000
DIC	66882.860			
pD	8334.470			
Random Part	Mean	95% CI		SD
Region Variance	0.089	0.032	0.214	0.049
Occupation Variance	0.003	3.00E-04	0.013	0.002
Individual Variance	5.968	5.667	6.255	0.149
Region MOR	1.027			
Region ICC	0.009			
Occupation MOR	0.727			
Occupation ICC	2.990E-04			
Individual MOR	21.350			
Individual ICC	0.638			
	Model 5			
	OR	95% CI		p
Intercept	0.002	0.001	0.002	0.000
Sex (ref: male)	1.142	1.018	1.277	0.010
Age	1.095	1.092	1.098	0.000
Has Tertiary Education (ref: up to secondary)	0.704	0.619	0.796	0.000
Gross monthly pay (GBP)	0.9999209	0.9998791	0.9999607	0.000
Job hours per week	1.001	0.998	1.004	0.180
DIC	66877.5			
pD	8337.190			
Random Part	Mean	95% CI		SD
Region Variance	0.087	0.031	0.204	0.046
Occupation Variance	0.003	5.00E-04	0.008	0.002
Individual Variance	5.991	5.712	6.263	0.144
Region MOR	1.024			
Region ICC	0.009			
Occupation MOR	0.725			
Occupation ICC	2.817E-04			

Individual MOR	21.493			
Individual ICC	0.639			
	Model 6			
	OR	95% CI		p
Intercept	0.002	0.001	0.006	0.000
Sex (ref: male)	1.109	0.994	1.231	0.033
Age	1.095	1.091	1.098	0.000
Has Tertiary Education (ref: up to secondary)	0.696	0.616	0.786	0.000
Gross monthly pay (GBP)	0.9999211	0.9998809	0.9999591	0.000
Job hours per week	1.000	0.997	1.003	0.454
Works flexitime (ref: Not mentioned)	1.063	0.988	1.142	0.051
DIC	66891.7			
pD	8338.480			
Random Part	Mean	95% CI		SD
Region Variance	0.365	0.039	1.866	0.507
Occupation Variance	0.002	4.00E-04	0.007	0.002
Individual Variance	5.967	5.692	6.281	0.148
Region MOR	1.584			
Region ICC	0.038			
Occupation MOR	0.723			
Occupation ICC	2.467E-04			
Individual MOR	21.343			
Individual ICC	0.620			
	Model 7			
	OR	95% CI		p
Intercept	0.002	0.002	0.002	0.000
Sex (ref: male)	1.131	1.022	1.271	0.005
Age	1.094	1.090	1.098	0.000
Has Tertiary Education (ref: up to secondary)	0.694	0.606	0.792	0.000
Gross monthly pay (GBP)	0.9999383	0.9999039	0.9999719	0.000
Job hours per week	1.000	0.997	1.002	0.443
Works flexitime (ref: Not mentioned)	1.061	0.987	1.136	0.057
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)				
Not satisfied	1.094	0.964	1.243	0.092
Not very satisfied	1.031	0.944	1.121	0.253
Satisfied	0.897	0.828	0.965	0.000
Very Satisfied	0.813	0.725	0.910	0.000
DIC	66902.240			
pD	8329.880			
Random Part	Mean	95% CI		SD
Region Variance	0.094	0.034	0.233	0.052
Occupation Variance	0.002	0.003	0.007	0.002
Individual Variance	5.908	5.599	6.245	0.162
Region MOR	1.040			
Region ICC	0.010			
Occupation MOR	0.723			

Occupation ICC	2.616E-04			
Individual MOR	20.983			
Individual ICC	0.636			

Table D.3: Intermediate Models for Health Problems relating to Anxiety/Depression

Model 0

	OR	95% CI		p
Intercept	0.004	0.003	0.005	0.000
DIC	28940.020			
pD	4344.520			
Random Part	Mean	95% CI		SD
Region Variance	0.024	0.003	0.075	0.019
Occupation Variance	0.101	0.054	0.167	0.029
Individual Variance	7.723	7.240	6.745	8.182
Region MOR	0.840			
Region ICC	0.002			
Occupation MOR	1.056			
Occupation ICC	0.009			
Individual MOR	34.342			
Individual ICC	0.693			
	Model 1			

	OR	95% CI		p
Intercept	0.002	0.002	0.003	0.000
Sex (ref: male)	3.744	3.202	4.336	0.000
DIC	28876.930			
pD	4275.210			
Random Part	Mean	95% CI		SD
Region Variance	0.027	0.003	0.088	0.023
Occupation Variance	0.020	0.006	0.043	0.010
Individual Variance	7.377	6.927	7.891	0.248
Region MOR	0.851			
Region ICC	0.003			
Occupation MOR	0.824			
Occupation ICC	0.002			
Individual MOR	31.413			
Individual ICC	0.689			
	Model 2			

	OR	95% CI		p
Intercept	0.001	0.000	0.001	0.000
Sex (ref: male)	3.947	3.364	4.566	0.000
Age	1.035	1.029	1.041	0.000
DIC	28550.430			
pD	4228.600			
Random Part	Mean	95% CI		SD
Region Variance	0.031	0.039	0.372	0.026

Occupation Variance	0.012	0.001	0.011	0.009
Individual Variance	7.838	5.676	6.303	0.314
Region MOR	0.865			
Region ICC	0.003			
Occupation MOR	0.786			
Occupation ICC	0.001			
Individual MOR	35.354			
Individual ICC	0.702			
	Model 3			
	OR	95% CI		p
Intercept	0.001	0.000	0.001	0.000
Sex (ref: male)	3.855	3.262	4.428	0.000
Age	1.033	1.028	1.038	0.000
Has Tertiary Education (ref: up to secondary)	0.947	0.781	1.123	0.258
DIC	28593.630			
pD	4234.780			
Random Part	Mean	95% CI		SD
Region Variance	0.031	0.005	0.09	0.025
Occupation Variance	0.012	0.003	0.033	0.008
Individual Variance	7.732	7.011	8.372	0.325
Region MOR	0.864			
Region ICC	0.003			
Occupation MOR	0.788			
Occupation ICC	0.001			
Individual MOR	34.423			
Individual ICC	0.699			
	Model 4			
	OR	95% CI		p
Intercept	0.001	0.000	0.001	0.000
Sex (ref: male)	3.659	3.123	4.227	0.000
Age	1.034	1.029	1.039	0.000
Has Tertiary Education (ref: up to secondary)	1.004	0.820	1.193	0.501
Gross monthly pay (GBP)	0.9999349	0.9998733	0.9999983	0.023
DIC	28623.920			
pD	4238.690			
Random Part	Mean	95% CI		SD
Region Variance	0.038	0.004	0.135	0.054
Occupation Variance	0.012	0.003	0.029	0.007
Individual Variance	7.668	7.019	8.345	0.329
Region MOR	0.890			
Region ICC	0.003			
Occupation MOR	0.785			
Occupation ICC	0.001			
Individual MOR	33.861			
Individual ICC	0.697			

	Model 5			
	OR	95% CI		p
Intercept	0.001	0.000	0.001	0.000
Sex (ref: male)	3.650	3.169	4.241	0.000
Age	1.035	1.029	1.040	0.000
Has Tertiary Education (ref: up to secondary)	1.000	0.841	1.193	0.484
Gross monthly pay (GBP)	0.9999474	0.9998819	1.000005	0.04
Job hours per week	0.997	0.993	1.001	0.069
DIC	28586.44			
pD	4233.750			
Random Part	Mean	95% CI		SD
Region Variance	0.030	0.004	0.093	0.024
Occupation Variance	0.011	0.001	0.031	0.008
Individual Variance	7.771	7.295	8.319	0.264
Region MOR	0.863			
Region ICC	0.003			
Occupation MOR	0.780			
Occupation ICC	0.001			
Individual MOR	34.761			
Individual ICC	0.700			

	Model 6			
	OR	95% CI		p
Intercept	0.001	0.000	0.001	0.000
Sex (ref: male)	3.612	3.088	4.179	0.000
Age	1.033	1.028	1.038	0.000
Has Tertiary Education (ref: up to secondary)	0.999	0.824	1.230	0.465
Gross monthly pay (GBP)	0.9999481	0.9998802	1.000004	0.039
Job hours per week	0.996	0.992	1.001	0.074
Works flexitime (ref: Not mentioned)	1.091	0.971	1.219	0.069
DIC	28612.860			
pD	4234.550			
Random Part	Mean	95% CI		SD
Region Variance	0.031	0.004	0.918	0.024
Occupation Variance	0.014	0.003	0.035	0.008
Individual Variance	7.669	7.166	8.283	0.279
Region MOR	0.867			
Region ICC	0.003			
Occupation MOR	0.796			
Occupation ICC	0.001			
Individual MOR	33.876			
Individual ICC	0.697			

	Model 7			
	OR	95% CI		p
Intercept	0.001	0.000	0.001	0.000
Sex (ref: male)	3.732	3.157	4.337	0.000

Age	1.034	1.028	1.039	0.000
Has Tertiary Education (ref: up to secondary)	0.976	0.801	1.171	0.387
Gross monthly pay (GBP)	0.9999773	0.9999117	1.000027	0.235
Job hours per week	0.996	0.992	1.000	0.032
Works flexitime (ref: Not mentioned)	1.095	0.974	1.232	0.065
Job satisfaction: Total pay (ref: Neither satisfied nor dissatisfied)				
Not satisfied	1.641	1.318	2.016	0.000
Not very satisfied	1.224	1.054	1.415	0.008
Satisfied	0.996	0.861	1.155	0.470
Very Satisfied	0.847	0.701	1.017	0.041
DIC	28603.55			
pD	4232.610			
Random Part	Mean	95% CI		SD
Region Variance	0.032	0.005	0.09	0.023
Occupation Variance	0.014	0.003	0.033	0.008
Individual Variance	7.641	7.067	8.231	0.308
Region MOR	0.868			
Region ICC	0.003			
Occupation MOR	0.797			
Occupation ICC	0.001			
Individual MOR	33.632			
Individual ICC	0.696			