# The effect of health on the labour force outcome among working age individuals in the UK

Farzaneh Hemmati Torabi

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## Abstract

This thesis contains three empirical chapters on the effect of health on some key labour-force outcomes of working age individuals in the UK. In the first paper chapter two, the effect of health shocks on exit from employment among working age individuals using data from British Household Panel Survey was estimated. Factor analysis was used to model health as an unobservable concept with two correlated dimensions (mental and physical). Past mental and physical health status as well as mental and physical health deteriorations had significant effects on exit from employment.

In the second paper, I addressed the effect of changes observed in different components of income after acute health shocks were experienced among working age individuals. Identification arrived from exploiting uncertainty in the timing of an acute health shock, defined by the incidence of cancer, stroke, or heart attack. Results after coarsened exact matching, showed that health shocks significantly reduced labour income and increased welfare income, with younger male workers experiencing the greatest reduction in their net income and no significant increase in welfare income.

The impact of diabetes on exit from employment decisions of individuals in England was investigated in chapter four. Using data from English Longitudinal Survey of Aging, I utilised a recursive bivariate probit approach to test for the potential endogeneity of diabetes in employment outcomes. Parental history of diabetes was used as genetic instrumental variables. Results did not suggest that diabetes is endogenous. Investigation was advanced by employing a discrete time hazard model on the sample of male and female individuals aged 50 years or older in the first wave of ELSA, who were also in paid work. Results illustrated that being diagnosed with diabetes is associated with an increased hazard of leaving employment in estimated sample. Adverse effects on employment probability are higher among insulin or oral medication users.

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# Declaration

I declare that this thesis has been composed solely by myself and that it has not been submitted, in whole or in part, in any previous for another degree.

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# Chapter 1

## 1.1 Introduction

Influence of health on labour supply behaviour has long been recognised in the theoretical and empirical economic literature (van den Berg et al., 2006). Human capital is one of the theoretical frameworks, used extensively to understand the effects of health on employment (Ogundari et al., 2018). Based on this framework, health has been viewed as one of the determinants of individuals' productivity in the market place and, moreover, it has been referred to as the main determinant of the total amount of time one can spend on commodities and wealth creation (Grossman, 1972). However, the majority of empirical researchers have used the context of standard intertemporal labour supply models to understand the impact of a decline in individual's health on labour supply. Based on this theoretical framework, health deteriorations can be expected to lower wages and raise the relative valuation of leisure. Both effects will work to lower work hours, though the magnitude depends on the extent to which health declines are unpredicted and also on the assumptions made on the extent to which they are expected to persist (Gustman et al., 1986).

The manner in which health affects labour participation has been studied extensively and a significant number of empirical papers point to the links between health and labour market risks, while the exact relationship between the two and the extent of the effect remains unclear (Blundel et al., 2017). There are several reasons for this lack of agreement on the magnitude of these effects. First, any effects of health on labour-force participation are highly likely to be socially determined.

Government policy in promoting labour-market inclusion of individuals with impaired health, as well as disabled workers within various organisations, can play a substantial role in implementing a fairer society for all workers (Cai et al., 2014). Through social security and welfare arrangements, government policy influences how individuals and organisations react and can adjust to unpredictable health shocks (Börsch -Supan et al., 2008; Gruber et al., 2004; García-Gómez, 2013). Healthcare-provision arrangements vary greatly between countries. In the US, where many employees have an employer-backed insurance service, the labour supply increases after an adverse health-shock event due to an envisaged rise in future healthcare cover and its related costs (Madrian, 1994; Kapur, 1998; Bradley et al., 2013). In most European countries, where nationally funded healthcare services are in place, the same pattern is not observed as out-of-pocket expenditures play a limited role in healthcare funding (O'Dowd, 2018). The second reason for the observed diversity in the reported effects of health on employment is that the definition of health varies widely from study to study (Bound, 1991). While estimates of the effects of health on labour supply are quite sensitive to the measure used, there is no agreement in the literature on the best method of measuring health (Disney et al., 2006). Two empirical approaches to quantifying health's association with labour market outcomes have been developed. The first approach was to estimate the effect of general health status, which ideally would portray an individual's ability and desire to work. Such measures can be referred to as "work capacity". However, in practice, the majority of empirical research only used one form of self-reported general health status and failed to model health as a multi-dimensional concept (Blundell at al., 2017). It has been argued that including multiple or more comprehensive health measures considerably increases the explanatory power of regression models (Manning et al., 1982).

Health is one of the main determinants of wages, hours and labour force participation among groups as diverse as recent graduates, single mothers and older individuals who are reaching their retirement age. Each week in the UK, one million workers take time off due to sickness, while most return to work within days, around 17000 individuals reach their sixth week of statutory sick pay and at this point, almost one in five people will remain off sick and eventually leave work (hse.gov.uk, 2005). This can have serious effects on such individuals and their families, as well as employers, government and wider society. Financial losses due to lost employment income, productivity costs, occupational or statutory sick payments and Liability Compulsory Insurance (ELCI) premiums are some of the impacts on these individuals, their employers and wider society as a whole. Government costs include state benefits, lost tax receipts and NHS treatment expenditures (hse.gov.uk, 2019).

The relationship between health and employment is a dynamic process that can be modelled more accurately using data from longitudinal surveys. Panel data methods can aid with addressing and reducing the confounding effects of reverse causality and simultaneity bias (Smith, 2004). In this thesis, longitudinal surveys were used to map both gradual and sudden deterioration in health as well as employment history of individuals. Surveys were selected according to the main research question in each chapter in order to provide the best answer to the question; in particular, available data was utilised to make comparisons between the magnitudes and extent to which different people from various age and socio-economic backgrounds are affected. Clearly, people can experience health problems in different stages of their lives and the job market-related outcomes can vary substantially depending on the patient's age. Incentives for staying in employment and career options available after health deteriorations are closely related to job tenure, pension and overall wealth and structure of households. These can vary between younger and older individuals and need to be accounted for when interpreting empirical results. In addition, some people may never enter the job market as a consequence of suffering severe health problems in childhood. This work does not cover this specific aspect of health's effect on labour force inactivity. I restricted my attention to people who were in the working age bracket and had been in paid work at some point during their participation in considered surveys. The aim was to go beyond estimating an average effect of health on exit from employment and provide finer details which enabled a comparison between affected people in the UK and identify the sub-groups that were more vulnerable when experiencing health problem.

The main objective of my second chapter was to estimate the magnitude of the effect of deterioration in general health on the probability of exit from employment among working age individuals in the UK. The manner in which labour force outcomes for these diverse groups are affected is dependent on the nature of the health problem. According to World Health Organisation (WHO), health is a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity (WHO.int.com, 2016). Motivated by this definition of health, I took a closer look at the concept of work capacity and how a comprehensive description of health can be captured based on various health measures provided in British Household Panel Survey (BHPS). Although there is overwhelming evidence on the effect of mental health on the ability and desire to participate in labour force market (Almond et al., 2003), there are only a handful of studies that provide a comparison between magnitude of the effect of deterioration in physical and mental health on employment. Using factor analysis, health measures were constructed to compare people with respect to their general mental and physical health. While most well-known health measures are not clear measures of physical or mental health, extracting two distinct measures that distinguish between mental and physical health enabled me to account for these two aspects of health simultaneously, and test whether these two aspects of health differed with regards to their effect on employment. Moreover, factor analysis sheds light on what people have on their mind when answering health-related questions, and the manner, in which distinct dimensions of health are related to each other.

Third chapter of this work aims to provide details on financial circumstances of individuals after they have experienced an acute health shock for the first time. One of the main challenges in identifying the effect between health and labour market outcomes is that there is potentially an effect of previous labour market outcomes on health and thus the potential for reverse causality. One of the suggested approaches to mitigate this problem was to use sudden variation in health, which was exogenous relative to income and labour force participation as well as controlling for past health (Smith 2005). However, measuring and identifying such health shocks is not easy and consequently very few empirical studies have employed this framework. In the third chapter of this work, studies such as Datta Gupta et al. (2011) and Zantomio et al. (2016) are followed in order to investigate the effect of health shocks as measured by the incidence of cancer, stroke or myocardial infarction on different component of income among working age individuals in the UK.

There are plausible reasons to justify the choice of these health problems as exogenous health shocks. First, these problems are less likely to be misreported and exaggerated compared with milder issues, hence the magnitude of justification bias will be minimised (Baker et al., 2004). Additionally, even though genetic inheritance, lifestyle choices and chronic health problems play a significant role in the development of these health shocks, in most cases the exact timing and probability of occurrence remains unexpected (Zantomio et al., 2016). Coarsened Exact Matching (CEM) method was used to control for the selection-on-observables problem as individuals experiencing such health shocks and those who do not, may not necessarily be identical prior to treatment (Iacus et al., 2011). Further regression analysis has been conducted to capture variations in different components of individual’s income and investigate whether and to what extend the potential reduction in labour income is compensated by income received from the welfare system.

The fourth chapter of this thesis considers the effect of diabetes on early retirement in England. It is estimated that in the UK, the population aged over 65 will grow twice as fast as the working age population and will account for about 24% of the total population by 2037 (Office for National Statistics 2015). This will decrease ratio of the number of working age taxpayers over older individuals who receive pension and social welfare. An aging population, accompanied by a lower ratio of social security contributors to recipients will cause a significant challenge to government policies and sustainability of pensions as well as social and healthcare services (Hofäcker, 2015). Therefore, encouraging working age people to stay in work is one of the priorities for UK government.

Three factors contribute significantly to rates of early withdrawal from the labour market: wealth, health and caring duties. Although around 60% of older workers remain fit, healthy and keen to work, the major causes of economic inactivity in the age group 50 to state pension age is ill health (parliament.uk, 2011). Four million older people in the UK are affected by chronic health conditions and this is estimated to rise due to an ageing population (ons.gov.uk, 2018). It is predicted that by 2030, around seven million older people will have some form of long-term medical condition (ageuk.org.uk, 2019). The number of people with diabetes has been steadily increasing in the UK and based on current population trends; by 2035 4.9 million people will have diabetes (gov.uk, 2016). Therefore, gaining an insight into the effect of chronic diseases on labour force participation can assist with defining policy measures that are essential to increase labour participation among chronically ill individuals.

Discrimination is one of the contributing factors that increases probability of exit from employment following a health deterioration event. The first utilitarian provisions to reduce and address workplace disability discrimination were introduced in 1995 (National Equality Panel, 2010). The Disability Discrimination Act protected individuals living in Britain who had a physical or mental impairment with sever and long-term effects hindering their ability to carry on with normal day-to-day activities. The ‘disability employment gap’ which represented the difference in the employment rate of disabled people and those not deemed as being disabled was one of the indicators reflecting the scale of the discrimination disabled individuals experienced. In April-June 2020, the employment rate for disabled people was reported as 53.6% while this was 81.7% for others, indicating a significant 28.1 percentage points difference (Powell, 2020).

It has been argued that factors such as life-style choices can affect the diabetic status and labour market outcomes simultaneously (Smith, 2005). Therefore, using the genetic history of each individual as an instrumental variable, the potential for endogeneity of diabetes status and early retirement was assessed in the fourth chapter of this work. The other characteristic of diabetes is that in line with other chronic health conditions, it increases the likelihood of complications and co-morbidities. People with diabetes can vary substantially with regards to their levels of ability and desire to work as their condition develops over a long period of time. However, majority of existing literature uses binary measures and considers diabetics as one homogeneous group from which the average effect of the condition on employment probabilities is estimated. This work contributed to literature by investigating whether and to what extent labour market-related disadvantages differed among diabetics and explored which factors led to early retirement in England. Using data from 7 waves of the English Longitudinal Survey of Aging from 2002 to 2014, a discrete time hazard model was estimated. The sample consisted of male and female individuals between 50 and state pension age as well as being in paid work at the first wave of the survey. Results showed that hazard of leaving employment was higher among both diabetic men and women compared with non-diabetic counterparts and the difference was statistically significant. The effect of being diagnosed with diabetes on probability of withdrawal from employment was higher among patients who used insulin or oral medications. These findings were consistent even after including controls for onset of other comorbidities such as stroke and heart problems. In addition, no significant outcomes were observed when duration of diabetes was controlled for in survival analysis; suggesting that categorising diabetics based on the years since they have been diagnosed was not a good predictor of probability of exit from employment.

The structure of this thesis is as follows: chapter 2 investigates effects of mental and physical health on exit from employment using BHPS data. Chapter 3 addresses effect of acute health shocks on different components of income among working age people. Chapter 4 is concerned with diabetes and its effect on early retirement: Does duration and intake of medicines matter? Chapter 5 represents the overall conclusion of this thesis. References are reported at the end of each chapter and Appendix is provided after each chapter's references.

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# Chapter 2

## 2. Effects of mental and physical health on exit from employment

### 2.1 Introduction

Employment is generally the most important means of obtaining adequate economic resources and full participation in society, with work being central to social roles and status. “Increasing employment and supporting people into work are key elements of the UK Government’s public health and welfare reform agendas” (Waddell and Burton, 2006).

For an individual, health problem is one of the main reasons for leaving the labour market and empirical findings suggest that health has a significant effect on labour force status of individuals (Chirikos, 1993). A substantial number of people in Britain leave work every year and mention health as the main reason for their exit from employment. According to the Organisation for Economic Co-operation and Development (OECD), each year up to 370,000 people leave work due to illness and injury, equivalent of 1% of the working age population. Only 1 in 4 returns to work a year later (OECD.org, 2014).

In this paper, magnitudes and dynamics of the impact health deteriorations have on exit from employment among people who hold a job is explored. Health deterioration can happen gradually. An individual may feel progressively worse over the years finally reaching a stage where their health is poor enough to force them out of employment. Alternatively, heath deterioration can occur over a shorter time frame, such as a broken bone or recurring back issues. I controlled for past health to capture the gradual deterioration of health and identify a health shock when an individual experiences transition from good or fair health to poor or very poor health between two consecutive years. Clearly, people who experience health problems in earlier stages of their life may never enter the job market. This work does not cover that aspect of health's effect on labour force behaviour. As this study was interested in the effect of health on exit from employment, only individuals who had a job at least for a year during their participation in British Household Survey were considered.

Although literature on the relationship between employment and health has inherently focused on the effects of health on retirement decisions, health can be an important determinant of labour force supply in any age group. British young people are twice as likely to be out of work due to health reasons as they are in other rich countries (OECD, 2017). In Britain, two-fifths of people claiming benefits due to depression or mental health problems are aged between 20 and 34. In addition, health can play an important role in decline of labour force participation by influencing decisions for early retirement (Auer and Fortuny, 2000).

The manner in which health shocks affect exit from employment depends on two main factors. Firstly, the nature of the health shock and secondly, the nature of the job. When a health shock affects capacity of work, it can push individuals out of employment. However, depending on the severity of the health shock people may choose to reduce working hours or change their professions.

It was assumed that health shocks can indirectly and directly affect work capacity. Direct effect is when a health problem affects the main skills and abilities that an individual requires to do the job, e.g. a surgeon or a pianist with Parkinson's or Arthritis. On the other hand, a computer programmer with the same health problem may still be able to manage to continue to work and use advanced technology to overcome this barrier (no direct effect). However, the computer programmer with arthritis may find doing daily activities very difficult and time consuming. As a result, time for rest and leisure will decrease. Chirikos (1993) argued that due to increased need for rest or self-care, the actual amount of time spent on leisure will be decreased. On the other hand, people may need more time to do non-labour activities that are crucial for being able to supply labour. These factors contributed to valuing leisure time more compared to time individuals had better health and led to increase in probability of reduced working hours or exit from the labour market (Chirikos, 1993). In this paper, this aspect of health and its subsequent influence on employment is called indirect effect of health on work capacity.

In the case of indirect effect of health on work capacity or when direct effect of a health problem is not strong enough to make it impossible to do the job, an individual may prefer to reduce working hours or move to a part-time job. This decision is better suited for people who are in professions that enable them to do flexible hours, while earned salaries will be sufficient to maintain an acceptable life standard. Individuals who are trained in more than one skill or area of expertise (Multi-skilled) may manage to change their field of work and find a job that suits their new health conditions and even overcome the direct effect of health on working capacity. This change however may lead to a salary downgrade. For example, a surgeon with arthritis may turn to teaching and stay in work. Because education is one of the main determinants of marketable skills, I assumed that people with lower educational attainments and limited skills will be more likely to exit employment when a health shock is experienced.

Working capacity requires different sets of skills in different types of occupations. Therefore, depending on the type of job, health problems can affect work related skills in various ways. In this work, I divided different occupations in two general groups of manual and non-manual jobs and assumed that these two categories of jobs required different sets of skills that make it possible to compare people's response to health shock with respect to the type of job they hold.

I also split health problems into two main categories of mental and physical. One reason for this categorisation is that how mental and physical health are perceived in society and by the patients are different. There is evidence to suggest that physical and mental health are related to employability and therefore job loss in different ways (Kennedy, 2012). While around 38% of claimants list mental illness as the main reason for their claim, mental health does not receive the same attention as physical health. People with mental health problems frequently experience stigma and discrimination, not only in the wider community, but also from service providers (Bailey et al., 2013). This is exemplified in part by lower treatment rates for mental health conditions and an underfunding of mental healthcare relative to the scale and impact of mental health problems (Bailey et al., 2013). I tested whether the magnitude of the effect of physical and mental health problems is different for men or women in presence of mild or strong shocks. One other main difference between mental and physical health problems is that even common mental health issues can significantly reduce quality of leisure time (for example lack of sleep and energy). This means that indirect effect of mental health can reduce productivity and working capacity regardless of the type of job an individual has. In addition, skills such as time and stress management that are essential requirements in most professions can become disrupted with the onset of mental health problems. This is how direct effect of mental health comes into play. I also investigated whether individuals who held manual jobs were at higher risk of job loss when confronted with physical health problems compared to those with a non-manual job. This is due to the fact, that a physical health problem can directly affect their work capacity while, people in non-manual occupations may be less vulnerable to direct effect of physical health shocks as their main expertise is not dependent on their physical well-being.

The concept of health is comparable to notion of ability, meaning that while one has some idea of what is being implied by the term, it is nevertheless challenging to measure it (Griliches, 1977). In exploring the relationship between health and employment, the first step is to achieve a set of measures of health that shows ability and desire to work (Madarian, 1999). My aim was to construct health measures which enabled us to compare people with respect to their mental and physical health. For example, how should we compare two individuals who report that their health affects the type or amount of the job they can do, but one of them also reports that his/her health affects his/her daily activities as well. As previously argued, ill health can affect people in different ways and all these aspects can be important. Now let’s consider another question such as “how do you rate your health compared to people in your age group?” What if one person rates their health as poor and the other one rates it as average. Doesn’t this mean that the person with the poor rating has some other health issue that is not being captured in the survey or has higher severity of the mentioned health problem compared to the average? I think that these extra pieces of data are valuable and should not be ignored. Therefore, we need a mechanism that enables us to sum up all this information and make it possible to compare overall mental and physical health of individuals.

While most well-known health measures such as those mentioned above are not clear measures of physical or mental health, constructing two distinguished measures of mental and physical health is essential in this work. To address these issues, explanatory factor analysis was used to test whether it was possible to model physical and mental health as two distinguished, but correlated latent variables using several common health measures. A confirmatory factor analysis model based on information gained from the explanatory model and past literature was then assembled. One advantage of using factor analysis was that there was no requirement to assume that each indicator measured only a single specific dimension of health as cross-loadings were allowed.

This study uses 18 waves of British household Panel Survey to obtain estimates of the impact of sudden health deterioration on the probability of transition from employment to being economically inactive among working age individuals in the UK. Several well-known health measures were considered to model physical and mental health as two correlated latent variables using explanatory and confirmatory factor analysis. Therefore, this enabled comparison of the magnitude of effect of mental and physical health shocks on probability of exit from employment. Furthermore, to test whether mental and physical health deteriorations showed varied effects on people engaged in different professions, working individuals were categorised into manual and non-manual jobs. Manual job category included skilled, partly skilled or non-skilled manual workers as well as people working in the armed forces. Non-manual jobs included occupations which were listed as skilled non-manual, managerial or technical and professional. Additionally, BHPS data permit an analysis with separate estimates of the impact of health for males and females to allow for comparisons across gender.

### 2.2 Health & labour force behaviour (theory and empirical evidence)

The empirical literature on the effects of health on labour force behaviour is mostly focused on how health affects retirement decisions (Hurd, 1999). A number of researchers including Bound et al. (1999), Au et al. (2005), Disney et al. (2006), Hagan et al. (2006), Rice et al. (2006) and Zucchelli et al. ( 2007) looked at individuals older than 50 and showed that reduction in health status had an explanatory power for retirement decisions. Among Spanish workers aged between 50 and 64, the probability of continued working decreased with the severity of the shock as shown by Jiménez-Martin et al. (2006). As demonstrated by Smith (2004), there was a 15% decrease in the probability of working for individuals older than 50, who suffered a health shock and even though this negative effect decreased every year, it still remained significantly high at approximately 4% even five years after the shock. Empirical researches have determined that health and financial incentives provided by social security schemes and pension plans both play an important role in retirement decisions.

There are fewer studies that focus on involvement of health on labour market transitions among all working age people. However, early labour market exits are more likely to cause even more adverse outcomes. Younger individuals are more likely to experience economical inactivity after a health shock. Long-term poverty is very likely among this group of people as the probability of re-entry into work is greatly diminished in such individuals (Jones et al., 2015).

Lindeboom et al. (2006) produced an event history model for transitions between work and disability states among working age individuals using British National Child Development Study (NCDS). To create this model, they utilised unscheduled hospital appointments as an indicator of health shocks. Their findings showed that the effects of health shocks in early stages of life on employment were not direct, but rather act through the inception of a permanent disability, which escalated by 138% after the onset of a health shock. Also demonstrated was the finding that onset of a disability at age 25 reduced the probability of employment at age 40 by 20%. Messer and Berger (2004) used the US Health and Retirement Survey and compared effect of permanent and temporary health deteriorations on wage, working hours and employment. They showed that lasting adverse health conditions diminished both wages and hours worked. The size of the effect was almost double for men compared to women. On average, total working hours of affected men was

6.3% less and they earned 6.3% less compared to healthier men. Also, the larger effects of health on labour outcomes were found on prime-age individuals, as the peak of loss of wages after the onset of a permanent illness occurred at ages 40-49 for males (wages are 12.1% lower) and 30-39 for females (wages are 9.2% lower). Short-term health conditions had little impact on hourly wages or hours worked.

Dano (2005) focused on injuries caused by road accidents and found that there were both short and long-term adverse effects on the probability of being employed for Danish male. This effect holds even when those in receipt of disability benefits were excluded from the analysis. Effects of a health shock on the prospects of leaving employment and inactivity was investigated by Garcia-Gómez et al. (2006) on the Spanish working age population. They demonstrated that for those exposed to a health shock the probability of remaining in employment decreased by 5% and the probability of entering inactivity increased by 3.5%. Similar outcomes have been shown for other European countries (Garcia-Gómez et al., 2008).

Calendar data from the first seven waves of the BHPS was used by Böheim et al. (2000) to examine transitions from unemployment to part-time work, self-employment and economic inactivity. Their findings showed that the existence of a health condition that restricts the type or quantity of work observed before a period of unemployment, doubled the exit rate from unemployment into economic inactivity.

Studies such as Jones et al. (2015) focused only on acute health shocks caused by stroke or cancer. These health shocks were more likely to be unforeseen and less exposed to the chance of misreporting compared to milder conditions. However, this approach lacked generalisability as results were based on labour force response to these specific health conditions.

None of the empirical works mentioned so far have compared effects of mental and physical health on labour force behaviour outcomes. In most of these studies, precise and distinguishable measures of both mental and physical health are not included in empirical estimations and these two aspects of health are lumped together. For example; Garcia-Gomez et al. (2009) looked at the effect of health on labour market exit and entries. They constructed an index of health using a latent variable approach. They then went on to use predicted values of self-assessed health obtained from ordered probit estimation in which objective measures of health were used as explanatory variables, while self-assessed health was the independent variable. The main reason for adopting this method was to eliminate potential justification bias in self-reported health measures. Nonetheless, their index of health mixed both mental and physical aspects of health and included a self-reported measure of mental health (GHQ) separately in their estimated model. Subsequently, it is unclear what exactly is the coefficient of index of health measures in comparison with the coefficient of mental health identifier.

To my best knowledge, only Pacheco et al. (2014) distinguished between mental and physical aspects of health and examined whether they are related in different ways to people’s labour force behaviour. They made use of six health status indicators including three measures of physical health (health limiting, pain and energy) and three measures of mental health (depression, health-social, health accomplishment) to estimate the effect of health on labour force participation. Their results suggested that only physical health-limiting problems had significant negative impact on propensity of employment among men. In contrast, the probability of being employed among women was negatively affected by pain and mental health-accomplishing aspects as well as physical health-limiting dimensions (Pacheco et al. 2006). They acknowledged that all of their health measures were highly correlated. This is one of the drawbacks of including multiple health indicators in a model because it makes it difficult to interpret the results (Bound et al., 1999). This problem was tackled with implementing factor analysis and using correlated health measures to form latent measures of mental and physical health.

As suggested by Chirikos (1993), a valid and reliable measure of health was essential to establish the relationship between health and labour force behaviour. This valid measure of health enabled me to capture health differences over time and across individuals. However, there is still no common measure of health status employed by all researchers. Multidimensionality of health could be the reason for diversity in health measures used. Various studies concentrate on different dimensions of health and thus the magnitude of reported effect of health on labour force behaviour alters depending on the measures used (Currie et al., 1999). In general, estimated effect was larger when self-assessed health variables were used, and smaller when specific impairment, functional limitations, or mortality experience indices were considered (Chirikos, 1993).

In summarising the literature on this subject, there were no perfect measures of health to be found for estimating the effect of health on labour supply. There were arguments for and against using self-assessed health. Although, there was a justification endogeneity concern over self-assessed health (unemployed people may report their health worse than employed people to justify their economical inactivity), the empirical evidence on its existence was neither robust nor consistent with the hypothesis in the literature. Therefore, use of self-assessed health measures is still popular in predicting the effect of health on labour force participation (Cai et al., 2006).

Majority of previous literature considered either physical or mental health and did not include both aspects in the empirical estimations (e.g. Jones et al., 2015; Pelkowski et al. 2004). In addition, usually a limited number of health measures were used in empirical research that led to capturing only one segment of the multidimensional concept of work-related health. Data limitations could be one reason for these shortcomings.

This study makes use of several health measures that encircle both physical and mental health status and contributes to literature by exploring the relationship between several well-known measures of health using explanatory factor analysis. Extracted latent physical and mental health measures were used to estimate the effect of health deteriorations on the probability of exit from employment among working age individuals. I made use of both self-assessed health and specific health problems to achieve a general and more accurate picture of people’s health each year and constructed two separate measures of health that captured overall mental and physical health status of individuals. As previously explained, direct and indirect effect of health on working capacity can only be captured through gathering relevant, sufficient information on different aspects of people's health status.

## 2.3 Data

British Household Panel Survey (BHPS) is the UK's first socio-economic household panel survey. BHPS interviews and follows the same individuals every year. Questions cover many dimensions of people's lives such as income, labour market status, health, psychological well-being, education and household composition. Such data provide essential information, enabling researchers to study the link between health and employment. When I began writing this chapter in 2013, only 3 waves from understanding society were available. It was clear that making use of 18 waves of BHPS could provide greater capacity for modelling the complexity of relationship between health and employment compared to 3 waves available in understanding society.

The initial sample of 5050 households was collected in 1991 containing over 10,000 adult individuals. Other initial samples used in various national panels had a similar size. Data has been gathered for 18 years and changes in people's lives can currently be identified over a period from 1991 to 2008 (18 waves). During this time, people may leave the sample due to various reasons. However, year-on-year response rates have consistently been 95-96 percent over years (Lynn et al. 2006).

Scottish and Welsh boost samples were added in 1999 and Northern Ireland was added in 2001. Each of these samples contained approximately 1900 households who were selected with clustered and stratified design.

I first conducted factor analysis on all these individuals including 169292 observations throughout 18 waves of BHPS. The breakdown of the employment rate with respect to health status is provided in table 6.

To measure labour force behaviour in this study, I identified people who had carried out “any paid job” using outcomes from two related questions asking if the respondents have had a paid job last week and if not whether he/she has a job, but was away from it? Therefore, in this method, people who answered “yes” to both or one of these questions were considered as working. Paull (2002) suggested that combination of these two questions provides the closest measure to the International Labour Organisation (ILO) definition of employment in BHPS. Here I define “inactive” as being out of work and not looking for any kind of paid work in the last 2 week or last four weeks. I included two different groups of people in my estimation sample; people who have been in work during two consecutive years and people who have been inactive in the current year, but in employed. People who were inactive during this survey were excluded from the sample. Also, people who moved from employment to unemployment have been removed from the estimated sample. I then went on to compare people who entered inactivity from employment with those who stayed employed.

Unemployed and inactive people were separated from each other as they had two different economic statuses. Unemployed people actively looked for a job, however inactive people decided not to work for a while. Estimated sample included men aged 16-64 and women 16-59 years old, excluding individuals in full-time study and maternity leave.

Sample of estimate was selected, and the strategy motivated by the procedures used by Lechner and Vázquez Álvarez (2004) and García-Gómezand et al., (2006) was adopted. I considered a window of two years (t and t+1) for each observed individual which resulted in creation of sequences of two years over the timespan covered by the data. For each sequence, individuals who were in employment or self-employment at t (the start of the sequence) were selected. These individuals can be employed, unemployed or economically inactive at t+1. The treatment or health shock is experienced if individuals that had reported good health at t, reported poor health at t+1. I estimated the effect of this health shock on probability of being economically inactive at t+1.

The sample used for the regression analysis contained 54,421 observations for men including 8,519 individuals that on average were observed in the sample for 6.4 years. Women's samples included 8,710 individuals with an average of 6.1 years remaining in the sample, providing 53,171 observations.

In this chapter, effect of health on exit from employment and entering inactivity was explored. Health measures considered and the method they were utilised are explained below.

### 2.3.1 Health variables

Most of the previous literature considered either physical or mental health and did not include both aspects in the empirical estimations (e.g. Jones et al., 2015; Pelkowski et al., 2004). In addition, usually a limited number of health measures were used in empirical research that led to capturing only one segment of the multidimensional concept of work-related health. Data limitations could be one reason for these shortcomings.

This study made use of several health measures that encircle both physical and mental health status and contributed to literature by exploring the relationship between several well-known measures of health using explanatory factor analysis. Extracted latent physical and mental health measures were used to estimate the effect of health deteriorations on the probability of exit from employment among working age individuals. I made use of both self-assessed health and specific health problems to achieve a general and more accurate picture of people's health each year and constructed two separate measures of health that captured overall mental and physical health status of individuals. As previously explained, direct and indirect effect of health on working capacity can only be captured through gathering relevant information on different aspects of people's health status.

In BHPS there is a group of separate health measures relating to specific health issues such as 1-arm, leg or hands 2-sight, 3-hearing, 4-skin or allergy, 5-chest or breath, 6-heart or blood, 7-stomach or digestion, 8-diabetes, 9-anxiety or depression, 10-alcohol or drugs, 11-epilepsy, 12-migraine. So far in the literature, all these variables have been used together. For example; Gomez et al. (2006) and Jons et al. (2010) used all these 12 groups of variables to predict the latent health index of Self Assessed Health (SAH). Burchardt (2000) used a binary variable indicating whether a person had at least one of these 12 health problems. She suggested that these variables could be a measure of an individual's model of disability.

Two other measures of health in BHPS, asked people: "Does your health in any way limit your daily activities compared to most people of your age?" and "Does health limit the type or amount of work?" The outcome obtained from these questions depends very much on respondent's concept of health and their daily activities/lifestyle and are highly correlated among working age people in my sample (70%). These measures of health are widely used in literature, particularly when focusing on long term disability as the main research interest (Bell et al. 2009). When answering these questions participants can refer to either their mental or their physical health. For instance, a person with depression may find it difficult to do her or his grocery shopping. On the other hand, the same daily activity can be difficult for someone experiencing mobility issues. We use explanatory factor analysis to see which aspect of health is mainly considered in answering these questions.

GHQ-12 is another set of variables considered. GHQ stands for General Health Questionnaire**.** These were initially used for screening a psychiatric illness, but were recently widely used as an indicator of psychological well-being (MacDowell, 2006). GHQ-12 is a shortened version of the GHQ-60 and is embedded in the self-completion questionnaire component of BHPS (Goldberg et al., 1988). This reduced form contains 12 individual components that cover concentration, sleep loss due to worry, perception of role, capability in decision making, whether constantly under strain, perception of problems in overcoming difficulties, enjoyment of day-to-day activities, ability to face problems, loss of confidence, self-worth, general happiness and whether suffering from depression or unhappiness. All items have a 4-point scoring system that ranges from a 'better/healthier than normal' option, through to a 'same as usual' and a 'worse/more than usual' to a 'much worse/more than usual' option. The exact wording depends upon the particular nature of the item.

The exact question that is asked in BHPS as follows: please think back over the last 12 months about how your health has been. Compared to people of your own age, would you say your health has been excellent, good, fair, poor or very poor? This measure of health is seen as an indicator of perceived health status based on the individual’s concept of the norm for their age (Jones, 2004). With people’s varying expectations, this measure may change over time. The subjective nature of this measure provides a personal insight into an individual’s health. Several studies have looked at associations between SAH and mortality rates. Most have concluded that a significant independent linkage exists when various health status indicators and other relevant covariates are considered (Idler et al., 1997). Researchers such as David e al. (1981) and Kruse et al. (1994) questioned what SAH really measured and their results suggested that this variable mainly reflected physical health problems and to lesser extent mental issues.

Health satisfaction (Satisfaction) is the last question that is considered in this work. Participants were asked to answer the following question: How dissatisfied or satisfied are you with your health how satisfied or dissatisfied they were with their health status and individuals are asked to score their satisfaction from 1 to 7 while not satisfied at all is scored as 1 and 7 corresponds with being completely satisfied. Correlation between health satisfaction measure of health and SAH is 67%.

This measure of health is used in several empirical works, for example Riphahn (1999) explored how employment and economic well-being of older German workers were affected by health shocks. Health shocks are defined as sudden deterioration of health satisfaction at least five point on the scale of zero to ten. This measure also has been used as an indicator of perceived health in studies such as Ronellenfitch et al. (2004) who investigated health deterioration among immigrants from eastern Europe to Germany. Also, Ravesteijn et al. (2018) used health satisfaction measured on an integer scale from 0 to 10, as their main outcome variable in investigating the role of occupation on health of working age people using German socioeconomic panel..

**2.4 Modelling health**

Table one describes how variables mentioned in the section 2.1 are used in factor analysis model. I constructed a binary variable based on each of the health measures to identify people with poor health and avoided mixing people with mild conditions with ones with poor and very poor conditions. This kind of identification is very common and recommended in the literature (Riphahn, 1999; Burchardt, 2000).

In addition, interpretation and comparison of the loadings in factor analysis is easier when all the measures are either binary or continuous.

**Table 1**: Health variables and descriptions in BHPS and how they have been used in modelling health

| Variables | Description |
|---|---|
| Conditions | Question in BHPS: Please see page 34 for the list of variables. Mean 0.05, standard deviation: 2.6<br>Binary variable: Equal to 1 if at least one of the health questions is reported and 0 otherwise.<br>(arm leg or hands, sight, hearing, skin or allergy, chest or breath, heart or blood,<br>stomach or digestion, diabetes, epilepsy, migraine) |
| Daily | Question in BHPS: "Does your health in any way limit your daily activities compared to most people of your age?"<br>Mean 0.18, standard deviation: 0.09<br>Binary variable: Equal to 1 if respondent answers yes to the following question and 0 otherwise |
| Work | Question in BHPS: "Does health limit type or amount of work?"<br>Mean 0.2, standard deviation: 0.81<br>Binary variable: Equal to 1 if respondent answers yes to the following question and 0 otherwise |
| SAH | Question in BHPS: "Pease think back over the last 12 months about how your health has been. Compared to people of your own age, would you say your health has been excellent, good, fair, poor or very poor."<br>Mean 2.5, standard deviation: 0.09<br>Binary variable: Equal to 1 if respondent reports poor or very poor heath to the following question and 0 otherwise |
| GHQ | Question in BHPS: Please see page 36 for the complete list of the variables<br>Mean 1.82, standard deviation: 2.7<br>Binary variable: Equal to 1 if respondent scores more than 3 with caseness scoring and zero otherwise |
| Satisfaction | Question in BHPS: "How dissatisfied or satisfied are you with your health?"<br>Mean 3.6, standard deviation: 1.04<br>Binary variable: Equal to 1 if respondent scores 6and 7 in the scale from 1 to7 and zero otherwise |

*This question was not asked in wave 9. We used a similar question provided in wave 9, which asked participants "In general would you say your health is?" and response options were Excellent, Good, Fair and Poor. SAH is coded as one for those that reported poor health and zero was assigned to others.

"Condition" is constructed based on only physical health conditions, and therefore does not include anxiety, depression, alcohol and drug issues, which clearly refer to psychological problems or risky behaviour to have a purely physical measure of health. I constructed this measure of health as a binary variable to indicate whether a person had at least one of the 10 physical health problems. Although constructing a binary variable based on whether an individual suffered from one of these health issues meant that all health problems were being weighted equally. However, there was no established method of comparing the importance of different health problems (Burchardt, 2000). Questions about anxiety and depression were not included in estimations as these were captured by GHQ-12. Alcohol and drug problems were out of this paper's scope. Constructing a measure that purely measured physical health problems helped me decide which extracted latent variable in factor analysis mainly stood for physical aspects of health. The exact wording of the question is listed below:

Q1. Problems or disability connected with; arms, legs, hands, feet, back, or neck (including arthritis and rheumatism)

Q.2 Do you have any of the health problems or disabilities listed on this card (28)? Difficulty in seeing (other than needing glasses to read normal size print)

Q3. Do you have any of the health problems or disabilities listed on this card (28)? Difficulty in hearing

Q4. Do you have any of the health problems or disabilities listed on this card (28)? Chest/breathing problems, asthma, bronchitis

Q5. Do you have any of the health problems or disabilities listed on this card (28)?

Heart/blood pressure or blood circulation problems

Q6. Do you have any of the health problems or disabilities listed on this card (28)?

Stomach/liver/kidneys

Q7. Do you have any of the health problems or disabilities listed on this card (28)?

Diabetes

Q8. Do you have any of the health problems or disabilities listed on this card (28)?

Migraine or frequent headaches

Q9. Do you have any of the health problems or disabilities listed on this card (28)?

Cancer

Q10. Do you have any of the health problems or disabilities listed on this card (28)?

Stroke.

In this paper caseness scoring was used for GHQ-12. The 'better/healthier than normal' and the 'same as usual' answers were scored as 0 and the' worse/more than usual' or the 'much worse/more than usual' option was scored as 1. Therefore, the higher the score, the more severe the condition. Many studies have used this derived variable as an indicator of mental health (Gatrell et al., 2004, Apouey et al., 2010).

Grouping all 12 questions of GHQ-12 together meant that GHQ-12 was considered as a unidimensional scale. This assumption can be supported by findings based on various works such as results obtained from principal components analysis used by Banks (1980), which examined the factor structure of GHQ12 in three different samples. Results supported the existence of just one major factor (Banks et al., 1980). Winefield (1989) confirmed a very high internal consistency reliability of items in the GHQ-12 in their samples as evidence for unidimensionality of the measure (Winefield et al., 1989). The evidence in the literature for unidimensionality of the GHQ-12 is based on a high internal consistency of the items, and the results of principal components analysis. However, there was no definite conclusion on the factor structure of the GHQ-12. This scale has been hypothesised to contain two factors (Andrich &Van Schonbroeck 1989; Gureje 1991, Martin 1999) or three factors (Cheung, 2002, Werneke et al., 2000; Worsley et al., 1977). Using caseness scale, people with scores more than 3 are indicated as experiencing poor mental health as this is the recommended threshold for 12-item version of GHQ (Goldberg et al. 1997).

The exact 12 questions asked in BHPS are as followed:

Q1. Have you recently.... been able to concentrate on whatever you're doing?
Q2. Have you recently.... lost much sleep over worry?
Q3. Have you recently.... felt that you were playing a useful part in things?
Q4. Have you recently... . felt capable of making decisions about things?
Q5. Have you recently.... felt constantly under strain?
Q6. Have you recently.... felt you couldn't overcome your difficulties?
Q7. Have you recently.... been able to enjoy your normal day-to- day to day activities?
Q8. Have you recently.... been able to face up to problems?
Q9. Have you recently.... been feeling unhappy or depressed
Q10. Have you recently.... been losing confidence in yourself?
Q11. Have you recently.... been thinking of yourself as a worthless person?
Q12. Have you recently.... been feeling reasonably happy, all things considered?

### 2.4.1 Exploratory factor analysis

Exploratory factor analysis (EFA) as a statistical method was used to uncover the underlying structure of the set of health variables described in table 1. EFA is a technique within factor analysis whose overall aim is to describe the underlying relationships between measured variables.

In this analysis, exploratory factor analysis identified only two latent factors with eigenvalues greater than one (table 2). This means that these two common factors explained most of the variation among health measures considered. The fit statistics obtained from the analysis confirms that the model with two non-orthogonal factors provides a better fit to data compared to the model that explains common variation of the observed measures only by one factor.

According to the results presented in table 3, there was a clear pattern that suggested each health measure is only affected by one of the factors and only SAH is defined by both factors. These results suggest a meaningful and straightforward intuition on the two dimensionalities of the health measures used. Work, Conditions and Daily are mainly determined by first factor and second factor accounts for variations in responses provided to GHQ and Satisfaction. Although SAH loads on both factors, its loadings are greater on first factor compared to the second one. As we mentioned before, literature is not clear about what aspect of health is exactly measured by health measures such as work, daily, satisfaction and there is a limited literature suggesting that SAH measures both mental and physical health. However, we know that GHQ clearly measures mental health and Conditions is constructed to measure only physical health. The fact that GHQ only loads on second factor and Condition only on first factor, make it possible to conclude that first factor accounts for physical aspect of health and second factor can be seen as a latent measure of mental health. To test the generaliability of findings from an EFA based on pooled sample, I split the sample randomly into two halves, repeated EFA on each half and compared the results. Factor loadings and fit indices remained almost the same on the analysis on each half and the full data set. Using this information, confirmatory factor analysis was used to extract two separate measures of mental and physical health.

**Table 2**: Fit indices for Exploratory Factor Models

| Models | eigenvalues | $X^2$ | DF | CFI | RMSEA |
|---|---|---|---|---|---|
| 1 Factor | 2.454 | 6505.073 | 9 | 0.962 | 0.059 |
| 2 Factors | 1.102 | 468.518 | 4 | 0.997 | 0.022 |

**Table 3**: Geomin Rotated Loadings (N= 169292)

| | Factor one | Factor two |
|---|---|---|
| Work | 0.707 | -0.025 |
| Conditions | 0.524 | 0.088 |
| Daily | 0.87 | 0.002 |
| GHQ | 0.047 | 0.579 |
| SAH | 0.544 | 0.366 |
| Satisfaction | 0.002 | 0.804 |

### 2.4.2 Confirmatory factor analysis

The following equations describe my confirmatory factor analysis (CFA) model using robust diagonally weighted least squares corrected for variance and means (WLSMV). Results obtained from EFA was used to form the CFA model. Equations 2.1-2.7 summarise this model. In these equations, Physical stands for latent physical health and Mental indicates latent mental health. Both latent variables were modelled as continuous variables and were allowed to be correlated with each other. As indicated before, each observed health measure (Condition, Daily, Work, SAH, Satisfaction, GHQ) was transformed to a binary variable that was equal to one when the respondent reported poor or very poor health. Residuals were assumed to have normal distribution (Probit model) and not correlated to each other.

Physical by measures of physical health:

Pr (Condition=1|Physical) = Φ (Physical$\beta$1) (2.1)

Pr (Daily=1|Physical) = Φ (Physical$\beta$2) (2.2)

Pr (Work=1|Physical) = Φ (Physical$\beta$3) (2.3)

Pr (SAH=1|Physical) = Φ (Physical$\beta$4) (2.4)

Mental by measures of mental health:

Pr (SAH=1|Mental) = Φ (Mental$\beta$5) (2.5)

Pr(Satisfaction=1|Mental) = Φ(Mental$\beta$6) (2.6)

Pr (GHQ=1|Mental) = Φ(Mental$\beta$3) (2.7)

In these equations, physical stands for latent physical health and mental indicates latent mental health. Both latent variables were modelled as continuous variables and allowed to be correlated with each other. As indicated before, each observed health measure (Condition, Daily, Work, SAH, Satisfaction, GHQ) was transformed to a binary variable that was equal to one when the respondent reported poor or very poor health. Residuals were assumed to have normal distribution (Probit model) and not correlated to each other. Where Pr denotes probability, and Φ is the Cumulative Distribution Function (CDF) of the standard normal distribution. The parameters $\beta_i$ is estimated by maximum likelihood.

Physical and Mental are Standardised factor loadings and standard errors for this model considering pooled data across years are presented in Table 1. This model is re-estimated on each wave and results suggested a similar pattern. It appears that all loadings were significant and relatively similar. SAH had the smallest loading on both mental and physical categories which was predictable as I assumed that SAH was explained by both mental and physical aspects of health. Daily had the largest loadings among components of physical health and satisfaction was the variable that had been explained the most by mental. Table 2 presents fit statistics for my two-factor model. This model produced a good fit statistic. The statistically significant chi-square value showed less than satisfactory overall fit for this model. Jöreskog and Sörbom (1993) pointed out that the use of chi-square is based on the strict assumption that the model holds exactly in the population. A consequence of this assumption is that models that hold approximately in the population will be rejected in a large sample (Jöreskog et al., 1993). In order to overcome this problem of sample size, Browne and Cudek (1993) suggested using the Root Mean Square of Approximation (RMSEA) as the index of fit.

The RMSEA estimates the overall amount of error and is a function of the fitting function value relative to the degrees of freedom. This fit statistic should not exceed 0.08 and a value less than 0.05 suggests a very good fit (Brown et al. 1993). Table 2 shows 0.044, demonstrating a very good fit for the model. As recommended by Hoyle and Panter (1995), Comparative Fit Index (CFI) is also used here. This fit index assesses how much better the model fits compared with a baseline model, usually the independence model (Joreskog et al., 1993). The indices lie between 0 and 1, and values above 0.95 indicate a better model fit (Hu et al., 1999). Table 2 shows that two-factor model produced a CFI index that was more than the acceptable cut-off (0.992).

The square of standardised loadings represented the proportion of the variance in the underlying continuous and latent aspect of each categorical observed health measures that could be explained by the corresponding factor of the hypothesised model. These values are presented as $R^2$ Estimate in tables 4. Variance of residuals ($1-R^2$) is also presented in table 4.

**Table 4**: Standardised factor loadings and standard errors of variables

| | Loadings | $R^2$ | S.E | P-values | Residual variance |
|---|---|---|---|---|---|
| Physical by | | | | | |
| SAH | 0.691 | 0.478 | 0.008 | 0 | 0.522 |
| Work | 0.756 | 0.571 | 0.002 | 0 | 0.429 |
| DAL | 0.882 | 0.778 | 0.002 | 0 | 0.222 |
| Conditions | 0.713 | 0.508 | 0.003 | 0 | 0.492 |
| Mental by | | | | | |
| Mental by | | | | | |
| GHQ | 0.655 | 0.429 | 0.004 | 0 | 0.508 |
| SAH | 0.598 | 0.357 | 0.009 | 0 | 0.643 |
| Satisfaction | 0.859 | 0.738 | 0.005 | 0 | 0.262 |

Number of observations: 171071

**Table 5**: Fit statistics for two-factor model

| Tested model | Number of items | Chi-square | df | RMSEA | CFI |
|---|---|---|---|---|---|
| two-factor | 6 | 2627.89 | 7 | 0.044 | 0.992 |

In order to be able to categorise people's health using extracted latent health measures, I divided each of the predicted latent health measures into 5 quintiles based on the pooled sample over years including both men and women (descriptive and regression-based results were robust to the use of year-specific quintiles). As greater values of latent variables correspond to worse health, the fifth quintile indicated worst health reported.

In the whole sample of working age people, the number of observations for women exceeded that of men (79,541 men and 89,751 women). In general, it was observed that women experienced worse health compared to men. For example; 17.69% of men and 22.15% of women are included in fifth quintile of mental health. 17.77% of men are categorised to the fifth quintile of physical health, whereas for women this value is 22.09%. In this work, I do not assume that this difference is based on systematic differences in reporting behaviour among men and women. If we divide samples between genders then we see that some men who are in the 4$^{th}$ quintile will be shifted to the 5$^{th}$ quintile and in the regression models we will no longer able to compare results of health shocks and health status of men with women.

Tables 6 and 7 show the mean and standard deviation of latent mental and physical measures for each quintile. Standard deviations of 5$^{th}$ quintile of both mental and physical is greater compared to other quintiles among men and women, suggesting that people's level of health in this quintile has a larger variation compared to people in other quintiles.

The employment rate for each level of health is also shown in these tables. According to tables 3 and 4 for both men and women there is a significant difference in the employment rate of people who reported poorest mental or physical health. People who are in poor physical health have a lower employment rate compared to those who experience poor mental health. Being in the 4$^{th}$ quintile of mental health also corresponded to a lower employment rate compared to the first three quintiles. However, 4$^{th}$ quintile of physical health demonstrated similar rate of employment among first four quintiles. Tables 6 and 7 also indicate the number of people moving from first 4 quintiles to the fifth quintile between two consecutive years. The total number of women who reported this type of health deterioration (physical or mental) was slightly higher compared to men. 10.6% of women in my sample reported this kind of mental health transition, whereas this was 8.8% for men. The percentage of women experiencing this kind of physical health transition was 9.4% compared to 7.8% for men. Considering means of each quintile between men and women, there was no noticeable differences. These facts suggested that there was not much difference in pattern of reporting level of health between men and women, but women are more likely to experience health deteriorations. Probability moving to 5$^{th}$ quintile is significantly higher among people whose health was classified in 4$^{th}$ quintile in the previous year.

**Table 6:** Mental and physical latent health divided in to 5 quintiles, moving towards poorest reported health and employment rate for men

| Male subjects | | | | |
|---|---|---|---|---|
| | Mean | Standard deviation | Employment Rate | Moved to fifth quintile next year |
| **Latent Mental health** | | | | |
| Poor (fifth quintile) | 1.513 | 0.484 | 55% | |
| Fair (forth quintile) | 0.334 | 0.235 | 76% | 2510 (0.15)* |
| Good (third quintile) | -0.087 | 0.1 | 83% | 797 (0.05) |
| Very good (second quintile) | -0.349 | 0.171 | 84% | 1,673 (0.07) |
| Excellent (first quintile) | -0.612 | 0.275 | 86% | 1,019 (0.05) |
| **Latent physical health** | | | | |
| Poor (fifth quintile) | 0.629 | 0.181 | 48% | |
| Fair (forth quintile) | 0.117 | 0.083 | 83% | 2,000 (0.12) |
| Good (third quintile) | -0.01 | 0.066 | 83% | 1,695 (0.10) |
| very good (second quintile) | -0.262 | 0.032 | 84% | 540 (0.03) |
| Excellent (first quintile) | -0.252 | 0.17 | 86% | 699 (0.03) |

*Percentages in last column= (number of people Moved to fifth quintile at t+1/ Number of the people in original quintile at t)

**Table 7:** Mental and physical latent health divided in to 5 quintiles, Moving towards poorest reported health and employment rate for women.

| Female subjects | | | | |
|---|---|---|---|---|
| | Mean | Standard deviation | Employment rate | Moved to fifth quintile next year |
| **Latent Mental health** | | | | |
| Poor(fifth quintile) | 1.542 | 0.513 | 48% | |
| Fair (forth quintile) | 0.374 | 0.235 | 65% | 3,987 (0.14)* |
| Good (third quintile) | -0.08 | 0.103 | 70% | 1,128 (0.06) |
| Very good (second quintile) | -0.33 | 0.168 | 72% | 2,163 (0.09) |
| Excellent (first quintile) | -0.61 | 0.277 | 74% | 1,141 (0.05) |
| **Latent physical health** | | | | |
| Poor (fifth quintile) | 0.624 | 0.182 | 43% | |
| Fair (forth quintile) | 0.123 | 0.081 | 71% | 3,069 (0.13) |
| Good (third quintile) | -0.014 | 0.067 | 71% | 2,475 (0.12) |
| Very good (second quintile) | -0.258 | 0.035 | 72% | 727 (0.03) |
| Excellent (first quintile) | -0.251 | 0.172 | 74% | 803 (0.04) |

*Percentages in last column= (number of people Moved to fifth quintile at t+1/ Number of the people in original quintile at t)

### 2.5 Estimation Strategy

I analysed the impact of health on exit from employment and entering into economical inactivity for working age women (16-59) and men (16-65) separately. As I looked at exit from employment between two consecutive years, for each person any observations at t for whom information on labour status at t+1 or t-1 is not available was excluded from sample. My interest was to see whether lagged health status or recent health deterioration among other explanatory factors, influenced leaving employment and becoming economically inactive.

This paper examined the short-run effect of health shocks on probability of transferring from employment to being economically inactive. In the early stages of being diagnosed with a new mental or physical health problem affected individuals tend to be occupied with hospital appointments and adapting to new advert circumstances imposed as a result of their sudden health deteriorations. Demonstration of these immediate effects of health shocks on employment trajectories are important as they showed that newly diagnosed patients are likely to experiment becoming economically inactive and encounter even more problems in their personal and financial lives. This is an important issue that needs to be integrated and highlighted. Consequently, these short-run spells of exit from employment can lead to other long-term adverse effects. I acknowledge that this study can be extended and enriched with investigating long-term trends and sequences of employment patterns of those who have been affected.

The sample contained 54,421 observations for men including 8,519 individuals that on average were observed in the sample for 6.4 years. Women's sample included 8,710 individuals with an average of 6.1 years remaining in the sample, providing 53,171 observations.

Our empirical specifications are based on equation 2.8:

$$y_{it+1} = x'_{it}\beta_1 + h1'_{it}\beta_2 + h2'_{it+1}\beta_3 + \mu_i + \varepsilon_{it} \qquad (2.8)$$

The dependent variable $y_{it+1}$ is a dummy which identifies whether the individual was in employment (including self-employed people and part-time) at t and inactive at t+1 and is equal to zero when an individual works for two consecutive years.

Being inactive means not working and not searching for work during last 2 weeks or 4 weeks . $h1_{it}$ is a vector containing the health status (representing the long-term physical and mental health status) at t. In some models $h1_{it}$ stands for health status in the previous year, while in others it represents the moving average between time t and t-2. Using moving average excludes estimations only on people who have been in the survey at least for four consecutive years and reduces the number of observations. On the other hand, it has the advantage of controlling health status during a longer period. $h2_{it+1}$is health deterioration measure between t and t+1 (representing recent changes in physical and mental health status). Defining health shocks based on a sudden change of health status is a common way of identifying a health shock. For example; Bradley et al. (2013) determined three kinds of adverse health shocks. Given that self-reported health status considered is recorded as excellent, very good, good, fair, or poor, they identified a health Self-Report Decline

(SRD) as a shift from “excellent,” “very good,” or “good” health status in the first interview to “fair” or “poor” health status in the second. Several other studies use the same approach for capturing health shocks. Cai et al. (2013) and Riphahn (1999) used similar identification to capture health deterioration and its effect on labour force behaviour. $x_{it}$ is a vector of control variables including characteristics of the individuals and their household that may affect labour force participation choices.

These variables are as follows: Being part time worker, whether spouse/partner is employed/self-employed. Number of children categorised with respect to their age group ranging from 0 to 15 years old, log of household income at t-1(previous income has been included to reduce the fact that exit from employment being the main determinant of the size of the household income), job classifications(party skilled, skilled manual or armed forces, skilled non manual, managerial or technical with non-skilled as reference category), academic qualification (categorised as no qualification, O/CSE, A level/HND with having a degree and higher as the reference group), housing ownership status (Own house with mortgage, housing authority/council house, renting with owning house own right as the reference), regional controls ( wales, Scotland, midlands, south west, south east, north east, north west) age groups and time (wave) dummies. Very similar variables have been used in different academic and imperial research concerning the effect of health and employment status (Anderson et al., 1985; Berthoud et al., 2014)

$\mu_i$ is the individual specific unobserved heterogeneity (in the form of unobserved time-invariant individual effects). $\varepsilon_{it}$ is the error term assumed to have a probability density function with logistic distribution.

Individuals who moved from employment to unemployment between time t and t+1 were excluded from the sample as the main interest was identifying the effect of health shocks on the immediate decision of being out of the labour market and that is best captured by moving from employment to being economically inactive. Unemployed individuals actively look at finding a new job which means these individuals find themselves physically and mentally fit enough to work again. They may be looking for a new job that accommodates for their new health status and there is a clear indication that they are still interested in returning to employment. However, considering people who move from employment to economically inactiveness enabled me to consider the sub-sample that experienced potentially severest labour market related consequences after facing a health shock. I acknowledge that this estimation can be improved by including people who moved from employment to unemployment. Ordinal Logistic Models can be a good choice in demonstrating and comparing different scenarios and sequences that can emerge after an employment episode is ended.

Unbalanced panel data was used in all the regression analysis however, longitudinal weights provided with BHPS were used to mitigating bias caused by attrition and non-response. The longitudinal respondent weights chose cases with full interview at each wave in the BHPS. These cases were re-weighted to take into account previous wave respondents lost due to refusal at the current wave or because of other forms of sample attrition. Thus, the longitudinal weight at any wave address losses between each adjacent pair of waves up to that point in addition to the initial respondent weight at wave one. These weights also included the deceased, people who have moved into institutions or otherwise gone out-of-scope. These fail to give an interview not through non-response but due to a terminating event which resulted in their leaving the population of interest (Lynn, 2006).

In order to control for unobserved heterogeneity that may be correlated with the explanatory variables a fixed effect model (conditional logit) was estimated. Hassmann test rejects the null that $\mu_i$ is not correlated with the regressors (explanatory variables) which means non-linear (logistic) random effect model is inconsistent. Lindeboom (2012) in the Elgar Companion to Health Economics suggested estimating fixed effect model when effect of health on work or effect of work on health is estimated separately. Using fixed effect models enabled me to control for individual specific unobserved time invariant factors which were correlated with health status such as genetic makeup, quality of nutrition during childhood or ability to cope with stress. However, fixed effect models only considered individuals that reported change in their labour force status and excluded individuals that stayed in work during their participation in the survey (individuals economically inactive over the course of the sample are excluded as I compared individuals who worked during two consecutive years with those who were working at time t and were economically inactive at t+1).

I also estimated random effect models including means of time-variant variables to consistently estimate the parameters of random effects model while relaxing the assumption that the explanatory variables are correlated with the unobserved heterogeneity (Mundlak, 1978). I adopted Wooldridge (2010) method which is developed for unbalanced panel data. Therefore, mean value of the time varying explanatory variables were included in the estimated random effect probit model. This can also help with interpreting average marginal effects as the marginal effects of logit fixed effect can only be calculated based on the assumption that individual fixed effect equal to zero. Also, linear fixed effect models were estimated and reported in the Appendix (table 13) for robustness check. The pattern and size of the coefficients were similar to marginal effects reported as main results for working age men and women separately.

Number of women who reported change in their labour force status exceeded those of men, leading to more men being excluded from sample as a result of using fixed effect models. There are 7,004 men (44,593 observations) and 6,149 women (36,005 observation) who have been at least 2 years in our data set and have been working all the years with reporting no exit from employment. Seven percent of these people experience mental shock and 6 percent of them experience physical health shock (three percent of them experienced both mental and physical shocks). The likelihood of experiencing health shocks among these people is slightly lower than that among people who had a change in their labour force status (ten percent of them reported a mental health shock and 7 percent reported a physical health shock). Therefore, these results might be bias due to exclusion of people who experienced health shock, but did not exit employment. The difference between results obtained from fixed effect and random effect models can also be caused by the fact that random effect models assume that the entity's error term is not correlated with the predictors which allows for time-invariant variables to play a role as explanatory variables. I estimated random effects with exclusion of individuals who had been working during the course of their participation in the survey to see to what extend variation of the estimated results was due to the different assumption correlation of the $\mu_i$ with regressors.

The dependent variable showed whether an individual had changed his or her labour force status between t and t+1. Results from such estimations enabled me to compare the level of health effects at t or being in poor health at time t with effect of deterioration in health between t and t+1 on exit from employment.

I included conventional human capital variables such as; age, highest level of education (having a degree or higher qualification as the reference point) and number of children in the household. Job characteristics such as being a part-time worker, unskilled worker, managerial/technical, skilled manual/non-manual partly skilled were considered (professional workers were the reference point). Household characteristics such as household income and whether a partner works or not (reference point is that partner is not working or not having a partner) were being taken into account. In all estimations, year and regional specific controls were considered. Age, year and region of residence controls are included in all the estimations. In empirical estimations extracted, latent measures of mental and physical health were used to control for level of health. In order to identify transition into poor mental and physical health I also constructed two other dummies that were equal to 1 if the individual was in poor health at time t+1, but was not in poor health (fifth quintile) at time t. These dummy variables were called mental health transition (worse) and physical health transition (worse). Slightly different variables were constructed for identifying mental and physical health transitions and poor mental and physical health. Here being in first 3 quintiles means being in good health and being in 4$^{th}$ an 5$^{th}$ is equivalent to being in poor health. Therefore, health transformation is identified as being in first 3 quintiles at t and being in two last quintiles at t+1(mental health transitions2 and physical health transitions2Comparison between results based on two different definitions is provided. Table of the main results are shown in the next section and complete tables of estimations are included in the appendix.

Unbalanced panel data was used in all the regression analysis however, longitudinal weights provided with BHPS were used to mitigating bias caused by attrition and non-response. The longitudinal respondent weights chose cases with full interview at each wave in the BHPS. These cases were re-weighted in order to take into account previous wave respondents lost due to refusal at the current wave or because of other forms of sample attrition. Thus, the longitudinal weight at any wave address losses between each adjacent pair of waves up to that point in addition to the initial respondent weight at wave one. These weights also include the deceased, people who have moved into institutions or otherwise gone out-of-scope. These fail to give an interview not through non-response but due to a terminating event which resulted in their leaving the population of interest.

## 2.6 Results

In this section a number of different specifications for equation 2.8 is presented. In table 8 results show two sets of estimations; all estimated models include physical and mental health transition between t and t+1, but model I includes mental and physical health status at t and model II controls for moving average of mental and physical health including t, t-1 and t-2. Controlling for health status and health deterioration together is based on the intuition that health status is a long-term measure of health, which is mainly known to the individual. Health status is one of the factors used by the individual to decide on their desired equilibrium position and consequently affects the probability of their labour market participation. On the other hand, health shocks/deteriorations by their nature are less predictable events that may force individuals to revise their equilibrium labour market position and make a decision that suits their new conditions better. In table 8, health shocks are dummies that are equal to 1 if a person's health deteriorates from any quintile at time t to the 5th quintile at time t+1. Results displayed that regardless of controlling for health status at time t or moving average, both mental and physical health shocks had statistically significant effects on probability of leaving employment towards inactivity. Influence of deterioration in physical health is always greater compared to deterioration in mental health for both men and women. Marginal effects calculated for model I in table 8 for men and women indicated that experiencing physical health shock increased probability of exit from employment 1.2 percentage points more than mental shock among men. This difference was 4.6 percentage points for women and statistically significant. These results were in line with descriptive statistics provided in tables 6 and 7 in section 4.2. Results in tables 6 and 7 show that for both men and women employment rates of people in worse physical health was less than those in worse mental health. Results of model I and II show gender difference in response to health shocks. For lagged health constant, mental health shock increased the probability of leaving employment for men further compared to women (7.4 percentage points based on model II and this difference was statistically significant). The long-term effect of mental health status was also greater for men compared to women and this difference was 10 percentage points (model II) and statistically significant when I controlled for moving average. However, models I and II did not suggest a clear pattern of effect of physical health problems among men and women. Garsia Gomes et al. (2009) did not control for mental and physical health separately and found that the effect of health shocks was greater on men's exit from employment compared to women.

**Table 8**. Logistic fixed effect. Effect of health transition and health status on exit from employment to inactivity

| | Men | | | | Women | | | |
|---|---|---|---|---|---|---|---|---|
| | **I** | **M.E** | **II** | **M.E** | **I** | **M.E** | **II** | **M.E** |
| Mental health t | 0.836** | 0.107* | | | 0.342** | 0.081 | | |
| | (0.136) | | | | (0.090) | | | |
| Moving average (mental) | | | 1.213** | 0.294** | | | 0.773** | 0.192** |
| | | | (0.301) | | | | (0.192) | |
| Mental health transition (worse) | 0.493** | 0.057* | 0.448** | 0.110** | 0.202* | 0.049* | 0.146* | 0.036 |
| | (0.118) | | (0.135) | | (0.082) | | (0.094) | |
| Physical health t | 0.624** | 0.080* | | | 0.543** | 0.130* | | |
| | (0.131) | | | | (0.088) | | | |
| Moving average (physical) | | | 0.603** | 0.147** | | | 0.507** | 0.126** |
| | | | (0.303) | | | | (0.189) | |
| Physical health transition (worse) | 0.641** | 0.069* | 0.523** | 0.130** | 0.389** | 0.095* | 0.302** | 0.075** |
| | (0.121) | | (0.133) | | (0.088)** | | (0.101) | |
| Log likelihood | -1,974.70 | | -1317.87 | | -4,193.77 | | -2891.69 | |
| Number of observations | 10,468 | | 6,210 | | 17,067 | | 11,598 | |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region control. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. Marginal effects are calculated at sample means. * $p<0.05$; ** $p<0.0$

**Table 9**. Logistic fixed effect. Effect of health transition and health status on exit from employment to inactivity (second version of health transitions)

| | Men | | | | Women | | | |
|---|---|---|---|---|---|---|---|---|
| | **I** | **M.E** | **II** | **M.E** | **I** | **M.E** | **II** | **M.E** |
| Mental health t | 0.916** | 0.154 | | | 0.424** | 0.103 | | |
| | (0.137) | | | | (0.092) | | | |
| Moving average (mental) | | | 1.231** | 0.285** | | | 0.810 | 0.202** |
| | | | (0.362) | | | | (0.192)** | |
| Mental health transition(worse) | 0.406** | 0.074 | 0.362** | 0.087* | 0.178* | 0.044* | 0.178* | 0.054* |
| | (0.113) | | (0.132) | | (0.078) | | (0.089) | |
| Physical health t | 0.385** | 0.065 | | | 0.439** | 0.106** | | |
| | (0.125) | | | | (0.085) | | | |
| Moving average (physical) | | | 0.291 | 0.068 | | | 0.415** | 0.104* |
| | | | (0.299) | | | | (0.187) | |
| Physical health transition(worse) | 0.103 | 0.019 | 0.082 | 0.018 | 0.225** | 0.055** | 0.201* | 0.050* |
| | (0.116) | | (0.139) | | (0.079) | | (0.091) | |
| Log likelihood | -2,999.74 | | -1,333.973 | | -4,603.17 | | -2,985.79 | |
| Number of observations | 10,468 | | 6,210 | | 17,067 | | 11,598 | |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region control. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. Marginal effects are calculated at sample means. * $p$<0.05; ** $p$<0.01

**Table 10**. Logistic fixed effect. Effect of health transition and health status on exit from employment to inactivity (dividing manual and non-manual jobs)

| | Men | | | | Women | | | |
|---|---|---|---|---|---|---|---|---|
| | **Manual** | **M.E** | **Non-manual** | **M.E** | **Manual** | **M.E** | **Non-manual** | **M.E** |
| Mental health t | 0.705** | 0.135* | 0.867** | 0.115* | 0.412** | 0.063* | 0.361** | 0.071** |
| | (0.192) | | (0.230) | | (0.155) | | (119) | |
| Mental health transition(worse) | 0.534** | 0.112* | 0.584** | 0.090* | 0.385** | 0.0.65* | 0.254** | 0.047* |
| | (0.170) | | (0.192) | | (0.135) | | (0.122) | |
| Physical health t | 1.104** | 0.199* | 0.381 | 0.05 | 0.763** | 0.11* | 0.309* | 0.060 |
| | (0.186) | | (0.226) | | (0.149) | | (0.123) | |
| Physical health transition(worse) | 0.970** | 0.213* | 0.142 | 0.019 | 0.376** | 0.063* | 0.043 | 0.008 |
| | (0.170) | | (0.205) | | (0.143) | | (0.112) | |
| Log likelihood | -866.633 | | -, | | -128.087 | | -2325.860 | |
| Number of observations | 4,021 | | 4,120 | | 4,823 | | 9,725 | |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region control. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. Marginal effects are calculated at sample means. * $p$<0.05; ** $p$<0.01

**Table 11**. Logistic fixed effect. Effect of health transition and health status on exit from employment to inactivity excluding individuals older than 50 years old.

| | Men | | | | Women | | | |
|---|---|---|---|---|---|---|---|---|
| | **I** | **M.E** | **II** | **M.E** | **I** | **M.E** | **II** | **M.E** |
| Mental health t | 1.043** | 0.247* | 0.873** | 0.082* | 0.319** | 0.076* | 0.304** | 0.097* |
| | (0.176) | | (0.115) | | (0.107) | | (0.079) | |
| Mental health transition(worse) | 0.502** | 0.112* | 0.518** | 0.043 | 0.274** | 0.063* | 0.257** | 0.065* |
| | (0.161) | | (0.100) | | (0.097) | | (0.072) | |
| Physical health t | 0.544** | 0.129** | 0.131 | 0.052 | 0.404** | 0.096* | 0.384** | 0.072* |
| | (0.178) | | (0.111) | | (0.113) | | (0.078) | |
| Physical health transition(worse) | 0.689** | 0.149* | 0.690** | 0.064* | 0.320** | 0.074* | 0.343** | 0.089* |
| | (0.172) | | (0.104) | | (0.109) | | (0.078) | |
| Log likelihood | -1,087.79 | | -6,300.52 | | -2,880.24 | | -11,185.5 | |
| Number of observations | 7,723 | | 54,423 | | 10,681 | | 53,171 | |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region control. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses.
Marginal effects are calculated at sample means. * $p$<0.05; ** $p$<0.0

Considering all models, regardless of controlling for level of mental and physical health at time t or moving average during past three year, these measures have significant effects on the probability of leaving employment among both women and men, indicating therefore significance of long-term effect of health on working age individuals. Results from table 12 in the appendix section, indicate that both men and women who do a part-time job have a higher probability of exiting labour force market compared to full-time workers and this effect was statistically significant. Men with an employed spouse had a lower probability of leaving work compared to those who did not have a working spouse or did not live as a couple. Effect of household income was not significant for both men and women. Having children between 0 to 2 and 3 to 4 years old significantly increased the probability of exit for women and having children 5-11 and 12-15 significantly decreased probability of leaving work for employed women. People with no academic qualification or having only achieved O/CSE or A-level grade were more likely to leave employment compared to those with a university degree or higher. Job types on the other hand did not reflect a significant effect on the probability of leaving employment. People in all ages were less likely to leave their job compared to individuals 16-20 years old. In table 9, an alternative definition for health shocks (transitions) was used. Here, a health shock is experienced when a person's health status changes from first three quintiles at t to 4th and 5th quintile at t+1 (milder health shocks). Estimated coefficients for models I and II for men (table 9), show that experiencing milder physical health shock did not affect the probability of exiting from work significantly for men. However, a worse health status has a significant effect on men's exit from work in the following year. Milder physical shocks display significant effects on likelihood of leaving work for women in both model I and II. Nevertheless, the magnitudes of marginal effects were smaller than those in previous versions of health shocks for women (Model I table 8), but the difference was not statistically significant. It was mentioned in section 4.2 tables 6 and 7 that employment rate among men and women, whose level of health belonged to 4th quintile of physical health did not differ from those whose level of physical health belonged to first three quintiles. These results propose that people, especially men are more likely to leave their jobs, when their physical health alters to the poorest quintile reported. Milder mental health shocks on the other hand still have significant effects on men and women. These findings reveal a very important difference on how both men and women react to physical shocks compared to mental shocks. Physical shocks are significantly effective on probability of leaving work for men, only when they experience a sudden change and report worse levels of health in the sample, whereas deteriorations towards both fourth and fifth quintiles of mental health still can have significant effects on exit from work for both genders.

In order to explore whether mental and physical health deteriorations show varied effects on people in different professions, I divided working individuals into manual and non-manual jobs. Manual job category included skilled, partly skilled or non-skilled manual workers as well as people working in the armed forces. Non-manual jobs included occupations which were listed as skilled non-manual, managerial or technical and professional.

Results from this model (table 10) suggested that men and women who did manual jobs were vulnerable against both mental and physical health (the effect of both health shocks were statistically significant). On the other hand, physical health shocks did not increase the probability of exit from employment among men and women who had non-manual jobs. Mental health shocks had a significant effect on the likelihood of exit from employment among non-manual job holders and the marginal effects were not significantly different with those who held manual jobs.

### 2.6.1 Sensitivity analysis

In order to check whether the above reported results were driven mainly by the effect of older individuals, I excluded people older than 50 years old from sample and re-estimated the model presented in table 11 model I. Results presented in table 11 show that similar to table 8 (when all the working age people were included in the sample), mental and physical shocks, mental and physical health status and being in poor mental and physical health had a significant effect on exit from employment for both men and women. These findings were consistent with results obtained by Garsia-Gomes et al. (2009) as they did not find substantial differences in the effect of health on exit from employment, when they excluded older people from their sample. Similar to results estimated for all working age sample, based on marginal effects, physical health shocks had a greater impact on increasing the probability of exit from employment compared to mental shocks (the difference is statistically significant). When considering only younger individuals in estimations the effect of both mental and physical shocks was greater on men compared to women, but these differences were not statistically significant. Main results were also robust to the exclusion of part-time workers and self-employed individuals.

Model II in table 11 represents results based on random effect estimations with inclusion of mean of time-variant covariates. Findings suggest very similar pattern for the effect of health shocks but lagged physical health status does not appear to have significant effects on the probability of leaving employment among men. One possible reason for these findings is that when I consider the whole sample, there are men that continue in employment regardless of their physical health status, whereas results using fixed effect model only considers individuals that experience moving in or out of economic inactivity.

Results of random effect models were robust to the exclusion of all the individuals who were in the survey at least for two consecutive years and were always in employment. Estimated linear fixed effect models are presented in table 17 (appendix). The significance and signs of the variables of interest remain the same as the logistic fixed effect models. These results suggest that the main difference between random and fixed effect models is caused by the difference in the assumption made about correlation of the $\mu_i$ and explanatory variables.

## 2.7 Conclusion

This paper analysed the role of mental and physical health on exit from employment and entering economical inactivity among working age men and women. The scarcity of research on younger aged workers can largely be ascribed to a lack of adequate secondary sources of data. This was likely due to a low rate of health shock events of sufficient magnitude to cause labour supply adjustments in this age group. However, given the potential impact on income and household members, study on such individuals is essential and warrants serious consideration. 18 years of BHPS data was used to explore the relationship between health and employment over a long period of time. In research works that focus on relationships between health and employment, there is no agreement on the best way of measuring health. My first aim in this paper was to achieve a set of measures for health that showed ability and desire to work. It has been argued that health problems can affect working capacity through various pathways such as main skills and abilities that an individual requires to do the job or by increasing the time people need to do non-labour activities that are crucial in order to remain active in the labour market. To address multidimensionality of health both as a concept and in relation to working capacity, I suggested constructing a measure of health using factor analysis, based on several well-known health measures. In the literature, researchers tend to control only for physical or mental health or their measure of health combines both mental and physical aspects of health together. Using factor analysis enabled me to extract distinct latent measures for overall mental and physical health and compare the adverse effects of mental health shocks on employment with that of physical health shocks.

Results point to a significant reduction in labour market participation when mental or physical health shock is experienced. Effect of strong physical health deterioration is always seen to be greater, compared to strong mental health for both genders. However, milder physical health shocks no longer have significant effects on men and the impact of mild mental health shocks is greater than mild physical shocks for both men and women. Such comparisons suggest that both men and women react differently towards declines in mental and physical health and men have higher threshold for exiting from employment due to physical health. Men leave employment only when a sudden health shock leads to very poor physical health. I found considerable evidence of heterogeneity in observed health shocks. Manual job holders were vulnerable against both physical and mental health shocks, whereas physical health shocks did not significantly reduce the probability of leaving employment among non-manual job holders.

My work is subject to several potential limitations. First, reverse effect of work on health is not addressed in estimated models. As discussed before, literature does not suggest any solutions for the endogeneity between employment and health. Some researchers suggest using health shocks based on experiencing stroke, cancer or unscheduled hospital admissions. This approach can reduce justification bias and is less predictable, but still these health problems are caused by underlying health issues, which could be caused by adverse effects of work on health. In addition, using these forms of health shocks do not address the effects of deterioration in overall mental and physical health, which is one of the main motivations behind this work. The second limitation is that my empirical models cannot explain the reasons behind some of our main findings. Therefore, further research is required in a future project on explanatory mechanisms behind different outcomes based on gender and occupation. Previous literature suggested that the main effect of a health shock on labour supply is observed in the short-run and rarely any adjustments occur at a later stage. Hence, I only considered the short-run labour supply adjustments of a sudden health shock.

## 2.8 Appendix

**Table 9 (continued).** Logistic fixed effect for men and women: Effect of health transition and health status on exit from employment to inactivity

| | Men | | Women | |
|---|---|---|---|---|
| | I | II | I | II |
| Mental health t | 0.836<br>(0.136)** | | 0.342<br>(0.090)** | |
| Poor mental health t | | 0.808<br>(0.130)** | | 0.364<br>(0.085)** |
| Mental health transition(worse) | 0.493<br>(0.118)** | 0.612<br>(0.132)** | 0.202<br>(0.082)* | 0.223<br>(0.089)* |
| Physical health t | 0.624<br>(0.131)** | | 0.543<br>(0.088)** | |
| Poor physical health t | | 0.683<br>(0.135)** | | 0.559<br>(0.094)** |
| Physical health transition(worse) | 0.640<br>(0.121)** | 0.689<br>(0.133)** | 0.389<br>(0.088)** | 0.462<br>(0.097)** |
| Part time t | 0.258<br>(0.119)* | 0.277<br>(0.120)* | 0.313<br>(0.069)** | 0.316<br>(0.069)** |
| Spouse working at t | -0.546<br>(0.127)** | -0.569<br>(0.127)** | 0.005<br>(0.085) | 0.000<br>(0.085) |
| Children 0-2 | 0.372<br>(0.167)* | 0.398<br>(0.166)* | 0.532<br>(0.090)** | 0.546<br>(0.090)** |
| Children 3-4 | 0.302<br>(0.161) | 0.297<br>(0.162) | 0.343<br>(0.090)** | 0.340<br>(0.090)** |
| Children 5-11 | 0.045<br>(0.101) | 0.033<br>(0.101) | -0.118<br>(0.057)* | -0.124<br>(0.057)* |
| Children 12-15 | 0.036<br>(0.108) | 0.023<br>(0.107) | -0.427<br>(0.074)** | -0.436<br>(0.074)** |
| Log household income | 0.023<br>(0.077) | 0.022<br>(0.077) | -0.051<br>(0.050) | -0.046<br>(0.050) |
| Unskilled | 0.253<br>(0.304) | 0.212<br>(0.303) | 0.671<br>(0.271)* | 0.680<br>(0.271)* |
| Partly skilled | 0.325<br>(0.256) | 0.319<br>(0.255) | 0.626<br>(0.244)* | 0.625<br>(0.244)* |
| Skilled manual or armed forces | 0.270<br>(0.252) | 0.286<br>(0.252) | 0.599<br>(0.254)* | 0.594<br>(0.254)* |
| Skilled non-manual | 0.070<br>(0.246) | 0.068<br>(0.245) | 0.316<br>(0.240) | 0.314<br>(0.240) |
| Managerial or technological | -0.067<br>(0.224) | -0.062<br>(0.223) | 0.183<br>(0.231) | 0.187<br>(0.231) |
| No qualifications | 1.331<br>(0.596)* | 1.417<br>(0.589)* | 1.959<br>(0.392)** | 1.921<br>(0.393)** |
| Highest qualification O/CSE | 2.195<br>(0.346)** | 2.214<br>(0.345)** | 1.688<br>(0.242)** | 1.665<br>(0.242)** |
| Highest qualifications A level/HND | 2.070<br>(0.292)** | 2.065<br>(0.290)** | 1.780<br>(0.211)** | 1.779<br>(0.211)** |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region control. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. * $p$<0.05; ** $p$<0.0

**Table 9 (continued).** Logistic fixed effect for men and women: Effect of health transition and health status on exit from employment to inactivity

| | **Men** | | **Women** | |
|---|---|---|---|---|
| | I | II | I | II |
| Own house with Mortgage | -0.353 | -0.367 | -0.369 | -0.358 |
| | (0.145)* | (0.145)* | (0.109)** | (0.109)** |
| Housing authority | -0.165 | -0.156 | -0.176 | -0.151 |
| | (0.256) | (0.255) | (0.170) | (0.170) |
| House is rented | -0.301 | -0.279 | -0.428 | -0.389 |
| | (0.228) | (0.226) | (0.152)** | (0.152)* |
| Wales | 0.238 | 0.250 | -0.646 | -0.631 |
| | (0.773) | (0.776) | (0.432) | (0.437) |
| Scotland | 0.957 | 0.806 | 0.115 | 0.152 |
| | (0.710) | (0.719) | (0.561) | (0.562) |
| Midlands | 0.663 | 0.674 | 0.012 | 0.019 |
| | (0.524) | (0.524) | (0.328) | (0.325) |
| South west | 0.874 | 0.896 | -0.015 | -0.007 |
| | (0.564) | (0.558) | (0.327) | (0.329) |
| South east | -0.142 | -0.104 | -0.391 | -0.373 |
| | (0.420) | (0.414) | (0.257) | (0.257) |
| North east | 1.221 | 1.166 | 0.026 | 0.040 |
| | (0.669) | (0.668) | (0.376) | (0.376) |
| North west | 1.909 | 1.898 | -0.587 | -0.550 |
| | (0.664)** | (0.665)** | (0.391) | (0.392) |
| Age2024 | -1.087 | -1.085 | -0.679 | -0.700 |
| | (0.177)** | (0.176)** | (0.137)** | (0.137)** |
| Age2529 | -2.211 | -2.245 | -0.782 | -0.816 |
| | (0.263)** | (0.262)** | (0.177)** | (0.177)** |
| Age3034 | -3.203 | -3.223 | -1.070 | -1.078 |
| | (0.333)** | (0.333)** | (0.215)** | (0.215)** |
| Age3539 | -3.579 | -3.630 | -1.429 | -1.437 |
| | (0.388)** | (0.388)** | (0.250)** | (0.250)** |
| Age4044 | -3.771 | -3.802 | -2.306 | -2.315 |
| | (0.439)** | (0.440)** | (0.292)** | (0.292)** |
| Age4549 | -4.283 | -4.259 | -2.446 | -2.440 |
| | (0.490)** | (0.490)** | (0.332)** | (0.332)** |
| Age5054 | -4.051 | -4.025 | -1.979 | -1.954 |
| | (0.533)** | (0.532)** | (0.374)** | (0.374)** |
| Age5559 | 1.050 | 1.053 | 0.933 | 0.938 |
| | (0.181)** | (0.180)** | (0.129)** | (0.129)** |
| Age6064 | -1.454 | -1.445 | | |
| | (0.609)* | (0.609)* | | |
| Log likelihood | -1,974.70 | -1,992.11 | -4,193.77 | -4,254.81 |
| Number of observations | 10,468 | 10,468 | 17,067 | 17,060 |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region control. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. * $p<0.05$; ** $p<0.0$

**Table 10 (continued).** Logistic Random effect for men and women: Effect of health transition and health status on exit from employment to inactivity

| | Men | | Women | |
|---|---|---|---|---|
| | I | II | I | II |
| Mental health t | 0.873 | | 0.304 | |
| | (0.115)** | | (0.079)** | |
| Poor mental health | | 0.679 | | 0.276 |
| | | (0.107)** | | (0.074)** |
| Mental health transition(worse) | 0.518 | 0.645 | 0.257 | 0.278 |
| | (0.100)** | (0.109)** | (0.072)** | (0.077)** |
| Physical health t | 0.131 | | 0.384 | |
| | (0.111) | | (0.078)** | |
| Poor physical health | | 0.352 | | 0.415 |
| | | (0.113)** | | (0.080)** |
| Physical health transition(worse) | 0.690 | 0.719 | 0.343 | 0.391 |
| | (0.104)** | (0.112)** | (0.078)** | (0.084)** |
| Part time at t | 0.722 | 0.729 | 0.530 | 0.530 |
| | (0.105)** | (0.105)** | (0.063)** | (0.063)** |
| Spouse working at t | -0.297 | -0.287 | 0.041 | 0.037 |
| | (0.103)** | (0.102)** | (0.074) | (0.074) |
| Children 0-2 | 0.234 | 0.246 | 0.085 | 0.085 |
| | (0.137) | (0.137) | (0.078) | (0.078) |
| Children 3-4 | 0.310 | 0.307 | 0.063 | 0.054 |
| | (0.139)* | (0.138)* | (0.078) | (0.078) |
| Children 5-11 | 0.029 | 0.040 | -0.221 | -0.222 |
| | (0.082) | (0.082) | (0.050)** | (0.049)** |
| Children 12-15 | -0.017 | -0.014 | -0.356 | -0.354 |
| | (0.089) | (0.089) | (0.061)** | (0.061)** |
| Log household income | 0.472 | 0.474 | 0.271 | 0.273 |
| | (0.060)** | (0.059)** | (0.046)** | (0.046)** |
| Unskilled | 0.039 | 0.057 | 0.615 | 0.626 |
| | (0.260) | (0.258) | (0.253)* | (0.252)* |
| Partly skilled | 0.245 | 0.260 | 0.481 | 0.472 |
| | (0.222) | (0.221) | (0.233)* | (0.232)* |
| Skilled manual or armed forces | 0.218 | 0.233 | 0.477 | 0.455 |
| | (0.219) | (0.218) | (0.242)* | (0.241) |
| Skilled non-manual | -0.029 | -0.010 | 0.271 | 0.259 |
| | (0.215) | (0.214) | (0.229) | (0.228) |
| Managerial or technical | -0.082 | -0.055 | 0.216 | 0.213 |
| | (0.198) | (0.197) | (0.222) | (0.221) |
| No qualifications | 2.100 | 2.125 | 1.380 | 1.394 |
| | (0.453)** | (0.451)** | (0.323)** | (0.321)** |
| Highest qualifications O/CSE | 2.266 | 2.287 | 1.505 | 1.536 |
| | (0.279)** | (0.280)** | (0.202)** | (0.201)** |
| Highest qualifications A-level/HND | 2.397 | 2.414 | 1.521 | 1.540 |
| | (0.238)** | (0.239)** | (0.180)** | (0.180)** |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region control.in all random effect models, means of time-varying variables for each individual is included. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. * $p$<0.05; ** $p$<0.01

**Table 10. (continued).** Logistic Random effect for men and women: Effect of health transition and health status on exit from employment to inactivity

| | Men | | Women | |
|---|---|---|---|---|
| | I | II | I | II |
| Own house with mortgage | -0.019 | -0.026 | -0.185 | -0.193 |
| | (0.118) | (0.118) | (0.093)* | (0.092)* |
| Housing authority | 0.139 | 0.129 | -0.062 | -0.065 |
| | (0.208) | (0.206) | (0.142) | (0.141) |
| House is rented | 0.032 | 0.043 | -0.225 | -0.232 |
| | (0.178) | (0.178) | (0.131) | (0.131) |
| Wales | 0.511 | 0.469 | -0.593 | -0.421 |
| | (0.623) | (0.627) | (0.413) | (0.427) |
| Scotland | 0.907 | 0.814 | 0.483 | 0.731 |
| | (0.716) | (0.716) | (0.505) | (0.505) |
| Midland | 0.173 | 0.210 | -0.123 | 0.088 |
| | (0.426) | (0.423) | (0.281) | (0.301) |
| South west | 0.754 | 0.729 | 0.160 | 0.311 |
| | (0.441) | (0.440) | (0.284) | (0.307) |
| South east | 0.197 | 0.198 | -0.955 | -0.193 |
| | (0.370) | (0.369) | (0.220)** | (0.248) |
| North east | 0.792 | 0.811 | 0.044 | 0.235 |
| | (0.515) | (0.513) | (0.351) | (0.363) |
| North west | 1.517 | 1.481 | -0.619 | -0.439 |
| | (0.501)** | (0.500)** | (0.356) | (0.369) |
| Age2024 | -0.508 | -0.490 | -0.489 | -0.462 |
| | (0.136)** | (0.136)** | (0.107)** | (0.106)** |
| Age2529 | -1.051 | -1.053 | -0.431 | -0.422 |
| | (0.197)** | (0.197)** | (0.128)** | (0.127)** |
| Age3034 | -1.396 | -1.379 | -0.605 | -0.583 |
| | (0.240)** | (0.239)** | (0.141)** | (0.141)** |
| Age3539 | -1.355 | -1.338 | -0.927 | -0.887 |
| | (0.271)** | (0.271)** | (0.151)** | (0.151)** |
| Age4044 | -1.332 | -1.326 | -1.522 | -1.490 |
| | (0.298)** | (0.298)** | (0.159)** | (0.158)** |
| Age4549 | -1.509 | -1.480 | -1.665 | -1.624 |
| | (0.327)** | (0.326)** | (0.161)** | (0.160)** |
| Age5054 | -1.029 | -1.015 | -1.369 | -1.329 |
| | (0.346)** | (0.345)** | (0.162)** | (0.162)** |
| Age5559 | 0.849 | 0.821 | 0.724 | 0.716 |
| | (0.137)** | (0.136)** | (0.092)** | (0.092)** |
| Age6064 | 0.702 | 0.687 | | |
| | (0.379) | (0.378) | | |
| Log likelihood | -6,300.52 | -6,344.56 | -11,185.05 | -11,265.46 |
| Number of observations | 54,423 | 54,423 | 53,171 | 53,171 |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region control.in all random effect models, means of time-varying variables for each individual is included. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. * *p*<0.05; ** *p*<0.01

**Table 11 (continued).** Logistic fixed effect for men and women: Effect of health transition and health status on exit from employment to inactivity (Second version of defining health transitions)

| | Men | | Women | |
|---|---|---|---|---|
| | I | II | I | II |
| Mental health t | 0.916 | | 0.424 | |
| | (0.137)** | | (0.092)** | |
| Poor mental health2 | | 0.342 | | 0.258 |
| | | (0.128)** | | (0.085)** |
| Mental health transition2 (worse) | 0.406 | 0.317 | 0.178 | 0.178 |
| | (0.113)** | (0.131)* | (0.078)* | (0.089)* |
| Physical health t | 0.385 | | 0.439 | |
| | (0.125)** | | (0.085)** | |
| Poor physical health2 | | 0.414 | | 0.098 |
| | | (0.133)** | | (0.088)* |
| Physical health transition2 (worse) | 0.103 | 0.180 | 0.225 | 0.159 |
| | (0.116)** | (0.138)* | (0.079)** | (0.092)* |
| Part time t | 0.254 | 0.301 | 0.323 | 0.328 |
| | (0.119)* | (0.118)* | (0.069)** | (0.069)** |
| Spouse working at t | -0.552 | -0.566 | 0.001 | -0.009 |
| | (0.126)** | (0.126)** | (0.085) | (0.084) |
| Children 0-2 | 0.409 | 0.400 | 0.531 | 0.522 |
| | (0.165)* | (0.163)* | (0.090)** | (0.090)** |
| Children 3-4 | 0.269 | 0.267 | 0.339 | 0.337 |
| | (0.156) | (0.160) | (0.090)** | (0.089)** |
| Children 5-11 | 0.026 | 0.026 | -0.123 | -0.133 |
| | (0.101) | (0.100) | (0.057)** | (0.057)* |
| Children 12-15 | 0.045 | 0.039 | -0.424 | -0.442 |
| | (0.107) | (0.106) | (0.074)** | (0.073)** |
| Log of household income | 0.024 | 0.032 | -0.046 | -0.045 |
| | (0.077) | (0.076) | (0.050) | (0.050) |
| Unskilled | 0.264 | 0.204 | 0.676 | 0.667 |
| | (0.302)* | (0.300) | (0.271)* | (0.270)* |
| Partly skilled | 0.320 | 0.287 | 0.640 | 0.637 |
| | (0.254)** | (0.252)** | (0.244)** | (0.243)** |
| Skilled manual or armed forces | 0.283 | 0.239 | 0.619 | 0.607 |
| | (0.251) | (0.249) | (0.245)* | (0.253)* |
| Skilled non-manual | 0.069 | 0.044 | 0.333 | 0.331 |
| | (0.245) | (0.243) | (0.239) | (0.239) |
| Managerial or technical | -0.065 | -0.088 | 0.202 | 0.200 |
| | (0.223) | (0.222) | (0.230) | (0.230) |
| No qualifications | 1.320 | 1.428 | 1.941 | 1.925 |
| | (0.593)* | (0.590)* | (0.391)** | (0.390)** |
| Highest qualification O/CSE | 2.240 | 2.268 | 1.656 | 0.634 |
| | (0.345)** | (0.344)** | (0.241)** | (0.241)** |
| Highest qualifications Alevel/HND | 2.076 | 2.077 | 1.770 | 1.760 |
| | (0.290)** | (0.344)** | (0.210)** | (0.209)* |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region control as well as survey panel weights provided by BHPS. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. * $p$<0.05; ** $p$<0.0

**Table 11 (continued).** Logistic fixed effect for men and women: Effect of health transition and health status on exit from employment to inactivity (Second version of defining health transitions)

| | Men | | Women | |
|---|---|---|---|---|
| | I | II | I | II |
| Own house with mortgage | -0.353 | -0.342 | -0.358 | -0.347 |
| | (0.145)* | (0.144)* | (0.109)** | (0.109)** |
| Housing authority | -0.186 | -0.163 | -1.177 | -0.159 |
| | (0.225) | (0.253) | (0.170) | (0.169) |
| House is rented | -0.304 | -0.260 | -0.416 | -0.393 |
| | (0.224) | (0.225) | (0.152)** | (0.151)** |
| Wales | 0.171 | 0.166 | 0.100 | -0.107 |
| | (0.105) | (0.777) | (0.079) | (0.079) |
| Scotland | -0.118 | -0.150 | -0.189 | -0.201 |
| | (0.105) | (0.105) | (0.078)* | (0.078)** |
| Midlands | 0.043 | 0.028 | -0.049 | -0.025 |
| | (0.102) | (0.102) | (0.079) | (0.079) |
| South west | -0.010 | -0.026 | -0.008 | -0.044 |
| | (0.128) | (0.127) | (0.098) | (0.098) |
| South east | -0.101 | -0.110 | -0.059 | -0.064 |
| | (0.112) | (0.112) | (0.081) | (0.081) |
| North east | 0.059 | 0.061 | -0.054 | -0.060 |
| | (0.111) | (0.111) | (0.087) | (0.087) |
| North west | 0.231 | 0.208 | -0.163 | -0.175 |
| | (0.117)* | (0.116) | (0.092) | (0.092) |
| Age 20-24 | -0.771 | -0.731 | -0.675 | -0.642 |
| | (0.112)** | (0.112)** | (0.090)** | (0.090)** |
| Age 25-29 | -1.547 | -1.490 | -0.814 | -0.772 |
| | (0.141)** | (0.141)** | (0.095)** | (0.095)** |
| Age 30-34 | -1.683 | -1.590 | -1.069 | -1.007 |
| | (0.147)** | (0.146)** | (0.097)** | (0.097)** |
| Age 35-39 | -1.624 | -1.524 | -1.283 | -1.204 |
| | (0.145)** | (0.144)** | (0.098)** | (0.098)** |
| Age 40-44 | -1.511 | -1.393 | -1.574 | -1.498 |
| | (0.143)** | (0.142)** | (0.104)** | (0.103)** |
| Age 45-49 | -1.598 | -1.457 | -1.469 | -1.368 |
| | (0.149)** | (0.148)** | (0.105)** | (0.104)** |
| Age 50-54 | -1.032 | -0.898 | -1.103 | -1.001 |
| | (0.137)** | (0.136)** | (0.104)** | (0.104)** |
| Age 55-59 | 0.889 | 0.871 | 0.740 | 0.741 |
| | (0.118)** | (0.116)** | (0.088)** | (0.088)** |
| Age 60-64 | 0.901 | 0.990 | | |
| | (0.128)** | (0.129)** | | |
| Log likelihood | -2,999.74 | -2,038.86 | -4,603.17 | -4,714.74 |
| Number of observations | 9,468 | 9,468 | 17,067 | 17,067 |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region control as well as survey panel weights provided by BHPS . Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. * $p$<0.05; ** $p$<0.0

**Table 12 (continued).** Logistic fixed effect for men and women: Effect of health transition and health status on exit from employment to inactivity excluding older individuals

| | Men | | Women | |
|---|---|---|---|---|
| | I | II | I | II |
| Mental health t | 1.043 | | 0.319 | |
| | (0.176)** | | (0.107)** | |
| Poor mental health t | | 0.989 | | 0.267 |
| | | (0.167)** | | (0.102)** |
| Mental health transition(worse) | 0.502 | 0.642 | 0.274 | 0.275 |
| | (0.161)** | (0.176)** | (0.097)** | (0.105)** |
| Physical health t | 0.544 | | 0.404 | |
| | (0.178)** | | (0.113)** | |
| Poor physical health | | 0.723 | | 0.566 |
| | | (0.183)** | | (0.115)** |
| Physical health transition(worse) | 0.689 | 0.721 | 0.320 | 0.422 |
| | (0.172)** | (0.185)** | (0.109)** | (0.118)** |
| Part time at t | 0.281 | 0.310 | 0.320 | 0.322 |
| | (0.143)* | (0.143)* | (0.078)** | (0.078)** |
| Spouse work at t | -0.506 | -0.528 | 0.277 | 0.267 |
| | (0.168)** | (0.168)** | (0.099)** | (0.099)** |
| Children 0-2 | 0.304 | 0.336 | 0.505 | 0.517 |
| | (0.168) | (0.167)* | (0.091)** | (0.091)** |
| Children 3-4 | 0.305 | 0.297 | 0.286 | 0.283 |
| | (0.165) | (0.165) | (0.090)** | (0.090)** |
| Children 5-11 | 0.088 | 0.075 | -0.160 | -0.165 |
| | (0.106) | (0.106) | (0.058)** | (0.058)** |
| Children 12-15 | -0.024 | -0.048 | -0.460 | -0.466 |
| | (0.123) | (0.122) | (0.077)** | (0.077)** |
| Log of household income | -0.040 | -0.055 | -0.141 | -0.137 |
| | (0.089) | (0.089) | (0.056)* | (0.056)* |
| Unskilled | 0.457 | 0.400 | 0.758 | 0.751 |
| | (0.388) | (0.386) | (0.324)* | (0.324)* |
| Partly skilled | 0.437 | 0.422 | 0.569 | 0.555 |
| | (0.341) | (0.339) | (0.291) | (0.291) |
| Skilled manual or armed forces | 0.400 | 0.423 | 0.568 | 0.557 |
| | (0.343) | (0.341) | (0.303) | (0.303) |
| Skilled non-manual | 0.261 | 0.250 | 0.265 | 0.251 |
| | (0.335) | (0.333) | (0.288) | (0.287) |
| Managerial or technical | -0.127 | -0.126 | 0.082 | 0.073 |
| | (0.315) | (0.314) | (0.281) | (0.280) |
| No qualifications | 0.788 | 0.872 | 1.678 | 1.645 |
| | (0.599) | (0.593) | (0.435)** | (0.435)** |
| Highest qualification O/CSE | 1.700 | 1.690 | 1.461 | 1.457 |
| | (0.355)** | (0.354)** | (0.250)** | (0.250)** |
| Highest qualifications A-level/HND | 1.847 | 1.823 | 1.650 | 1.655 |
| | (0.296)** | (0.293)** | (0.214)** | (0.215)** |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region and survet panel weights provided with BHPS. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. * *p*<0.05; ** *p*<0.0

**Table 12 (continued).** Logistic fixed effect for men and women: Effect of health transition and health status on exit from employment to inactivity excluding older individuals

| | Men | | Women | |
|---|---|---|---|---|
| | I | II | I | II |
| Own house with mortgage | -0.065 | -0.058 | 0.064 | 0.086 |
| | (0.223) | (0.222) | (0.152) | (0.152) |
| Housing authority | 0.078 | 0.086 | 0.232 | 0.269 |
| | (0.314) | (0.312) | (0.202) | (0.203) |
| House is rented | 0.018 | 0.034 | -0.053 | -0.016 |
| | (0.272) | (0.271) | (0.183) | (0.183) |
| Wales | 0.017 | 0.046 | -0.410 | -0.398 |
| | (0.769) | (0.771) | (0.424) | (0.428) |
| Scotland | 0.726 | 0.520 | 0.967 | 0.992 |
| | (0.712) | (0.723) | (0.638) | (0.636) |
| Midlands | 0.388 | 0.434 | 0.354 | 0.358 |
| | (0.569) | (0.573) | (0.336) | (0.335) |
| South West | 0.610 | 0.613 | -0.185 | -0.195 |
| | (0.601) | (0.600) | (0.336) | (0.337) |
| South East | -0.055 | -0.063 | -0.283 | -0.270 |
| | (0.448) | (0.444) | (0.259) | (0.260) |
| North East | 1.064 | 0.976 | 0.125 | 0.145 |
| | (0.669) | (0.669) | (0.376) | (0.377) |
| North West | 1.831 | 1.810 | -0.153 | -0.111 |
| | (0.783)* | (0.782)* | (0.393) | (0.394) |
| Age 20-24 | -0.634 | -0.636 | -0.494 | -0.509 |
| | (0.184)** | (0.183)** | (0.141)** | (0.141)** |
| Age 25-29 | -1.201 | -1.226 | -0.331 | -0.359 |
| | (0.287)** | (0.286)** | (0.186) | (0.186) |
| Age 30-34 | -1.620 | -1.629 | -0.274 | -0.283 |
| | (0.377)** | (0.376)** | (0.231) | (0.231) |
| Age 35-39 | -1.413 | -1.441 | -0.290 | -0.302 |
| | (0.464)** | (0.463)** | (0.275) | (0.275) |
| Age 40-44 | -1.020 | -1.017 | -0.835 | -0.854 |
| | (0.547) | (0.546) | (0.326)* | (0.327)** |
| Age 45-50 | -1.196 | -1.133 | -0.477 | -0.484 |
| | (0.635) | (0.632) | (0.379) | (0.380) |
| Log likelihood | -1,087.76 | -1,096.35 | -2,880.24 | -2.880.05 |
| Number of observations | 7,723 | 7,723 | 10,681. | 10,681 |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region and panel survey weights provided by BHPS. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. * $p$<0.05; ** $p$<0.0

**Table 13.** Linear fixed effect model. Effect of health transition and health status on exit from employment to inactivity

| | Men | Women |
|---|---|---|
| Mental health t | 0.09 | 0.34 |
| | (0.08)* | (0.09)** |
| Mental health transition (first version) | 0.09 | 0.15 |
| | (0.03)** | (0.04)** |
| Physical health t | 0.12 | 0.22 |
| | (0.07)** | (0.08)** |
| Physical health transition (first version) | 0.22 | 0.39 |
| | (0.04)** | (0.046** |
| Part time t | 0.21 | 0.42 |
| | (0.06)* | (0.11)* |
| Spouse working at t | -0.32 | 0.005 |
| | (0.11)** | (0.17) |
| Children 0-2 | 0.12 | 0.32 |
| | (0.11) | (0.07)** |
| Children 3-4 | 0.07 | 0.34 |
| | (0.16) | (0.09)** |
| Children 5-11 | 0.061 | -0.32 |
| | (0.10) | (0.77) |
| Children 12-15 | 0.05 | -0.42 |
| | (0.10) | (0.09)** |
| Log household income at t | 0.24 | -0.051 |
| | (0.17) | (0.050) |
| Unskilled | -0.02 | 0.09 |
| | (0.23) | (0.22) |
| Partly skilled | 0.09 | 0.32 |
| | (0.18) | (0.24) |
| Skilled manual or armed forces | 0.32 | 0.59 |
| | (0.07)* | (0.25) |
| Skilled non-manual | 0.06 | 0.31 |
| | (0.24) | (0.24) |
| Managerial or technological | -0.08 | 0.12 |
| | (0.21) | (0.23) |
| No qualifications | 0.22 | 0.43 |
| | (0.09)* | (0.12)** |
| Highest qualification O/CSE | 0.18 | 0.21 |
| | (0.06)** | (0.04)** |
| Highest qualifications A level/HND | 0.09 | 0.12 |
| | (0.05)** | (0.02)** |
| Own house with Mortgage | -0.17 | -0.36 |
| | (0.09)* | (0.10)** |
| Housing authority | -0.03 | -0.12 |
| | (0.11) | (0.17) |
| House is rented | -0.30 | -0.14 |
| | (0.18) | (0.15) |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region control and panel survey weights provided in BHPS data. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. * $p$<0.05; ** $p$<0.0

**Table13** (continued). Linear fixed effect model. Effect of health transition and health status on exit from employment to inactivity

| | | |
|---|---|---|
| Wales | 0.12 | -0.64 |
| | (0.54) | (0.43) |
| Scotland | 0.38 | 0.13 |
| | (0.15)* | (0.42) |
| Midlands | 0.04 | 0.03 |
| | (0.15) | (0.38) |
| South west | 0.08 | -0.01 |
| | (0.18) | (0.19) |
| South east | -0.03 | -0.06 |
| | (0.16) | (0.25) |
| North east | -0.14 | 0.07 |
| | (0.15) | (0.17) |
| North west | -0.28 | -0.31 |
| | (0.17) | (0.14) |
| Age2024 | -0.08 | -0.10 |
| | (0.21) | (0.13) |
| Age2529 | -0.38 | -0.46 |
| | (0.17)* | (0.17)** |
| Age3034 | -0.37 | -1.22 |
| | (0.21) | (0.21) |
| Age3539 | -0.33 | -0.42 |
| | (0.20) | (0.25) |
| Age4044 | 0.43 | -0..30 |
| | (0.20)** | (0.29) |
| Age4549 | 0.44 | -0.32 |
| | (0.20)** | (0.33) |
| Age5054 | 0.51 | -0.09 |
| | (0.21)** | (0.24) |
| Age5559 | 0.50 | 0.42 |
| | (0.18)** | (0.12)** |
| Age6064 | 0..45 | -- |
| | (0.28)* | -- |
| R square (overall) | 0.31 | 0.29 |
| Number of observations | 54,423 | 53,171 |

Notes: Dependent variable takes the value 1 if the individual is inactive at time t+1 but working at time t and takes the value 0 if the individual works at time t and time t+1. All models also include year and region control and panel survey weights provided in BHPS data. Coefficients from the fixed effects logit are reported as well as standard errors in parentheses. * $p<0.05$; ** $p<0.0$

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# Chapter 3

## 3. Effect of acute health shocks on different components of income among working age people

### 3.1 Introduction

Although the link between health and socio-economic status is well documented, the causal roots of this relationship are not easy to identify (Deaton and Paxson, 1998; Goldman, 2001; Fuchs, 2004). Evidence from the social and medical sciences confirm that when people are financially better off, they tend to live and work in healthier environments, have access to the best medical care available, and have sufficient income to spend on the goods, foods and services that help with maintaining a healthier lifestyle. However, the potential positive effect of income on health can be mitigated by negative factors such as longer working hours and work-related stress (Halla et al., 2013).

When health is considered as a form of human capital, as Grossman (1972) suggests, it is plausible to argue that people with good physical and mental health are able to work longer and harder than people suffering from mild or severe health problems. Healthier children are likely to stay in school longer and attain a higher standard of education, gain more social and technical skills and consequently earn a better salary when they enter the workforce. The rate of time preference is an alternative pathway that can explain the positive correlation of health and socio-economic status without referring to any causal link. In this framework, an individual who is better off financially is more likely to invest in human capital, which leads to their healthier life-style (Adam et al., 2003). This group also tend to hold less physically demanding jobs. On the other hand, poor health tends to lead to lower income as people may lose some of their productive working hours and become less efficient. The next phase might involve being dropped out of the labour market altogether or being unable to get promoted. One of the strategies adopted by a number of researchers is to identify a new health shock, while controlling for past health to isolate the effect of a new health event (Smith, 2005). This sudden variation in health can be exogenous relative to income and labour force participation. Measuring and identifying such sudden and unanticipated health shocks is the main challenge facing analysts aiming to identify the causal relationship between health and income. Both are mutually affected by each other as well as by other relevant forces (Smith, 2005). It can be argued that a higher income can increase the probability of gaining access to enhanced, regular and timely healthcare. In addition, a higher level of health literacy and an adoption of a healthier life-style, such as healthy diet and regular exercise are more likely to maintain health. Very few empirical studies have investigated the casual impact of health on employment and income using various forms of identifiable health shocks. Wing Han Au et al. (2005) used quick deterioration in self-assessed health to model labour market outcomes. Similarly, Riphahn (1999) suggested defining negative health shocks as a sudden and substantial drop in satisfaction with health, and Wagstaff (2007) used a substantial reduction of body mass index. Effects of workplace (and non-workplace) accidents on employment and income have been investigated in some other studies such as Reville and Schoeni (2001) and Crichton et al. (2005), while Moller Dano (2005) and Halla et al. (2013) estimated the effect of severe road accidents on labour market participations. Gracia Gomez et al. (2013) restricted their attention to acute hospitalization episodes.

I followed studies such as Smith (2005), Datta Gupta et al. (2011) and Jones et al. (2013) by investigating the effect of health shocks as measured by the incidence of cancer, stroke or myocardial infarction. There are plausible reasons to justify this choice of health problems as exogenous health shocks. First, these problems are less likely to be misreported and exaggerated compared with milder problems so that the magnitude of justification bias will be minimised (Baker et al. 2004). Additionally, even though genetic inheritance, lifestyle choices and chronic health problems play a significant role in the development of these health shocks, in most cases the exact timing and probability of occurrence remains unexpected (Jones et al. 2003).

I also used coarsened exact matching (CEM) to control for bias caused by observable confounding as the treated and the control groups were not necessarily identical before treatment (Grazia Gomez, 2011). CEM is one of a class of monotonic imbalance bounding matching methods which bound the maximum imbalance in some feature of the empirical distributions through an *ex ante* choice by the user. It also has been shown that CEM reduces both the error in estimating the average treatment effect and the amount of model dependence (Iacus et al., 2008). Any estimated outcome depends on the modelling assumption and different causal inferences can be drawn based on different specifications. King et al. (2006) described model dependence as the difference, or distance, between the predicted outcome of dependent variable values based on any two plausible alternative model. Matching methods pre-process observational data and weaken the link between treatment variable and control variables. If data quality is sufficient such that appropriate matches become available, causal effect estimates do not vary substantially based on alternative parametric modelling assumptions (Ho et al., 2007). This study also attempts to control for the potential correlation among unobservable characteristics, affecting both health shock incidence and labour market outcomes by combining matching with fixed effect and lag dependent models (Heckman et al., 1998).

Health problems such as cancer, stroke and heart failure affect many people in the UK and can cause substantial adverse effects on working-age people's socio-economic status. 352,197 people in the UK were diagnosed with cancer in 2013 (Cancer Research UK 2016). Cancer causes more than one in four of all deaths in the UK. Some patients may experience a drop in their income due to time away from work because of cancer-onset side effects (Bennett et al., 2008; Lauzier et al., 2008). It has been suggested that particular sub-groups of patients, such as those with lower incomes, may be more vulnerable to the adverse financial and economic consequences of cancer (Arozullah et al., 2004; Langa et al., 2004). Each year, around 110,000 people have a stroke in England. The brain injuries caused by strokes are the main reason for disability among British adults and over half of all stroke survivors are left with a form of disability (www.nhs.uk, 2016). Myocardial Infarction (MI) is another common condition affecting approximately 150,000 people per year in the UK (Trends in coronary heart disease, 2011). Affected individuals are highly likely to struggle with daily activities and may find it impossible to return to full-time occupation. Although old age is one of the most important risk factors for health problems mentioned above, the number of working-age people with these health problems is not negligible. Adults aged 25-49 contribute 10% of all new cancer cases and female cases are twice as many as males in this age group (Cancer Research UK 2014). 26 percent of all strokes in the UK occurred in people aged under 65 years old. The number of people having strokes aged 20 to 64 increased by 25% from 1990 to 2010 worldwide. Around 1 in 150 strokes in the UK was reported among those aged under 20 (stroke.org.uk, 2016).

When and how patients return to work after treatment is related to different factors, such as type of work, nature of recovery, personal characteristics, financial resources and health insurance cover. Many people return to their previous full-time occupations, but others may have to decrease their hours or take up jobs better suited to this new condition. There are also affected individuals who may never be able to return to work due to the long-term side effects of their illness. In a country such as the UK, with universal healthcare coverage and disability insurance, the welfare system is one of the main factors shaping the labour market's response to health shocks (Datta Gupta et al., 2011). In this paper, I contributed to the literature by investigating whether and to what extend potential reductions in labour income were compensated by the financial supports available from the UK welfare system. While most of the previous empirical research using British data limited its focus to the effect of health shocks on unemployment, I set out to explore different potential pathways that could lead to alterations in different components of income following a health shock. My results showed the degree to which labour income, welfare income, benefits and total income were affected after onset of cancer, stroke and heart failure.

The focus of published literature has been on the effect of health shock on employment. In this work I focused on the income loss after health shock. Although it was clear that becoming economically inactive or unemployed were main reasons for loss of income among people who were previously employed or self-employed. Taking into account alterations in income shed more light on diverse scenarios and the extent to which individuals suffered financially even if they stayed at work. In addition, the magnitude of change in social benefits that affected individual receive can be examined to investigate if it compensates for their income loss.

Almost all affected individuals needed some time away from work when undergoing treatment. In the UK, all employed (not self-employed) individuals whose work ability is affected by health problems are entitled to statutory sick pay. This is paid for by employers for a maximum period of 28 weeks (www.gov.uk, 2016). Depending on the individual's employment contract, some employees may additionally qualify for occupation or company sick pay. Individuals who are not fit to return to work after 28 weeks are entitled to apply for Employment and Support Allowance (ESA). Incapacity Benefit (IB) has been replaced by ESA since 2008. IB was paid to working age people who had contributed sufficient national insurance contributions in the relevant tax years. EAS has both a contributory and means tested part. People may receive either or both depending on their contribution history and their income and savings (www.disabilityrightsuk.org, 2014). Self-employed individuals are also entitled to claim ESA conditioned on whether they have paid the correct amount of national insurance contribution. Disability living allowance is also available for people under 65 who find it difficult to walk or look after them. This benefit is made up of a care and a mobility component. People with terminal illness such as cancer receive the disability living allowance care component at the highest rate. Even people who return to work can experience substantial loss in overall income or labour income. Therefore, they may become entitled to a range of benefits that are available for people on low income. Some of these benefits include income support, working tax credit, housing benefit and working tax benefit (www.citizensadvice.org.uk, 2016).

The main aim of this work was to investigate the magnitude of change in different sources of income following an acute health shock. This paper took advantage of available longitudinal data set from Understanding Society using survey waves 2009 to 2014 to explore the effect of negative health shocks on different components of income among working age men and women (www.understandingsociety.ac.uk, 2015). Results provide an in-depth insight to income dynamics and impact of social welfare payments among affected people after the economic crisis of 2008. I included labour market active individuals and compared different income components of people who experienced cancer, stroke or heart failure for the first time with those who had never experienced any of these health shocks. Combining coarsened exact matching with parametric regression, I argued that within my research design the health shock was quasi experienced and enabled me to investigate causal effects of interested health shocks on different component of individual income.

### 3.2 Data

This paper used the UK's largest household longitudinal survey, The UK Household Longitudinal Survey (UKHLS). UKHLS includes 40,000 households. In addition to household questioner which is answered by the household representative, all adults older than 16 living in the household are asked questions on a wide range of themes such as their ethnicity, financial problems, employment status, expectations and aspirations, their social network and family, health and mental well-being, neighbourhood and proportion of time spent on work or leisure. This survey studies individuals in their changing household contexts and this setting is essential to avoid bias caused by focusing only on the unchanged households in analysing people's behaviour (Giles, 2001).

Pathways to income loss caused as a consequence of an acute health shock can be summarised as follows; a loss of income is a significant source of concern and the biggest financial impact among people experiencing acute health shocks. The manner in which loss of income occurs, and its effects are dependent on the impacted individual's stage in life, household circumstances as well the length of time that such a loss of income lasts. Among people who were employees at the time of their health decline, to have spent at least a period of time receiving only Statutory Sick Pay and in other cases the length of time people needed to take off work meant that their entitlement to Statutory Sick Pay had also ended, leaving some with no income at all. Health deterioration can also lead to temporary financial loss among self-employed people, during periods when they were not fit to work. People who return to work can be the only sub-group that can manage their finances despite the temporary loss of income. However, a major health shock can also cause a permanent loss of incomes, with very serious negative consequences for a household's finances. This could be as a direct result of a diagnosis: it is possible that diagnosed individuals become dismissed from their jobs, while receiving or recovering from treatment or recovery period. In conjunction with the emotional and mental distress caused by facing a health shock, individuals can feel less employable. They are sometimes seen as less able to manage stress or endure the physical burden of day to day job. The burden of additional expense or loss of income resulting from cancer led most people to need to draw on resources other than their regular income at some point since their diagnosis. For many, this involved using up savings, using social benefits, turning to commercial borrowings or accepting financial help from friends or family.

Understanding society is a critical data source as it is one of the few UK surveys that contains information on individuals' income and health. The main motivation of this research was the effect of health shock on income alterations. Therefore, I considered several different types of income to ensure accuracy of obtained results. This was made possible as understanding society provides detailed information on different component of individuals income as well as sources of unearned income such as savings, investments and social benefits. Understanding

Society is the data source for the Department for Work and Pensions publication on income dynamics (Fisher et al., 2019). In addition, its large sample size offers new opportunities to study sub-groups that may be too small for separate analysis using other studies. Understanding Society will also support inter-disciplinary research on issues such as health and income and enabled me to consider a wide range of other socioeconomic variables which can influence both health and income outcomes.

The richness of this panel data set allowed me to compare sub-groups of populations (for example heterogeneity in labour market responses to health shocks among younger individuals or people in poverty) and match individuals with respect to the relevant socioeconomic and demographic characteristics. Due to the large number of sample households, the fieldwork for each wave takes two calendar years to complete. These data provide the information on the wellbeing and health of the participants prior to joining the survey which enables us to identify individuals who have already experienced the onset of a health shock. Their income and labour market adjustment might be different to that for individuals who experience these health shocks for the first time. Over the course of the sample, individuals were asked about specific health problems in the current year. They are then asked different sets of questions depending on participation history. For example; being a new participant or having been interviewed the year before or whether there was a gap between participated years. Using this information, we can build up a comprehensive picture of the health status of participants. A battery of standard health indicators covers self-assessed health, the presence of a long-standing illness or disability, different types of limitations in activities of daily living (ADLs), and information about health habits and behavioural risk factors, via past and current smoking participation and intensity.

I considered short-run effect of health shocks on income alteration (within a year). It was one of the limitations of this work. However, previous research (Smith, 2005) found most of the income adjustment after an acute health shock was immediate and tended to persist afterwards. Therefore, identifying the short-term changes in income was of great value. Another limitation which is imposed by the data that affects our analysis is that the exact time difference between diagnosis of the health shock and reported employment status or monthly income is not known. This difference can be anything between a couple of days to almost 12 months. Therefore, we are not able to distinguish between the immediate effects of health shocks on income with those after several months.

Basic demographic information including age, gender, race, marital status, number of children, and household size, together with socioeconomic characteristics including highest educational qualification, individual and household income from various sources, and housing tenure was used. With respect to labour market activity, at each wave respondents are asked about employment status (including self-employment), type of occupation, the number of hours worked (including overtime hours, both paid and unpaid), incomes, job satisfaction and other job and employer characteristics.

Understanding Society collects detailed information each wave on income. All individuals aged 16 or more are asked to report: incomes from main and second jobs, social security benefits, state and private benefits and private transfers and investment income. Net and Gross monthly income are estimated from the individual income components described below. When gross income is calculated, incomes components are gross which means, before taxes and National Insurance contributions are deducted and also before tax deduction from non-pay income (rental income), which is assumed to be reported gross. The term “net” refers to net of taxes on incomes and national insurance contributions. It is constructed as the sum of the six income components described below. The six component of individual net income are as follows: Component 1: Labour income, this is the sum of three incomes components: net usual pay; net self-employment income; net pay in second job. Component 2: Miscellaneous income, This measure captures receipts reported in the income data file if people report receiving “educational grant (not student loan or tuition fee loan)”, “payments from a family member not living here”, or “any other regular payment (not asked in Wave 1)”. This is assumed to be reported net of tax. Component 3: private benefit income, This includes receipts reported in the income data file where one of the following payments are reported: “trade union / friendly society payment”, “maintenance or alimony”, or “sickness and accident insurance”. This is assumed to be reported net of tax. Component 4: investment income , This measure represents receipts reported in income record if one of the following are reported: “a private pension / annuity”, “rent from boarders or lodgers (not family members) living here”, “rent from any other property”. Also, monthly income from savings and investments, estimated as the annual income from savings and investments divided by 12 is added. All these sources are assumed to be reported net except for rent from other property which is assumed reported gross, and a tax liability is deducted. Component 5: pension income, this includes receipts reported in the income data file when individuals report receiving “a pension from a previous employer”, or “a pension from a spouse’s previous employer”. This is assumed to be reported net of tax. Component 6: social benefit income, This component includes receipts reported in income record where “state retirement (old age) pension”, “a widow’s or war widow’s pension”, “a widowed mother’s allowance / widowed parent’s allowance”, “pension credit (includes guarantee credit & saving credit)”, “severe disablement allowance”, “industrial injury disablement allowance”, “disability living allowance”, “attendance allowance”, “carer’s allowance (formerly invalid care allowance)”, “war disablement pension”, “incapacity benefit”, “income support”, “job seeker’s allowance”, “child benefit (including lone-parent child benefit payments)”, “child tax credit”, “working tax credit (includes disabled person’s tax credit)”, “maternity allowance”, “housing benefit”, “council tax benefit”, “foster allowance / guardian allowance”, “rent rebate (NI only)”, “rate rebate (NI only – offset against rates)”, “employment and support allowance”, “return to work credit”, “in-work credit for lone parents”, “other disability related benefit or payment”, “income from any other state benefit (not asked in Wave 1), “universal credit” (from Wave 4), “personal independence payments” (from Wave 4). This is assumed to be reported net of tax. Personal gross monthly income can be decomposed into three subcomponents: labour income equal to the sum of gross usual pay, self-employment pay and gross second-job pay; annual income from savings and investments and monthly income from benefits and other sources (Fisher et al., 2019).

## 3.3 Empirical strategy

The empirical strategy exploits changes in health induced by the first onset of an acute health shock (cancer, heart attack and stroke). I considered the effect of the acute health shocks occurring between two consecutive years (t-1and t) on different component of income at time t. These estimates identify the short run income change, observed at time t. the acute health shock is considered unanticipated because conditioned on the observed health status of an individual, the actual occurrence and timing of it is not exactly predictable (Trevisan et al., 2015).

Acute health shocks are denoted by a binary indicator which is equal to 1 if an individual experienced her/his first acute health shock between t and t-1, and zero otherwise. The sample for analysis is restricted to who would both be younger than the statutory retirement age and older than compulsory full-time education age at time t. To allow the inclusion of a lag in the analysis, individuals should be observed for at least two consecutive years and are included in the sample from the first year they report themselves as employed or self-employed. These participants are followed up over the course of the survey and are permitted to exit from work and still included in the estimated data. I also excluded those who had experienced these health problems prior to their participation in the survey because income and labour market behaviour adjustments had occurred sometime before the start of my analysis and this could dilute the estimated effect first health shocks on income. All new participants were asked about their health history in the first year of their participation in the survey and the full list included: asthma; arthritis; congestive heart failure; coronary heart disease; angina; heart attack (myocardial infarction); stroke; emphysema; over-active thyroid (hyperthyroidism); under-active thyroid (hypothyroidism); chronic bronchitis; liver condition (any kind); cancer or malignancy; diabetes; epilepsy; high blood pressure; and clinical depression.

Every wave, all new entrants are asked “has a doctor or other health professional ever told you that you have any of these conditions?
1.Asthma, 2.Arthritis, 3.Congestive heart failure, 4.Coronary heart disease, 5.Angina, 6.Heart attack or myocardial infarction, 7.Stroke, 8.Emphysema, 9.Hyperthyroidism or an over-active thyroid, 10.Hypothyroidism or an under-active thyroid, 11.Chronic bronchitis, 12.Any kind of liver condition, 15.Epilepsy, 16.High blood pressure, 17. Clinical depression, 96. None of these.
Participants who report any of the health problems listed above will be asked “Do you still have the condition?”

Also, all the participants who have been interviewed before are asked “Since last interview, has a doctor or other health professional newly diagnosed you as having any of the following conditions? If so, which ones?
Health shocks are identified if a person faces Congestive heart failure, Heart attack or myocardial infarction, stroke or cancer for the first time in his/her lifetime over the course of the survey. Out of 88053 observations, 534 individuals who experienced health shock for the first were identified.

In order to define treatment and control group, Selection on observables identification approach suggested by Sianesi (2004). In a dynamic treatment assignment setting at any point in time t, a subset of individuals that just experienced their first acute health shock between time t and t-1, are considered as the treatment group. The subgroup of individuals, selected from the subset who have not been hit by the acute health shock up to time t, are regarded as the potential controls (Trevisan et al., 2015) below is a brief description of variables which were used for matching process.

Poor self-reported health is based on the following question: In general, would you say your health is? Options are 1. Excellent, 2. Very good, 3. Good, 4. Fair, 5. Poor. Poor self-reported health is equal to 1 if poor health is reported and 0 otherwise.

Long-term health problem or disability is based on the question below and is equal to 1 if any of the health-related difficulties are reported and zero otherwise. Question in the survey: Does this/Do these health problem(s) or disability(ies) mean that you have substantial difficulties with any of the following areas of your life? 1. Mobility (moving around at home and walking), 2. Lifting, carrying or moving objects, 3. Manual dexterity (using your hands to carry out everyday tasks), 4. Continence (bladder and bowel control), 5. Hearing (apart from using a standard hearing aid), 6.Sight (apart from wearing standard glasses), 7.Communication or speech problems, 8.Memory or ability to concentrate, learn or understand, 9. Recognising when you are in physical danger, 10. Your physical co-ordination (e.g. balance), 11. Difficulties with own personal care (e.g. getting dressed, taking a bath or shower), 12. Other health problem or disability. 96, None of these

Smoker is based on the question that askes “Do you smoke cigarettes? Please do not include electronic cigarettes (e-cigarettes)” and takes on value 1 if an individual has reported yes as an answer in at least one of the waves.

Question on ever high blood pressure, ever diabetes, ever coronary heart disease and ever angina are based on 2 questions on a set of diagnosed health conditions and are equal to 1 if a participant repots being diagnosed with any of these health conditions at some point in their life. The questions are as following:

"has a doctor or other health professional ever told you that you have any of these conditions? And Since last interview, has a doctor or other health professional newly diagnosed you as having any of the following conditions? If so, which ones?

" Since last interview, has a doctor or other health professional newly diagnosed you as having any of the following conditions? If so, which ones?

(1. Asthma, 2. Arthritis, 3.Congestive heart failure, 4. Coronary heart disease, 5. Angina, 6.Heart attack or myocardial infarction, 7.Stroke, 8.Emphysema, 9. Hyperthyroidism or an over-active thyroid, 10. Hypothyroidism or an under-active thyroid, 11.Chronic bronchitis, 12.Any kind of liver condition,13.Cancer or malignancy, 14.Diabetes,15. Epilepsy,16. High blood pressure, 17. Clinical depression, 96. None of these)

Descriptively comparing individuals who experienced acute health shocks with those not affected would only estimate the causal effect of health shocks if these shocks were randomly distributed in the sample (Table 1 and 2). However, the average characteristics of the sample of affected individuals are statistically different to those of the control group with respect to most covariates included in the matching. The treated group is older and has a higher proportion of smokers in the year before the health shock. There are pronounced differences with respect to education, race, general health and history of experiencing conditions such as high blood pressure, diabetes, congestive heart failure, coronary heart disease and angina among treated and control group, suggesting that the incidence of health shock is correlated with some of the observable characteristics. Descriptive analysis also revealed some differences between men and women. For example, unlike men, the distribution of labour income and of holding a part-time job was not significantly different for the treatment and control groups of women and lagged mental health among treated women was significantly worse than in control group, but this difference was not evident among men.

I pre-processed the data using a non-parametric matching method to account for some or all the potentially confounding effect of pre-treatment control variables by reducing the covariate imbalance between the treated and control groups. This study employed Coarsened Exact Matching (CEM) which was a Monotonic Imbalance Bounding (MIB) matching method. While traditional matching methods usually imply a trade-off in the balance achieved across different conditioning variables, the CEM approach allows - at the cost of a reduced sample size - to reduce the imbalance in any chosen confounder with no detrimental effect on the balancing of others (Iacus et al. 2011). This monotonic imbalance bounding property is achieved by coarsening selected variables into meaningful groups and performing exact matching on the coarsened data, so that balance is achieved in the full joint distribution of coarsened variables, accounting for interactions and non-linearities. Clearly, as the number of co-founders increases, CEM may result in a progressively reduced sample size as exact matches with the set of potential controls become more difficult to locate. In our setting, it is therefore employed to ensure that adequate balancing is achieved with respect to those confounders deemed most relevant for capturing endogenous selection into experiencing an acute health shock. This allows for adjusting the imbalance on one variable without affecting on the maximum imbalance of any other (Iacus et al., 2012). CEM makes use of a multidimensional exact matching algorithm and applies it to cells identified by categorising continuous variables into discrete intervals or by reshaping categorical variables into fewer coarsened categories. CEM’s algorithm identifies a range of strata with the same coarsened values of matching variables and restricts the matched data to areas of common empirical support by omitting unmatched observations from both treated and control samples. Furthermore, CEM meets the congruence principle, requiring the equality of the data and analysis space. Methods that do not hold this principle often produce implausible results (King and Zeng, 2006).

Following Ho et al. (2007), I combined matching with parametric regression models to obtain causal inferences about the Average Treatment effect on the Treated (ATT) from secondary data. Using the weights produced by Coarsened Exact Matching (CEM), the sample was reprocessed so that the resulting comparison group was as similar as possible to the treated group (Iacus et al., 2012). I also tested the robustness of findings by comparing these results with those obtained using alternative identifying assumptions. The alternative approaches are based on fixed effects and lag-dependent models. The incidence of a health shock and an individual's unobservable characteristics can be correlated and unobserved differences between the treated and comparison samples may also result in difference in incomes for these two groups. For example, developing cancer may be correlated with unhealthy lifestyle or underdeveloped life skills unobserved in the data (poor diet or poor stress management). This, in turn, may depend on a particular unobserved individual characteristic such as personal motivation or work ethics. Individuals with such characteristics may have a higher chance of developing an acute health condition and also have greater likelihood of income a lower income. Even if the effect of the unobserved characteristics is not significant, not controlling for the average difference in unobservable characteristics of the cancer and comparison groups can cause an overestimation of the effect of health shocks on incomes (Jeon, 2014).

Fixed effects models control for differences between the treated and comparison samples by eliminating time-invariant unobserved characteristics that can be correlated with both incidence of acute health shock and incomes. Lagged dependent models on the other hand control for previous incomes and are more appropriate when the unobserved omitted variables are not time invariant. These two models are not nested and controlling for both time invariant variables and lagged dependent variables causes inconsistency in the model. Therefore, I estimated each of these models separately, using the weights obtained from the exact coarsen matching for men and women.

The identification strategy relied on the assumption that conditional on the set of confounding variables and lagged outcomes, the occurrence of a health shock can be treated as an exogenous shock. The approach to estimation of the treatment effect involved a combination of coarsened exact matching (CEM) and propensity score matching to ensure common support and adequate covariate balance, followed by parametric regression analysis on the balanced data. This followed the method for estimating the average treatment effect on the treated (ATT) set out in Ho et al. (2007).

The central idea in CEM is to first coarsen each observed variable into meaningful groups that preserve information defined by the analyst. Then exact match algorithm is applied on coarsened data. The original (un-coarsened) values of the matched data is retained and observations with the same values for all the coarsened variables are placed in a single stratum. Finally, comparison observations within each stratum are weighted to equal the number of intervention observations in that stratum. Weights are calculated as described below.

Where S is a set of strata denoted to the same coarsened value of X $s \in S$ $T^s$ represents the treated units in stratum s and $M_t^s$ denotes the number of treated units in the stratum. Similarly, $C^s$ stands for the control unites in stratum and $M_c^s$ number of control units in that stratum. The number of matched units are, respectively, for treated and controls $M_t$ and $M_c$. CEM weights for each matched unit i in stratum s are calculated as described in equation 3.1 below:

$$w_i = \begin{cases} 1, & i \in T^s \\ \frac{\mathrm{Mc}}{\mathrm{Mt}} \frac{M_t^s}{M_c^s}, & i \in C^s \end{cases} \qquad (3.1)$$

The weighted regression accounts for potential confounding effects of observable characteristics as at t-1. By applying this matching procedure, it was possible to find 9083 controls for 447 of treated matches (87 of treated observations are excluded). Estimation sample consisted of 534 treated units out of 88053 potential control units in the pre-processed sample. Although the number of treated individuals was small, this was not atypical for this kind of studies (Johns et al. 2013). Full list of the variables used for matching is presented in table 1 and 2. P values obtained after applying CEM show that no differences between the mean of treated and the matched comparison sample remained. All these variables are included in the regression analysis, although this does not alter the health shock’s effect because as a result of reweighting, the health shock is mean-independent conditioning on the matching variables.

The linear regression was based on the specifications are based on equation 3.2:

$$y_{it} = x'_{it-1}\beta_1 + h1'_{it}\beta_2 + \mathrm{u_i} + \varepsilon_{it} \qquad (3.2)$$

The dependent variable $y_{it}$ is a natural logarithm of income of individual i at time t. $h1'_{it}$ is a dummy which identifies whether the individual experienced health shock at time t and takes on value of one when an individual has faced health shock and zero otherwise. $x'_{it-1}$ is a vector containing the weighted (based on CEM weights) health status and socioeconomic variables of individual i at t-1. $\varepsilon_{it}$ is the error term assumed to have a probability density function with logistic distribution and $u_i$ is the individual specific shock which is assumed to be independent of explanatory variables (random effect assumption).

When probability of the eligibility for different welfare income was investigated a nonlinear model as described below was employed. It is assumed that diabetes is a binary variable which might be endogenous and take value 1 if individual i reports being diagnosed with diabetes at time t and 0 otherwise. The employment equation is given by:

$$Welfare^*_{it} = ß_0 + ß_1X_{it-1} + ß_2Diabetes_{it} + u_i + \varepsilon_{it} \qquad (3.3)$$

where $welfare^*_{it} > 0$ ($Welfare^*_{it} = 1$) and $Welfare^*_{it} < 0$ ($Welfare_{it} = 0$) indicates that individual i is receiving a specific form of welfare income or otherwise at time t; $X_{it-1}$ denotes various control variables that has been used in CEM and weighted based on CEM weights (full list of variables demonstrated in table 1). $B_1$ is the vector of coefficients associated with $X_{it-1}$; $u_i$ represents the individual specific unobservable and time invariant. $\varepsilon_{it}$ is a time-specific idiosyncratic shock.

**Table 1:** Mean of variables used for CEM (women)

| | Full sample | | | Matched sample | | |
|---|---|---|---|---|---|---|
| | Control | Treatment | P value | Control | Treatment | P value |
| Age (16-30/31-40/41-50/51-60) | 4.22 | 3.21 | *** | 4.27 | 4.27 | - |
| Long term health problem or disability (t-1) | 1.61 | 1.49 | *** | 1.63 | 1.63 | - |
| Poor self-reported health (t-1) | 0.06 | 0.02 | *** | 0.021 | 0.021 | - |
| Smoker (t-1) | 0.13 | 0.15 | - | 0.14 | 0.14 | - |
| Ever high blood pressure till t-1 | 0.03 | 0.042 | *** | 0.049 | 0.049 | - |
| Ever diabetes till t-1 | 0.02 | 0.07 | *** | 0.0714 | 0.0714 | - |
| Ever congestive heart failure till t-1 | 0.08 | 0.052 | *** | 0.06 | 0.06 | - |
| Ever coronary heart disease till t-1 | 0.04 | 0.06 | *** | 0.074 | 0.074 | - |
| Ever angina till t-1 | 0.01 | 0.032 | *** | 0.039 | 0.039 | - |
| Married/cohabiting t-1 | 0.57 | 0.574 | - | 0.591 | 0.591 | - |
| Number of children | 0.36 | 0.509 | *** | 0.333 | 0.333 | - |
| highest qualification: Degree | 0.37 | 0.34 | ** | 0.35 | 0.35 | - |
| highest qualification: A-level/ GCSE | 0.36 | 0.42 | ** | 0.349 | 0.349 | - |
| highest qualification: Other qualification | 0.31 | 0.41 | - | 0.407 | 0.407 | - |
| highest qualification: None | 0.2 | 0.36 | ** | 0.342 | 0.342 | - |
| White | 0.86 | 0.94 | - | 0.962 | 0.962 | - |
| Permanent or temporary job at t-1 | 0.94 | 0.95 | - | 0.972 | 0.972 | - |
| Full time or part time job at t-1 | 1.27 | 1.24 | - | 1.283 | 1.283 | - |
| Quintile of household income | 2.17 | 2.128 | - | 2.121 | 2.121 | - |
| Working at t-1 | 0.91 | 0.9 | - | 0.929 | 0.929 | - |
| Year of interview | 3.55 | 3.54 | - | 3.6 | 3.6 | - |

Source: UKHLS, wave 1- 5
Notes: p values for tests of equality of means between treated and controls were calculated
***p<0.01, **p<05, *p<0.1 , __ No statistically significant difference

**Table 2:** Mean of variables used for CEM (men)

| | Full sample | | | Matched sample | | |
|---|---|---|---|---|---|---|
| | Control | Treatment | P value | Control | Treatment | P value |
| Age (16-30/31-40/41-50/51-60) | 3.865 | 3.154 | *** | 3.95 | 3.95 | - |
| Long term health problem or disability (t-1) | 1.74 | 1.553 | *** | 1.587 | 1.587 | - |
| Poor self-reported health (t-1) | 0.022 | 0.092 | *** | 0.042 | 0.042 | - |
| Smoker (t-1) | 0.25 | 0.44 | - | 0.29 | 0.31 | - |
| Ever high blood pressure till t-1 | 0.158 | 0.251 | *** | 0.312 | 0.312 | - |
| Ever diabetes till t-1 | 0.094 | 0.164 | *** | 0.382 | 0.382 | - |
| Ever congestive heart failure till t-1 | 0.002 | 0.0097 | *** | 0.0072 | 0.0072 | - |
| Ever coronary heart disease till t-1 | 0.038 | 0.051 | *** | 0.063 | 0.063 | - |
| Ever angina till t-1 | 0.006 | 0.048 | *** | 0.042 | 0.042 | - |
| Married/cohabiting t-1 | 0.62 | 0.751 | *** | 0.775 | 0.775 | - |
| Number of children | 0.489 | 0.331 | *** | 0.293 | 0.293 | - |
| highest qualification: Degree | 0.308 | 0.236 | *** | 0.237 | 0.237 | - |
| highest qualification: A-level/ GCSE | 0.33 | 0.419 | *** | 0.349 | 0.349 | - |
| highest qualification: Other qualification | 0.312 | 0.396 | *** | 0.407 | 0.407 | - |
| highest qualification: None | 0.287 | 0.332 | *** | 0.342 | 0.342 | - |
| White | 0.85 | 0.909 | *** | 0.927 | 0.927 | - |
| Permanent or temporary job at t-1 | 0.939 | 0.956 | - | 0.968 | 0.968 | - |
| Full time or part time job at t-1 | 1.146 | 1.082 | ** | 1.073 | 1.073 | - |
| Quintiles of household income | 2.167 | 2.231 | - | 2.206 | 2.206 | - |
| Working at t-1 | 0.909 | 0.93 | - | 0.923 | 0.923 | - |
| Year of interview | 3.532 | 3.544 | - | 3.525 | 3.525 | - |

Source: UKHLS, wave 1- 5

Notes: p values for tests of equality of means between treated and controls were calculated

***p<0.01, **p<05, *p<0.1, - No statistically significant difference

### 3.4 Results

In this section, estimated effect of acute health shocks on the reported income is presented. My main analysis was based on weighted linear or logit regression based on the distribution of the dependent variable. However, both weighted fixed effect and lag dependent models are estimated for robustness check. First columns in tables 3-8 show estimates of health shock effects on income of time t, while the acute health shock has been developed during time t and t-1. These estimations are not conditional on working (zero labour income are included in this analysis), and they include income losses caused by transitions from employment before health shock occurrence to non-employment following diagnosis. Estimated sample only included working age individuals who were employed or self-employed at some point during the survey. In order to gain more detailed information on the effect of health shocks on income, the sub-samples of those who continued to be employed after the health shock has also been investigated separately as well as being included in the main estimated sample. Estimates in third columns in tables 3-8 are conditional on remaining in employment (zero labour incomes excluded). Results represent the effect of acute health shocks on survivors who are able and willing to stay at work.

Results indicated that when health shock is experienced, net labour income and income from benefits are the main components of the total income that are affected. Changes in these components are the principal determinant of the alteration in total gross or net income. Other sources of income such as investment, pension or second job (not presented here) were considered, but no significant changes related to these components of income were observed. Results presented here are based on both gross and net income. However, income analysts prefer working with net income as this shows amount available for spending after direct taxation is taken into account. Findings indicated that the reduction in net income of affected people was smaller compared to losses in gross income. This was due to the nature of the taxation system in the UK as the distribution of net income was less unequal than that of gross income (Berthoud, 2012). The benefit income variable used in this paper includes all the net income obtained from government support. This enabled consideration of all financial aid people received after the onset of the health shock.

When all working age men and women were considered, experiencing an acute health shock led to a significant reduction in labour income (men 23% and women 24%) and benefit income showed a significant increase (men 31% and women 32%). Considering gross income, only ATT estimated for male survivors showed a significant reduction compared to their counterparts who were never diagnosed with any form of the health shock. No significant effect was found on net income of men or women. When the effect of health shock was estimated conditional on working, workers diagnosed with acute health shock earned 3% less at time t than their counterparts from the comparison sample and this difference was no longer statistically significant.

Each of the female and male samples were divided into two sub-samples, including individuals 16-49 years old and people older than 49 years old. Men younger than 49 years old are the only sub-group that experienced significant reduction in their net income (8%) and no significant increase in the income received from welfare system. On the other hand, men older than 50 years old experienced 35% increase in their benefit income and no significant reduction in net or gross income. These clear differences between two age groups of men did not appear to hold among women. None of the sub-groups of women faced significant reduction in their gross or net income. Older women experienced a significant fall in their labour income (23%) and a significant increase in their benefit income (18%). Younger women reported a 6% (significant) reduction in their labour income and an 8% increase (significant) in benefit income. The significant rise in benefit income was experienced even when sample was restricted to individuals who continued working after the onset of the health shock among all the working age sub-groups of both genders except younger men.

Next, the robustness of findings was tested using alternative identifying assumptions and both fixed effect and lag dependent models were considered. Obtained results were broadly similar and suggested the same pattern discussed above based on original regression models. Tables 5 and 6 present results for men and women. Patterns emerged based on these results were in line with previously presented results and confirmed differences in income changes between younger and older men. It was also evident that after young men, it was younger women who on average experienced the lowest rate of increase in welfare income.

**Table 3**: Effect of acute health shock on income component of working age men

| | All men | All men Conditioned to working | Men (16-49) | Men (16-49) Conditioned to working | Men (50-65) | Men (50-65) Conditioned to working |
|---|---|---|---|---|---|---|
| Log of gross monthly income | -0.06* | -0.03 | -0.11* | -0.14 | -0.18 | 0.11 |
| | (0.09) | (0.19) | (0.09) | (0.17) | (0.21) | (0.17) |
| Log of net monthly income | -0.03 | -0.04 | -0.08* | -0.06 | -0.18 | 0.11 |
| | (0.19) | (0.15) | (0.06) | (0.1) | (0.21) | (0.16) |
| Log of labour income | -0.23** | -0.13 | -0.28* | -0.093 | -0.20* | -0.15 |
| | (0.09) | (0.81) | (0.073) | (0.97) | (0.11) | (0.63) |
| Log of income from benefit | 0.31** | 0.23* | 0.24 | 0.13 | 0.35* | 0.16* |
| | (0.038) | (0.019) | (0.61) | (0.168) | (0.13) | (0.085) |
| Number of observations | 4,637 | 4,297 | 1,739 | 1,688 | 2898 | 2,609 |

** Significantly different from reference category (p<0.01),
* Significantly different from reference category (p<0.05)
Note: Results are estimates for a linear regression model with Coarsened Exact Matching (CEM) weights. All regressions conditional on the full set of control variables listed in Subsection 2.3

**Table 4**: Effect of acute health shock on income component of working age women

| | All women | All women Conditioned to working | women (16-49) | Women (16-49) Conditioned to working | Women (50-65) | Women (50-65) Conditioned to working |
|---|---|---|---|---|---|---|
| Log of gross monthly income | -0.08 | -0.02 | -0.02 | -0.141 | -0.05 | -0.08 |
| | (0.15) | 0.096 | (0.2) | (0.19) | (0.2) | (0.16) |
| Log of net monthly income | -0.07<br>(0.15) | -0.02 | -0.02 | -0.13 | -0.03 | -0.07 |
| | -0.24 | 0.092 | (0.19) | (0.19) | (0.199) | (0.18) |
| Log of labour income | (0.04)** | (0.09) | -0.18* | -0.16 | -0.23** | -0.05 |
| | | | (0.13) | (0.2) | (0.06) | (0.19) |
| Log of income from benefit | 0.28 | 0.12 | 0.06* | 0.04* | 0.18** | 0.08* |
| | (0.08)** | (0.81) | (0.06) | (0.04) | (0.07) | (0.06) |
| Number of observations | 4,893 | 4,459 | 2,419 | 2,304 | 2,285 | 1,988 |

** Significantly different from reference category (p<0.01)
* Significantly different from reference category (p<0.05)
Note: Results are estimates for a linear regression model with Coarsened Exact Matching (CEM) weights. All regressions conditional on the full set of control variables listed in subsection 2.

**Table 5:** Different age group of men and women; Effect of acute health shock on income, Lag dependent models.

| | All men | Men (50-65) | Men (16-49) | All women | Women (50-65) | Women (16-49) |
|---|---|---|---|---|---|---|
| Log of gross monthly income | -0.08* | -0.15 | -0.21** | -0.17 | -0.08 | -0.14 |
| | (0.012) | (0.196) | (0.13) | (0.14) | (0.18) | (0.23) |
| Log of net monthly income | -0.05 | -0.15 | -0.11** | -0.15 | -0.15 | -0.15 |
| | (0.181) | (0.195) | (0.14) | (0.14) | (0.18) | (0.29) |
| Log of labour income | -0.36** | -0.25** | -.0.32** | -0.29** | -0.30** | -0.06* |
| | (0.14) | (0.14) | (0.17) | (0.09) | (0.11) | (0.04) |
| Log of income from benefit | 0.39** | 0.41** | 0.18 | 0.27** | 0.23** | 0.05* |
| | (0.059) | (0.08) | (0.71) | (0.10) | (0.09) | (0.04) |
| Number of observations | 4,637 | 2,898 | 1,739 | 4,893 | 2,294 | 2,599 |

** Significantly different from reference category (p<0.01)
* Significantly different from reference category (p<0.05)
Note: Results are estimates for a lag dependent regression model with Coarsened Exact Matching (CEM) weight. All regressions conditional on the full set of control variables listed in Subsection 2.3

**Table 6:** Different age group of men and women; Effect of acute health shock on income, fixed effect model.

| | All men | Men (50-65) | Men (16-49) | All women | Women (50-65) | Women (16-49) |
|---|---|---|---|---|---|---|
| Log of gross monthly income | -0.11* | -0.21 | -0.18** | -0.083 | -0.017 | -0.098 |
| | (0.15) | (0.160) | (0.14) | (0.11) | (0.132) | (0.153) |
| Log of net monthly income | -0.19 | -0.19 | -0.17** | -0.073 | -0.006 | -0.072 |
| | (0.16) | (0.16) | (0.18) | (0.103) | (0.134) | (0.151) |
| Log of labour income | -0.41** | -0.33** | -0.32** | -0.47** | -0.38* | -0.17** |
| | (0.19) | (0.18) | (0.21) | (0.21) | (0.27) | (0.37) |
| Log of income from benefit | 0.37** | 0.34** | 0.11 | 0.31** | 0.26* | 0.06* |
| | (0.35) | (0.41) | (0.91) | (0.10) | (0.09) | (0.08) |
| Number of observation | 4,637 | 2,526 | 1,233 | 4,893 | 2,244 | 1,961 |

** Significantly different from reference category (p<0.01)
* Significantly different from reference category (p<0.05)
Note: Results are estimates for a lag dependent regression model with Coarsened Exact matching (CEM) weight. All regressions conditional on the full set of control variables listed in Subsection 2.3

Table 7 reports the impact of experiencing health shock on the probability of becoming entitled to receiving various income benefits. Recipients of disability benefit significantly increased among all age groups in both genders. Sick, disable or incapacity benefit is the only benefit that is not means-tested amongst state benefits. All other benefit entitlements vary depending on household income. When health shock affects men aged 50-65, this shock is likely to influence the whole household as these men are more likely to have a family and be the main breadwinner. 72% of older men are married whereas only 44% of men younger than 50 are married. In addition, 78 percent of older men who live with their partners are the main breadwinner whereas, 71 percent of younger cohabiting men earn more than their partners. Hence, men who are older than 49, become entitled to a wider range of available benefits.

The results for child benefit recipients demonstrated a small, but significant increase in only men older than 50. This could be due to changes introduced by the then coalition government in January 2013, where benefits received gradually decreased as the income of the highest earning parent rose above £50,000. This benefit was completely removed when income reached £60,000. Prior to 2013 every child regardless of parent’s income was entitled to this benefit. Therefore, at the time of this study data for only 2 years was available.

Results for income support indicated that the likelihood of receiving this benefit after an acute health shock was enhanced in older men (aged 50 to 65). To receive this benefit, incomes and savings of the whole household are assessed. In this generation, it is more likely for the main wage earner to be a man, henceforth the household’s overall income is more likely to be negatively affected, pushing their entitlement over the threshold for receiving this benefit. If you consider the total income from various benefits, men aged 50 to 65, tend to have a higher probability of receiving more than one benefit at a time. This could be due to men within this age group being the household's main breadwinner.

**Table 7**: Effect of acute health shock on probability of receiving different benefit income

| | Men 50-65 | Men 16-49 | women 50-65 | women 16-49 |
|---|---|---|---|---|
| Income support | 0.0123 | 0.0002 | 0.0005) | 0.0095 |
| | (0.0109)* | (0.032) | (0.042) | (0.014) |
| Sick, disable or incapacity Benefit | 0.081 | 0.082 | 0.094 | 0.052 |
| | (0.003)** | (0.038)** | (0.03)** | (0.027)** |
| Child benefit | 0.006 | 0.002 | 0.033 | 0.004 |
| | (0.002)** | (0.052) | (0.023) | (0.018) |
| Tax credits (working tax credit or child tax credit) | 0.022 | 0.026 | 0.027 | 0.0044 |
| | (0.025) | (0.054) | (0.024) | (0.05) |
| Housing or council tax benefit | 0.002 | 0.045 | 0.053 | 0.01 |
| | (0.016) | (0.003)** | (0.025) | 0.031 |
| Income from any other state benefit | 0.0179 | 0.0002 | 0.007 | 0.008 |
| | (0.013)** | (0.043) | (0.012) | (0.013) |
| No of Observation | 2,898 | 1,739 | 2,285 | 2,419 |

** Significantly different from reference category ($p<0.01$)
 * Significantly different from reference category ($p<0.05$)
Note: Results are estimates for a probit regression model with Coarsened Exact Matching (CEM) weight. Average Marginal Effects are reported. Standard errors in prentices. All regressions
conditional on the full set of time-variant control variables listed in Subsection 2.3.

### 3.5 Conclusion

The issue of economic consequences of acute health shocks and the mechanisms behind observed responses to these shocks have remained relatively unexplained. Published research papers on this topic have mainly explored different forms of exit from employment among older working individuals. Early retirement therefore has been the primary focus of researchers on this topic. It has been assumed that strong health shocks are not prevalent among younger people is one of the main reasons for the younger age groups being largely excluded from studies. Majority of published research on British workforce found a significant decrease in labour market participation in response to an acute health shock. Although among workers no adjustment in hours and incomes was detected in the short-term. It is noteworthy to mention however, that the focus of these publications was not the effect of health shocks on income. To contribute to the current literature, I first investigated different components of income and investigated if lack of significant reduction in income among British working age was due to an increase in benefits income after health deterioration. Similarly, I looked at whether there was heterogeneity in income adjustment with respect to individual's pre-shock characteristics.

Using data from the longitudinal survey of household in the UK (UKHLS), this paper offers a new insight on the labour supply responses to acute health shocks experienced by workers of all ages. UKHLS data has been collected from 2008 to 2014 and provides an up-to-date insight into the British society. In this paper, onset of a stroke, cancer or major heart problems such as myocardial infraction that are unpredictable at the time of onset and tend to have a sudden occurrence are defined as acute health shocks. Such conditions tend to be less likely to be misreported compared to conditions that develop gradually over a longer time frame. Non-parametric coarsened exact matching was used followed by parametric estimation of the average treatment effect for the treated and considered different component of income as independent variables. My findings indicated significant reduction in labour income, indicative of a reduction in employment as shown in previous published literature. A significant increase was also observed in total income from benefits. However, there were differences in the magnitude of the change observed in labour and benefit income among different age groups of men and women. For example, men younger than 49 years old are the only sub-group that experienced significant reduction in their net income (8%) and no significant increase in the income received from welfare system, while men older than 50 years old experienced 35% increase in their benefit income and no significant reduction in net or gross income. The increase in benefit income received by women younger than 50 is smaller than that among their older counterparts (6% compared to 18%).

To investigate these results further, the impact of experiencing health shock on the probability of becoming entitled to receiving various income benefits was examined. Recipients of disability benefit significantly increased among all age groups in both genders. This is the only state benefit that is not means-tested. All other benefit entitlements vary depending on household income. This explained why child benefit and income support were increased only when older men experienced acute health shock. This shock is likely to influence the whole household as these men are more likely to be married and have children (72% of them are married while only 44% of younger men are married). According to these results younger people were less likely to benefit from social welfare after a health shock as most benefit allowances are designed to support families and prevent them from entering into poverty.

In this paper, limited number of data (5 waves) constrained assessment of the labour supply effects. I focused on the short-run effect of health shock as sample size can be significantly reduced due to panel attrition when further extended time frame is considered. Future work can mitigate this problem by combining BHPS with the understanding society data. However, previous published materials indicated that the greatest effect was seen shortly after an onset of a health shock (Halla et al., 2003; Smith, 2005). As additional waves of data become available, further research can be directed at affected individuals and these can be followed over a longer period, providing detailed insights into the effects of health shocks on working age individuals over a longer time frame.

The main challenge in this area of research remains identifying drivers of response to acute health shocks. Our results showed that labour income reduction was the main reason for reduced income and social benefit income was the main source of income that people relied on immediately after facing an acute health shock. Reduction in labour income can be due to individuals changing their preferred labour supply as perceiving a reduced life expectancy relevant to their intertemporal decision-making, or because of stronger preferences for leisure or other activities. However, a different type of intervention could arise if individuals, or subgroups of them, preferred remaining in the labour market, but work related impeded such a decision.

Policy makers need to consider which one of these two sets of pathways are the main reasons for individual’s response to health shock. If labour market exit occurs as a result of individual’s financial constraints, policy interventions aimed at retaining them in the labour market should be considered strongly. Policies aimed at improving the financial incentives to remain active are appealing to people who desire to stay at work. Obtained results showed that there was a difference in the magnitude of the reduction in income with respect to sex and age. The observed diversity in change of income showed there must be variety of policies in place to support different subgroup of individuals when they face an acute health shock. Therefore, policy makers should avoid grouping all individuals who suffer from an acute health shock as one coherent group. There is substantial evidence showing that all the individuals who face an acute health shock experience a reduction in their total income. but the ones that become unemployed suffer a significant reduction, which is not fully compensated for with the social benefit income they receive.

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# Chapter 4

## 4. Diabetes and its effect on early retirement: Does duration and intake of medicines matter?

### 4.1 Introduction

The rise in life expectancy has altered the demography of populations worldwide (Lutz et al. 2008) and meeting the needs of an ageing population is one of the main concerns of policy makers in developed countries such as Britain (Walker, 2018). Ageing is associated with a higher probability of experiencing poor health and early withdrawal from the labour market (Leijten et al., 2015). For most people, longer life coincides with more years spent with chronic disability. In the UK, the number of individuals aged 50-69 are about twice those aged 15-24. As a consequence, number of people in the UK with one or more long-term condition is expected to increase in the near future (ONS, 2015). Many studies suggest that ongoing care and support to assist individuals affected by chronic health conditions will impose substantial pressures on the health and social care services. This is sometimes coupled with considerable out-of-pocket expenditure for individuals (Paez et al., 2009; Weir et al., 2018).

Recent studies have confirmed that, in addition to the direct costs associated with health problems, substantial indirect costs can be imposed on society and individuals through increased likelihood of leaving work and productivity loss, particularly as workers reach retirement age (Garcia-Gomez et al., 2010; Jones et al., 2010; Miah et al., 2007; Disney et al,. 2006). The dynamics associated with how employment is affected by health conditions differ according to the severity and nature of the health problems. From a policy making point of view, it is very important to have access to detailed information on how different health problems affect different groups of people. Therefore, in this paper, I focused on diabetes as one of the prevalent and rising forms of chronic health problems worldwide and also in the UK (Wiviott et al., 2019).

Even though there is documented evidence on the adverse effects of diabetes on employment, there is inadequate research on the dynamics and magnitude of the social and economic effects of diabetes on British workers (Diabetes.org.uk, 2018). By 2025, it is estimated that five million people will have diabetes in the UK. Type 2 diabetes, which includes 90 to 95% of all diabetic cases, is more prevalent particularly among older individuals. In England and Wales, in 2017, 19% of people aged 50 to 59 years old and 26% of those aged 60 to 69 were diabetic, compared with only 3.5 percent of people aged 30 to 39 and 10.6 percent of those aged 40 to 49 (Diabetes.co.uk, 2017). According to the 2018 position statement published by diabetic.co.uk, 37% of diabetic individuals who are in employment declared that their condition had caused them or a family member difficulty at work; 16% reported that they felt they had been discriminated against by their employer due to their diabetes. In addition, there is evidence suggesting that people with diabetes may have to work part-time or stop working prematurely because they feel they have to choose between their health and their job (Diabetes.co.uk, 2018).

Type 2 diabetes is a chronic disease that leads to elevated blood sugar (glucose) levels in affected individuals. As glucose receptors located on cell membranes no longer detect this ligand (glucose molecule), there is a gradual build-up of glucose in the body which can cause heart failure and eventually death if left untreated. Most symptoms of type 2 diabetes occur when blood sugar levels become abnormally high. Some of these early symptoms include excessive frequent or increased urination, excessive hunger, fatigue blurry vision or cuts that do not heal. A significant number of affected individuals are initially unaware of their elevated blood sugar levels, as early symptoms are ignored and regular check-ups are not conducted by physicians. High blood sugar levels lead to long-term harm to the body and causes serious health problems such as higher risk for heart disease, foot problems and amputations, nerve damage, eye sight issues, kidney disease and serious bladder infections. Some patients that are on medication may encounter a situation whereby their blood sugar levels fall dangerously low. This is known as hypoglycaemia and occurs as a result of dangerously low levels of blood sugar and in some cases is considered a medical emergency. The range and severity of symptoms and complications caused by diabetes differ from one patient to another and is sometimes associated with patient's level of awareness, health literacy and self-management (Diabetes Atlas, 2013).

Productivity losses, changes in workers preferences and perceived discrimination have been the main pathways considered to describe the mechanism through which diabetes affects labour market behaviour. As previously mentioned, type 2 diabetes is assumed to be associated with a reduction in productivity at work. Such a loss in productivity, increases the length of exposure to diabetes (Lavigne et al., 2003). While many people can manage their diabetes without it affecting their work routine. It is important for employers to become aware of the risks for employees with diabetes. Some employees (especially those with type 2 diabetes) may struggle with undertaking shift work or long commutes as changes to the timing of medication and diet can affect their condition and may cause unease and stress. For example, if a diabetic person's blood sugar falls below an optimum level, they can suffer from a hypoglycaemic episode, and can feel faint, weak, and even lose consciousness (fittowork.org, 2017). Some studies have investigated the prevalence and risk factors of perceived diabetes-related discrimination in workplaces. For instance, Puder et al. (2009) found that perceived diabetes-related discrimination in the workplace and by work-related insurances is a common problem in Switzerland. They suggested that introduction of effective non-discrimination legislation for patients with chronic illnesses was a necessary action in supporting affected individuals (Pudor et al., 2009). In addition, as is the case with other health problems, individuals changed their preferred labour supply as perceiving a reduced life expectancy relevant to their intertemporal decision-making.

Most empirical studies on diabetes have considered all the diabetics as one group and estimated an average effect of the condition on employment probabilities. However, it is very important to be able to map progression, severity and complications and comorbidities of this chronic condition to understand which factors and dynamics actually lead to adverse labour market outcomes. So far, Rumball-Smith et al. (2014) is the only study that has investigated the effect of diabetes on working age males and females in England using a nationally representative data. They reported that diabetes had a 40 percent increase in the rate of labour-force exit, compared to people without the disease. The novelty of their work lies on using data from different OECD countries. However, the weakness of this work is that they only used 3 first wave of English longitudinal study of aging and self-reported diabetes status was the only measure considered. In this study I aimed to establish a more accurate picture of how diabetes affects labour market outcomes in England. I took a closer look into the existing differences among diabetic sufferer and posed the following question; does the probability of exit from employment vary amongst diabetic individuals and if so, what is the best proxy for identifying patients with a higher risk of early retirements? This approach took into account the variety, nature and severity of symptoms and their effect on exit from employment.

I aimed to investigate whether and to what extent labour market related disadvantages differ among diabetic people. I considered the duration of the condition and use of medicine/insulin as two potential proxies of severity, and investigated the association of these two factors with early-retirement decisions and comorbidities. I also made use of biomarker data provided by ELSA to identify pre-diabetics and undiagnosed diabetics. Biomarker data is considered to be more objective and less prone to measurement errors compared to self-reported health measures. Although, due to scarcity of data some analysis based on biomarker data were merely descriptive and not used in longitudinal regression analysis, but was instead used to shed light on other aspects of the illness, aiding deeper understanding of how labour market participation was affected (Buescher et al., 2010; Tunceli et al., 2010).

In comparison with Understanding Society and British Household Panel Survey (BHPS), ELSA has the advantage of providing parental history of diabetes. This information had significant importance in this research as it enabled me to investigate existence of potential exogeneity between exit from work and being diabetic among working age individuals. The English Longitudinal Study of Ageing (ELSA) is a study of people aged 50 and over and their younger partners, living in private households in England. The initial sample (Cohort 1) was drawn from households that had previously responded to the Health Survey for England (HSE) in 1998, 1999 or 2001. The ELSA sample has been designed to represent people aged 50 providing detailed information on their health, income, employment and household composition.

There are very few studies that have previously investigated heterogeneity among diabetic patients in the context of labour market participation. Kraut et al. (2001) argued that the most obvious adverse effect was experienced when related complications limited an individual's ability to work and compared the labour force participation rate and unemployment rate of diabetic people (with and without complications) with those of nondiabetic individuals among working-age men and women in Canada. Controlling for time since diabetes diagnosis or the duration of diabetes has also been used to capture the progression of the condition and the difficulty imposed on diabetic people on a daily basis (Minor, 2011). Minor et al. (2016) compared the effect of undiagnosed diabetes with diagnosed cases and concluded that the labour market penalty that undiagnosed individuals with type 2 diabetes experienced was similar to very recently diagnosed populations. Distinguishing between people who used oral medication or insulin and those who did not, is an alternative proxy for the severity of this chronic condition. Chatterji et al., (2016), used hazard models to report that only diabetes with medication significantly decreased the probability of being still employed among men who were approaching retirement age in the US.

In the recently published studies where authors looked at the effect of diabetes on employment, the possibility of endogeneity of diabetes has been taken into account using family history of diabetes as an instrument. Reverse causality and omitted variable bias can lead to biased results. Type of occupation can affect the lifestyle people adopt and an unhealthy lifestyle can have an influential effect on the probability of developing diabetes. A job with long office hours might push a person's diet or pattern towards a more unhealthy, inactive lifestyle due to reduced leisure time, increasing the person's risk for diabetes. Furthermore, unobserved factors, such as personal characteristics, could simultaneously influence a person's employment as well as his or her diabetes status and so introduce omitted-variable bias. A person with poor stress-management skills could be less productive in his or her work, increasing the risk of being laid off, and he or she could simultaneously develop unhealthy eating habits such as comfort eating as a mechanism for coping with stress leading to higher chances of developing diabetes (Araiza et al., 2018)

Latif (2009) used Canadian data to estimate the effect of diabetes on an older Mexican American population between 1996 -1997. Employing IV models, diabetes was found endogenous only among men and to be overestimated when exogeneity was assumed. According to Minor (2011), diabetes was endogenous among American females in the National Health Interview Survey (NHIS), and the effect was found to be underestimated if treated as exogenous. Using IV estimates, type 2 diabetes was found to have a significant negative effect on female employment chances during 2006. Brown et al. (2005) found diabetes to be endogenous for women but not for men in the US. The results of the Instrumental Variable (IV) estimation suggested no significant effect on men which, compared with the adverse effect found using standard probit models, indicated an overestimation of the effect for men when endogeneity was not accounted for. However, the effect was negative and significant for women based on both IV and probit estimations. Seuring et al. (2015) estimated the impact of diabetes on employment in Mexico using data from the Mexican Family Life Survey (MxFLS) during 2005. Using an instrumental variable estimation strategy, they found no indication of diabetes being endogenous while significantly decreasing employment probabilities for men by about 10 and 4.5 percentages for women. Accordingly, in some cases, not accounting for endogeneity can lead to biased estimate of the impact of diabetes on employment. All the studies mentioned above used cross sectional data except Minor (2011), who distinguished between type1 and type 2 diabetes. Their focus has been on addressing the potential endogeneity of diabetes status and estimate an average effect of self-reported diabetes status on labour market outcomes. To the best of my knowledge, there has been no study to test for endogeneity of diabetes on the working age population in the England, hence my decision in this paper is to use parental history of diabetes provided in ELSA and test for potential endogeneity among older male and female separately.

There are other specific health conditions that can impact employment among working age groups in a similar manner to that of diabetes. For instance, Laires et al., (2018) demonstrated an association between Osteoarthritis (OA) and early exit from employment before retirement age in the Portuguese population. They showed a significant relationship between OA and early exit as well as an economic burden amounting to roughly 0.4 percent of Portugal National Gross Domestic Product. Such an impact needs government intervention and relevant policies that target such groups and enable those that can and want to re-enter the job market to do so in a meaningful way. This condition was also included in this work’s estimation strategy. Kidney problem is another example of a specific and chronic health problem that has been mentioned as a factor contributing to exit from employment especially among the 50 years and older individuals who have been in employment. This condition has been recognised as one of the diabetes comorbidities (Atkins et al., 2010).

## 4.2 Data and descriptive statistic

Eight waves of the English Longitudinal Study of Ageing (ELSA), a longitudinal panel data set consisting of people aged 50 and over, including their partners, living in private households in England was used. Akin to its companion household data set, USA health and retirement study, ELSA is a unique source of information on health and socioeconomic aspects of aging in England and describes the demographic, lifestyle, and health characteristics of older adults (Steptoe et al. 2013). ELSA is restricted to individuals older that individuals that are 50 years of old and above, however they are still in working age bracket. ELSA provides the older sub-group within the working age group which are more likely to experience chronic health problem such as diabetes (Ward et al., 2013). This study includes detailed information on household and individual demographics, physical and psychosocial health, work and pensions, income, assets and housing (Pierce et al., 2009).

The baseline sample of ELSA comprises all eligible participants from the Health Survey for England (HSE) in 1998, 1999, and 2001. The Health Survey for England (HSE) is an annual survey monitoring changes in the health and lifestyles of people all over the country that has been carried out since 1991. The first wave of ELSA was conducted in 2002-2003 with follow-up waves taking place every two years (Pierce et al., 2009). The baseline sample consisted of 12,099 participants with wave-to-wave response rates ranging from 73% to 82% of all eligible participants. The sample has been refreshed at wave 3, 4 and 6 to retain survey’s representativeness of the current population of people aged 50 years and over. Therefore, not all respondents have been part of the study since the first wave.

Besides the main interviews, the nurse visit has been carried out at alternative waves starting from wave 2 (2004-2005). Only core sample members who participated in an interview in person (i.e. not by proxy) at the relevant wave were considered for a nurse visit at that wave. The sample of wave 2 nurse data used in the following analysis consisted of 10305 individuals after the exclusion of 362 participants with proxy or partial interviews, 459 who did not consent to the mortality linkage, 5 who died the same month they granted their baseline interview and 260 with missing values in baseline variables (excluding body mass index (BMI)). The response rate for the nurse data is 87.3% for wave 2 and 85.7% and 84.3% in waves 4 and 6 (Hammer et al., 2014).

Percentage of proxy interviews in each wave (Full interview by proxy or Partial interview in person) was around 3 percent (Banks et al., 2008). To ensure the representativeness of the sample, nurse weights were used. These were available for each wave that included a nurse visit (Waves 2, 4, 6 and 8). The weighting strategy for blood sample intended to mitigate any bias due to differential non-response between completion of the nurse visit and giving a blood sample. A non-response weight for the blood sample was designed by taking the inverse of the estimated probability of responding. The final blood sample weight was constructed based on the nurse visit weight and the adjustment for non-response to the blood sample. The variables found to be related to probability of response were: (1) age-by-sex group, (2) Government Office Region, (3) social class, (4) self-assessed health, (5) whether a current smoker, (6) frequency of physical activity, and (7) limiting long-standing illness. The non-response weight was calculated as the inverse of the predicted response probabilities obtained from logistic regression model. The non-response weight was then combined with the interview weight to create the final non-response weight to use with the nurse visit data (Scholes et al., 2013).

Following questions were used to construct diagnosed diabetes status variable.

1-Has a doctor ever told that you have any of the conditions on this card? Code all that apply.

01 High blood pressure or hypertension 02 Angina 03 A heart attack (including myocardial infarction or coronary thrombosis) 04 Congestive heart failure,05 A heart murmur,06 An abnormal heart rhythm, 07 Diabetes or high blood sugar, 08 A stroke (cerebral vascular disease) ,85 Other answer - not code able 01 to 08,86 Irrelevant response - not code able 01 to 08,95 Any other hear trouble (SPECIFY), 96 None of these.

2-diabetes or high blood sugar diagnosis newly report (to understand which of these two conditions are reported, diabetic related question has been considered (use of medicine, knowledge

2-YEAR TOLD HAD DIABETES (This variable is used to reassure that the diabetes status in each wave is correctly specified)

3-WHETHER CURRENTLY INJECTS INSULIN

4-WHETHER IS CURRENTLY TAKING MEDICATION FOR DIABETES

(Copy paste from thesis for undiagnosed diabetes?)

Based on technique of ‘feeding forward’ data, certain responses that individuals report in previous waves were used to reassure the consistency of their responses across waves. As an example, a respondent who had previously reported a certain diagnosis would be asked at following waves to confirm the accuracy of previous diagnosis and whether they still had it. Previous answers were also used in the directing the computerised interviews. Following user guidance provided in each wave of ELSA, feed forward variable was used to correctly identify all those who had ever reported diabetes. In Wave 4 the variable applied to those who newly reported a diagnosis of diabetes or high blood sugar and to those who had reported diabetes or high blood sugar previously but had identified for their previous interview or who had not answered this question. In Wave 2 this question simply applied to those who had reported diagnosis of diabetes or high blood sugar either at Wave 1 or Wave 2. I used diabetes related questions such as age of diagnosis of diabetes, use of insulin and medication and year of being diagnosed and questions related to diabetes management and somebodies such as diabetes related eye problem and kidney problem to reassure the accuracy of the final diabetes status used in descriptive and parametric estimations.

Table1 describes the main variables used in this analysis. Participants were identified as having diabetes if they reported ever being told by a doctor that they had diabetes. Participants who did not report doctor-diagnosed diabetes were categorised as non-diabetics. In waves where nurse data was available (2, 4 and 6), I investigated whether individuals who have reported themselves as non-diabetics actually have prediabetes or undiagnosed diabetes. The haemoglobin A1c test (HbA1c) designed to indicate how well diagnosed diabetes is being controlled was used. This test has been recommended for diagnosing diabetes as well as prediabetes (American Diabetes Association, 2010). Compared with alternative tests such as individual fasting or post-load blood glucose measurements, HbA1c is more reliable as it reports the average circulating glucose levels over the 2–3 months prior to the time of the test, which makes it a better predictor of subsequent diabetes (Selvin et al., 2007). Information drawn from fasting blood sample was used to identify prediabetes and undiagnosed diabetes. Prediabetes is described as a high-risk state where blood glucose levels are higher than normal, but lower than the threshold needed for a diagnosis of type 2 diabetes (Rebekah et al., 2007). Similar to type 2 diabetes, prediabetes is defined as a state in which the level of insulin production is lower than normal that leads the body to develop insulin resistance and thus lose its ability to use insulin effectively (Monnier et al., 2006).

In ELSA, blood glucose was only measured for those who had fasted and respondents were not asked to fast if they had diabetes or were on a treatment plan. Therefore, I do not have information on the level of HbA1c for every individual with diabetes and so cannot determine how well everyone manages their glucose level. Unfortunately, ELSA does not distinguish between different types of diabetes. However, I followed Sicree et al. (2011) by assuming that around 90 percent of the reported diagnoses are due to type 2 diabetes, which is estimated to be the population prevalence (Sicree et al., 2011).

Field work in ELSA is conducted by NatCen using experienced interviewers and nurses distributed round the country. A robust system of quality control is in place, and many of the interviewers have met the same respondents over several waves of data collection (Hardcastel et al., 2015).

One of the advantages of ELSA is that it provides information on parental diabetes, enabling me to construct an instrumental variable to test for endogeneity when impact of diabetes on employment is estimated. Parental diabetes identification is based on these questions: Has [^your / ^Name's] natural mother ever been told by a doctor that she has diabetes? Also, similar question about father is available: Has [^your / ^Name's] natural mother ever been told by a doctor that she has diabetes? This information was self-reported and there was no information on the age of diagnosis of diabetes of natural mother or father.

Participant's age, sex, marital status, ethnicity, wealth, education, and employment status are based on self-reported answers. Education was categorised as no qualifications, qualifications below a degree (A-level, GCSE or equivalent), or degree or higher (Au et al., 2015). Smoking status (current, former, or never smoker) was measured based on self-reported information. I identified individuals that reported poor or bad general health based on self-rated health measured on a 5-point scale from poor coded as 1 to excellent scored as 5. Body mass index (BMI) was calculated based on height and weight measured every 4 years by a nurse. BMI was then categorized as normal (below 25 kg/m2), overweight (25-29.9 kg/m2), and obese (30 kg/m2 and above) (Tanaka et al., 2012).

Detailed information on different aspects of wealth was included in all waves of ELSA. Total net non-pension household wealth was used to summarise the value of financial, physical and housing wealth owned by the household (i.e. a single respondent or a responding couple along with any dependent individuals) minus any debt. The estimation of this variable was based on 22 different wealth and debt components, which were either observed or imputed (Demakakos et al., 2015). Quintiles of net total non-pension household income has also been used. This measure was highly related to total household pension wealth in ELSA (Banks et al. 2005).

As favourable social position is associated with continued and longer working careers (Damman et al., 2016), I controlled for occupational classifications which were measured according to the National Statistics Socioeconomic Classification (NS-SEC) (Graham et al., 2006). The NS-SEC is the primary social classification in the United Kingdom and my study used the three-category version to measure socio-economic position (“managers and professionals”, “intermediate occupations”, and “routine and manual occupations”).

I also used information on cardiovascular and non-cardiovascular health problems that have been suggested by literature as having explanatory effect on labour market behaviour (Johnes et al., 2016). The cardiovascular health issues were heart failure, heart attack, and stroke. Non-cardiovascular conditions included arthritis, cancer or a malignant tumour (excluding minor skin cancer). Depressive symptoms were measured using the short-form Centre for Epidemiological Studies Depression (CESD) scale. Scores ranges from 0 to 8, with 4 or more symptoms used as a cut-off to indicate elevated depressive symptoms (Hamer et al. 2009). This measure reported whether participants for much of the time during the past week felt 1) depressed, 2) everything they did was an effort, 3) their sleep was restless, 4) happy, 5) lonely, 6) they enjoyed life, 7) sad or 8) they could not get going (NatCen Social Research., 2015). The 8-item CESD is closely related to usage of antidepressants and physician-diagnosed depression in an elderly population. It has additionally been validated for use in older European populations (Saczynski et al., 2015). Table 2 provides summery statistics for men aged between 50 and 65 and for women aged between 50 and 60 by diabetes status. About 13 percent of women and 22 percent of men reported diagnosed diabetes. The prevalence in the sample was in line with the national average for individuals in this age group (Diabetes UK, 2015): 6 percent of women and 8 percent of men had undiagnosed diabetes, and 14 percent of women and 13 percent of men met the criteria for prediabetes. On average, both men and women reported that they have been living with diabetes for more than 10 years. 57 percent of Men and 34 percent of women with diabetes are active in the labour market, which was significantly lower compared to non-diabetic men and women who had 64% and 51% employment rates respectively ($p<0.01$). Diabetic men and women were more likely to belong to a non-white ethnicity ($p<0.01$), have routine or manual jobs ($p<0.01$) and have non-working partners ($p<0.01$). It was observed that people with diabetes had on average lower total net wealth.

The difference between net household income was not statistically significant when a variable ranging from first to fourth quintiles (as presented in table 2) was used. Further investigations showed that diabetic men and women were more likely to belong to the first quintile (lowest income) ($p<0.01$) and less likely to belong to the third and fourth total net household quintiles ($p<0.01$). Probability of being in part-time as well as full-time employment was higher among non-diabetic men and women ($p<0.01$). Both men and women with diabetes were more prone to hold a manual or routine job and less likely to be in a professional or managerial role. However, the difference between highest academic qualifications

was statistically significant only between diabetic and non-diabetic women as the percentages of people with diabetes who held a degree and had no academic qualification was 6% and 36% respectively, in comparison to non-diabetic women: 13% and 27% ($p<0.01$). In addition, probability of being diabetic was

only associated with number of children among women and not men. Pregnant women were excluded from sample, hence gestational diabetes was not included, however, it is a known fact that gestational diabetes increases the probability of becoming type 2 diabetic in future. Captured data suggested that women with more pregnancies were more likely to become diabetic in the long-term (Sanderson et al. 2019).

Results indicated that health status seemed to be always significantly worse among those who had been diagnosed with diabetes, regardless of whether it was prevalence of acute, chronic, general self-reported or psychological health. The only exception was the probability of experiencing cancer, which was not significantly different between diabetic and non-diabetics sub-samples. Also, likelihood of being a current or past smoker was not statistically significant between diabetic and non-diabetic sub-samples. Moreover, people with diabetes were more likely to be overweight and obese, as well as having diabetic parents.

**Table 2**: Description of variables used

| | |
|---|---|
| Employment | Binary dependent variable; 1 If respondent states she/he is at paid work and 0 otherwise |
| Diabetes | 1 if respondents states that has been diagnosed with diabetes by a doctor |
| Undiagnosed | 1 if respondent has not been diagnosed by doctors but HbA1c> 6.4 (46mmol/mol) |
| Diabetes | 1 if respondent has been diagnosed by doctor or nurse and zero otherwise |
| Pre diabetic | 1 if 5.7% <= HbA1c =< 6.4% (39 - 46mmol/mol) |
| Diabetes duration | 1 if respondent has been diagnosed less than 4 years ago, 2 if 4 to 10 years, 3 if more than 10 years |
| Parents diabetes | 1 if one of the natural parents has been diagnosed with diabetes |
| General health | 1 if respondent reports bad general health and 0 otherwise |
| Self employed | 1 if respondent states the her/his man job as self-employment |
| professional job | 1 if job is identified as professional and managerial based on NS-SEC socioeconomic classifications |
| Intermediate job | 1 if job is identified as intermediate based on NS-SEC socioeconomic classifications |
| Routine/manual job | 1 if job is identified as routine or manual based on Ns-SEC socioeconomics classifications |
| Part time | 1 if main job is part time and zero otherwise |
| Degree and above | 1 if the respondents has a degree or a postgraduate degree and zero otherwise |
| A level and GCSE | 1 if the highest academic qualification is A level or GCSE and zero otherwise |
| No qualifications | 1 if respondent has no academic qualifications and zero otherwise |

**Table 2**: Description of variables used

| | |
|---|---|
| No of children | 0 if no child under 18 is in the household, 1 if 1/2 and 2 if there are more children |
| single/no partner | if currently has no partner, including widow and divorced |
| partner working | 1 if respondent's partner is working and 0 if there is no partner or partner doesn't work |
| Total HH income | quintiles of participant’s net total non-pension household income and zero otherwise |
| Net wealth of HH | quintiles of total net non-pension household wealth and zero otherwise |
| Heart failure | 1 if respondent ever had heart failure and zero otherwise |
| Stroke | 1 if respondent ever had stroke and zero otherwise |
| Cancer | 1 if respondent ever had cancer and zero otherwise |
| Arthritis | 1 if respondent has arthritis and zero otherwise |
| Ex-smoker | 1 if respondent used to smoke and zero otherwise |
| Current smoker | 1 if respondent currently smokes and zero otherwise |
| Age | age in years for descriptive and zero otherwise |
| Under weight | 1 if BMI = <18.5 and zero otherwise |
| Over weight | 1 if 25<=BMI =< 29.9 and zero otherwise |
| Obese | 1 if BMI >= 30 and zero otherwise |
| Depression | 1 if 4 or more depressive symptoms are reported based on CESD scale and zero otherwise |
| White | 1 if respondent is white and 0 if is from any other ethnicity |

**Table 2**: Comparing characteristics of diabetic and non-diabetic individual

| | Female | | | | | Male | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Diabetic | | Non-diabetic | | | Diabetic | | Non-diabetic | | |
| | Mean | SD | Mean | SD | T test | Mean | SD | Mean | SD | T-test |
| Employment | 0.34 | 0.47 | 0.51 | 0.5 | *** | 0.57 | 0.49 | 0.64 | 0.47 | *** |
| Undiagnosed^ Diabetes | | | 0.06 | 0.24 | | | | 0.08 | 0.28 | |
| Pre diabetic ^ | | | 0.14 | 0.34 | | | | 0.13 | 0.33 | |
| Diabetes duration | 2.4 | 0.74 | | | | 2.3 | 0.75 | | | |
| Parents diabetes | 0.45 | 0.49 | 0.21 | 0.4 | *** | 0.37 | 0.48 | 0.15 | 0.35 | *** |
| General health | 0.54 | 0.49 | 0.29 | 0.4 | *** | 0.47 | 0.49 | 0.21 | 0.41 | *** |
| Self employed | 0.02 | 0.14 | 0.06 | 0.24 | *** | 0.11 | 0.31 | 0.13 | 0.33 | ** |
| Professional job | 0.29 | 0.41 | 0.22 | 0.45 | ** | 0.36 | 0.48 | 0.41 | 0.49 | ** |
| Intermediate job | 0.27 | 0.41 | 0.28 | 0.45 | __ | 0.21 | 0.4 | 0.2 | 0.41 | __ |
| Routine/manual job | 0.51 | 0.5 | 0.42 | 0.5 | ** | 0.42 | 0.49 | 0.37 | 0.48 | ** |
| Part time | 0.19 | 0.39 | 0.32 | 0.46 | ** | 0.09 | 0.29 | 0.13 | 0.33 | *** |
| Degree and above | 0.6 | 0.24 | 0.13 | 0.32 | *** | 0.18 | 0.38 | 0.17 | 0.37 | __ |
| A-level and GCSE | 0.45 | 0.47 | 0.43 | 0.49 | __ | 0.43 | 0.49 | 0.37 | 0.48 | __ |
| No qualifications | 0.36 | 0.48 | 0.27 | 0.44 | *** | 0.21 | 0.4 | 0.21 | 0.41 | __ |
| No of children | 0.08 | 0.31 | 0.05 | 0.23 | ** | 0.09 | 0.32 | 0.1 | 0.48 | __ |
| Single/no partner | 0.31 | 0.29 | 0.23 | 0.21 | ** | 0.17 | 0.31 | 0.16 | 0.36 | __ |
| Partner working | 0.34 | 0.47 | 0.44 | 0.5 | ** | 0.47 | 0.49 | 0.5 | 0.49 | ** |
| Total HH income | 2.4 | 1.13 | 2.56 | 1.1 | __ | 2.7 | 1.1 | 2.7 | 1.07 | __ |
| Net wealth of HH | 2.3 | 1.3 | 3.1 | 1.4 | *** | 2.61 | 1.46 | 3.16 | 1.4 | *** |
| Heart failure | 0.05 | 0.21 | 0.02 | 0.14 | *** | 0.13 | 0.33 | 0.08 | 0.2 | *** |
| Stroke | 0.04 | 0.19 | 0.2 | 0.15 | ** | 0.7 | 0.26 | 0.03 | 0.18 | ** |
| Cancer | 0.11 | 0.31 | 0.12 | 0.33 | __ | 0.08 | 0.27 | 0.09 | 0.3 | __ |
| Arthritis | 0.47 | 0.51 | 0.4 | 0.49 | ** | 0.36 | 0.48 | 0.31 | 0.47 | ** |
| Ex-smoker | 0.39 | 0.48 | 0.38 | 0.48 | __ | 0.51 | 0.49 | 0.51 | 0.49 | __ |
| Current smoker | 0.19 | 0.39 | 0.18 | 0.38 | __ | 0.19 | 0.39 | 0.18 | 0.39 | __ |
| Age | 59 | 4.05 | 58.7 | 4.22 | ** | 59.2 | 4.11 | 59.05 | 4.08 | __ |
| Under-weight^ | 0.002 | 0.5 | 0.005 | 0.07 | __ | 0.004 | 0.07 | 0.004 | 0.07 | __ |
| Over-weight^ | 0.21 | 0.41 | 0.39 | 0.48 | *** | 0.36 | 0.49 | 0.46 | 0.49 | *** |
| Obese^ | 0.65 | 0.47 | 0.31 | 0.46 | *** | 0.53 | 0.49 | 0.29 | 0.45 | *** |
| Depression | 0.3 | 0.45 | 0.15 | 0.35 | *** | 0.18 | 0.38 | 0.11 | 0.31 | *** |
| White | 0.88 | 0.32 | 0.97 | 0.16 | *** | 0.92 | 0.26 | 0.98 | 0.15 | *** |

***p<0.01, **p<05, *p<0.1 , __ No statistically significant difference.
Note:8.2 percent of women and 5.8% women in the estimated sample for bivariate probit model had diabetes.
Number of observation: men (6157 including 1575 individuals), women (7633 including 1710 individuals)
^ These variables are asked only in wave 2,4 and 6.
The sample includes men and women older than 49 and younger than retirement age.

## 4.3 Empirical strategy

According to the literature, it is probable that unobserved factors related to the probability of developing diabetes are correlated with the unobservable factors that affect employment status (Brown et al., 2005). For example, high self-motivation or good social skills can increase both the propensity of being employed and the propensity of having a healthy lifestyle, which in turn decreases the chances of developing diabetes. On the other hand, lack of self-motivation or poor management of day-to-day stress can increase the probability of being unemployed, while also leading to an unhealthy diet and eventually, the onset of diabetes.

Following pervious research on diabetes and employment such as Latif (2009), Brown et al. (2009) and Seuring et al. (2015), a recursive bivariate probit model was used to test the possibility of endogeneity of diabetes and employment in data set. Using a recursive bivariate probit instead of two step probit instrumental variable routine was due to the fact that the latter model did not account for the potential endogeneity of a dichotomous variable (diabetes status) in a model where the dependent variable was binary (employment status) (Madala, 1983; Greene, 1998). Likewise, estimators such as ivprobit in STATA assumed that the endogenous regressors were continuous and not appropriate for use with discrete endogenous regressors (www.stata.com, 2019). The estimator suggested by Plum (2016) used quasirandom numbers (Halton draws) and maximum simulated likelihood to estimate the correlation between the error terms of both equations. One other advantage of bivariate probit models was the superior performance when treatment probabilities were low (Only 22% of men and 13% of women reported an occurrence of diagnosed diabetes in estimated sample) (Chiburis et al., 2012).

To allow for the potential endogeneity from omitting key influences on employment and diabetes, an instrumental variable analysis was conducted, where the instrumental variable was derived from information on whether an individual's biological parents had been diagnosed with diabetes. Studies that had used the family history of diabetes as an instrument for diabetes were Brown et al. (2005), for a Mexican-American community; Latif (2009) for Canada; Minor (2011) for women in the US; Lin (2011) considered Taiwan; and Seuring et al., (2015) used data on Mexico. All of these papers used cross sectional data. To fulfil the instrument's validity condition, family history of diabetes has to be significantly correlated with diabetes status of the individual, which is suspected to be endogenous regressor. Although medical literature does not suggest a single factor or exact pathway through which type II diabetes develops, it provides various results based on observations linking the strong associations between genetic factors and the onset of diabetes (Ridderstrale et al., 2009). For example, in the UK, having a family history of diabetes increases the probability of being diagnosed with this condition by 2 to 6 times in later life (Bonnefond et al., 2010).

The second condition required for validity of our instrument is that parental diabetes should not be directly correlated with the individual's own employment given their diabetes status. A diabetic parent is more likely to be exposed to prolonged jobless episodes, early exit from employment, unemployment, economic inactivity or early death. All of these factors can impose financial burden on the family and decrease the amount and quality of investment in children's education and talent that could eventually decrease the likelihood of employment among their offspring. The effect of parental diabetes on offspring's employment was controlled through education by including information on educational qualification.

Furthermore, this adverse effect can be mitigated through free and compulsory education available for all children up to 16 years old in England. Nevertheless, the quality of compulsory education can impact an individual's motivation and ability to undertake further education. It is presumable that diabetes can affect the offspring's employment decision directly by other routes than educational attainments and this can be one of the limitations of employing parental diabetes as instrument. Diabetes may deteriorate parental health to the extent that the offspring has or had to exit employment to become the primary care giver of his or her parents or chooses to take up work to financially provide for the parents. However, if this effect exists, it can be detected by the over-identification test (Seuring et al., 2015).

There were two questions in Life History Interview which asked participants to report some information on health and employment status of their parents. The exact wording of the questions are as follows: "When you were aged under 16, were either of your parents unemployed for more than 6 months when they wanted to be working?". When you were aged under 16, did your parents drink excessively, take drugs or have mental health problems? This question can potentially be used as an additional control to reflect on the impact of parental diabetes on probability of employment among resonances. However, life history was only carried out at wave 3 and taking part in Life History Interview was voluntary which meant this information was available for a fraction of the whole estimated sample and not for all participants.

To employ an IV strategy using a bivariate probit model in panel data, Plums (2016) routine, which accounts for the correlation in the time-specific and individual specific error terms was followed. This routine has been used in studies such as Co et al. (2018) and Carina et al. (2017). It is assumed that diabetes is a binary variable which might be endogenous and take value 1 if individual i reports being diagnosed with diabetes at time t and 0 otherwise. The employment equation is given by:

$$Employed^*_{it} = ß_0 + ß_1X_{it} + ß_2Diabetes_{it} + u_i + \varepsilon_{it} \qquad (4.1)$$

where $Employed^*_{it} > 0$ ($Employed^*_{it} = 1$) and $Employed^*_{it} < 0$ ($Employed_{it} = 0$) indicates that individual i is employed or otherwise at time t; $X_{it}$ denotes various control variables that affect the employment decision (full list of variables demonstrated in table A2). $B_1$ is the vector of coefficients associated with $X_{it}$; $u_i$ represents the individual specific unobservable and time invariant. $\varepsilon_{it}$ is a time-specific idiosyncratic shock. The diabetes equation is given by

$$Diabetes^*_{it} = \alpha_0 + \alpha_1X_{it} + \alpha_2Parentsdiabetes_i + \eta_i + \pi_{it} \qquad (4.2)$$

where $Diabetes^*_{it} > 0$ ($Diabetes^*_{it} = 1$) and $Diabetes^*_{it} < 0$ ($Diabetes^*_{it} = 0$) indicate where individual i is diabetic or not. The instrumental variable $Parentsdiabetes_i$ indicates whether if any or both of natural parents had ever been diagnosed with diabetes. The individual specific unobservable effect is captured by $\eta_i$ which is time invariant and $\pi_{it}$ represents the time-specific idiosyncratic shock. Equation 4.1 specification is identical to equation 4.1 and represents same probit random effect specifications. $\eta_i$ and $u_i$ are normally distributed with mean 0 and variances $\sigma^2_{\eta_i}$ and $\sigma^2_{u_i}$. $\pi_{it}$ and $\varepsilon_{it}$ are jointly normally distributed with means of 0 and variances equal to 1 and a correlation equal to ρ. Conditional on the $X_{it}$ , $u_i$ is IN (0, $\sigma^2_{\varepsilon}$) and independent of both $\varepsilon_{it}$ and $X_{it}$. This implies that the correlation between two successive error terms for the same individual is a constant (Arulampalam, 1996). Following Plum (2016) routine in STATA, I estimated Eq. (1) and Eq. (2) simultaneously, allowing for $\eta_i$ and $u_i$ to be correlated and also $\pi_{it}$ and $\varepsilon_{it}$ be correlated as well. If equations are independent of each other, correlation between $\pi_{it}$ and $\varepsilon_{it}$ will be equal to zero or statistically insignificant and it is assumed that endogeneity of diabetes is not a major concern in our estimated sample.

**4.4 Results**

Table 3 contains the bivariate random effects (panel) probit estimates for men and women. My main purpose for using bivariate probit models was to test the endogeneity of diabetes. The bivariate random effects (panel) probit estimates show that the correlation between the time specific residuals of the two equations are -0.16 and -0.24 for women and men respectively and are not significantly different from zero even at the 10 percent level. Since the cross-equation correlations are not significantly different from zero, we can be reasonably confident that estimating the effect of diabetes on employment for this age group will not be affected by endogeneity between diabetes and employment status. As there has not been any study similar to this on an English data set, it was not possible to compare these results with any published materials. It was well known that the endogeneity between diabetes and employment was closely related to the population sample studied. For example, Brown et al. (2005) found that diabetes was endogenous for older Mexican-American men, but not for women of the same age and ethnicity. Latif (2009) reported endogeneity among women and not men in Canada and Seuring et al. (2015) found no endogeneity among men or women in Mexico.

Moreover, obtained results were in line with the previous literature (Minor, 2011; Zhang et al. 2010). However, the bivariate model had larger standard errors. I also considered results of the linear IV model (table 1A appendix). According to test statistics based on linear IV method, parental diabetes can be regarded as sufficiently strong and a valid instrument for diabetes status of individuals. Kleibergen-Paap Wald F statistic for weak instruments is reported in table A1 and is 17.7 for men and 24.5 for female sub-samples (Kleibergen-Paap, 2006). These results were above the critical value of 19.93 for ten percent IV size and well above the rule of thumb of 10 for weak identification (Staiger et al., 1997).

**Table 3**: Bivariate random effect model

| | Female | | | | Male | | | |
|---|---|---|---|---|---|---|---|---|
| | Employment | | Diabetes | | Employment | | Diabetes | |
| Diabetes | -0.12* | (0.07) | | | -0.75* | (0.18) | | |
| Parents diabetes | | | 0.45** | (0.06) | | | 0.51** | (0.06) |
| General health | -0.48*** | (0.05) | 0.72** | (0.06) | -0.51 | (0.09) | 0.36** | (0.07) |
| Self employed | 1.82*** | (0.12) | -0.22 | (0.14) | 1.75*** | (0.12) | -0.1 | (0.11) |
| Professional job | -0.16** | (0.41) | 0.03 | (0.08) | -0.4** | (0.08) | 0.12 | (0.11) |
| Intermediate job | -0.11* | (0.05) | 0.03 | (0.07) | 0.09** | (0.06) | 0.02 | (0.11) |
| A-level and GCSE | -0.1** | (0.05) | 0.05 | (0.09) | -0.18** | (0.09) | -0.01 | (0.13) |
| No qualifications | -0.32*** | (0.06) | 0.06 | (0.1) | -0.23** | (0.09) | 0.06 | (0.15) |
| No of children | -0.25*** | (0.07) | 0.14 | (0.12) | -0.05 | (0.12) | -0.02 | (0.12) |
| Married | 0.72*** | (0.05) | -0.012 | (0.08) | 0.22** | (0.09) | -0.02 | (0.11) |
| Partner working | 0.58** | (0.04) | -0.15 | (0.07) | 0.56** | (0.06) | -0.08 | (0.09) |
| Total HH income | 0.33*** | (0.02) | 0.08** | (0.03) | 0.45 | (0.03) | 0.015 | (0.03) |
| Net wealth of HH | -0.12*** | (0.02) | -0.15** | (0.02) | -0.18*** | (0.02) | -0.1 | (0.03) |
| Heart failure | -0.42** | (0.13) | 0.48* | (0.13) | -0.28 | (0.12) | 0.11 | (0.14) |
| Stroke | -0.17** | (0.09) | -0.01 | (0.15) | -0.19** | (0.06) | 0.06 | (0.17) |
| Cancer | -0.18** | (0.04) | -0.04 | (0.07) | -0.21** | (0.08) | 0.06 | (0.13) |
| Arthritis | -0.24*** | (0.05) | -0.02 | (0.06) | -0.16*** | (0.06) | 0.07 | (0.09) |
| Ex-smoker | -0.04 | (0.03) | -0.002 | (0.06) | 0.01 | (0.06) | 0.05 | (0.11) |
| Current smoker | 0.04 | (0.05) | -0.13 | | -0.14 | (0.09) | 0.03 | (0.14) |
| Depression | -0.2** | (0.05) | -0.06* | (0.07) | -0.36*** | (0.09) | 0.03 | (0.1) |
| White | | | | | | | | |
| Age 50 54 | 0.9** | (0.04) | -0.27*** | (0.06) | 0.6** | (0.03) | -0.27*** | (0.05) |
| Age 55-59 | 1.33** | (0.07) | -0.24*** | (0.04) | 0.8** | (0.08) | -0.4** | (0.1) |
| Age 60 65 | 0.45** | (0.06) | 0.06** | (0.09) | 0.7* | (0.11) | -0.13* | (0.2) |
| Constant | -2.14** | (0.15) | -1.49** | (0.25) | -3.42** | (0.28) | -2.81** | (0.48) |
| N observation | 7633 | | | | | | 6157 | |
| N individuals | 1710 | | | | | | 1575 | |
| P | -0.16 | | | | | | -0.24 | |
| Wald test of p=0 | 0.56 | | | | | | 0.98 | |
| p value | 0.45 | | | | | | 0.32 | |

Table reports the simultaneously estimated coefficients of the equation 4.1 and 4.2. Standard errors are reported in parentheses. Data from 7 waves of ELSA
***p<0.01, **p<05, *p<0.1

## 4.5 Durational models

Econometric specification is based on the duration model stock-sampling approach of Jenkins (1995). A discrete-time hazard model was used to estimate the effect of diabetes onset on Exit for employment in England. A similar approach was employed by Chatterji et al. (2016) and Smith et al. (2014) to estimate the effect of diabetes on exit from employment among US and European populations respectively. This approach initially had been used by Jones et al. (2010) and Garcia-Gomez et al. (2010) to investigate the effect of health shocks on employment.

Following Jenkins (1995), the stock sample included individuals who were aged between 50 and the state pension age, working at wave one of ELSA and who had a full interview. These respondents were followed up through the subsequent seven waves until they first became non-employed or were censored. Censored respondents are those who drop out of the sample for reasons other than death, or respondents who work continuously throughout the survey period. By the end of the survey period, some participants completed duration data and stopped paid-work due to retirement, unemployment or disability. Non-employment is considered a permanent state and return to employment is not considered. Only people who were at the risk of exit from employment were included, therefore these individuals were excluded from the sample when they reached state pension age (65 for men and 60 for women).

An individual's duration of staying in the labour market was modelled using a hazard function. This represented an individual's conditional probability of leaving employment at age t, conditional on staying in employment until age t. Individual i's discrete-time hazard of exiting work, $h_{it}$ is formally defined as:

$$h_{it} = \Pr[T_i = t | T_i \geq t; X_{it}] \quad (4.3)$$

where $T_i$ is a discrete random variable representing the age at which the end of the employment spell occurs and $X_{it}$ is a vector of covariates, which may or may not vary over time (age).As suggested by Allison (1982) and Jenkins (1995), the sample log-likelihood function of the observed duration data can be simplified by defining a dummy variable $y_{it}$ which is equal to 1 if $t=T_i$ and the individual is non-censored, or $y_{it}=0$ otherwise. Therefore, for an individual who remains in employment, $y_{it}=0$ for all periods, whereas for those who stop working, $y_{it}=0$ for all periods except the period in which exit occurs, when $y_{it}=1$. The log-likelihood can be defined in a form familiar for the analysis of a binary variable $y_{it}$, where the unit of analysis is the spell period.

$$\text{Log L} = \sum_{i=1}^{n} \sum_{k=1}^{t_i} \log \frac{h_{ik}}{1 - h_{ik}} + \sum_{i=1}^{n} \sum_{k=1}^{t_i} \log(1 - h_{ik}) \quad (4.4)$$

Following Garcia-Gomez et al. (2010), Jones et al. (2010), a complementary log-log hazard rate was employed. That is, the hazard function for each individual i for wave t is written as follows:

$$h_{it} = 1 - \exp\{-\exp[\theta(t) + \beta' X_{it} + \gamma D_{it} + u_{it}]\} \quad (4.5)$$

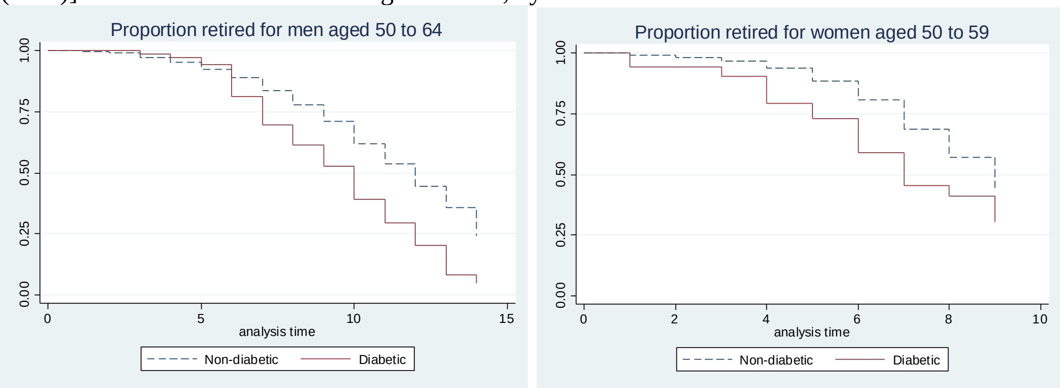
where $\theta(t)$ is the baseline hazard modelled as a step function by using dummy variables to represent each year of age at risk. $D_{it}$ is a dummy variable representing the individual's diabetes status in period t. In other words, if an individual i reports having been diagnosed with diabetes in period t, $D_{it} = 1$ and $D_{it} = 0$ otherwise. The complementary log-log link would be an appropriate choice as time is continuous and exit from employment can happen at any point in time while I only observed it in each wave. Results based on the c-log-log link should be more robust than those based on the logit link (Hedeker et al., 2000). A lagged measure of diabetes was also used in some alternative specifications to test the robustness of the obtained results.

As the initial employment spell at t = 0 in the sample period had no known starting point, a self-reported information provided with life history section of ELSA on employment history was used. Therefore, in all models a covariate capturing number of years since the spell of employment reported was included. This approach was similar to that taken by Garcia-Gomez et al. (2010) to address the initial conditions problem. As unobserved heterogeneity is a potential problem, this model was extended to the random effects complementary log–log model, which allowed for Corr $(u_{it_1},u_{it_2}) \neq 0$ when $t1 \neq t2$. The model was based on the assumption that the unobserved heterogeneity was normally distributed with mean zero. Using a likelihood ratio test, the null hypothesis that heterogeneity is zero was tested. A limitation of this approach was that the random effects were assumed to be uncorrelated with the explanatory variables, including the measure of diabetes.

## 4.6 Results

Sample of interest was comprised of a group of participants who were either employed or self-employed at the first wave of ELSA and at risk of exiting employment. The number of females in this sample was 1461, with 80 of these being diabetic. The stock sample of males consisted of 1694 individuals, 165 of whom reported diagnosed diabetes at wave one. The number of all observation was 9477 for the male and 6238 for the female sample. Non-parametric Kaplan–Meier estimator to illustrate the difference between the probabilities of survival in employment among diabetic and non-diabetic individuals was first used. As shown in Fig.1, it is evident that individuals with diabetes are less likely to remain in employment. The log-rank test for equality of survivor functions rejects the null hypothesis that the failure function is equivalent across diabetic and non-diabetic men and women. The $X^2$ values of the log rank test are is 0.14 for men and 0.19 for women with the p values of 0.0001 and 0.005 respectively.

**Fig.1.** Kaplan–Meier survival estimates and Long-rank and tests of equality of survivor functions [$\chi^2$ (Prob)] for men and women working at wave 1, by diabetes status




Main results were obtained from estimating the random effects discrete time hazard model and presented in table 4 for separate samples of male and female. As well as a set of socio-demographic and job-related controls which are listed in table

A2, these models include several dichotomous indicators for having had diabetes for 1–2, 3–5, 6–10, 11–20 and 21 or more years (with no diabetes as the baseline). Columns 1a of Table 4 (males) and Column 1b of Table 4 (females) represent results from a model which estimated the contemporises effect of onset of self-reported diagnosed diabetes at time t on the hazard ratio of exit from labour market. The hazard of labour-market exit is about 1.5 times greater for men who have been diagnosed with diabetes compared with male respondents who did not report diagnosed diabetes at time t and this effect is statistically significant at the 0.05 level. As represented in column 1b table 4, being currently diagnosed with diabetes is associated with a 70% increase in probability of women's exit from employment and this effect is statistically significant.

The magnitude of effect of diabetes varies based on the age group and county and regional differences. The only study comparable with this work was by Rumball-Smith et al. (2014) which used 3 first waves of ELSA. Findings based on self-reported doctor-diagnosed diabetes were in line with Rumball-Smith et al. (2014), who used data from the first 3 waves of ELSA along with data from surveys of aging populations in fifteen European countries, to estimate the effect of diabetes on early retirement. Rumball-Smith et al. (2014) reported that having diagnosed diabetes increased the risk of leaving labour force by about 40 percent across countries. Results showed a bigger effect for both men and women in this chapter which can be due to individuals being followed for a longer time period. Diabetic individuals' risk of unemployment increases as they get older because the prevalence and duration of diabetes increases among the stock sample. Similar results have been reported by Herquelot et al. (2011) suggesting 1.6 as hazard ratio associated with risk of early exit from employment among French population.

Data from baseline sample of ELSA which included information prior to wave one of ELSA to construct a lagged indicator for diagnosed diabetes at time t-1 was used. This information was provided by Health Survey for England (HSE) in 1998, 1999, and 2001. Hence, 22 cases of wave one was lost and obtained results were comparable to results from diagnosed diabetes at time t. These results indicated that lagged diagnosed diabetes had a statistically significant effect on the hazard ratio of exit from employment. The probability of exit from employment was increased by 90 per cent for women (column 2b); for men, this effect was a 70 per cent increase in hazard ratio (Column 2a).

In columns 3a and 3b, I combined the self-reported and the biomarker information to construct a measure of diabetes that included both diagnosed and undiagnosed diabetes. Obtained results were very similar to models that estimated only the effect of diagnosed diabetes on the probability of employment. The hazard ratio of failure (exit from employment) was 1.48 and 1.8 respectively for men and women and statistically significant at the 0.05 level. These results illustrated the effect all individuals experiencing diabetes regardless of a clinical diagnosis and reduced the magnitude of individual's knowledge of their own condition. Obtained results suggested that coefficient changed only slightly when both diagnosed and undiagnosed diabetes were combined. This approach has been adopted previously by Minor et al., (2016) and the coefficient based both specifications were very similar. It is true that undiagnosed diabetic individuals might spend less time on managing their illness but there is evidence in literature that undiagnosed and newly diagnosed diabetics have similar profiles with respect to broader health status and socioeconomic characteristics which can explain similarity observed in obtained results (Hill et al., 2013).

Columns 4a and 4b show the effect of diagnosed diabetes with and without medication. Based on these models, the effect of diagnosed diabetes with oral medication or insulin shots was statistically significant for both men and women (1.8 and 1.9 respectively). The estimated hazard ratio of diabetes without medication was 1.12 for women and 1.20 among men (Column 1a, Table 2). However, this association was not statistically significant. As no other similar empirical research on the British work-force is available, comparisons of these results could only be made with papers such as Chatterji et al. (2016). Here they reported that diabetes without medication and undiagnosed diabetes had no significant results on probability of staying in the labour market among older Americans. Considering that undiagnosed diabetes and diabetes without medications were more likely to be in the earlier stages of the disease, individuals might not be experiencing symptoms, and might not spend time managing their diabetes (since they are undiagnosed or not using medication). Therefore, their labour market status was less likely to be affected.

In models presented in table 4, dichotomous indicators of diabetes duration are included, but these controls do not show significant association with leaving employment. I also estimated models with dichotomous diabetes duration variables as the only measures of having diabase, but even for these models the observed results were not significant.

In this work I have compared the hazard ratio of duration of diabetes against hazard ratio of diabetes with medication and results showed that usage of insulin or medication by diabetic individuals was significantly associated with the risk of exit from employment. However, duration since being diagnosed with diabetes did not show a statistically significant effect. There is a strand of literature on relationship between diabetes and employment which considers the role of diabetic-related conditions or co-morbidities as the main pathway through which diabetes affects employment. I therefore carried out a set of descriptive investigations to compare the correlation between experiencing diabetes comorbidities with diabetes duration and use of medication and insulin. The purpose of these tests was to gain more insight on why diabetes duration's hazard ratio was not statistically significant, whereas the hazard ratio of diabetes with medication was significant. I considered kidney infections, use of ACE inhibitors and feet problems as three common diabetes comorbidities.

Averages of diabetes duration has been compared for each of the sub-groups that had diabetes and one of the mentioned comorbidities. These were compared with those diabetics who did not have that specific comorbidity. Averages of diabetes duration was not statistically significant among diabetic people who had each of these comorbidities compared with those who did not. The only statistically significant difference was observed among diabetic women who had kidney problems compared with other diabetic women who did not have this issue. On the other hand, the probability of having each of these comorbidities was statistically significantly higher among diabetic male and female who were using oral medication or insulin compared to those that were not. These findings suggested that usage of medicine and insulin was strongly associated with experiencing other diabetic related health problems. This is one of the reasons for considering usage of medicine and insulin as a good predictor of severity of diabetes in this estimated sample.

The hazard ratio of undiagnosed diabetes is 1.31 for men and 1.23 among women and was statistically significant at 95% confidence interval. The difference between hazard ratio of undiagnosed diabetes and hazard ratio of diagnosed diabetes was statistically significant at 90% confidence interval. Also, the difference between hazard ratio of diagnosed diabetes and diabetes with medicine has been tested and results indicated that this difference was not statistically significant. The insignificant difference between these two groups was not surprising as diabetics who used medicine or insulin were one of the sub-groups of all diagnosed diabetics. The main point highlighted based on presented survival analysis was that the significant adverse effect of diabetes on employment choices was experienced by diagnosed diabetics that used medicine or insulin and not among diagnosed diabetics that did not use medicine or insulin.

One limitation of these findings was that the information on diabetes was self-reported. As a result, I could only examine the effects of diagnosed diabetes, and accounted for the severity by the participant’s report on medication usage and insulin injection and the number of years since diabetes has been diagnosed. In waves 2, 4 and 6 of ELSA A1C levels of respondents who were not diabetic or were diabetic, but not on medication were collected. However, as this information was not available in every wave, it was not possible to use this as a separate measure in durational model and also could not consider effects of both diagnosed and undiagnosed diabetes or prediabetes on the probability of leaving employment.

**Table 4**: Effect of diabetes on leaving employment, Male and female

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | **1a** | **2a** | **3a** | **4a** | **1b** | **2b** | **3b** | **4b** |
| Diagnosed diabetes (t) | 1.50** | | | | 1.7*** | | | |
| | 0.27 | | | | 0.34 | | | |
| Diagnosed diabetes (t-1) | | 1.7*** | | | | 1.9*** | | |
| | | 0.32 | | | | 0.35 | | |
| Diagnosed and high (t) HAD | | | 1.48** | | | | 1.8*** | |
| | | | 0.24 | | | | 0.627 | |
| Diagnosed diabetes with medication (t) | | | | 1.8** | | | | 1.9*** |
| | | | | 0.35 | | | | 0.589 |
| Diagnosed diabetes without medication (t) | | | | 1.2 | | | | 1.119 |
| | | | | 0.33 | | | | 0.806 |
| diabetes 1-2 years | 1.2 | 1.3 | 1.4 | 1.3 | 1.8 | 1.7 | 1.7 | 1.4 |
| | 0.49 | 0.52 | 0.6 | 0.51 | 0.82 | 0.82 | 0.91 | 0.74 |
| diabetes 3 -5 years | 1.4 | 1.2 | 1.16 | 1.3 | 1.6 | 1.5 | 1.2 | 1.3 |
| | 0.51 | 0.48 | 0.51 | 0.49 | 0.81 | 0.78 | 0.48 | 0.45 |
| diabetes 6-10 years | 0.8 | 0.9 | 0.78 | 0.661 | 0.92 | 0.93 | 0.95 | 0.81 |
| | 0.28 | 0.31 | 0.26 | 0.221 | 0.32 | 0.33 | 0.33 | 0.31 |
| diabetes 11 -20 years | 0.91 | 0.8 | 0.84 | 0.74 | 0.61 | 0.58 | 0.62 | 0.57 |
| | 0.21 | 0.22 | 0.28 | 0.25 | 0.41 | 0.38 | 0.41 | 0.36 |
| diabetes 21 + | 0.75 | 0.9 | 0.43 | 0.32 | 0.91 | 0.87 | 0.86 | 0.76 |
| | 0.35 | 0.38 | 0.32 | 0.24 | 0.28 | 0.26 | 0.28 | 0.24 |
| Stroke | 1.28* | 1.29* | 1.28* | 1.3* | 1.08 | 0.88 | 1.11 | 1.09 |
| | 0.26 | 0.26 | 0.25 | 0.28 | 0.4 | 0.6 | 0.4 | 0.43 |
| heart problem | 1.13 | 1.15 | 1.12 | 1.18 | 1.09 | 1.12 | 1.09 | 1.12 |
| | 0.17 | 0.18 | 0.17 | 0.17 | 0.38 | 0.41 | 0.42 | 0.42 |
| cancer | 1.32** | 1.31* | 1.28** | 1.24* | 1.30** | 1.3** | 1.30** | 1.31** |
| | 0.13 | 0.14 | 0.13 | 0.13 | 0.21 | 0.21 | 0.2 | 0.2 |
| Arthritis | 1.19** | 1.19* | 1.21** | 1.21** | 1.21** | 1.18 | 1.21** | 1.22** |
| | 0.1 | 0.12 | 0.11 | 0.11 | 0.12 | 0.1 | 0.12 | 0.13 |
| Depression | 1.40* | 1.38* | 1.38* | 1.39* | 1.35* | 1.32 | 1.35* | 1.36* |
| | 0 .22 | 0.21 | 0.22 | 0.21 | 0.21 | 0.18 | 0.21 | 0.23 |
| p-value (LR test: rho= 0) | 0.496 | 0.496 | 0.493 | 0.498 | 0.495 | 0.493 | 0.493 | 0.493 |
| N of observation | 9477 | 9477 | 9477 | 9477 | 6238 | 6238 | 6238 | 6238 |
| N of individuals | 1,694 | 1,255 | 1,255 | 1,255 | 1461 | 1461 | 1461 | 1461 |

Notes: Table shows estimated hazard ratios and standard errors associated with selected covariates based on a random effects discrete time duration model. Standard errors are in parentheses. Other covariates included in all of the models but not shown in table are presented in table A2 Appendix. ***p <0.01, **p< 0.05.

All the models presented in this table included specific health conditions and the CESD indicator of depressive symptoms as an additional set of control variables. Becoming diabetic can increase the probability of developing other health conditions that independently have an explanatory effect on early-retirement decisions (Rodriguez-Sanchez et al. 2017). Among both males and females, cancer, depression and arthrosis show statistically significant increases in the hazard of leaving employment. Onset of stroke increases the risk of exit from paid work statistically significantly only among men (28%) and heart problems do not have statistically significant effect on the retirement decision of male or female individuals. It is not surprising that the onset of a range of chronic health conditions play an important role in older individual's likelihood of leaving employment and previous empirical research has found similar results (Jones et al., 2016). The exclusion of these covariates does not lead to any significant change in the effect of diabetes for males and females. The p-values of log- likelihood ratio test of heterogeneity is reported for every model and indicates that we fail to reject the null hypothesis that unobserved heterogeneity is zero at 1 per cent level and can confirm that in this estimated model unobserved heterogeneity is not important.

The effects of other socioeconomic covariates are consistent across different models, as presented in Table A2 in the Appendix. For example, the hazard of exit from employment was significantly increased by age compared to the youngest category as the baseline. In addition, the hazard of non-employment decreased as the log of household income and total wealth of household increased. For both the male and female stock samples, individuals with higher or first-degree education had a greater hazard of exit from employment compared with workers without any educational qualifications. These differences were around 60 percent for men and women and were statistically significant at 0.05 level. These findings were in line with studies such as García-Gómez et al. (2008). They also found that having a degree or higher education increased the hazard of employment among stock sample of non-working older males and females in the UK, suggesting that these individuals changed jobs more frequently. Living with a partner or being married seemed to decrease the hazard ratio of unemployment for both males and females by around 65%, as compared to baseline category (unmarried or non-cohabiting). Number of children under 18 years old increased the hazard ratio of non-employment for both male and female workers, but these effects were statistically significant only for women.

## 4.7 Conclusion

In this study the impact of diabetes on exit from labour force among workers aged between 50 and retirement, using 7 waves of English Longitudinal Survey of Aging was estimated. My first contribution to the existing body of literature was to test for the possibility of endogeneity between diabetes and employment in England. Employing bivariate probit model and parental diabetes status as the instrumental variable, diabetes was not found to be endogenous neither for males nor females. This study also adds to the existing body of evidence by providing estimates using durational analysis to ensure the correct sequence of exposure and outcome. The results indicate that women and men diagnosed with diabetes had 50 percent and 70 percent increase in the rate of labour force exit respectively, compared to those without this condition. Findings based on self-reported doctor-diagnosed diabetes are in line with Rumball-Smith et al. (2014), who used data from the first 3 waves of ELSA along with data from surveys of aging populations in fifteen European countries, to estimate the effect of diabetes on early retirement. Rumball-Smith et al. (2014) reported that having diagnosed diabetes increased the risk of leaving labour force by about 40 percent across countries. Results showed a bigger effect for both men and women. This was due to the fact that individuals were followed for a longer time period, and as these individuals got older both the prevalence and duration of diabetes increased among the stock sample.

Workers with diabetes tend to be more likely to experience difficulties in maintaining their job or find a new job compared with non-diabetic workers. Chronic or acute symptoms related to diabetes, along with side effects of medication can decrease the work ability and day-to-day functioning. These factors can decrease the chances of career advancement while increasing probability of facing work-place discrimination (Petrides et al., 2000) and poor work-place functionality (Tunceli et al., 2006), rates of absenteeism (Backer et al., 2006), and reduced productivity (Ramsey et al., 2002). This study attempted to go beyond estimating the average effect of diabetes on exit from employment to identify which diabetic people were more likely to exit from employment. The association of the duration of diabetes and intake of oral medication and insulin with each other and with some of diabetic comorbidities were investigated. Based on these results, the use of oral medication and insulin was a better proxy for experiencing other comorbidities and related symptoms compared with duration of diabetes. In addition, based on durational analysis, diabetic men and women who did not use oral medication or insulin did not experience significant reduction in the duration of employment whereas, the hazard ratios for leaving the work-force for diabetic men and women who were on medication or insulin was increased by 70 percent and 90 percent respectively. In contrast, a significant difference in probability of leaving employment based on the duration of the diagnosis was not found.

These findings have numerous policy implications. While healthcare costs associated with diabetes is well recognised and studied, the costs to employers and society resulting from the loss of labour have not been as well documented. As this study demonstrated, workers with diabetes who used insulin or oral medication left the labour market prematurely in England. This has the potential to cause additional costs on employers, including those costs associated with the recruitment and training of new staff. Therefore, policies that motivate pre-diabetics as well as diagnosed diabetics to improve their lifestyle and educates them to make healthier day-to-day choices can improve management of their conditions and delay the onset of severe symptoms requiring costly medications. If the probability of staying in work increases, the economic burden of this condition for both individuals and society might be minimised. Potential policy interventions include those outlined to reduce the risk of developing diabetes and programmes and policies which emphasise on the impact of social conditions and individual lifestyle to promote people's conscious decision to increase physical activities and healthy diet (Gov.uk, 2019). In addition, such programmes can help workers manage their condition with lifestyle intervention to minimise the risk and severity of associated diabetes complications. Finally, there may be strategies to support people with diabetes in their working lives. Both the public and private sectors could contribute to these interventions.

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## 4.9 Appendix

**Table A1:** Linear IV (random effect)

| | Female | | | | Male | | | |
|---|---|---|---|---|---|---|---|---|
| | Employment | | Diabetes | | Employment | | Diabetes | |
| Diabetes | -0.21 | (0.24) | | | - 0.31 | (0.39) | | |
| Parents diabetes | | | 0.091** | (0.012) | | | 0.04*** | (0.006) |
| General health | - 0.08** | (0.02) | 0.04** | (0.008) | - 0.12** | (0.03) | 0.09** | (0.006) |
| Self employed | 0.31*** | (0.02) | 0.002 | (0.009) | 0.39** | (0.02) | - 0.01 | (0.01) |
| Professional job | 0.11** | (0.02) | 0.008 | (0.01) | - 0.05** | (0.01) | 0.005 | (0.007) |
| Intermediate job | 0.09* | (0.02) | 0.012 | (0.01) | - 0.03 | (0.012) | 0.004 | (0.006) |
| A-level and GCSE | 0.023 | (0.012) | 0.003 | (0.032) | - 0.07** | (0.02) | 0.001 | (0.007) |
| No qualifications | - 0.008 | (0.02) | 0.01 | (0.014) | - 0.09** | (0.02) | 0.003 | (0.009) |
| No of children | 0.007 | (0.017) | 0.02* | (0.009) | - 0.07** | (0.02) | 0.009 | (0.01) |
| Married | 0.07** | (0.02) | 0.008 | (0.012) | 0.22** | (0.01) | 0.002 | (0.006) |
| Partner working | 0.13** | (0.01) | - 0.019* | (0.007) | 0.19** | (0.01) | - 0.01 | (0.005) |
| Total HH income | 0.12 | (0.005) | 0.012** | (0.003) | 0.1** | (0.006) | 0.007* | (0.002) |
| Net wealth of HH | 0.035** | (0.004) | - 0.008* | (0.002) | 0.22** | (0.01) | 0.013** | (0.001) |
| Heart failure | - 0.08* | (0.03) | 0.02 | (0.017) | - 0.08** | (0.044) | 0.09* | (0.02) |
| Stroke | - 0.02 | (0.04) | 0.018 | (0.02) | - 0.02 | (0.02) | 0.0009 | (0.014) |
| Cancer | - 0.008 | (0.03) | - 0.001 | (0.014) | - 0.08* | (0.04) | 0.006 | (0.06) |
| Arthritis | - 0.06* | (0.02) | 0.014 | (0.01) | - 0.07** | (0.009) | 0.001 | (0.004) |
| Ex-smoker | - 0.02 | (0.01) | 0.011 | (0.009) | - 0.008 | (0.01) | 0.003 | (0.005) |
| Current smoker | - 0.04 | (0.02) | - 0.006 | (0.014) | 0.004 | (0.01) | - 0.01 | (0.006) |
| Depression | - 0.06* | (0.02) | 0.007 | (0.01) | - 0.06* | (0.01) | - 0.004 | (0.007) |

Note: table shows estimated hazard ratio and standard errors associated based on a random effects discrete time duration model. Standard errors are in parentheses. ***p <0.01, **p< 0.05

**Table A1:** Linear IV (random effect) continued

| | Female | | | | Male | | | |
|---|---|---|---|---|---|---|---|---|
| | Employment | | Diabetes | | Employment | | Diabetes | |
| Age 50 54 | 0.24* | (0.02) | - 0.06** | (0.005) | 0.26 | (0.01) | -0.02* | (0.005) |
| Age 55-59 | 0.38* | (0.02) | - 0.08* | (0.01) | 0.41 | (0.02) | -0.02** | (0.009) |
| Age 60 65 | 0.22* | (0.02) | - 0.03** | (0.009) | 0.13 | (0.02) | -0.05** | (0.008) |
| Constant | 0.04* | (0.005) | 0.11* | (0.03) | | | 0.05* | (0.02) |
| N observation | 6157 | | | | | | 7622 | |
| N individuals | 1575 | | | | | | 2025 | |
| Endogeniety (H0: Diabetes exogenous) | 0.424 | | | | | | 0.12 | |
| Pvalue | 0.512 | | | | | | 0.73 | |
| F stat (H0: weak instruments) | 24.512 | | | | | | 17.743 | |
| Sargant test (H0:valid instruments) | 0.317 | | | | | | 0.735 | |
| P value | 0.471 | | | | | | 0.386 | |

Data from 7 waves of ELSA,

Note: table shows estimated hazard ratio and standard errors associated based on a random effects discrete time duration model. Standard errors are in parentheses. ***p <0.01, **p< 0.05

**Table A2**. Durational model. Effect of diabetes on leaving employment

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | **1a** | **2a** | **3a** | **4a** | **1b** | **2b** | **3b** | **4b** |
| Diagnosed diabetes (t) | 1.50** | | | | 1.7*** | | | |
| | 0.27 | | | | 0.34 | | | |
| Diagnosed diabetes (t-1) | | 1.7*** | | | | 1.9*** | | |
| | | 0.32 | | | | 0.35 | | |
| Diagnosed and high (t) HAD | | | 1.48** | | | | 1.8*** | |
| | | | 0.24 | | | | 0.627 | |
| Diagnosed diabetes with medication (t) | | | | 1.8** | | | | 1.9*** |
| | | | | 0.35 | | | | 0.589 |
| Diagnosed diabetes without medication (t) | | | | 1.2 | | | | 1.119 |
| | | | | 0.33 | | | | 0.806 |
| diabetes 1-2 years | 1.20 | 1.3 | 1.40 | 1.3 | 1.8 | 1.7 | 1.7 | 1.4 |
| | 0.49 | 0.52 | 0.6 | 0.51 | 0.82 | 0.82 | 0.91 | 0.74 |
| diabetes 3 -5 years | 1.4 | 1.2 | 1.16 | 1.3 | 1.6 | 1.5 | 1.2 | 1.3 |
| | 0.51 | 0.48 | 0.51 | 0.49 | 0.81 | 0.78 | 0.48 | 0.45 |
| diabetes 6-10 years | 0.8 | 0.9 | 0.78 | 0.661 | 0.92 | 0.93 | 0.95 | 0.81 |
| | 0.28 | 0.31 | 0.26 | 0.221 | 0.32 | 0.33 | 0.33 | 0.31 |
| diabetes 11 -20 years | 0.91 | 0.8 | 0.84 | 0.74 | 0.61 | 0.58 | 0.62 | 0.57 |
| | 0.21 | 0.22 | 0.28 | 0.25 | 0.41 | 0.38 | 0.41 | 0.36 |
| diabetes 21 + | 0.75 | 0.9 | 0.43 | 0.32 | 0.91 | 0.87 | 0.86 | 0.76 |
| | 0.35 | 0.38 | 0.32 | 0.24 | 0.28 | 0.26 | 0.28 | 0.24 |
| Stroke | 1.28* | 1.29* | 1.28* | 1.3* | 1.08 | 0.88 | 1.11 | 1.09 |
| | 0.26 | 0.26 | 0.25 | 0.28 | 0.4 | 0.6 | 0.4 | 0.43 |
| heart problem | 1.13 | 1.15 | 1.12 | 1.18 | 1.09 | 1.12 | 1.09 | 1.12 |
| | 0.17 | 0.18 | 0.17 | 0.17 | 0.38 | 0.41 | 0.42 | 0.42 |
| cancer | 1.32** | 1.31* | 1.28** | 1.24* | 1.30** | 1.3** | 1.30** | 1.31** |
| | 0.13 | 0.14 | 0.13 | 0.13 | 0.21 | 0.21 | 0.2 | 0.2 |
| Arthritis | 1.19** | 1.19* | 1.21** | 1.21** | 1.21** | 1.18 | 1.21** | 1.22** |
| | 0.1 | 0.12 | 0.11 | 0.11 | 0.12 | 0.1 | 0.12 | 0.13 |

Note: table shows estimated hazard ratio and standard errors associated based on a random effects discrete time duration model. Standard errors are in parentheses. ***p <0.01, **p< 0.05

**Table A2**. (Continued). Durational model. Effect of diabetes on leaving employment

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | **1a** | **2a** | **3a** | **4a** | **1b** | **2b** | **3b** | **4b** |
| Depression | 1.40* | 1.38* | 1.38* | 1.39* | 1.35* | 1.32 | 1.35* | 1.36* |
| | 0 .22 | 0.21 | 0.22 | 0.21 | 0.21 | 0.18 | 0.21 | 0.23 |
| White | 0.57 | 0.57 | 0.61 | 0.6 | 0.72* | 0.81* | 0.72* | 0.73* |
| | 0.35 | 0.35 | 0.36 | 0.37 | 0.32 | 0.34 | 0.28 | 0.31 |
| Intermediate job | 1.33** | 1.34** | 1.26** | 1.35** | 0.87 | 0.99 | 0.72 | 0.73 |
| | 0.18 | 0.18 | 0.16 | 0.2 | 0.19 | 0.22 | 0.27 | 0.21 |
| Professional job | 1.49 | 1.37 | 1.42 | 1.36 | 1.31 | 1.28 | 1.27 | 1.32 |
| | 0.45 | 0.43 | 0.45 | 0.45 | 0.48 | 0.48 | 0.58 | 0.51 |
| Degree and higher | 1.6** | 1.62** | 1.62** | 1.58** | 1.68** | 1.68** | 1.65** | 1.64** |
| | 0.18 | 0.15 | 0.15 | 0.16 | 0.16 | 0.18 | 0.19 | 0.17 |
| No of children | 0.68 | 0.68 | 0.71 | 0.69 | 0.56** | 0.57** | 0.56** | 0.58** |
| | 0.13 | 0.13 | 0.14 | 0.14 | 0.08 | 0.09 | 0.08 | 0.09 |
| Married | 0.66** | 0.67** | 0.66** | 0.65** | 0.37** | 0.37** | 0.38** | 0.37** |
| | 0.09 | 0.09 | 0.11 | 0.09 | 0.08 | 0.08 | 0.09 | 0.08 |
| partner working | 0.68*** | 0.68*** | 0.7*** | 0.68*** | 0.66** | 0.66** | 0.71** | 0.71** |
| | 0.07 | 0.07 | 0.08 | 0.07 | 0.11 | 0.11 | 0.12 | 0.11 |
| Total HH income (quintiles) | 0.48*** | 0.48*** | 0.49*** | 0.51*** | 0.54*** | 0.55*** | 0.54*** | 0.59*** |
| | 0.02 | 0.03 | 0.04 | 0.06 | 0.04 | 0.04 | 0.05 | 0.08 |
| Net wealth of HH (quintiles) | 1.34** | 1.34** | 1.45** | 1.42** | 1.19*** | 1.2*** | 1.21*** | 1.19*** |
| | 0.09 | 0.091 | 0.11 | 0.12 | 0.06 | 0.06 | 0.07 | 0.08 |
| Ex-smoker | 0.91 | 0.98 | 0.91 | 0.92 | 1.12 | 1.13 | 1.18 | 1.2 |
| | 0.09 | 0.09 | 0.12 | 0.11 | 0.18 | 0.18 | 0.18 | 0.2 |
| current smoker | 0.95 | 0.95 | 0.94 | 0.91 | 1.13 | 1.14 | 1.13 | 1.15 |
| | 0.15 | 0.15 | 0.16 | 0.17 | 0.18 | 0.18 | 0.19 | 0.21 |
| age 51 | 0.03*** | 0.04** | 0.031** | 0.032*** | 0.38 | 0.34 | 0.37 | 0.38 |
| | 0.04 | 0.04 | 0.04 | 0.05 | 0.15 | 0.13 | 0.17 | 0.15 |

Note: table shows estimated hazard ratio and standard errors associated based on a random effects discrete time duration model. Standard errors are in parentheses. ***p <0.01, **p< 0.05

**Table A2** (continued). Effect of diabetes on leaving employment, Male and female

| | Male | | | | Female | | | |
|---|---|---|---|---|---|---|---|---|
| | **1a** | **2a** | **3a** | **4a** | **1b** | **2b** | **3b** | **4b** |
| age 52 | 0.11*** | 0.12** | 0.11** | 0.13** | 0.3 | 0.32 | 0.31 | 0.31 |
| | 0.06 | 0.06 | 0.07 | 0.08 | 0.11 | 0.14 | 0.12 | 0.12 |
| age 53 | 0.29*** | 0.31** | 0.28** | 0.31** | 0.19 | 0.21 | 0.18 | 0.19 |
| | 0.08 | 0.09 | 0.08 | 0.09 | 0.07 | 0.08 | 0.07 | 0.07 |
| age 54 | 0.27*** | 0.28** | 0.32** | 0.33** | 0.25 | 0.25 | 0.28 | 0.27 |
| | 0.08 | 0.09 | 0.11 | 0.12 | 0.08 | 0.09 | 0.09 | 0.8 |
| age 55 | 0.39*** | 0.38** | 0.33** | 0.32** | 0.54 | 0.53 | 0.58 | 0.54 |
| | 0.09*** | 0.07 | 0.08 | 0.09 | 0.13 | 0.12 | 0.14 | 0.13 |
| age 56 | 0.4** | 0.41** | 0.42** | 0.41** | 0.8 | 0.81 | 0.79 | 0.72 |
| | 0.09 | 0.09 | 0.11 | 0.09 | 0.12 | 0.13 | 0.12 | 0.14 |
| age 57 | 0.49** | 0.51** | 0.48** | 0.48** | 0.76 | 0.78 | 0.77 | 0.77 |
| | 0.11** | 0.12 | 0.09 | 0.11 | 0.13 | 0.12 | 0.11 | 0.13 |
| age 58 | 0.45** | 0.46** | 0.47** | 0.45** | 0.81 | 0.82 | 0.86 | 0.83 |
| | 0.09 | 0.09 | 0.11 | 0.09 | 0.12 | 0.13 | 0.11 | 0.14 |
| age 59 | 0.79 | 0.81 | 0.78 | 0.82 | 0.88 | 0.84 | 0.83 | 0.82 |
| | 0.15 | 0.17 | 0.18 | 0.19 | 0.12 | 0.12 | 0.14 | 0.13 |
| age 60 | 0.81 | 0.87 | 0.89 | 0.91 | | | | |
| | 0.15 | 0.16 | 0.17 | 0.18 | | | | |
| age 61 | 1.2** | 1.25** | 1.26* | 1.12 | | | | |
| | 0.09 | 0.11 | 0.12 | 0.09 | | | | |
| age 62 | 0.79** | 0.72** | 0.73** | 0.75 | | | | |
| | 0.09 | 0.09 | 0.09 | 0.1 | | | | |
| age 63 | 1.34** | 1.32** | 1.25** | 1.34** | | | | |
| | 0.12 | 0.11 | 0.13 | 0.12 | | | | |
| age 64 | 1.21** | 1.29** | 1.25** | 1.26** | | | | |
| | 0.13 | 0.14 | 0.12 | 0.12 | | | | |
| p-value (LR test: rho= 0) | 0.496 | 0.496 | 0.493 | 0.498 | 0.495 | 0.493 | 0.493 | 0.493 |
| N of observation | 4,667 | 4,667 | 4,667 | 4,667 | 2,989 | 2,989 | 2,989 | 2,989 |
| N of individuals | 1,255 | 1,255 | 1,255 | 1,255 | 1,066 | 1,066 | 1,066 | 1,066 |

Note: table shows estimated hazard ratio and standard errors associated based on a random effects discrete time duration model. Standard errors are in parentheses. ***p <0.01, **p< 0.05

# Chapter 5

## 5.1 Conclusion

This thesis has examined a key issue in the economic literature: the effect of health problems in determination of labour market outcomes. Being in work enables individuals to undertake active roles within their community and maintain social and professional skills that enhance career prospects. Certain individuals facing health conditions might not be able to carry on with fulfilling their professional responsibilities. However, many such individuals can stay in work and with adequate support, avoid the potential negative impacts such as social exclusion and financial difficulties of becoming economically inactive. The costs associated with exit from employment are not only incurred by the individual and family members, but also by tax payers through central as well as local governments: OECD countries spend on average of about 1.2% of GDP (up to 2% when including sickness reimbursements) on disability benefits (OECD, 2009). Expenses incurred by excluding workers with partial capacity from the labour market have a serious impact on public expenditure decisions. Policy solutions should be in place by governments to support individuals who stay at work as well as those who decide or are forced to exit employment after a health shock occurs. Creating such policy interventions will require further research on how working age people respond to health deteriorations and steps taken by affected individuals to adjust to their new health status.

One of the core objectivise of this thesis was to discuss and address how health as a concept can be reported and measured in various methods within empirical studies and how each study represented a pathway and association between health and employment based on the selected health definition. Therefore, different health measures were considered in each of the three empirical studies presented in this thesis.

Specific issues that were investigated in this thesis included the impact of mental and physical health shocks on labour force participation; the change in different income components after an acute health shock; and the effect of diabetes on early retirement. These issues were examined both descriptively and using various econometric methods such as factor analysis, nonlinear fixed and random effect regression, exact Coarsened matching, bivariate probit regression and survival analysis. It should be noted that the approach used here was slightly different with studies that concentrate on registered disabilities or benefit recipients; individuals who have been through Work Capability Assessment as described in the UK government documents (www.gov.uk.health,conditions-disability-universal-credit 2020) and their claims have been approved as a measure of health issues. In this work, self-reported health problems, doctor diagnosis or biomarkers were used which mean a new group of individuals were included in estimations. These people might never be registered as disabled or could become registered as incapacitated only after the timespan of the study, while experiencing unemployment and financial difficulty in short-run as a result of their poor health.

Several insights were uncovered through presented analysis. A significant reduction in labour market participation is observed after a mental or physical health shock is experienced. This study contributed in the existing literature by providing evidence indicating a varied response between men and women towards deterioration in mental and physical health. For example, Men have a higher threshold for exiting from the labour market due to physical health. Therefore, exit from employment tended to occur when physical health suddenly deteriorated to a very poor state in men. Furthermore, considerable evidence of heterogeneity was observed with regards to the nature of occupation. For instance, manual job holders were vulnerable against both physical and mental health shocks, whereas physical health shocks did not significantly reduce the probability of leaving employment among non-manual job holders. From a broader angle it can be concluded that this study contributed to the literature on health and employment by providing evidence that supports biopsychological perspective suggested by Prince et al. (2007). This approach regarded mental and physical health as two interconnected components of general health status of an individual. These results emphasised that British society should move from regarding mental health issues as a less important matter compared to physical health and reach a point of awareness that its healthcare, social and welfare systems work together to develop an integrated care model, spanning people's physical, mental and social requirements (Mental Health Taskforce, 2016).

When acute health shocks were considered, findings indicated significant reduction in labour income, indicative of a reduction in employment as shown in previous published literature. Also, a significant increase in total income received from state support was observed in the estimated working age sample. However, there were differences in the magnitude of the change observed in labour and benefit income among different age groups of men and women. As an example, men younger than 49 years old were the only sub-group that experienced significant reduction in their net income (8%) and no significant increase in income received from welfare system, while men older than 50 years old experienced a 35% increase in their benefit income and no significant reduction in net or gross incomes. This study sheds light on how vulnerable individuals are when faced with an unpredicted health shock and tests whether financial aids and welfare supports are adequately provided when reduction of labour income takes place.

A number of empirical studies have investigated type, extent and reach of welfare support that working age individuals who left employment due to health-related issues experienced. Their results suggested that some individuals and sub-group of people experienced reduced access to welfare support and consequently received inadequate benefit coverage in comparison with other individuals. In addition, there were two other factors that contributed to the considerable inequity in the provision of support. Firstly, financial support was administered by various agencies and secondly, eligibility criteria for receiving support was numerous and multifaceted (Gardiner et al., 2019). In this study, I showed that younger men received less welfare money compared to men older than 50 years old. There can be other contributors on the probability of welfare support entitlement. Besides, some studies demonstrated negative impact on the sense of self-respect and discriminatory processes in the benefits system. These have negatively impacted the sense of self-respect and security experienced by claimants (Emanuel et al., 2000)

Associations between diabetes and exit from employment decisions touches issues related to an aging population in many countries and an increasing necessity for meeting the needs of a growing segment of the population who have contributed for years in taxes. Yet, this group may feel vulnerable and unsupported when facing health problems (Gusmano et al., 2018). Chronic health problems can cause invisible disabilities (Santuzzi et al., 2014). It has been argued that these class of health problems are more challenging to identify and evaluate in empirical research compared to established forms of disabilities (European patient forum, 2018). Chapter four of this thesis contributed to the previous published literature by shedding more light on the main pathways in which diabetes can increase the probability of exit from employment. The chronic nature of diabetes means that this condition tends to cause progressive symptoms and associated co-morbidities over time. Therefore, this work aimed to identify heterogeneity among sub-groups of diabetics based on the severity of their condition. Duration of diabetes since diagnosed and usage of insulin or oral medicine were proposed as two possible proxies for dividing diabetic individuals based on severity of their condition.

Results suggested that both duration of diabetes and use of oral medication/insulin were correlated with experiencing other comorbidities and related symptoms. However, use of insulin and oral medication/insulin combined was a stronger predictor of co-morbidities and exit from employment decisions compared with duration of diabetes. Based on durational analysis, diabetic men and women who were not on oral medication/insulin did not experience significant reduction in years of employment. The hazard ratios for leaving the work force for diabetic men and women who were on medication or insulin is increased by 70 percent and 90 percent respectively. In contrast, I did not find a significant difference in probability of leaving employment based on the duration of the diagnosis.

This work is subject to several shortcomings due to limitations associated with the available data. Except for the work carried out in chapter four, where durational modelling was used, only short-time effects of health shocks on labour outcome were estimated. Such abrupt and adverse effects cause disruption to individuals as well as poorly equipped families who are forced to cope with the consequences. In addition to the short-time adjustments, further decisions are taken by individuals over a number of years following a health shock. These lifestyle modifications can manifest themselves in different ways, such as moving to a part-time job, teleworking and benefitting from flexible working hours. Also, people may change their jobs to one better suited to their new health status. Further research can aid in identifying the government and employer's response to acute and chronic health shocks and investigate to what extent various options are available and favoured by different affected individuals. Capturing an accurate image of long-term adjustments after a health shock can contribute to the current literature. Such analysis would enable us to identify which occupations and organisations offer more options to their employees. This would enable researchers to make valuable policy recommendations to aid the most vulnerable affected individuals. It would also assist us identify whether labour market sections and occupations differ in terms of accommodating for the needs of affected individuals.

Studies with multidisciplinary perspectives that focus on both employment and health aspects are still constrained with data scarcity particularly on health measures and retrospective data on employment and income history. Capturing long-term employment and income trajectories, in combination with modelling health status in a detailed manner are challenging tasks for researchers in this field. Despite various publications in different disciplines that examine such issues, these studies face limitations as social science tends to treat health as a unitary concept while clinical and biomedical studies generally control for a single measure of social position. As an example, in most household surveys, biomarkers are not gathered as frequently as self-reported measures, making it difficult to compare obtained results with those based on self-reported health measures or combine them and construct a measure for severity or self-management. For similar reasons, in chapter 4 of this research I could not control for pre-diabetes in durational analysis and compared its effect with the effect of being diabetic in exit from employment. Therefore, further refined research is required to improve current state of our knowledge in order to suggest appropriate policy reforms and aid us achieve an accurate picture of decision-making steps and preferences of working age individuals in the UK.

Government has declared that supporting people with health issues to obtain or maintain their job, and be productive within the workplace, is a vital part of UK's economic success and contributes to the well-being of individuals, community cohesiveness and inclusion with different industries (Jones et al. 2012). Therefore, it is important that people are supported to gain employment and maintain economic independence for themselves and their families even when faced with long-term conditions and disabilities. It has been mentioned that "good work" is good for health and having a "good work" is one of the factors that prevents exit from employment due to health problem (publichealthmatters.blog.gov.uk, 2019). Suggested characteristics for a "good work" are providing opportunities for in-work development, flexibility to enable a reasonable work-life balance and protection from adverse working environments that can harm health (gov.uk, 2019). Therefore, further research can be conducted to consider the relationship between health and employment from this perspective. Information in the available household data sets can be used to construct measures related to these characteristics and to job quality and assess whether these measures have an effect on the probability of exiting employment after experiencing a health shock.

Investigating the pattern and probability of returning to work after facing a health shock can provide a valuable contribution to the literature. It will be beneficial to shed light on which factors indicate the likelihood of return to work after experiencing a health shock and identify what proportion of the exits are permanent leave from employment. Relatively few studies address the return to work issue following a health shock (Chen et al., 2020). The process of returning to work depends on individual's specific health problem, rehabilitation process and the option provided from their job or employer. Different studies use various definition for exit from employment and returning to work (Black-Schaffer et al., 1990) and some studies address indicators of readiness to return to work as oppose to actual return to employment (McMahon et al., 1998). Therefore, a great variety is observed in the reported percentage of people returning to the job market. As an example; studies that report likelihood of "considering return to work" after a stroke have reported 3% to 84% as the proportion of individuals that are willing to re-engage with work Rolene et al. (2011)

**5.2 References**

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