Effects of ill-health and health shocks on labour market outcomes under social protection constraints

Ken Chamuva Shawa

Thesis Submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy in Health Economics and Policy. The candidate has already achieved 180 credits for assessment of taught modules within the blended learning PhD programme.

December 2024

Abstract

This thesis examines the effects of ill-health and health shocks on labour market outcomes. To achieve this, given the paucity of meta-analyses on the topic, a systematic review and meta-analysis was initially undertaken which is presented as chapter two of the thesis. The results from the review and meta-analysis show statistically significant pooled estimates of the effects of ill-health and health shocks on hours worked and the probability of employment. These results justified the research questions pursued in the thesis, including specific analysis of Malawi where no work of this nature has been undertaken before and where evidence could be useful in policy terms.

To explore the effects of ill-health and health shocks on labour supply, in chapter three, data from Malawi were used to assess the effects of several proxies of health shocks and ill-health. This included illness/injury, hospital admission, and chronic illness, on the probabilities of wage employment, casual employment, job search and on hours of work. The chapter employed nearest neighbour propensity score matching to estimate Average Treatment Effects on the Treated (ATET). Overall, results of the analysis showed that a) individuals who reported to have suffered an illness or injury in the last fourteen days significantly reduced their probability of wage employment but increased the probability of casual employment; b) individuals who reported to have experienced a hospital admission in the last twelve months significantly reduced their probability of wage employment but increased their probability of casual employment; and c) individuals who reported that they suffered from a chronic disease significantly reduced both their probabilities of wage employment and casual employment. Furthermore, results showed that individuals who reported to have suffered an illness or injury in the last fourteen days, those who reported to have experienced a hospital admission in the last twelve months as well as those who reported that they suffered from a chronic disease, significantly reduced their weekly hours of work. Moreover, in terms of the probability of job search, the study found that individuals who reported to have suffered an illness or injury in the last fourteen days significantly reduced their probability of job search while those who reported that they suffered from a chronic disease significantly increased the probability of searching for a job. There was no statistically significant effect on the probability of job search for individuals who reported to have experienced a hospital admission in the last twelve months.

In chapter four, a wide range of count data models including negative binomial, zero-inflated negative binomial, Poisson, zero-inflated Poisson, and a two-part model were used to assess the joint effects of ill-health and health shocks together with social protection on the intensive margin of labour supply using rich data from Malawi. A standard OLS model was also estimated to provide baseline estimates which were not based on a count data model. Weekly hours of work were employed in the analysis. Results showed that a) individuals who suffered an illness/injury and benefited from social protection reduced their hours of work; b) individuals who had experienced a hospital admission and benefited from social protection increased their hours of work; and c) individuals with chronic illnesses who benefited from social protection reduced their weekly hours of work.

The results of the thesis have important policy implications for Malawi and other low- and middle-income countries (LMICs). More specifically, the evidence presented here can inform the development of health and labour policies, encompassing initiatives to facilitate job search through public employment services, enhance access to social protection, and strengthen primary healthcare and universal health coverage as well as the overall health infrastructure.

Acknowledgements

To come to its fruition this piece of work has benefited from many. First, I sincerely recognise the high-quality guidance throughout this thesis journey provided by my supervisors: Professor Bruce Hollingsworth and Associate Professor Eugenio Zucchelli. These astute researchers have shaped me a great deal. I leave the University as a better researcher in health economics, a better data analyst, a better writer. Their commitment to the consistent and useful monthly supervisory meetings signalled to me their utmost resolve to sharpen my skills and ensure I stand tall among high-ranking researchers in health economics. I am truly grateful.

Throughout my PhD journey at the Lancaster University, Division of Health Research, I encountered a truly inspiring academic environment. The academic excellence of staff who contributed to the course work left me with a conviction that I chose both the right university and programme of study. I am very grateful to all for their commitment to the academic cause.

It took one lecturer to suggest a WhatsApp group for all of us in the cohort. The benefits of this group have been overwhelming. From sharing our methodologies, our data challenges, our publications, to the general encouraging environment that pushed everyone to keep working. I want to thank all fellow students in our cohort. You were such a blessing!

I remain very indebted to the World Bank and the National Statistical Office of Malawi for granting me the permission to access the micro data sets of the various waves of the Malawi Integrated Household Surveys. The seamless process by which permission was granted to access the data encouraged my pursuits to research on Malawi and discover more on the topic. As I went on to discover that not many have tackled the topic in Malawi, I felt proud that I would be making an important original contribution to the much-needed evidence on the topic in my country. I am thankful to Dr. Helen Gorrill who proofread this work.

Dedication

I firmly dedicate this thesis to my beautiful and amazing daughters: Lumbani, Towela, Lindiwe, and my wife Jane.

Declaration of Authorship

I declare that this thesis is my own work and has not been submitted in substantially the same form for the award of a higher degree previously or elsewhere. Parts of the following chapters were either published, presented at conference, or submitted to the University of Lancaster's Division of Health Research as components of various courses as described below:

- A research proposal of this thesis was submitted to the University of Lancaster's Division of Health Research as a component of the course called *Principles of Research Design and Practical Research Ethics* (DHR 403).

- A protocol for chapter two was submitted to the University of Lancaster's Division of Health Research as part of the course called *Systematic Approaches to Literature Reviews and Evidence Synthesis* (DHR 523).

- A version of chapter two was published in *Systematic Reviews* relating to sections 2.1, 2.2, 2.3, 2.4, 2.5 and 2.6. It was published as:

  Shawa, K, C., **Hollingsworth**, B., & **Zucchelli**, E. (2024). A systematic review and meta-analysis on the effects of ill-health and health shocks on labour supply. *Systematic Reviews*, 13(1). https://doi.org/10.1186/s13643-024-02454-y

- A version of chapter four was published in *Health Economics Review.* It was published as:

  Shawa, K, C., **Hollingsworth**, B., & **Zucchelli**, E. (2024). Joint effects of ill-health, health shocks and social protection on the intensive margin of labour supply. *Health Economics Review,* 14(75). https://doi.org/10.1186/s13561-024-00548-w

- A version of chapter three was presented at the ILO Research Department Monthly Technical Issues Discussion on 26 May 2022 under the title "Effects of health shocks on labour market outcomes: Quasi-experimental evidence from Malawi".

- An abstract of a version of chapter three under the title "Effects of ill-health and health shocks on labour supply in Malawi" was accepted for a short oral presentation (7-8 papers in a 90-minute session) at the 15th World Congress of the International Health Economics Association held at the Cape Town International Convention Centre, July 8-12, 2023.

- Finally, the thesis author (KCS) is not aware of any conflict of interest in relation to the conduct of this thesis.

Word Count (Total): 39769

The author notes that the University of Lancaster requires a total of between 35,000 to 40,000 words for this thesis.

Contents

List of Tables

List of Figures

CHAPTER ONE

Introduction

1.1 Background

The interrelationship between health and work has long been recognised. Ill-health can adversely affect labour market outcomes and conversely poor working conditions may have negative effects on the physical and mental health of individuals. According to the World Health Organisation (WHO) (2023), the global disease burden is mainly caused by noncommunicable diseases (NCDs). NCDs are responsible for 41 million deaths each year representing 74 per cent of all global deaths (WHO, 2023). Furthermore, NCDs are the cause of 7 million deaths of people under the age of 70, and 86 per cent of these premature deaths occur in Low- and Middle-Income Countries (LMICs). Meanwhile, of all NCD deaths, 77 per cent are in LMICs (WHO, 2023). In 2019, four major NCDs (cardiovascular disease, cancer, chronic respiratory disease, and diabetes) collectively killed around 333 million people, which represented a 28 per cent increase compared to the year 2000. The WHO (2023) also reports trends in infectious diseases including HIV and Tuberculosis (TB), as well as Malaria. In 2021 there were 1.5 million new HIV infections globally, while a total of 10.6 million people fell ill with TB in 2021 with a global TB incidence rate rising by 36 per cent between 2020 and 2021. Worldwide, there were an estimated 247 million Malaria cases in 84 malaria-endemic-countries in 2021, while Global Malaria deaths rose from 568,000 in 2019 to 619,000 in 2021 (WHO, 2023). In 2021, the African region bore the highest burden, accounting for 95 per cent of global cases and 96 per cent of global deaths (WHO, 2023). The Organisation for Economic Cooperation and Development (OECD)/European Union (EU) (2016) showed that chronic diseases were responsible for the premature death of more than 550,000 people aged 25 to 64 each year across EU countries, and that this resulted in 3.4 million potential productive life years lost. Subsequently people living with chronic diseases including cardiovascular diseases, respiratory problems, diabetes, and serious mental health problems faced important labour market impacts that included reduced employment, early retirement, and lower income. For Chirikos (1993) chronic health conditions diminish not only the basic physical and mental capabilities but are disruptive to the functioning of work by making it difficult to perform some tasks and increasing the cost of performing these roles. This forces individuals with impaired health to either withdraw from labour markets or reduce hours of work. The OECD/EU (2016) determined that the employment rate of people aged 50-59 with one or more chronic diseases was lower than that of people who did not suffer from any disease. Thus, lowering the disease burden will contribute to vital gains in employment and livelihoods.

1.2 Background literature

Research in the health-labour relationship has tended to distinguish the effect of ill-health and that of health shocks on labour market outcomes. Ill-health such as chronic diseases tend to be long-term, while health shocks are sudden or unexpected (Leive & Xu, 2008). They both interrupt conventional work but to differing extents. Ill-health has mainly been operationalised using chronic illnesses (Alavinia & Burdof, 2008) such as diabetes, cardiovascular diseases, respiratory problems, and mental health challenges (Timbie et al. 2006). Studies utilising health shocks have used injuries, illness, hospitalisations and onset of chronic diseases (Datta Gupta et al. 2015; Wagstaff, 2007; Wagstaff & Lindelow, 2013; Zimmer, 2013), among other measures.

In consideration of mental health as a chronic disease and therefore constituting ill-health, Layard (2013) observed that mental health has adverse effects on earnings, educational attainment and ultimately on employment. With mental health responsible for 40 per cent of all illness under 65, it represents one third of disability and absenteeism in advanced countries and it is estimated that in the absence of mental illness, the costs of physical healthcare for chronic diseases would be one third lower (Layard, 2013). Germinario et al. (2022) used a longitudinal youth study (USA) to assess causality effects running through poor mental health to employment and earnings. They found that depression decreased employment by 10 per cent while earnings decreased by almost 27 per cent. They also found heterogeneous effects on labour market outcomes related to the seriousness or severity of poor mental health. To this end when depressive symptoms were categorised as none, little, mild and severe, they established that employment was reduced by 3 to 18 per cent from none to severe depression and earnings reduced from 11 to 44 per cent. When they ran the comparison from little to severe depression, they found employment reduction ranging from 3 to 16 per cent, while earnings reduced by 12 to 36 per cent. Cornwell et al. (2009) estimated labour market costs of poor mental health in Australia. Using different disorders to indicate the status of mental health they found that each disorder was associated with a 1.3 percentage point reduction in the probability of participating in labour markets. They argued that these effects were large, considering that most people had multiple disorders. Apart from reductions in the probability of participation in labour markets and in employment, mental disorders also significantly reduced levels of occupational skills.

The work of Ettner et al. (1997) using the National Comorbidity Survey of the USA analysed the impact of psychiatric disorders on labour markets and found significant reductions in employment of men as well as women. They also found reductions in hours of work, albeit small, and substantial reductions in income. They pointed out that the study results needed to be interpreted with caution because they were sensitive to both the econometric methods and model specifications. For Australia, Frijters et al. (2010) having controlled for bidirectional causality between work and health, found reductions in mental health had negative effects on the probability of labour participation. Specifically, they determined a 17-percentage points reduction in the probability of labour market participation following a one standard deviation decrease. For Bryan et al. (2022) using the UK Household Longitudinal Study even though the relationship between mental health and employment is a key policy issue, they noted that there has been a lack of work on reliable causal inference. Thus, their work exploited panel data using approaches that use selection on observables to feed information on selection on unobservables. They found a 1.6 percentage points reduction in the probability of employment following a transition into poor health. Banerjee et al. (2015) also found that mental illness negatively affected labour force participation and employment in the U.S. Helgesson et al. (2017) were interested in understanding labour market marginalisation arising from mental disorders of immigrants in Sweden, as well as young natives. Their results showed that individuals who suffered mental disorders faced a higher risk of disability pension of as high as 7 times those without. They also faced a risk of absence due to sickness which was twice as high, with a 20 per cent higher risk of unemployment compared to individuals without mental health reductions.

In addition to the effects of mental health on labour market outcomes another strand of work has concentrated on understanding the effects of diabetes, as a chronic disease, on labour market outcomes. Seuring et al. (2019) used data from Mexico to assess the effects of diabetes on employment probabilities, working hours and wages. An important innovation in this work was to analyse the effects of both diagnosed and undiagnosed diabetes. Apparently, this was a reaction to the realisation that for most individuals in LMICs, diabetes remains undiagnosed. The results showed that diabetes reduced the probability of being employed by 7.7 percentage points for men, and 6.3 percentage points for women. There were no significant effects on hours worked or wages. The study also established a gradual yearly fall in employment probabilities for men, compared to women. A key result concerned 68 per cent of individuals who had higher glycated haemoglobin but did not self-report a diagnosis and as such they remained undiagnosed. For this undiagnosed group, the results showed no significant relationships between diabetes and any measure of labour market outcome. This was an important result since it cautions that when results are based on self-reported diabetes, generalisations need to be avoided since there could be selectivity bias with individuals in poor health, and probably with long diabetes duration which has higher representation in the diagnosed population.

Using the South African General Household Survey (2018), Koch and Thsehla (2022) assessed the effects of diabetes on employment, unemployment, and labour force participation. After failing to accept the endogeneity hypothesis, the study employed multinomial logit models and found negative effects of diabetes on labour force participation and unemployment. Nevertheless, they did not find significant effects on employment. Related to this finding they argued that the employed were able to take steps to effectively manage their diabetes and therefore remained in employment. In their results, women had larger negative effects compared to men. Tunceli et al. (2005) utilised the Health Retirement Study to longitudinally examine the effects of diabetes on labour market outcomes in the U.S. Compared to men without diabetes, diabetic men had a 7.1 percentage points lower probability of employment. As for women with diabetes, their probability of employment was 4.4 percentage points lower than those without. Additionally, relative to women without diabetes, diabetic women experienced two additional loss days in a year. Furthermore, diabetic men were projected to have work limitations of up to 5.4 percentage points compared to non-diabetics, while women faced a 6 percentage points higher likelihood of work limitations. A systematic review on the effects of diabetes on labour market participation by Pedron et al. (2019) showed a negative impact of diabetes on disability pension as well as triggering early retirement and unemployment.

In the analysis of ill-health and chronic diseases as they relate to labour market outcomes, some work has also been devoted to the effects of cardiovascular diseases. The work of Fu et al. (2019) used Japanese data and found that due to cardiovascular diseases women's working probability reduced significantly by 15.4 percentage points. For individuals who were diagnosed but were aged 40, the likelihood of them working was low. While there were no effects for individuals under 40 years old, those aged 65 experienced a large reduction in work probabilities. Additionally, once diagnosed, the probability of participating in manual labour was hugely reduced. In terms of hours worked, individuals with cardiovascular diseases had their weekly hours reduced by five hours. Harris (2009) sought to understand the joint effects of diabetes and cardiovascular diseases using data from Australia, and found that together, diabetes and cardiovascular diseases strongly affected labour market outcomes, which mostly impacted men. Harris (2009) also reported indirect effects on labour market outcomes emanating from lipid abnormality, obesity, hypertension, and insufficient exercise.

Other chronic diseases studied have included musculoskeletal disease, digestive system respiratory diseases as well as HIV/AIDS. To this end, Zhao et al. (2023) used Chinese longitudinal data and discovered that musculoskeletal disease reduced individuals' incomes by 21.5 percentage points. Furthermore, digestive system diseases decreased earned income by 6.9 percentage points. Regarding respiratory problems Stabridis and Gamaren (2018) showed that in Mexico, firewood-induced indoor air pollution was responsible for the heightened prevalence of respiratory problems facing women. When used for cooking, firewood results in an increased prevalence of respiratory problems among women, and respiratory problems have a negative effect on labour participation. Stabridis and Gamaren's (2018) study recommended that alternatives with less pollution should be adopted. Regarding HIV/AIDS, Levinsohn et al. (2013) found that HIV status in South Africa increased the likelihood of unemployment by 6 to 7 percentage points. Also using South African data, Chicoine (2012) found that apart from decreasing employment, HIV/AIDS was responsible for decreases in wages from three percentage points to six percentage points among black South Africans.

Ill-health has also been operationalised by self-assessed health limitations and self-assessed health (Zucchelli et al*.*, 2010). When health limitations are used, sometimes individuals assess themselves as to whether they face limitations in daily activities. On the other hand, self-assessed health (SAH) could just be a ranking ranging from excellent to poor. When Zucchelli et al. (2010) used these configurations of ill-health with data from Australia for older workers, they found that both health limitations and self-assessed health significantly influenced choices of early exits from the labour market. Similarly, when García-Gómez et al. (2010) used health limitations they found negative effects on both entry into and exit out of labour markets. This study used data from the British Household Panel Survey (1991-2002).

Another important strand of work has been devoted to understanding the effects of health shocks on labour market outcomes using the onset of chronic diseases. It is vital to note that when measured at the onset (Datta Gupta et al. 2015), diseases such as cancer, strokes, or heart attacks, constitute health shocks rather than ill-health. In this respect Jones et al. (2020) pursued such a relationship when they analysed the effects of acute health shocks on labour markets in Europe. The onset of cancer, strokes, and heart attacks were responsible for substantial increases in the probability of market exit. Similar adverse results were discernible for both hours worked and earnings. The study also revealed that given a health shock, younger workers tended to have a stronger attachment to the labour market compared to older workers. Additionally, women and older workers - as well as individuals with severe limitations and impairments - experienced stronger impacts. Candon (2019) and Smith (2005) also used a new diagnosis of strokes, cancer, heart problems as well as lung disease as health shocks in their works - and found adverse effects on labour market outcomes.

Another way to operationalise health shocks is to use hospital admissions. Through an event study, Dobkin et al. (2018) using the Health and Retirement Study of the USA analysed effects of hospitalisations on adults using the Health and Retirement Study. Hospitalisations were found to trigger increases in out-of-pocket expenditure and unpaid medical bills, as well as bankruptcy for non-elderly adults. Overall, hospital admissions were responsible for decreases in earnings, income, as well as access to credit. Uninsured non-elderly adults experienced larger increases in unpaid bills and bankruptcy rates compared to the insured non-elderly adults. Results of the work of Mommaerts et al. (2020) who used data from European countries, China and the United States, showed heterogeneity in the effects of hospital admissions in the economic outcomes of older workers. American workers experienced higher health expenditures and earning reductions than European workers who were well protected from the adverse effects. In China, out-of-pocket expenditures increased, but there were no negative effects on labour market outcomes. Arguably, the heterogeneity in the results was due to differences in social protection systems (Mommaerts et al., 2020). García-Gómez et al. (2013), using Dutch hospital data, established that acute hospitalisation resulted in post-shock personal income losses. Even so, neither employment nor income subsequently recovered.

Other research has used accident data to operationalise health shocks. Parro and Pohl (2021) considered the effects of accidents in Chile and found that among men any type of accident decreased the probability of employment by 8.4 percentage points initially, but this decreased further in the second and third years to 11.2 percentage points and 14.8 percent respectively. Taken together, an accident induced a reduction in employment of 14 percentage points relative to the mean, before the accident was observed, over the three years. Furthermore, a fall by 16 percentage points in earnings was observed over the three years. Nevertheless, this was after declines of 11 percentage points, 17 percentage points, and 22 percentage points in the first, second and third years respectively, following an accident. Dworsky and Powell (2022) showed that workplace injuries were responsible for huge declines in both employment and earnings in California. There were persistent but shrinking earning losses when measured as a percentage of counterfactual earnings which decreased by 19.6 percentage points in the first to the fourth year, post injury, to 10.9 percentage points over years 10 to 14 after an injury was experienced. The study also revealed an association between incentives attributable to social security's disability and retirement programme and labour force exits among injured workers aged 55 or over. This was however not the case for earlier studies. Empirical results from Zucchelli et al. (2010) using data from Australia for older workers who operationalised health shocks by serious injury or illness showed that health shocks significantly influenced choices of early exits from the labour market.

While studies have often focused on the effects of ill-health and health shocks on individuals experiencing illness or shock, there has also been interest regarding the effect of health shocks affecting a spouse or another member of the family (García-Gómez et al., 2011). Lundberg (1985) espouses the concept of "added worker effect" which typically relates to a spousal increase in the labour supply temporarily following a partner's health shock. This is done to protect the family from income losses (Coile, 2004). Using data from Chile, Acuña et al. (2019) tested this hypothesis using the onset of arthritis, asthma, and hypertension. Results showed evidence of the added worker effect due to a husband's diagnosis of arthritis. They further determined that such effect faded away with age emphasising the importance of considering life cycle stages in understanding effects of health shocks on labour market outcomes. Lundberg (1985) also found evidence of the added worker effect, as did Coile (2004) who used new cancer diagnoses. Similarly, McGeary (2009) using Health and Retirement Study (USA) found that the labour supply of both sexes was influenced first by their own health shocks, and secondly, by health shocks experienced by their spouses. Heath et al. (2019) found that in Ghana when a household member faced a health shock, men were 9 percentage points more likely to work during the family member's sickness. Risk averse men, those from relatively poorer households, and those with higher earnings in the household, were affected the most.

Using data from the Netherlands, Rellstab et al. (2020) examined the labour market effects of children following unexpected parental hospitalisation. The argument running through the study related to the understanding that when parents get hospitalised, children's labour supply is affected because they take up caregiving and invariably experience mental stress. The results showed no effects on earnings or employment for both men and women. Similarly, there were no effects on the full population as well as on the sub-sample of care givers. The study concluded that the Netherlands has an extensive public coverage of formal long-term care which is supported by well-established part-time work which presents an opportunity to avert any adverse health effects of members of the family without needing to negatively impact family labour supply.

Another important dimension has been the effect of ill-health and health shocks in the presence of social protection. Mommaerts et al. (2020) observed that the heterogeneous effects of hospital admissions on economic outcomes of older workers in USA, Europe and China could be explained by differences in social protection systems. Similarly, García-Gómez (2011) argued that the heterogeneous effects of health shocks on labour market outcomes found in the study of European countries could be explained by the variations in social security arrangements in different countries. Using the Health and Retirement Study of the USA Candon (2019) found that when health shocks and eligibility for social security were examined jointly, weekly hours were reduced by three to four hours. However, this only affected men and not women across age groups. Definitions of health shocks and sub-groups suggested that the results were driven by men who returned to work with impaired health. French (2005) empirically showed that in the United States, the tax structure of the social security system and pensions were key determinants of the observed high job exit rates at ages 62 and 65.

In summary, some key issues are discernible from past research on the effects of ill-health or health shocks on labour market outcomes. First, while this work is extensive it is heavily skewed towards developed countries with much less evidence coming from countries in Africa. Second, a variety of proxies have been used for ill-health and health shocks. Studies that have sought to understand the effects of ill-health on labour markets have resorted to using chronic diseases such diabetes, strokes, heart disease, cardiovascular diseases, poor mental health, psychiatric disorders, musculoskeletal diseases, and HIV/AIDS. Furthermore, in some cases, ill-health (Zucchelli et al., 2010) has been measured by self-assessed health limitations and self-assessed health (SAH). On the other hand, measures of health shocks have included illness or injury, hospital admissions, the on-set of chronic diseases, and accidents. Thirdly, with regards to labour market variables, studies have sometimes estimated the effects of these ill-health and health shocks on the probability of employment, wages or earnings, hours of work, entry into labour markets and labour market exit, while the probability of job search has rarely been examined. Fourthly, the focus of studies has been threefold. The most common has been to understand the effects of ill-health and health shocks on the labour markets outcomes of those directly experiencing ill-health with the elderly, the most researched demographic group. Additionally, work has also put emphasis on spousal effects. This involves testing the "added worker effect" which states that spouses will increase labour supply if their spousal partner faces ill-health or a health shock to protect their family income. Finally, the role of social security in the health-labour relationship has been pursued.

Given the variables in our data sets, the thesis has used suffering a chronic illness as a proxy for ill-health while illness/injury and hospitalisation have been used as measures of health shocks. The thesis has used the probability of employment, hours worked, and job search as labour market outcomes. There is value in using job search because this has hitherto not been commonly examined in previous studies.

With most of the work on the effects of ill-health or health shocks on labour market outcomes undertaken in developed countries, this thesis contributes to filling the gap regarding evidence on the health-labour relationship in LMICs. Developing countries have different characteristics of labour markets compared to developed countries and they tend to have high proportions of their workers in informal employment with generally inefficient and constrained social protection systems. In this regard there is an urgent need of an evidence-based narrative that resonates with these countries' economic structures and realities. Thus, the thesis takes a new and important step to analyse the effects of ill-health and health shocks on labour market outcomes in Malawi, a low-income country situated in Southern Africa. The country has an informal employment rate of 83 per cent, and an effective social protection rate of only 21.3 per cent (ILO, 2018). The country's GDP was severely affected by COVID-19, growing by only 0.8 per cent in 2020, exacerbating the many existing challenges in the labour market. One important consideration is whether the labour market impacts of ill-health and health shocks will share any similarity with those of the developed world, given the differing socio-economic and labour market contexts.

1.3 Theoretical Framework

Theoretically the Grossman model (1972) premised on Becker's (1965) household-production notion underpins the health-labour discourse (Tompa, 2002). Becker's argument is that utility is a function of final consumption as well as one's time as opposed to market goods and services. The Grossman model presents health or healthy time as embodying both the characteristics of a final consumption good as well as a capital good since it is an input in processes of production. The Grossman model is a presentation of the human capital theory whose prime argument is that an individual's knowledge stock and health, work to increase her productivity in market as well as non-market activities. Nevertheless, health capital affects these activities differently from other types of human capital. Specifically, health capital is associated with the availability of the total amount of healthy time. On the other hand, knowledge capital influences the productivity of the time spent on the activities (Tompa, 2002). In the model, there exist interactions between human capital types including education and health. Essentially education is correlated with efficiency of gross health investment while time preference is seen as an intermediating variable.

It is possible to characterize an individual's labour supply as a function of health through the Grossman model. In the model health is endogenously determined but education is exogenous. As expounded by Currie and Madrian (1999) health capital depreciates and needs continuous investment. Moreover, health is a vital feature of human capital, and an important input into market and non-market production at the individual level. Overall, health affects productivity in four ways (Bloom & Canning, 2000). Firstly, healthy individuals possess better physical status and energy allowing them to report to work more often. Secondly, there is an incentive for individuals with longer life expectancy to invest more in schooling potentially receiving better returns from their investments. Thirdly, given expectation of longer life, individuals react by increasing their savings for retirement. Finally, reduced fertility rates arising from better health and survival of young children, may induce higher rates of labour force participation. Potentially this would increase per capita income for working individuals.

As argued by Goryakin et al. (2014) the health and labour relationship is not a linear one and depends on how labour supply decisions are made with the effect ambiguous *a priori.* While an individual's improvement in health may reduce the incidence of illness and increase the availability of healthy time, whether a working individual will allocate some of the additional healthy time available to work or leisure is not clear. Consequently, whether the individual will increase labour supply or not cannot be determined *apriori*. Pintor et al. (2024) observe that since individuals pursue income for consumption as well as time for leisure, the outcome will be influenced by the balance between the counteracting substitution and income effects. The substitution effect occurs when improved health increases productivity and therefore earnings

of time that has already been allocated to work. The potential increase in earnings influences a rise in supply of labour. On the other hand, the income effect manifests itself when an individual is able to maintain the same amount of income due to increases in both productivity and earnings while working less time than before. Essentially this means that labour supply will only increase if and only the substitution effect offsets the income effect (Currie & Madrian, 1999; Pintor et al., 2024). Fundamentally, both increasing or reducing labour supply are a reflection of a welfare-enhancing behaviour when compared to the no health improvement scenario (Pintor et al., 2024). This will be born in mind in the interpretation of results of this thesis.

1.4 Approach

The study employs a quantitative research paradigm, under a positivist epistemology (Schrag, 1992), to explore the effect of ill-health and health shocks on labour market outcomes. This approach is amenable to the study at hand because it is premised on objectivism, empiricism and science (Park et al., 2020; Ryan 2024). Under the positivist epistemology, knowledge is discovered and not constructed by human beings (Ryan 2024). Positivism (Caldwell, 1980; Ryan 2024; Schrag, 1992) with its practice of objectivism, entails systematic testing of hypotheses using physical data, and concepts are operationalised to measurable units (Hausman, 2000). In the present study, concepts such as ill-health, health shocks and labour market outcomes have been operationalised and defined quantitatively to allow for quantitative data analysis. Ideally, a positivist epistemology allows focus, ensures credible analysis and the theoretical underpinning entails better control of the research process (Crossan, 2003; Scotland, 2012; Aliyu et al., 2014).

1.5 Structure of the thesis

This thesis is presented as three individual chapters. One of the chapters forms a systematic review and meta-analysis, while the other two are empirical research chapters. The chapters analyse an overlapping theme: ill-heath, health shocks, and labour markets. Each chapter has a specific conclusion and associated policy implications. Although this is the case, there is a chapter that presents the general conclusions and policy implications emanating from the three papers.

CHAPTER TWO

A systematic review and meta-analysis on the effects of ill-health and health shocks on labour market outcomes

2.1 Introduction

Work on ill-health and health shocks as they relate to labour markets has been on the increase. While ill-health may entail a long-term diagnosis such as a chronic disease, health shocks are unexpected negative events and illnesses that impact an individual's overall health status (Leive & Xu, 2008), manifesting themselves in different ways. They are known to disrupt conventional work by affecting the performance of tasks (Chirikos, 1993) and labour supply. Health shocks have been defined in a variety of ways in empirical studies. For instance, sudden illness or injury (Bonfrer & Gustafsson-Wright, 2016; Heath et al., 2019), the occurrence of accidents (Dano, 2005), and sudden drops in self-assessed health and the onset of chronic conditions (García-Gómez, 2011). On the other hand, ill-health has been exemplified by mental health (Layard, 2013), psychiatric disorders (Ettner et al*.,* 1997), diabetes (Rodríguez-Sánchez & Cantarero-Prieto, 2017; Seuring et al., 2019) and health limitations (Zucchelli et al., 2010) among other configurations.

Recently the COVID-19 crisis revitalised interest in the health-labour relationship. Unlike measuring the direct effects of a health shock such as injury, work on COVID-19 mainly focussed on the effects of policies adopted to curb the disease on labour market and other outcomes. In this sense, the approach was rather different from the approach this chapter takes. For instance, using the "policy-effects" approach, the ILO showed that in relation to the last quarter of 2019, in 2020 8.8 per cent of global working hours were lost due to COVID-19 related policies of work closures and social distancing. This translated into 255 million full-time equivalent jobs (ILO, 2021). Similarly, Gupta et al. (2020) showed that the USA employment rate fell by 1.7 percentage points for every extra 10 days that were subjected to social distancing. The OECD (2021) showed a total decline of online job vacancies of up to 50 per cent in Australia, Canada, New Zealand, the United Kingdom, and the United States - due to COVID-19 related policies.

The negative link between ill-health or health shocks on labour market outcomes not withstanding (Dobkin et al., 2018; Harris, 2009; Jones et al., 2020; Zucchelli et al., 2010), there are studies in which ill-health and health shocks have had a positive link with some labour market outcomes depending on context. Trevisan and Zantomio (2016) found that compared to women, men increased the number of hours worked by one hour per day following a health shock. Lenhart (2018) also found some evidence of increasing weekly hours worked after a health shock for individuals suffering mild shocks.

While empirical literature on the effects of ill-health and health shocks on labour market outcomes is vast, systematic reviews and particularly meta-analyses have been uncommon. Perhaps the closest to the topic is the study conducted by Pedron et al. (2019) who synthesised results on the link between diabetes and labour market participation. Thirty studies were included in the analysis and the results showed that diabetes-induced unemployment, early retirement, and receipt of disability pension. However, no meta-analysis was conducted. Alam and Mahal (2014) assessed the effects of health shocks on a household's level economic outcomes more broadly, including, the burden of out of pocket, spending for health, and supply of labour with an emphasis on LMICS. Again, no meta-analysis was undertaken. Similarly, Hayward et al. (2016) did not conduct a meta-analysis when they synthesised results of the impact of high functioning autism on labour force participation of females. Moreover, systematic reviews that were conducted in reference to the COVID-19 pandemic were mainly focused on health as an outcome and not labour markets (see for example Hatmi, 2021; Li [JW] et al., 2020; and Li [X] et al., 2020).

Therefore, the objective of this chapter is to produce pooled estimates of the effects of ill-health and health shocks on hours of work and the probability of employment. This provides three main contributions to the literature. First, it offers a comprehensive systematic review on the relationship between health and labour market outcomes. Second, it goes beyond a standard qualitative synthesis by performing a meta-analysis to quantify the combined effects of ill-health and health shocks on hours of work and probability of employment. This will be able to offer policymakers more accurate and credible evidence as pooled effects have the advantage of being based on larger sample sizes.

2.2 Methods

a) Identification of studies

The key electronic databases searched were EconLit and Medline. However, grey literature via ProQuest was also searched. A modified PICO search strategy based on the "working age" population that included persons aged 15 and older[1] was used. The intervention(s) were ill-health and health shocks, and the outcome of interest were hours worked and the probability of employment. Literature was searched based on the concepts of ill-health, health shocks and labour market outcomes. Relevant synonyms were used for these concepts. Ill-health and health shocks included illness, injury, disease, cancer, diabetes, HIV/AIDs, tuberculosis, stroke, heart attack, cardiovascular diseases, respiratory diseases, major depression, hypertension, myocardial infarction, and infectious diseases. Labour market outcomes included labour supply, earnings, wages, probability of employment, employment, hours worked, labour market, labour income, labour force participation, retirement (García-Gómez, 2011; Heath et al., 2019 and Jones et al., 2020). Free text words were utilised, and the search in Medline exploited major medical subject headings (MeSH). Boolean operators "OR" and "AND" were used. "OR" was used with synonyms within a particular concept. "AND" was utilised to combine the search results for different concepts. To further refine the search *wild cards* (Hayward et al., 2014), *proximity search* and *subject search* (including abstract and titles) were pursued. Further, truncation was applied on some search terms to ensure different forms were searched simultaneously. Furthermore, snowballing (Pedron, 2019, Preston et al., 2016) - which entails hand searching for more articles from bibliographies of selected papers - was employed to ensure a comprehensive set of articles. The search range was 2000 to 2021.

b) Inclusion criteria

Articles were included based on the following inclusion criteria:

i) Articles that had a clearly defined ill-health or health shock variable and hours worked, or the probability of employment as an outcome.

[1] The ILO definition of working age was adopted. See https://ilostat.ilo.org/resources/concepts-and-definitions/description-labour-force-statistics/.

ii) Articles that had utilised quantitative techniques to analyse the effects of ill-health and health shocks on hours worked and probability of employment including those that had used mixed methods if they had sufficient quantitative analysis involving ill-health or health shocks and hours worked, and probability of employment.
iii) There were no language restrictions.

c) Exclusion criteria

Papers were excluded according to the following criteria:

i) Articles that did not have a clear labour market outcome (hours of work and probability of employment) even if they had a clearly defined variable of ill-health or health shock.
ii) Articles that did not quantitatively analyse the effects of ill-health and health shocks on hours of work and probability of employment.
iii) Commentaries that only exposed some aspects of the ill-health or health shocks and labour supply relationship but did not have relevant extractable information.

d) Data extraction and tool

The study adapted a data extraction tool from the Joanna Briggs Institute (JBI)'s Reviewer's Manual (see Appendix 2A)[2]. The data extracted fell into five main categories. The first category involved study details, which included the study identification, the date of extraction, the title of the study, the author(s) of the study, the year of publication, and the journal in which the paper was published. The second category focused on the study methods, which included study aims, study design, study setting, recruitment of participants, study duration, study characteristics, outcome variable(s) and how they were measured, the key independent variables (ill-health and health shocks) and how they were measured, other independent variables and how they were measured, exposure of interest, ethical approval information, and methods of data analysis. Results formed the third category. This involved extracting information regarding descriptive statistics; regression methods used; coefficients and their

[2] The tool is obtainable at https://wiki.joannabriggs.org/display/MANUAL/5.5.7+Data+extraction.

signs, standard errors, confidence intervals, p-values; diagnostic tests undertaken; robustness checks; and results of sensitivity analysis. The fourth category included information regarding policy implications and subsequent recommendations.

e) Data analysis

A meta-analysis was undertaken (see Bosu et al., 2017; Bosu et al*.,* 2019; Higgins et al*.,* 2019; Pedron et al., 2019; and Petitti, 2000) to synthesise the results of the papers on the effects of ill-health and health shocks on hours worked and the probability of employment. Study characteristics were summarised using descriptive statistics and reported the relationship between ill-health or health shocks and labour market outcomes in bivariate and multivariate analyses. To determine effect size statistics or treatment effects, partial correlation coefficients (see, for example, Cipollina et al*.,* 2018; Heimberger, 2020; and Psaki et al., 2019) linking ill-health and health shocks to labour market outcomes were considered. Heterogeneity tests were conducted to determine the use of fixed effects versus random effects models (Bosu et al., 2017). Heterogeneity (Song, 1999) was explored using Cochrane's Q chi square test (Bosu, 2017; Higgins, 2003). However, due to the known challenges in detecting true homogeneity (Higgins, 2003) and its general low power (Song et al., 2001), this was complemented by the I^2 test (Bown & Sutton, 2010). Subsets of studies were separated to allow a more accurate analysis of the sources of heterogeneity in the effects of ill-health and health shocks on hours worked and the probability of employment and to estimate the pooled effect of ill-health and health shocks on hours worked and probability of employment. Meta-regressions were used to further explore the sources of heterogeneity and forest plots were employed to display point estimates and corresponding confidence intervals for individual studies and the summary statistics.

f) Publication bias (reporting bias)

First, funnel plots were used to assess publication bias. Thereafter, the Begg's test (Begg and Mazumdar, 1994; Sutton, 2000) was employed. Moreover, a *trim and fill* methodology (Sutton, 2000) was undertaken to further explore publication bias. The methodology of trim and fill entailed firstly, eliminating studies starting with the least powerful until funnel plot symmetry was achieved, and a new estimate produced; and secondly, reflecting the eliminated studies in the pooled estimate line, and putting in new studies.

g) Risk of bias tool

A risk bias tool for non-randomised studies called the ROBINS-I[3] developed by Sterne et al. (2016) was used (see McGuinness & Higgins, 2020). It contains seven domains: bias due to confounding, bias due to selection of participants, bias due to classification of interventions, bias due to deviation from intended interventions, bias due to missing data, bias in measurement of outcomes, and bias in selection of reported results. The tool gives options to assess the risk of bias of papers on each of these domains as critical, serious, moderate, low and no information. For papers included in this systematic review and meta-analysis, the risk of bias for most of the domains was adjudged to be low.

h) Overall quality of evidence

The Grading of Recommendations Assessment, Development, and Evaluation (GRADE) criteria were used to assess the overall quality of evidence (Bosu et al., 2017). The tool examines study design, risk of bias, consistency, directness, precision, and publication bias. The definitions of grades are given as very low, low, moderate, and high.

i) Calculation of effect sizes

Following the work of Cipollina et al. (2018), Heimberger (2020), and Psaki et al. (2019), partial correlation coefficients were used as effect sizes in this review. This required different conversions from a variety of models and their results into partial correlation coefficients.[4]

2.3 Results

2.3.1 Study flow and characteristics (PRISMA)

The PRISMA flow chart (Fig 2.1) shows four stages in the search process: identification, screening, eligibility, and inclusion. A total of 1,328 records were identified from both

[3] The tool is available at https://www.riskofbias.info/welcome/home.
[4] See Appendix 2B for the formulae used to convert coefficients into partial correlations.

databases (1,205) and those identified through other sources (123). A total of 778 duplicates were removed and 550 records remained. The 550 records were screened against titles and abstracts, and 472 papers were deemed irrelevant. The rejected articles, though topical had no explicit quantitative analysis undertaken. 78 papers were assessed to be eligible for the analysis. However, out of the 78 records, 59 articles were further excluded because although explicit quantitative analysis was made, the outcome variables were different from those of the focus of our work: hours worked, and the probability of employment. To this end, nineteen records were included in the quantitative synthesis or meta-analysis. Out of the nineteen records, eight articles analysed the effects of ill-health and health shocks on hours of work, while twelve records focused on the probability of employment. The eight papers in the analysis of hours of work contributed a total sample size of 117,656 and a total of 33 data points. On the other hand, papers that analysed the effects of ill-health and health shocks on the probability of employment produced a combined sample of 248,485 with data points totalling 25.

The rest of the results section is organised as follows: Sub-section 2.3.2 discusses the effects of ill-health and health shocks on hours worked and sub-section 2.3.3 presents results of the effects of ill-health and health on probability of employment.

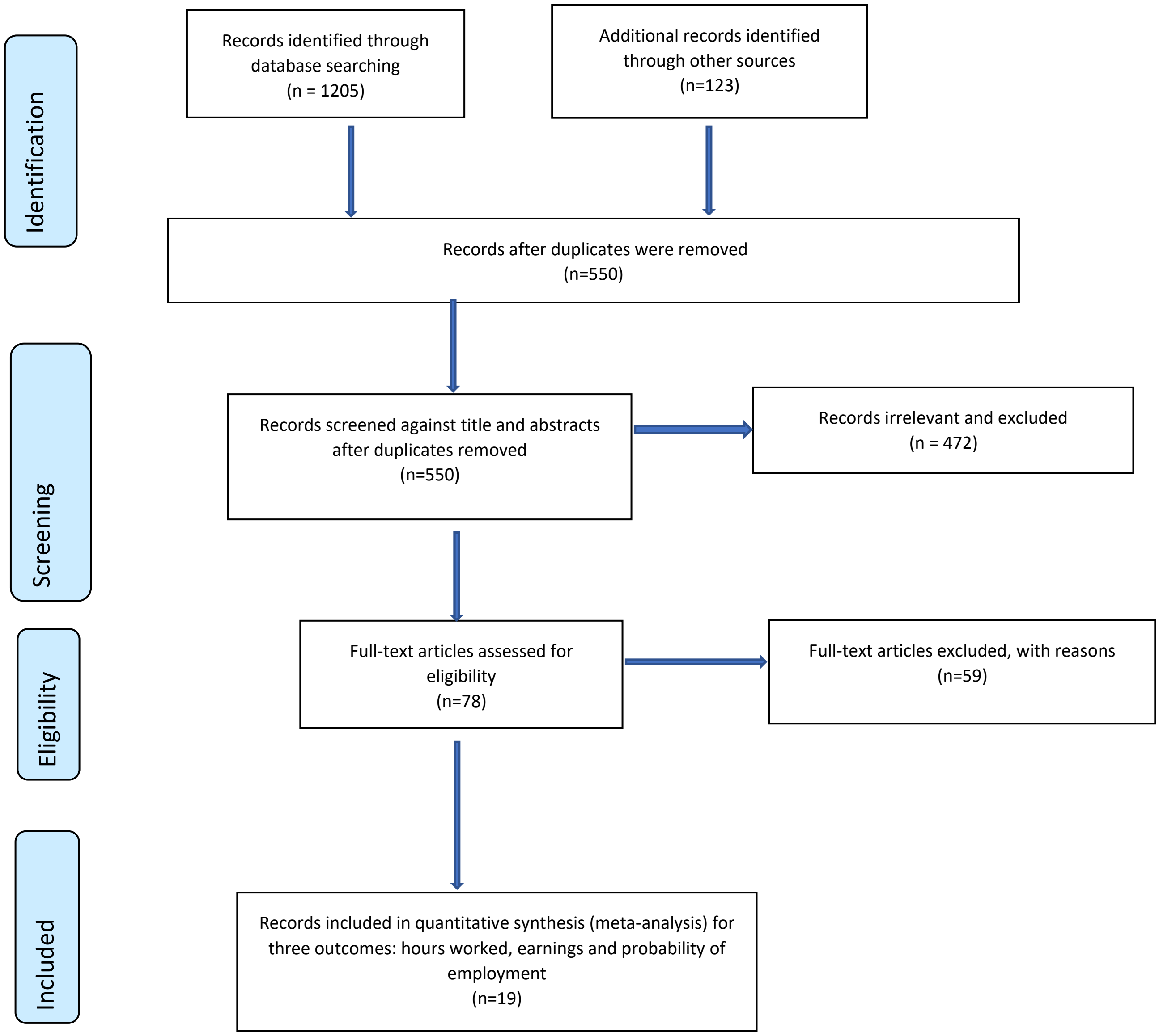

Figure 2. 1 PRISMA Flow Chart https://www.researchgate.net/figure/PRISMA-2009-flow-diagram-PRISMA-flow-diagram-for-study-selection-From-Moher-D_fig1_313582814

2.3.2 Effects of ill-health and health shocks on hours worked

a) Search results

Out of the nineteen papers retained, eight papers investigated the effect of ill-health and health shocks on hours worked. Papers by Bradley et al. (2002), Alam (2015), Shen et al. (2019), Kumara & Samaratunge (2018), and Candon (2019) used either multiple definitions of ill-health and health shocks or multiple samples and as such they were repeated in the analysis. Consequently, the eight papers in the analysis of hours of work contributed a total combined sample size of 117,656 and a total of 33 data points. Papers used different measures of ill-health and health shocks as shown in Table 2.1. Bradley et al. (2002) used breast cancer, diabetes, high blood pressure, heart disease, strokes, pulmonary hypertension, and depression. Andersen (2015) utilised severe mental disorders, while Kumara and Samaratunge (2018) used non-communicable illness including diabetes, heart disease, paralysis, cancer, asthma, mental illness, arthritis, and epilepsy. Rees and Sabia (2015) employed migraine headaches, while Alam (2015) made use of the experience of their own illness of their mother and father. Additionally, Shen et al. (2019) focused on spousal chronic illness while Candon (2019) and Rocco et al. (2011) looked at chronic diseases.

Table 2. 1: Measures of ill-health and health shocks used in the different studies

Author	Ill-health or health shock measure
Bradley et al. (2002)	breast cancer, diabetes, high blood pressure, heart disease, stroke, pulmonary hypertension, depression.
Andersen (2015)	severe mental disorders
Kumara & Samaratunge (2018)	non-communicable disease, diabetes, heart disease, paralysis, cancer, asthma, mental illness, arthritis, epilepsy.
Rees & Sabia (2015)	migraine headache
Alam (2015)	own illness of mother, own illness of father
Shen et al. (2019)	spousal chronic illness
Candon (2019)	chronic disease
Rocco et al. (2011)	chronic disease

Geographically, 50 per cent of the papers investigating the relationship between ill-health and health shocks on hours worked used data from developed countries. The USA dominated this category. Developing countries included China, Tanzania, Sri-Lanka, and Egypt.

Papers also used different econometric approaches. The majority, 62.5 per cent of the articles used the standard Ordinary Least Squares (OLS) regression technique. The remaining papers utilised natural experiments incorporating Propensity Score Matching and Difference-in-Differences methodologies. Different categories or groups were used. For instance, Bradley et al. (2002) included women conditional on working; Shen et al. (2019) analysed spousal chronic effects on women and husbands; and Alam (2015) concentrated on illnesses of parents and how these affected their working hours.

b) Overall effect size, sub-group effect sizes, and heterogeneity

(i) Overall effect size

The overall effect size for the effect of ill-health and health shocks on hours worked was estimated using a random effects model and is shown in Fig 2.2. The pooled estimate is negative and highly significant (partial r = -0.05, $p < 0.001$). This confirms that although individual studies may have differing results, their combined effect is negative. Some individual studies such as those conducted by Bradley et al. (2002); Andersen (2013); Rees and Sabia (2015); and Shen et al. (2019) produced positive coefficients as can be seen from Fig 2.2.

(ii) Sub-group effect sizes

An assessment of sub-group analyses regarding the effects of ill-health and health shocks on hours worked was conducted by geographical region, that is developed vs developing countries, by model type, and by the publication year. Fig 2.3 shows effect sizes pertaining to geography.[5] The pooled estimate corresponding to studies from developing countries is negative and highly significant (partial r = -0.09, 95% CI: [-0.15, -0.04]). Again, this shows that while there may be positive effects such as those seen in the results of studies conducted by Shen et al. (2019), the overall effect of ill-health and health shocks from combined studies from developing countries is negative and statistically significant. Similarly, a negative and highly significant pooled estimate corresponding to results from developed countries was found (partial r = -0.01, 95% CI: [-0.02, 0.01]).

[5] Studies from developing countries were assigned a value of 0 and those from developed countries were assigned a value of 1.

In terms of model type[6] (Fig 2.4) the effect size produced by the papers that used the OLS regression formulation was negative and highly statistically significant (partial r = -0.02, 95% CI: [-0.05, -0.00]). Similarly, the pooled estimate associated with non-OLS regression models was negative and statistically significant (partial r = -0.09, 95% CI: [-0.16, -0.03]). This shows that irrespective of the type of model used the combined effects relating to ill-health and health shocks on hours worked is negative. Further, as captured in Fig 2.5 effect sizes relating to the publication years of 2002, 2011, 2016, 2018, and 2019 were all statically significant as shown by the 95% confidence intervals where all pooled estimates fell within the intervals.

[6] Studies that used OLS were assigned a value of 0 and those that used other techniques were assigned a value of 1.

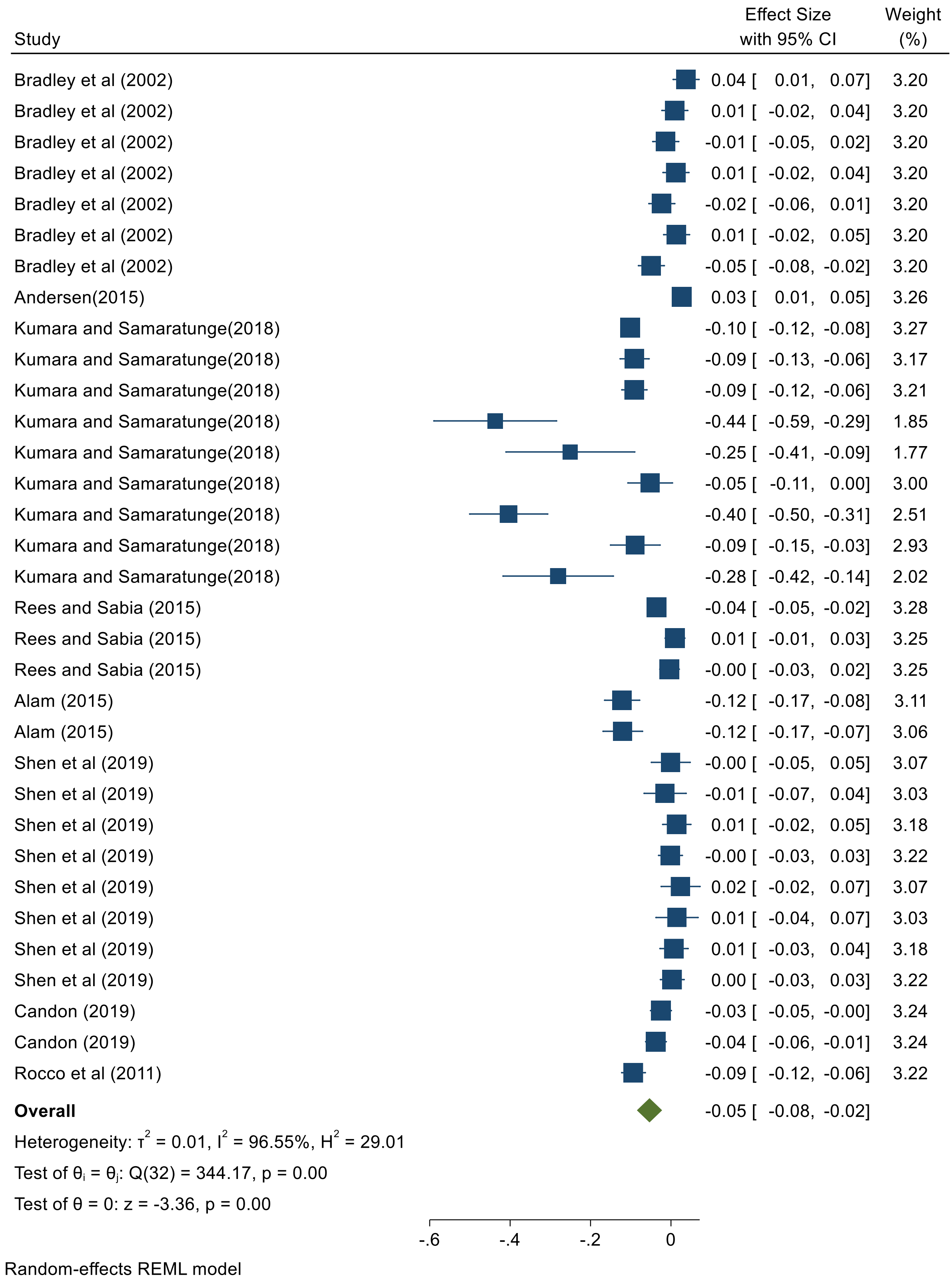

Figure 2. 2 Effect sizes of ill-health and health shocks on hours worked.

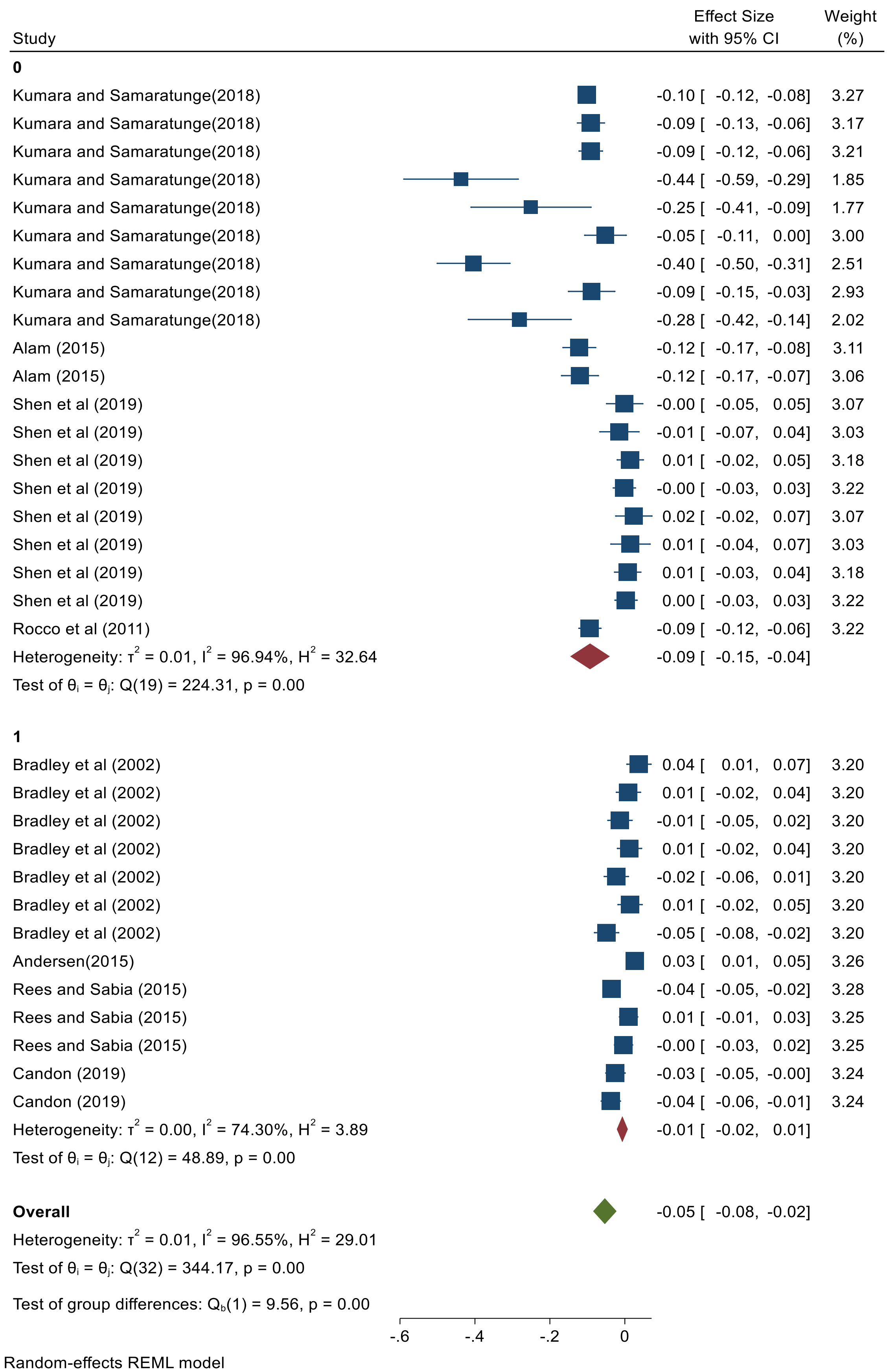

Figure 2. 3 Effect sizes of ill-health and health shocks on hours worked by geographical region.

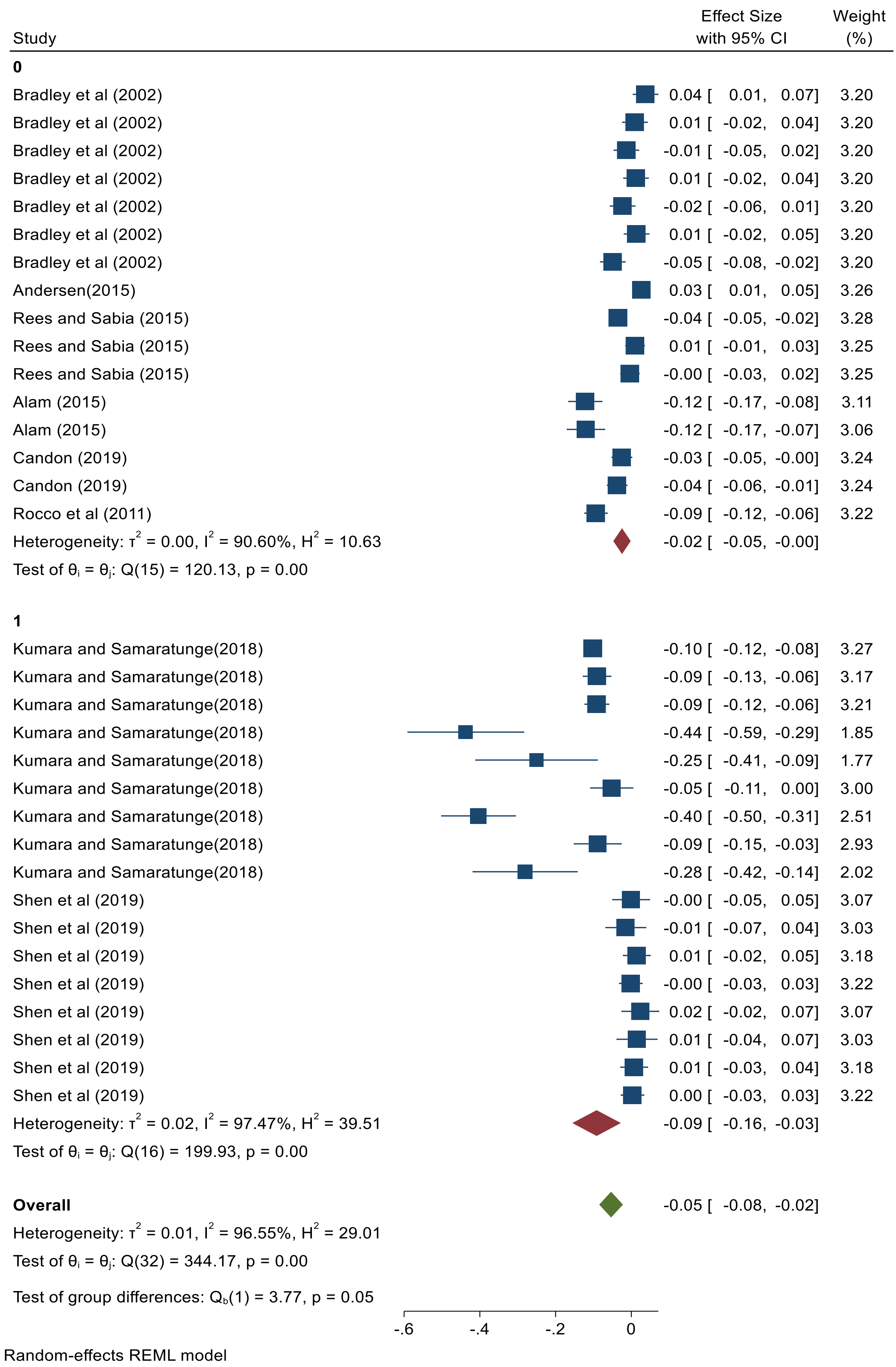

Figure 2.4 Effect sizes of ill-health and health shocks on hours worked by type of model used.

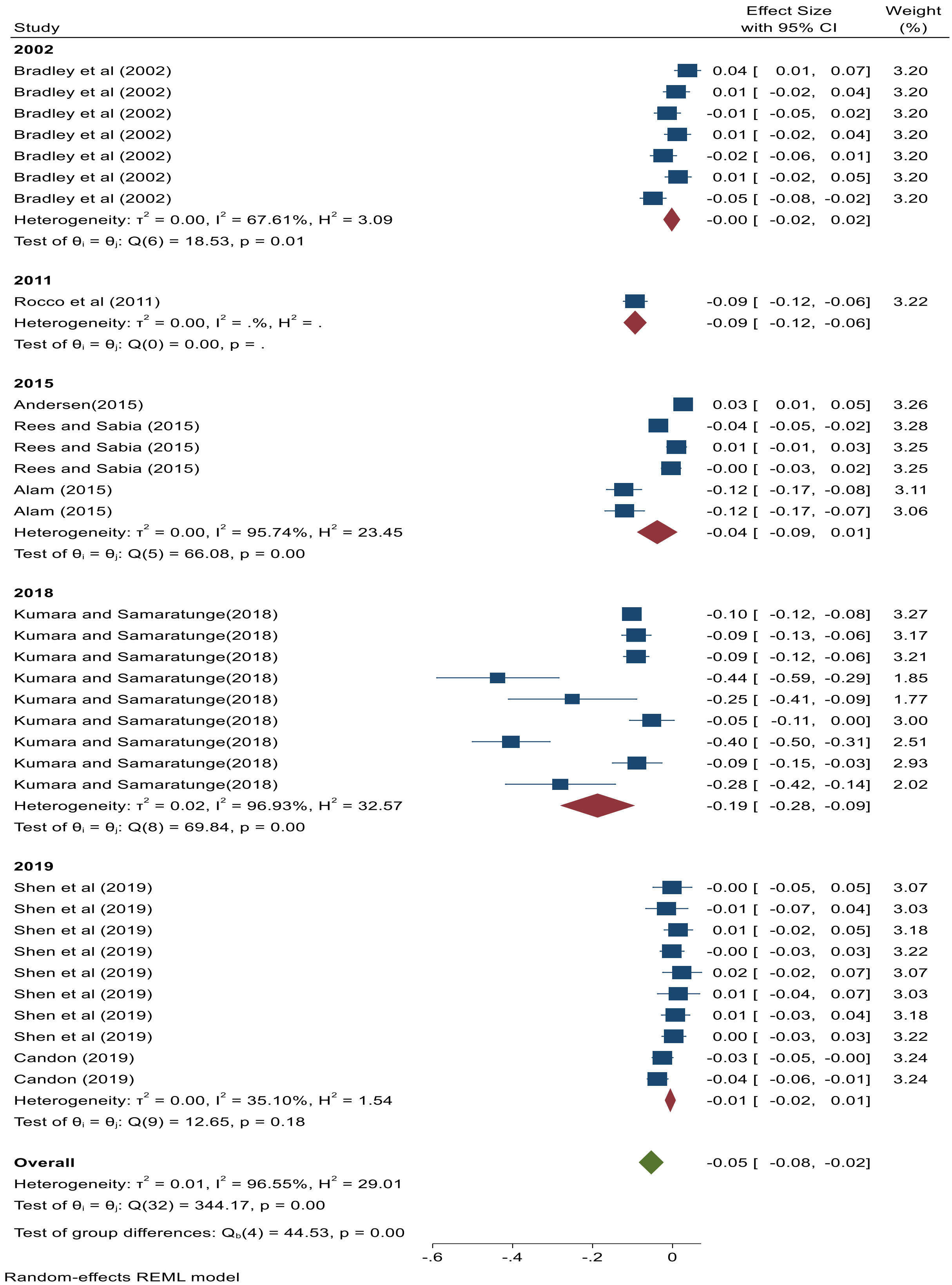

Figure 2. 5 Effect sizes of ill-health and health shocks on hours worked by publication year

(iii) Heterogeneity

When the random effects model for the overall pooled estimate (Fig 2.2) was considered, substantial heterogeneity was observed among studies. This is evidenced by the Q statistic which has a value of 344.17 ($p < 0.001$) showing high statistical significance. This was further confirmed by results of the I^2 test which showed 96.6% of variability across studies.

In the sub-group analysis by region (Fig 2.3), considerable heterogeneity coming from studies from developing countries was observed. These studies exhibited an I^2 value of 96.94% with a Q statistic value of 224.31 ($p < 0.001$) compared to an I^2 value of 74.3% with a Q statistic value of 48.9 ($p < 0.001$) exhibited by studies from developed countries. These results imply considerable heterogeneity among studies in the sub-groups. Region or geography was therefore found to be an important source of heterogeneity. The test of group differences also displayed a highly significant Q statistic, implying that the two groups were significantly different.

In as far as the distinction between model types is concerned (Fig 2.4) while both categories showed high heterogeneity, studies that used quasi-experimental designs exhibited more variability than those that were OLS based. Concerning the articles that employed quasi-experimental designs the I^2 value reported was 97.5% with a Q statistic value of 199.93 ($p < 0.001$) compared to 90.6% for OLS based studies with a Q statistic value of 120.13 ($p < 0.001$). From the results, both sub-groups exhibited considerable heterogeneity among studies. In this sense, model type was an important source of heterogeneity. Furthermore, the test for group differences showed that significant differences existed between the two groups.

Publication year was also a significant source of heterogeneity (Fig 2.5). Papers published in 2018 were responsible for the highest level of heterogeneity, followed by 2002 studies, and 2015 studies, in that order. Papers authored in 2019 accounted for only 35.1% of variability while there was only one paper published in 2011 whose contribution was negligible. The test of group differences also showed statistically significant differences across years.

To further explore the sources of heterogeneity, multivariate (Table 2.2) and univariate (Table 2.3) meta-regressions were estimated using sample size, geography, model type and year of publication as covariates (see for example Bosu & Bosu, 2021; Bosu et al., 2019; and Baker et al., 2009). The results of multivariate meta-regression showed that no variable was responsible for heterogeneity. However, univariate meta-regressions revealed that geography, sample size model type and publication year were significant sources of heterogeneity. The coefficient of geography was positive and highly significant (at 1% level) while those of sample size, model type and publication year were only significant at the 10% level. Thus, considering both the sub-group analyses and univariate meta-regressions - geography, model type, sample size, and publication year were all significant sources of heterogeneity.

Table 2. 2: Multivariate Meta Regression: Random-effects meta-regression

meta_es	coef	z	P>|z|
Cons	1.964 (7.013)	0.28	0.779
Publication Year	-0.001 (0.003)	-0.30	0.765
Model type	0.042 (0.059)	0.71	0.480
Sample size	5.75e-06 (6.83e-06)	0.84	0.400
Geography	0.090 (0.067)	1.49	0.136

Test for residual homogeneity: Q res = chi2(28) = 218.08   Prob> Q res =0.0000
Note: The number of observations is 33 with a combined total sample size of 117,656
Note: Figures in parentheses are standard errors
Note: Values in the table were rounded off to three decimal places.

Table 2. 3: Univariate Meta Regression: Random-effects meta-regression

meta_es	geography	sample size	publication year	model type
Cons	-0.085 *** (0.019)	-0.093*** (0.027)	7.471 (4.731)	-0.057* (0.031)
Coef	0.079*** (0.029)	0.099* (0.0568)	-0.004* (0.002)	-0.026* (0.014)

***P<0.01, ** P<0.05, * P<0.1
Note: The number of observations is 33 with a combined total sample size of 117,656
Note: Figures in parentheses are standard errors
Note: Values in the table were rounded off to three decimal places.

c) Reporting bias

Reporting bias was explored in three ways: through a funnel plot, Begg's test, and a trim-and-fill technique. The results of the funnel plot (Fig 2.6) showed that there could be some level of asymmetry since not all dots representing studies fell under the limits of the lines representing the pseudo 95% confidence intervals. However, the Begg's test (Table 2.4) failed to reject the null hypothesis of "no small study effects". This result was supported by the trim-and-fill approach when imputed on the right (Table 2.5), which adjusted the pooled effect estimates to account for funnel plot asymmetry and showed no evidence of reporting bias, as the imputed value was 0, while the effect size for the "observed" and the "observed + imputed" remained the same at -0.053. Given these results, it can be concluded that there were "no small-study effects" when the trim-and fill followed imputation to the right. However, results of the Begg's test were contradicted by the trim-and-fill approach when imputed to the left (Table 2.6) which shows seven imputed studies adjusting the number of studies to 40 and having a significant effect size of -0.76 (95%CI: -0.106, -0.045). With the Begg's test and the trim and fill imputation to the right showing absence of publication bias, and the funnel plot along with the left imputed trim and fill signalling some level of publication bias, it can be argued that there was no substantial publication bias.

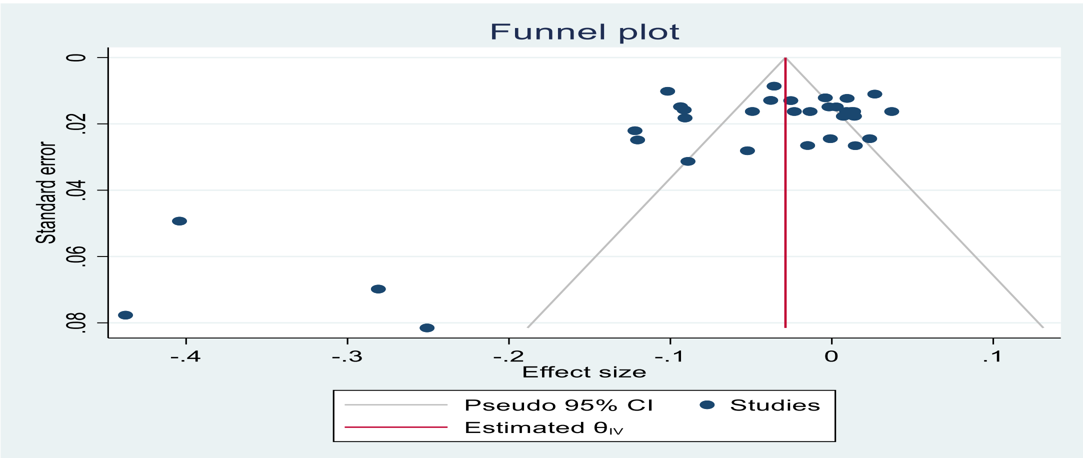

Figure 2. 6 Funnel Plot for the effect of ill-health and health shocks and hours worked.

Table 2. 4: Results of Begg's tests for small-study effects

Begg's Test		
Kendall's Score	**Z**	**Prob > |z|**
-120.00 (64.539)	-1.86	1.939

****P*<0.01, ** *P*<0.05, * *P*<0.1

Table 2. 5: Nonparametric trim-and-fill analysis of publication bias, linear estimator, imputing on the right: random effects model

Number of studies	Observed	Imputed
33	33	0
Studies	**Effect Size**	**95% Conf. Interval**
Observed	-0.053	(-0.085, -0.022)
Observed + Imputed	-0.053	(-0.085, -0.022)

Table 2. 6 : Nonparametric trim-and-fill analysis of publication bias, linear estimator, imputing on the left: random effects model

Number of studies	Observed	Imputed
40	33	7
Studies	**Effect Size**	**95% Conf. Interval**
Observed	-0.053	(-0.085, -0.022)
Observed + Imputed	-0.076	(-0.106, -0.045)

d) Discussion

Understanding how ill-health and health shocks relate to hours worked by individuals is a vital area of work in the health-labour relationship. Apart from directly influencing earnings or incomes, hours of work are an important issue in relation to the quality of work. Several studies have assessed the effects of ill-health and health shocks on hours of work. Some of these studies include those conducted by Seuring et al. (2019) who found that diabetes reduced hours of work among workers in Mexico; Ettner et al. (1997) who observed that psychiatric disorders were associated with reductions in hours of work; and Frijters et al. (2010) who found a negative effect of mental health on hours worked, among others. While most papers have found a negative link between ill-health/health shocks and hours of work, some studies have established contrary results. For instance, Trevisan and Zantomio (2016) found that men increased the number of hours worked following a health shock, while Lenhart (2018) observed increases in hours worked after mild shocks.

Given the rather mixed results in the literature regarding the relationship between ill-health/health shocks and hours of work, the results of this sub-section of the systematic review and meta-analysis are crucial. The negative statistically significant pooled estimate (partial $r = -0.05$, $p < .001$) signifies that although some effects could be positive in this relationship, overall, we expect a negative relationship between ill-health/health shocks and hours of work. The sub-group analysis in terms of developing and developed countries also showed negative highly significant coefficients of pooled estimates. This consensus is significant to the way the relationship between ill-health/health shocks and hours of work could be viewed both in developing and developed worlds. It is also important to note the higher heterogeneity among studies from developing countries ($I^2 = 96.94\%$; $Q=224.3$, $p<0.001$) compared to those from developed countries ($I^2 = 74.3\%$; $Q=48.89$, $p<0.001$). This may signal an issue needing further investigation in the way we look at the health-labour relationship in developing and developed countries.

The pooled estimates of the relationship between ill-health/health shocks and hours of work were also negative and statistically significant in relation to model type. Those papers that used models other than OLS such as quasi-experimental methods were associated with a pooled estimate of -0.09 ($p < 0.001$) while those that employed OLS were associated with a pooled estimate of -0.02 ($p < 0.001$). Additionally, there was higher heterogeneity among studies that employed models other than OLS compared to those that used OLS. This may signal that econometric techniques used are an important factor in understanding the health-labour relationship as well as heterogeneity. The year of publication was found to be an important factor too with each year being associated with a significant estimate. Wide heterogeneity was observed as well.

Undoubtedly, an important innovation in this work was to undertake meta regressions to further explore heterogeneity beyond sub-group analysis. The results showed that although in a multivariate setting no variable seemed to be responsible for the heterogeneity, a consideration of univariate regressions revealed that the coefficient of geography was positive and highly significant at the 1% level, while the coefficients of sample size, publication year, and model type were only marginally significant (at 10% level). This is an important result which works to signal that when undertaking multivariate regressions in meta studies, a closer look at individual univariate effects may help unravel aspects of the relationship that may be hidden in the broader analysis.

More importantly the negative and significant estimated effect sizes signal the relevance of the relationship between health and labour and show that ill-health and health shocks play an important role in this relationship. While no causality is assumed, the results may imply that policy interventions aimed at containing losses in hours of work should consider the negative effects of ill-health and health shocks on hours worked. The results highlight the importance of instituting social protection policies, disability benefits, and unemployment benefits to cushion losses in working hours.

e) Conclusion

In this sub-section, a systematic review and meta-analysis on the effects of ill-health and health shocks on hours worked was undertaken. Using the meta-analysis, negative statistically significant effect sizes of the effect on ill-health and heath shocks on hours of work were established overall. Moreover, negative statistically significant effect sizes in sub-groups involving developed countries, developing countries, OLS based models, non-OLS based models, and publication years were found. It is indicative, therefore that results of this meta-analysis, which used a large, combined data set, seem to reliably confirm that ill-health and health shocks reduce hours of work. In relation to heterogeneity across studies, substantial heterogeneity characterising the overall effects as well as in sub-groups was found. Moreover, meta regressions as well sub-group analyses revealed that geography, sample size, model type and publication year were significant sources of heterogeneity. The results are novel in that this is probably one of the few meta-analyses on the topic of health and hours worked, directly filling the gap regarding the understanding of the pooled effects of ill-health and health shocks on hours worked. The study may be relevant for understanding policies regarding social protection, disability allowances and other relevant policies emanating from the health-labour relationship but more importantly relating to the effects of ill-health and health shocks on hours worked.

2.3.3 Effects of ill-health and health shocks on the probability of employment

a) Search results

From the nineteen papers that satisfied the inclusion criteria, twelve papers investigated the effects of ill-health and health shocks on the probability of employment. The twelve papers contributed a total of 25 data points culminating into a total combined sample size of 248,485. This is mainly because authors such as Schofield et al. (2013), Wang et al. (2014), and Kumara and Samaratunge (2018) utilised different versions of exposures that define ill-health and health shocks. The different health shock exposures used are given in Table 2.7. Schofield et al. (2013) used one chronic condition, two chronic conditions, three chronic conditions, and four or more chronic conditions. Jarl et al. (2020) used common mental disorders, Bates et al. (2018) employed chronic conditions, and Carter et al. (2013) used hospitalisation and cancer. Pedersen et al. (2014) used long term sickness, Goryakin et al. (2014) used ill-health, Wang et al. (2014) utilised both chronic disease and depression. Kumara and Samaratunge (2018) used diabetes, heart disease, paralysis, cancer, asthma, mental illness, arthritis, García-Gómez et al. (2013) used acute hospitalisation, and Rocco et al. (2011) used chronic disease. Furthermore, Schuring et al. (2013) employed perceived ill-health while Van den berg et al. (2010) used chronic disease.

Table 2. 7: Ill-health and health shock exposures used by authors

Author	Exposure
Schofield et al. (2013)	1chronic condition, 2 chronic conditions, 3 chronic conditions, 4 or more chronic conditions
Jarl et al. (2020)	common mental disorders
Bates et al. (2018)	chronic condition
Carter et al. (2013)	hospitalisation or cancer
Pedersen et al. (2014)	long term sickness
Goryakin et al. (2014)	ill-health
Wang et al. (2014)	chronic disease, depression, both chronic disease and depression
Kumara & Samaratunge (2018)	any non-communicable disease, diabetes, heart disease, paralysis, cancer, asthma, mental illness, arthritis
García-Gómez et al. (2013)	acute hospitalisation
Rocco et al. (2011)	chronic disease
Schuring et al. (2013)	perceived ill-health
Van den berg et al. (2010)	chronic disease

In terms of geography, papers covered both developing and developed countries. Most of the papers (56 per cent) used data from developing countries including China, Sri-Lanka, and Egypt. Developed countries included Australia, Sweden, New Zealand, Countries of the former Soviet Union, the Netherlands, and some countries belonging to the European Union.

Varying estimation methods and designs were employed. Up to 48 per cent of the relationships were analysed through logistic regressions with odds ratios duly reported. 40 per cent utilised quasi-experimental designs focusing particularly on propensity score matching and average treatment effects. Papers comprising 8 per cent used standard Ordinary Least Squares while only 4 percent employed a cox proportional hazard approach.

b) Overall effect size, sub-group effect sizes, and heterogeneity

i) Overall effect size

A random effects model was employed to estimate the overall effect size (Fig 2.7). The value of the effect size was -0.09 ($p = 0.01$) and was significantly different from zero. This was the case even when some studies exhibited positive effect sizes. These included those conducted by Jarl et al. (2020); Wang et al. (2014); Schuring et al. (2013) and Van den berg et al. (2010). The negative pooled estimate confirmed that when results of individual studies are combined, the effect of ill-health and health shocks on the probability of employment is negative and statistically significant.

ii) Sub-group effect sizes

In terms of sub-group analysis, the effect sizes or pooled estimates by region, model type and publication year were assessed. Fig. 2.8 shows effect sizes of ill-health and health shocks on the probability of employment by geography[7]. Results of papers from developing countries showed a pooled estimate of -0.13 (95% CI: [-0.23, -0.03]) which was significantly different from zero. Similarly, papers from developed countries produced a negative significant pooled estimate of -0.05 (95% CI: [-0.14, 0.04]).

Using model type (Fig 2.9)[8], both groups produced a negative significant pooled estimate. Studies employing OLS were associated with a pooled estimate of -0.04 (95% CI: [-0.10, -0.03]). On the other hand, studies that used non-OLS based models produced a pooled estimate of -0.15 (95% CI: [-0.26, -0.04]). Moreover, in terms of publication year, all effects sizes corresponding to years 2010, 2011, 2013, 2014, 2018, and 2020 were significantly different from zero as observed from the 95 per cent confidence intervals. The test of group differences also showed significant differences across years.

iii) Heterogeneity

When the random effects model for the overall pooled estimate (Fig 2.7) was considered, substantial heterogeneity was observed among studies. This is evidenced by the Q statistic value of 3806.53 ($p < 0.001$) showing high statistical significance. This was further confirmed by results of the I^2 test which showed 99.5% of variability across studies.

[7] Studies from developing countries were assigned a value of 0 and those from developed countries were assigned a value of 1.
[8] Here studies that used OLS were assigned a value of 1 and those that used other techniques were assigned a value of 0.

When seen in terms of heterogeneity, both sub-groups (papers from developed countries and developing countries), exhibited very high values of I^2 and presented significant sub-group Q statistics (Fig 2.8). Studies from developed countries were associated with an I^2 value of 99.6 per cent and a Q statistic value of 3409.54 ($p < 0.001$). Studies from the developing world were associated with an I^2 value of 98.17 percent and a Q statistic value of 148.97($p < 0.001$). Region therefore is seen to be an important source of heterogeneity.

Regarding model type (Fig 2.9), models using non-OLS based methods exhibited an I^2 value of 99.4 per cent and a Q statistic value of 438.94 ($p < 0.001$) while those that used OLS produced an I^2 value of 98.9 per cent and a Q statistic value of 3806.53 ($p < 0.001$). This implied high heterogeneity within both sub-groups. The results mean that model type is an important source of heterogeneity among studies. Further, group differences by model type (Fig 2.14) were found significant at the 10 per cent level.

In terms of the year of publication (Fig 2.10), group differences showed a significant statistic indicating significant sub-group difference. Judging by Q statistics, years of publication 2018 (Q=125.28, p<0.001), 2013(Q=344.82, p<0.001), and 2014 (Q=10.21, p=0.04), in that order dominate as sources of heterogeneity. I^2 values were also high for 2018 (I^2=99.03%), 2013 (I^2=98.45%) and 2014 (I^2 =94.56%). I^2 values for 2010, 2011, and 2020 were not calculated and the Q values were given as zero.

To further assess the sources of heterogeneity, meta regressions were estimated using publication year, model type, sample size, and geography as independent variables. Multivariate meta regressions showed no significant moderators (Table 2.8). However, univariate meta regressions (Table 2.9) revealed that model type was statistically significant at the 10 per cent level. Sample size, geography and publication year were not significant in the univariate meta-analysis. Considering both the sub-group analysis and the meta regression geography, model type, and publication year were important sources of heterogeneity among studies that investigated the relationship between health shocks and the probability of employment.

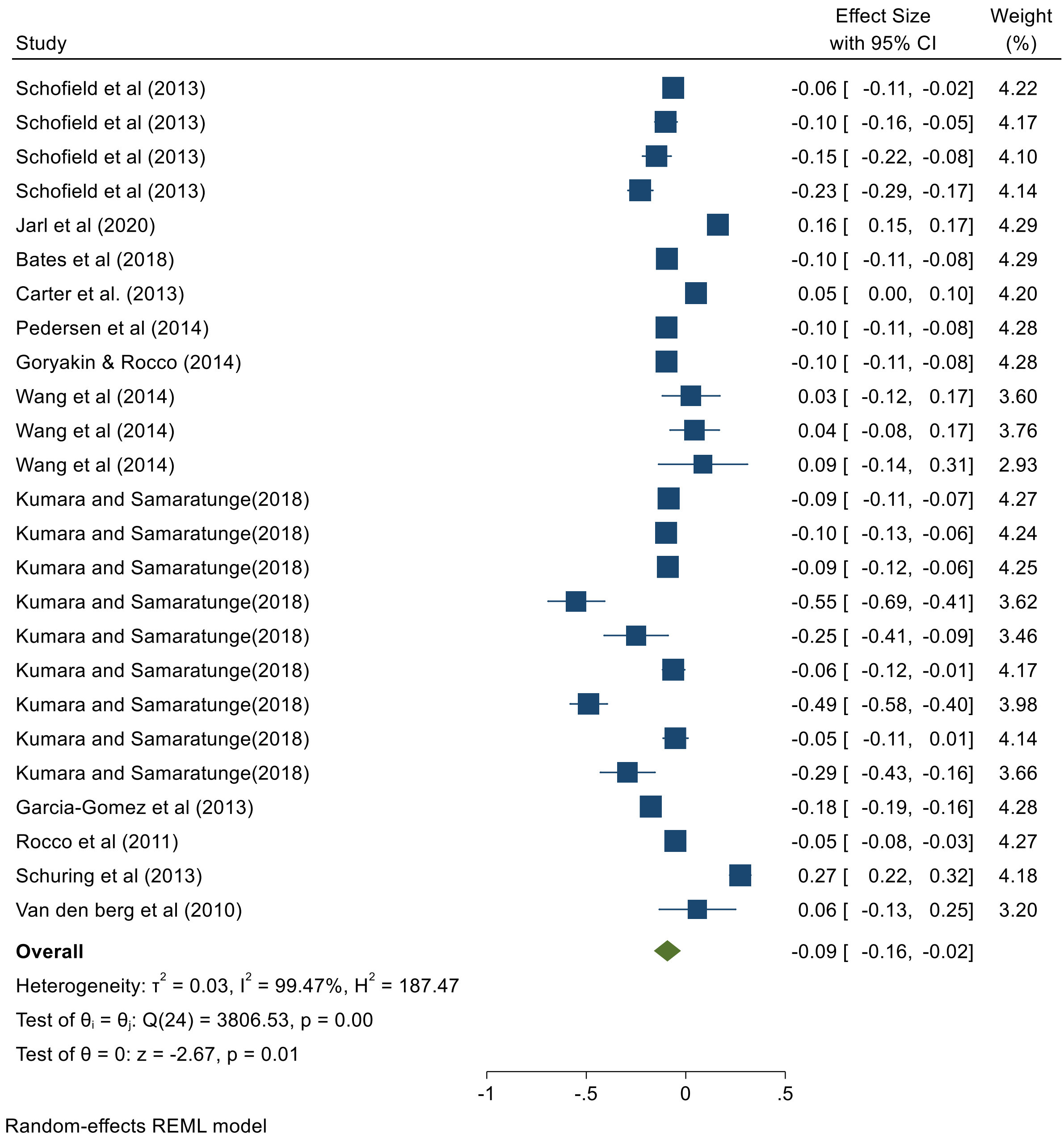

Figure 2. 7 Effect sizes of the ill-health and health shocks on the probability of employment

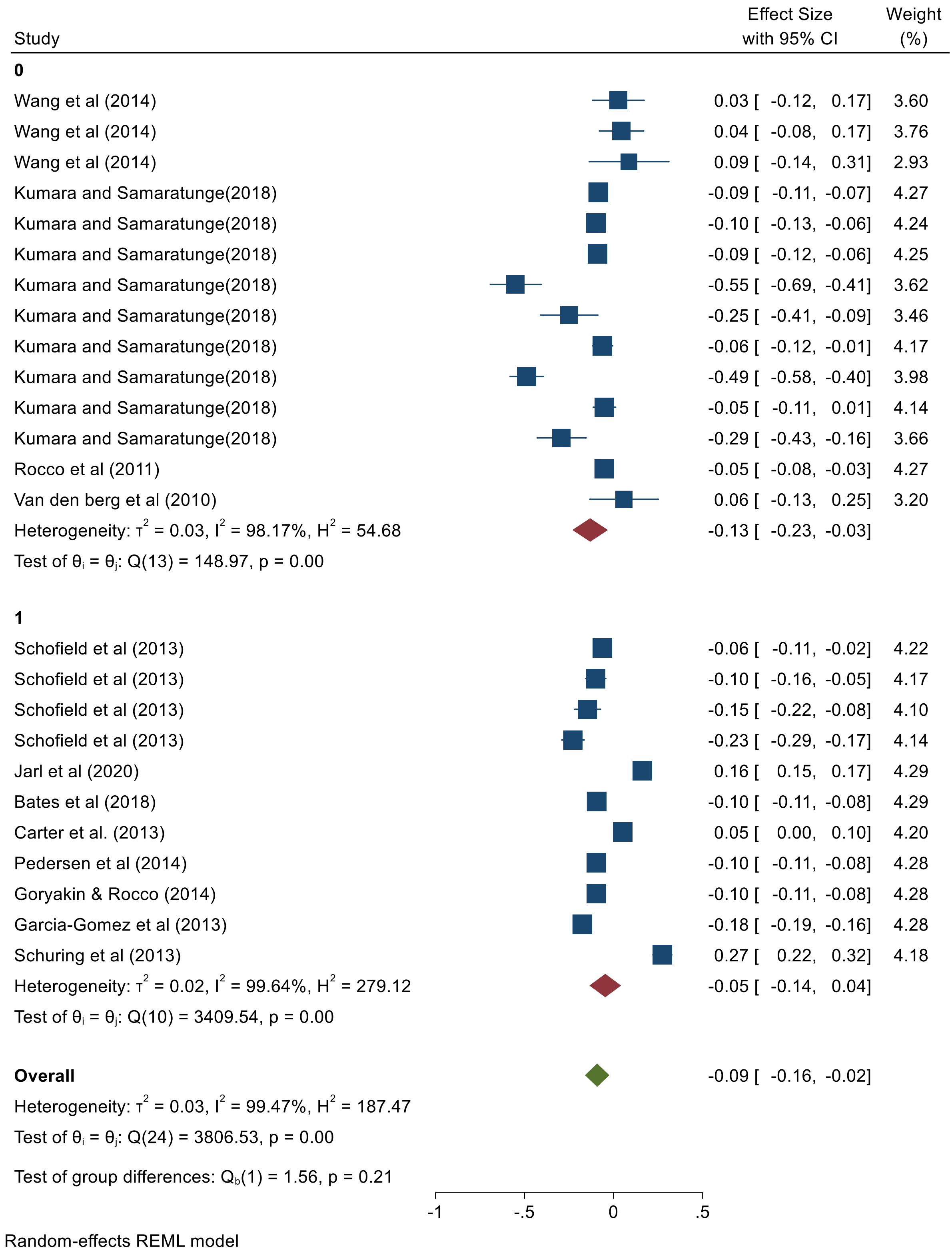

Figure 2.8 Effect sizes of the effects of ill-health and health shocks on probability of employment by geography

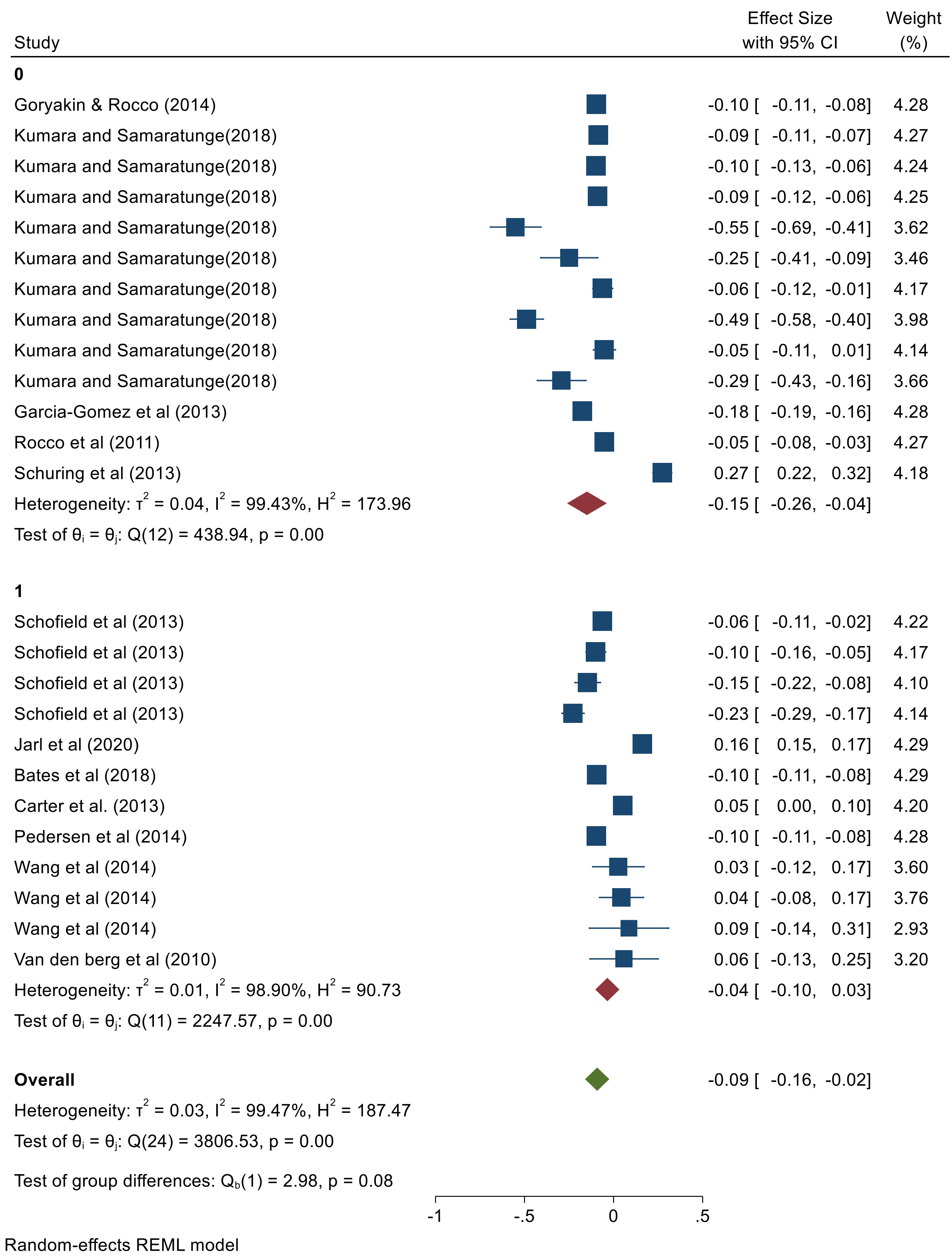

Figure 2. 9 Effect sizes of the effects of ill-health and health shocks on probability of employment by model type

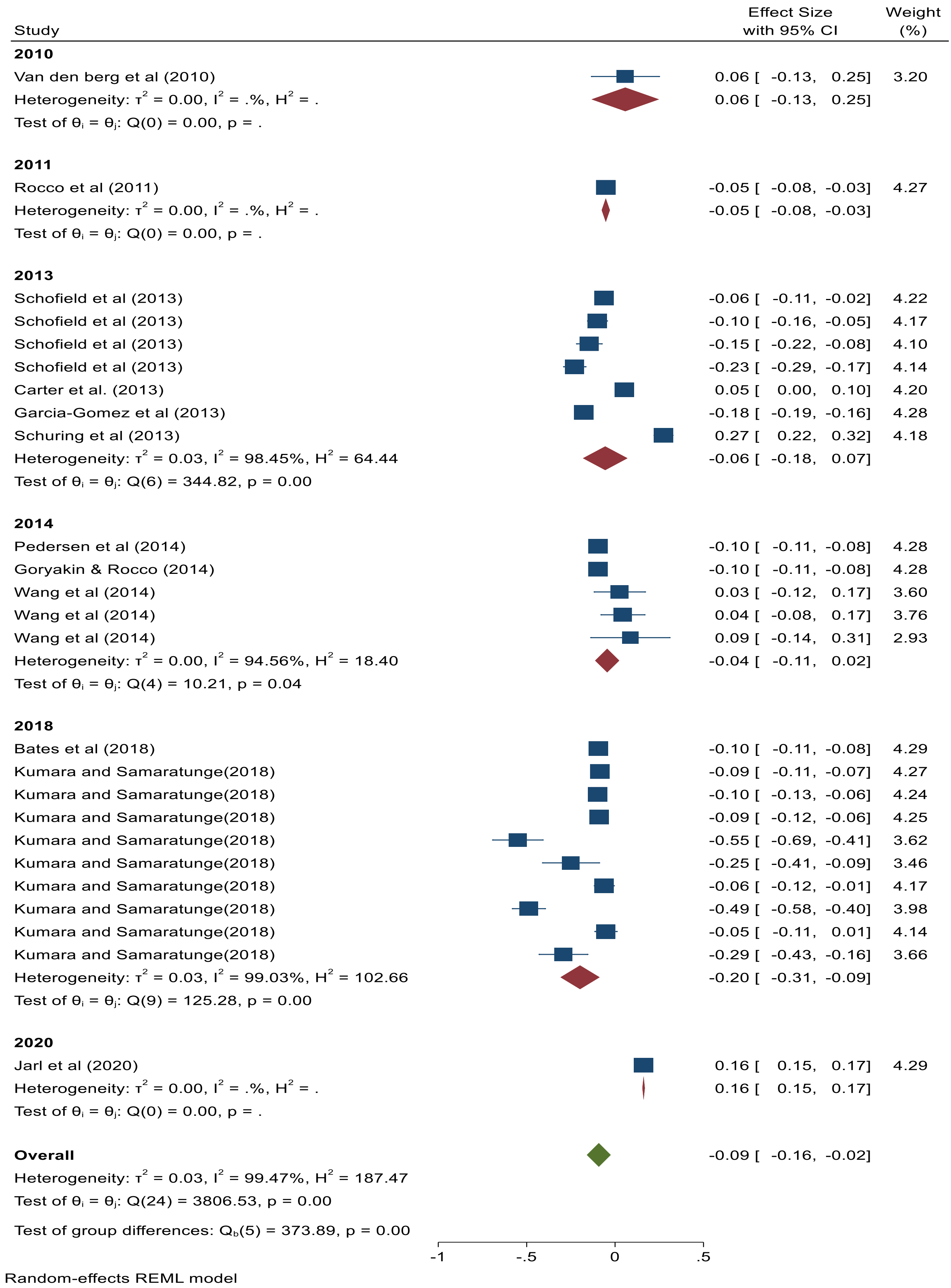

Figure 2. 10 Effect sizes of the effects of ill-health and health shocks on probability of employment by publication year

Table 2. 8: Multivariate Meta Regression: Random-effects meta-regression

meta_es	coef	z	P>|z|
Cons	41.144 (32.943)	1.25	0.212
Publication Year	-0.020 (0.016)	-1.25	0.210
Model type	0.056 (0.084)	0.67	0.504
Sample size	2.41e-06 (2.21e-06)	1.09	0.276
Geography	- 0.025 (0.092)	-0.27	0.789

Test for residual homogeneity: Q res = chi2(28) = 1189.86 Prob> Q res =0.0000
Note: The number of observations is 25 with a combined total sample size of 248,485.
Note: Figures in parentheses are standard errors.
Note: Values in the table were rounded off to three decimal places.

Table 2. 9: Univariate Meta Regression: Random-effects meta-regression

meta_es	geography	sample size	pub year	model type
Cons	-0.132*** (0.047)	-0.112*** (0.039)	37.436 (25.253)	-0.147*** (0.046)
Coef	0.085 (0.068)	1.90e-06 (1.69e-06)	-0.019 (0.013)	0.116* (0.067)

****P*<0.01, ** *P*<0.05, * *P*<0.1
Note: The number of observations is 25 with a combined total sample size of 248,485.
Note: Figures in parentheses are standard errors.
Note: Values in the table were rounded off to three decimal places.

c) Reporting bias

The funnel plot (Fig 2.11) shows some evidence of asymmetry, and this is supported by the Begg's test (Table 2.10) which gives a significant Kendall's score. However, the trim-and-fill approach (Table 2.11) of publication bias when imputed to the right showed no evidence of publication bias. On the other hand, when imputed to the left, the trim-and-fill approach (Table 2.12) produced six imputed studies increasing the number of studies to 31 with an associated

“Observed + Imputed” value of -0.092 (95%CI:[-0.160, -0.024]). Overall, these results mean that that there is some level of publication bias.

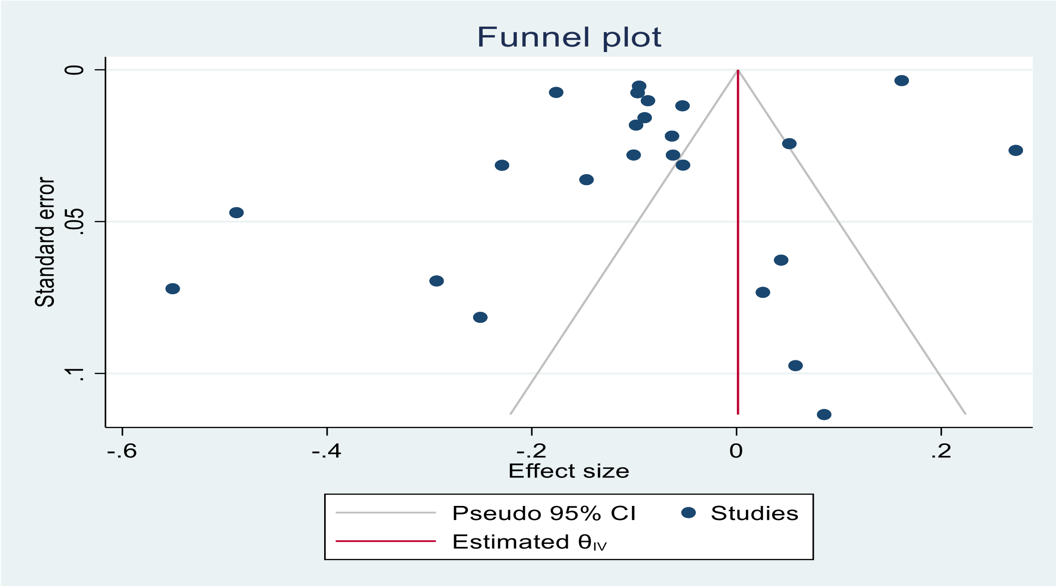

Figure 2. 11 Funnel Plot for Health Shocks and the probability of employment

Table 2. 10: Results of Begg’s tests for small-study effects

Begg’s Test		
Kendall’s Score	**Z**	**Prob > |z|**
101.00*** (42.794)	2.34	0.0195

***P<0.01, ** P<0.05, * P<0.1

Table 2. 11: Nonparametric trim-and-fill analysis of publication bias, linear estimator, imputing on the right: random effects model

Number of studies	**Observed**	**Imputed**
25	25	0
Studies	**Effect Size**	**95% Conf. Interval**
Observed	-0.092	(-0.160, -0.024)
Observed + Imputed	-0.092	(-0.160, -0.024)

Table 2. 12: Nonparametric trim-and-fill analysis of publication bias, linear estimator, imputing on the left: random effects model

Number of studies	**Observed**	**Imputed**
31	25	6
Studies	**Effect Size**	**95% Conf. Interval**
Observed	-0.092	(-0.160, -0.024)
Observed + Imputed	-0.153	(-0.226, -0.080)

d) Discussion

Work on understanding the effects of ill-health and health shocks on the probability of employment has gained prominence over the years. Aleksandrova et al. (2021) found up to 2.1 percentage point reduction in the probability of employment in Russia following a health shock. Bryan et al. (2022) found a 1.6 percentage reduction in the probability of employment following transition into poor health. Seuring et al. (2019) established that diabetes reduced the probability of employment by 7.7 percentage points for men in Mexico and by 6.3 percentage points for women. Tunceli et al. (2005) found that compared to men without diabetes, men with diabetes had a 7.1 percentage point lower probability of employment. Fu et al. (2019) estimated that cardiovascular diseases reduced women's employment probability by 15.4 percentage points in Japan. Parro and Pohl (2021) found that accidents decreased the probability of employment by 8.4 percentage points initially, but this increased with the number of years. García-Gómez et al. (2013) established that acute hospitalisation lowered the probability of employment substantially. Kumara and Samarutunge (2018) showed that non-communicable diseases reduced the probability of employment in Sri-Lanka.

While individual studies have indeed established a negative link between ill-health and health shocks and the probability of employment, it was necessary to assess the statistical significance of a pooled estimate in this area through a meta-analysis. The random effects model that was used to estimate the overall effect size of the ill-health and health shocks on the probability of employment produced a negative statistically significant coefficient of -0.09 ($p < 0.001$). This result is important as it confirms that ill-health and health shocks have a negative significant influence on the probability of employment overall.

The random effects model also showed significant sub-group effects sizes with papers from developing countries registering a pooled estimate of -0.13 compared to -0.05 for developed countries. It is noteworthy that both sub-groups displayed wide heterogeneity. Again, the negative statistically significant sub-group effects sizes or pooled estimates by geography confirmed that the effect of ill-health and health shocks on the probability of employment is negative overall, in each sub-group. Similarly negative statistically effect sizes were obtained by model type. Here results showed that papers that used non-OLS based models were associated with a pooled estimate of -0.15 compared to -0.04 for papers that used the OLS regression method. This result is important because it shows that econometric methods used in meta-analysis of ill-health, health shocks, and the probability of employment matter. Further, the test of group differences showed that the groups separated by model type were statistically different from zero. Furthermore, sub-group analysis by publication year showed that each year used produced a significant estimate with a test of group differences also showing a highly significant statistic implying significant differences across years. High heterogeneity was displayed across the years.

While the sub-group analysis showed geography, model type and publication year as significant sources of heterogeneity, multivariate meta regression produced insignificant coefficients. Model type was however marginally significant in the univariate analysis. This signals the importance of going beyond multivariate meta-analysis to univariate methods to unravel hidden effects that can only show up at the univariate level.

e) Conclusion

In this sub-section a systematic review and meta-analysis was undertaken on the effects of ill-health and health shocks on the probability of employment. Using partial correlations, the overall effect size was estimated by employing a random effects model. The analysis found a negative statistically significant pooled effect of ill-health and health shocks on the probability of employment. This worked to confirm that ill-health and health shocks, with individual studies combined through a meta-analysis, will have a negative effect on the probability of employment. Sub-group analyses along with meta-regressions were undertaken to address the observed high heterogeneity among studies. Geography, model type and publication year were found to be significant sources of heterogeneity. In terms of assessing reporting bias, a funnel plot, the Begg's test, and the trim-a-fill methodology were used. The funnel plot showed some form of asymmetry, the Begg's test rejected the hypothesis of no small reporting bias and the trim and fill approach when imputed to the left showed evidence of publications bias. While the trim and fill approach when imputed to the right showed no evidence of bias, given results from other tests it was concluded that there was some level of publication bias. In this regard results needed to be interpreted with caution. The meta-analysis results relating to the effects of ill-health and health shocks on the probability of employment are novel in that this is the first meta-analysis on the topic directly filling the gap in knowledge relating to the understanding of pooled effects of ill-health and health shocks on the probability of employment. Overall, the study is relevant for understanding policies regarding social protection, disability allowances and other relevant policies emanating from the health-labour relationship and particularly from the analysis of the effects of ill-health and health shocks on the probability of employment.

2.4 Evaluation of bias, and grade and assessment of quality

a) Evaluation of bias

The ROBINS-I (Risk of Bias in Non-Randomized Studies-of Interventions) tool (McGuinness & Higgins (2020) developed by Sterne et al. (2016) was used to evaluate risk of bias. As captured in Figure 2.12 which was created using Risk-of-bias Visualization (robvis)[9], most papers were determined to have low risk bias on all the seven domains. While some papers recorded a judgement of "Moderate "in some domains, the overall judgement of "Low" was achieved. Using the ROBINS-I tool, risk of bias was assessed based on seven domains which include: bias due to confounding, bias due to selection of participants, bias due to classification of interventions, bias due to deviation from intended interventions, bias due to missing data, bias in measurement of outcomes, and bias in selection of reported results.

[9] The Risk-of-bias Visualization(robvis) is an R package and Shiney web app for visualizing risk-of-bias assessments developed by McGuinness and Higgins (2020).

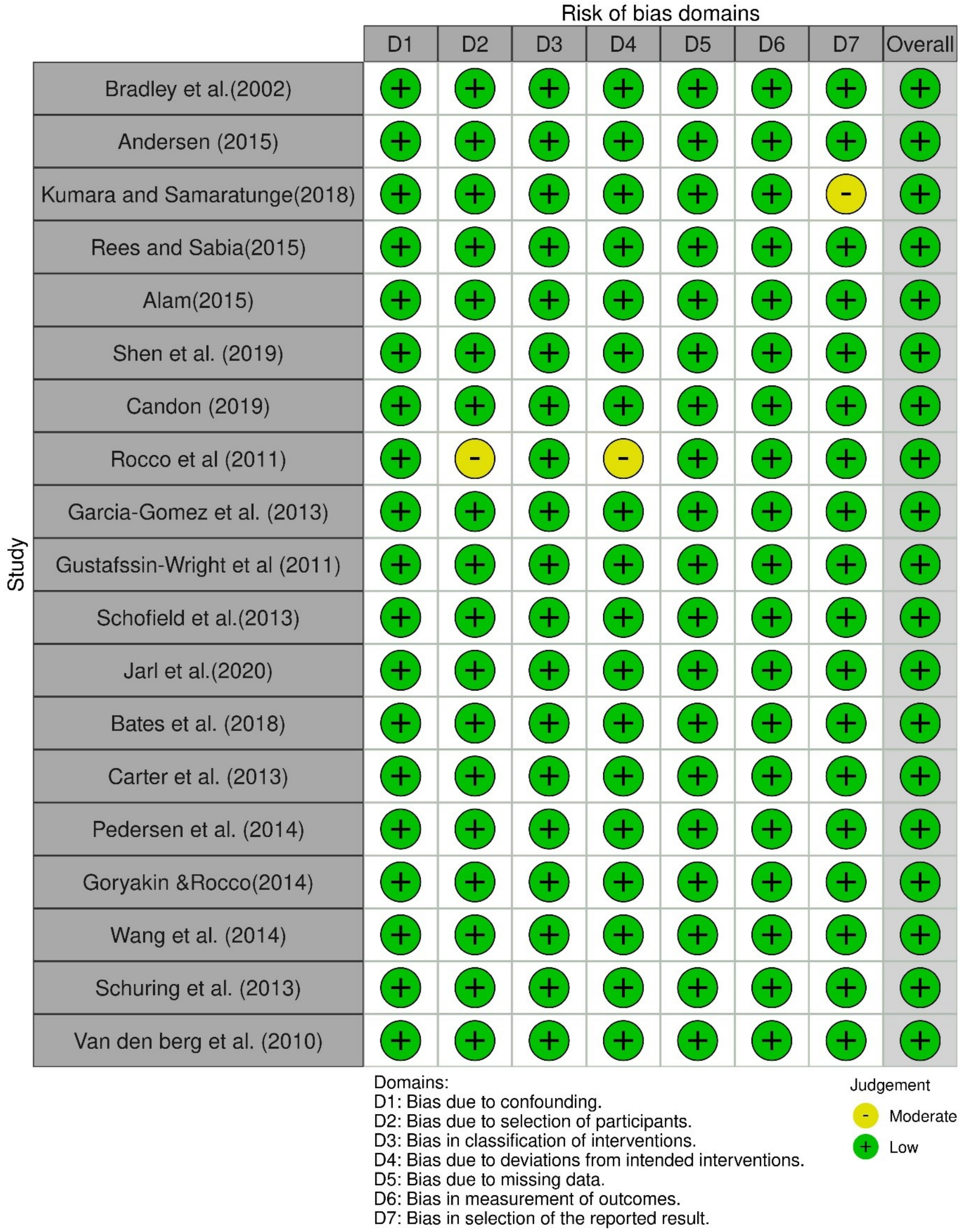

Figure 2.12 Risk of bias traffic light plot of ROBINS-I assessments created using robvis

b) Grade and assessment of quality

It is noted that the data combined were from studies whose designs were observational. Therefore, these studies precluded randomisation or blinding to reduce bias as is the case in Randomised Control Trials (RCTs) (Bosu et al., 2019). Since the study design precluded randomness, it was ranked to have low quality evidence (Table 2.13). Nevertheless, the data provided moderate quality evidence of the effect sizes. This includes the effect sizes estimated by sub-group analysis and the results of the meta-regressions. Risk of bias was ranked low since most of the studies embodied a low risk of bias on several domains (see Figure 2.12). Consistency was ranked moderate since despite substantial heterogeneity among studies the sources of heterogeneity were properly determined using sub-group analysis and meta regressions. Most studies analysed direct effects of ill-health and health shocks on affected individuals. However, some analysed spousal effects on women and husbands thereby introducing some indirectness of evidence. Thus, directness of evidence was ranked to be of moderate quality. Precision was rated high since the combined studies allowed for 117,656 for the ill-health/heath shock-hours worked relationship, and 248,485 for the case of the probability of employment which narrowed the confidence intervals. Moreover, most studies used data sets from nationally representative surveys which ensured generalisability. In the analysis of publication bias no substantial bias was detected in the effects of ill-health and health shocks on hours of work. However, tests showed some level of publication bias in the probability of employment meta-analysis. Consequently, quality evidence regarding publication bias was adjudged to be moderate in confidence.

Table 2. 13: Quality of evidence

Domain	Quality Rating	Comment
Study design	Low	Study designs of included papers were observational and so precluded blinding and randomization to reduce risk of bias.
Risk of bias	High	Most information is taken from studies (included studies) at low risk of bias
Consistency of results	Moderate	There was considerable heterogeneity among studies. However, the study explored the heterogeneity through sub-group analysis and meta regressions
Directness of evidence	Moderate	Most included papers analysed direct effects of health shocks and ill-health on affected individuals. However, some analysed spousal effects on women and husbands thereby introducing some in directedness.
Precision of results	High	The analysis had a large sample size comprising 117,656 individuals and consequently achieved narrow confidence intervals with a positive impact on precision. Additionally, most studies used nationally representative surveys allowing generalisation and applicability
Publication bias	Moderate	Using the funnel plots, Egger's test and the Begg's test we did not evidence of publication bias

2.5 Strength and limitations

The major strength of this review is that it is the first to use a meta-analysis combining results of several individual studies in relation to the effects of ill-health and health shocks on hours worked and the probability of employment. The studies were identified through a meticulous search process that ensured unbiasedness. The review has also respected PRISMA guidelines therefore having the conformity advantage to the quality expected of systematic reviews. Quality assessments of risk bias, reporting bias, and use of GRADE have all worked to the advantage of this review. The review has provided credible evidence using large samples in relation to the effects of ill-health and health shocks on hours of work and the probability of employment.

The review has some limitations which need to be noted. First, the analysis suggests the presence of substantial heterogeneity in the effects of ill-health and health shocks on hours worked and the probability of employment. While this might be seen as a limitation, the sources of heterogeneity were comprehensively examined and identified. Subgroup analyses and meta-regressions established that factors such as sample size, geography, model type and publication year were the main drivers of heterogeneity. However, the drivers of heterogeneity were mainly established in univariate analysis as opposed to the multivariate analysis. Second, while considered together, the tests used to assess reporting bias showed in general, no substantial reporting bias. In all outcomes the funnel plot displayed some asymmetry, and both trim and fill tests when imputed to the left, showed some level of publication bias in the analysis of hours worked. In the probability of employment meta-analysis, the Begg's test also showed some evidence of publication bias. This means that results with regards to reporting bias should be interpreted with caution.

2.6 Conclusions and policy implications

This chapter has presented a systematic review and meta-analysis on the effects of ill-health and health shocks on hours of work and the probability of employment. The paucity of systematic reviews and meta-analyses in the analysis of ill-health or health shocks and labour markets motivated this work. Following a carefully devised search strategy articles that analysed the effects of ill-health or health shocks on the two labour market outcomes were obtained. Two vital sets of criteria were developed: one for inclusion and one for exclusion. The inclusion criteria involved articles that had a clearly defined ill-health or health shock variable and at least one of the following outcomes: hours worked or probability of employment; and articles that had utilised quantitative techniques to analyse the effects of ill-health and health shocks on hours worked and probability of employment. There were no language restrictions. The exclusion criteria targeted articles that did not have a clear labour market outcome even if they had a clearly defined ill-health variable or a health shock; articles that did not perform a quantitative analysis of the relationship being studied (ill-health/health shocks and labour market outcomes) and were only qualitative in nature; and commentaries that only exposed some aspects of the health shocks and labour supply relationship but did not have relevant extractable information. To address the effects of ill-health and health shocks on the two labour market outcomes, the review was organised in two sub-sections that dealt with effects on hours of work and effects on the probability of employment. This was vital as it provided a useful guide in identifying attributes for the PhD research.

Two core electronic databases were used in the literature search. These included EconLit and Medline. Relevant grey literature was also incorporated. The search strategy involved a modified version of the PICO. Under the PICO framework, working age population was used. The intervention involved individuals experiencing ill-health or health shocks, and labour market outcomes included hours of work and the probability of employment. An appropriate search strategy was developed that included the use of synonyms to capture Ill-health and health shocks including such words as illness, injury, disease, cancer, diabetes, HIV/AIDS, tuberculosis, strokes, heart attack, major depression, hypertension, myocardial infarction, and infectious diseases. For labour market outcomes the search included such words as labour supply, employment, probability of employment, hours worked, labour market, labour income, labour force participation, retirement, among others.

A total of nineteen papers were included in the analysis. From these papers data were extracted using a data extraction tool from the Joanna Briggs Institute (JBI)'s Reviewer's Manual. The first category involved study details, which included the study identification, the date of extraction, the title of the study, the author(s) of the study, the year of publication, and the journal in which the paper was published. The second category detailed the study methods, which included study aims, study design, study setting, recruitment of participants, study duration, study characteristics, outcome variable(s) and how they were measured, the key independent variables (ill-health or health shocks) and how they were measured, other independent variables and how they were measured, exposure of interest, ethical approval information, and methods of data analysis. The results formed the third category. This involved extracting information regarding descriptive statistics; regression methods used; coefficients and their signs, standard errors, confidence intervals, p-values; diagnostic tests undertaken; robustness checks; and results of sensitivity analysis. The fourth category included information regarding policy implications and subsequent recommendations.

To examine the effects of ill-health and health shocks on hours worked and the probability of employment, overall effect sizes were estimated using a random effects model with results reported through forest plots. Sub-group analyses were performed to test statistical significance of sub-group pooled estimates and understand the sources of heterogeneity. To further characterise the sources of heterogeneity, meta regressions were employed. Moreover, funnel plots, the Begg's test and the trim-and fill analysis were used to test for reporting bias.

Regarding the effects on hours of work, a negative statistically significant pooled estimate was found. The negative statistically significant pooled estimate signified that although some effects could be positive in this relationship from the literature, overall, when studies are combined in a large sample, a negative relationship between ill-health or health shocks and hours of work may be expected. Further sub-group analyses showed that for both developed and developing countries, effect sizes were negative and statistically significant. This result might help shape an understanding on how the effects of ill-health and health shocks on hours of work should be viewed in both the developed and developing countries. Furthermore, the chapter found that the pooled estimates of the relationship between ill-health and health shocks and hours of work were also negative and statistically significant in relation to model type. Additionally, sub-group analyses and meta regressions revealed that overall, geography, model type, sample size and publication year were important sources of heterogeneity. Moreover, through using the funnel plots, the Begg's test, as well as the trim and fill methodology, the chapter found that there was no substantial reporting bias involving the effects of ill-health and health shocks on hours of work. However, some level of publication bias was detected in the effects on the probability of employment.

Regarding probability of employment, through the random effects model, the chapter found a negative statistically significant overall effect size of the effect of ill-health and health shocks on the probability of employment. This is an important result as it does not deviate from results of individual studies reported in the literature and in this paper. Furthermore, the chapter found that effect sizes for groupings of developed and developing countries were also significant showing some consistency in the results of the effects of ill-health and health shocks on the probability of employment despite the structural differences that exist between these worlds. Furthermore, the study established statistically significant effect sizes or pooled estimates of sub-groups formed by model type. This is again an important result because it shows that the choice of econometric methods matters, used in analyses of ill-health, health shocks and the probability of employment. Additionally results from the sub-group analysis by publication year showed that the publication year had significant estimates as well, and that the test of group difference showed significant differences across years. In relation to heterogeneity, all models exhibited substantial heterogeneity. Moreover, the sub-group analysis and meta regressions showed geography, model type and publication year as significant sources of heterogeneity. Finally results of the reporting bias discernible from funnel plots, the Begg's test, and the trim and fill approach showed some level of reporting bias in the analysis of the effects of ill-health and health shocks on the probability of employment. This means that the results of this analysis should be interpreted with caution.

In general, the negative and significant estimated effect sizes in the effect of ill-health and health shocks on the two labour outcomes - hours of labour, and the probability of employment - signal the relevance of the relationship between health and labour and shows that ill-health and health shocks play an important role in this relationship. This implies that policy interventions aimed at containing losses in hours of work, and reductions in probability of employment should bear in mind this negative relationship. More importantly this highlights the importance of instituting social protection policies, disability benefits, and unemployment benefits to cushion losses in working hours, labour income and loss of employment. The results are also a call for further research to particularly understand the effects of health shocks in countries with poor social security systems and high informal employment. Such countries also tend to have poor health systems in general. The author wishes to take up this research in the next two chapters by looking at data from Malawi.

Thus, given the results of this systematic review and meta-analysis showing negative statistically significant pooled estimates of the effects of ill-health and health shocks on hours worked and the probability of employment, the thesis delves deeper to fully understand how such ill-health and health shocks affect labour market outcomes in Malawi. Thus, chapter three employs the nearest neighbour propensity score matching to estimate Average Treatment Effects on the Treated (ATET) of the effects of ill-health and health shocks on probability of employment, hours worked and job search. Furthermore, chapter four seeks to understand what happens to the intensive margin of labour supply using weekly hours of labour when ill-health and health shocks are assessed jointly with social protection. The analysis uses count data models namely the negative binomial, zero-inflated negative binomial, Poisson, zero-inflated Poisson, and a two-part model. A standard OLS model was also estimated to produce some baseline estimates not based on a count data model.

CHAPTER THREE

Effects of ill-health and health shocks on the probability of employment, hours of work, and job search: Evidence from Malawi

3.1 Introduction

There is a large body of evidence on the effects of health on labour market outcomes. However, this literature has traditionally focused on developed countries (see for example Conley & Thompson, 2013; Jones et al. 2020; Tisch, 2015; Zucchelli et al., 2010) and less is known on the relationship between health and work in low and middle-income countries (LMICs). Research on the impact of ill-health and health shocks on labour supply has taken different directions based on policy concerns such as social protection provision and disability insurance. Subsequently there has been considerable work conducted in the developed world assessing the effects of ill-health and health shocks on labour market exits or probability of employment and the role of social protection systems (García-Gómez, 2011).

From the literature, analysing the effects of ill-health and health shocks on the probability of employment has been a common feature in the health-labour relationship. Ill-health has mainly been operationalised using chronic illnesses such as respiratory problems, cardiovascular diseases, diabetes, and mental health challenges. Others have also used health limitations and self-assessed health to operationalise chronic illnesses. On the other hand, health shocks have been measured by such variables as injuries, illness, hospitalisations, and the onset of chronic diseases. A common finding has been that ill-health and health shocks reduce the probability of employment (Shawa et al., 2024). In this regard, a study by Kumara and Samarutunge (2018) in Sri-Lanka - who used non-communicable diseases that included arthritis, asthma, heart disease, cancer, diabetes, paralysis, mental illness, and epilepsy - found that these chronic illnesses reduced the probability of employment. Still using chronic diseases as their study focus, Seuring et al. (2019) estimated that diabetes reduced the probability of employment by 6.3 percentage points for women as well as by 7.7 percentage points for men in Mexico. These results were corroborated by the work of Tunceli et al. (2005) who found that in relation with men who were not suffering from diabetes, those with diabetes had a 7.1 percentage point lower probability of employment. Similarly, when Bryan et al. (2022) considered the impact of poor health on the probability of employment in Japan, they found a 1.6 percentage point reduction in the probability of employment due to transition into poor health. Additionally, Fu et al. (2019) using cardiovascular diseases as a measure of ill-health, found that Japanese women reduced their employment probability by 15.4 percentage points.

In terms of health shocks, Aleksandrova et al. (2021) found up to 2.1 percentage points reduction in the probability of employment in Russia following a health shock while Parro and Pohl (2021) found that accidents decreased the probability of employment by 8.4 percentage points. García-Gómez et al. (2013) also observed that acute hospitalisation lowered the probability of employment substantially. Rocco et al. (2011) showed that the elderly and the less educated may suffer larger drops in the probability of employment following a health shock in Egypt. For Bridges and Lawson (2008), ill-health considerably lowered the probability of being in formal employment, especially among women in Uganda. Further, Levinsohn et al. (2013) found that HIV status in South Africa increased the likelihood of unemployment by 6 to 7 percentage points. For the less educated, the reduction was higher and ranged between 10 to 11 percentage points.

The other way of looking at the probability of employment is to consider exits from the labour market since some workers either transition into other jobs or re-enter the market from a spell of unemployment after their exit. In this regard Zucchelli et al. (2010) using data from Australia for older workers, showed that health shocks significantly influenced choices of early exits from the labour market. Similarly, Tisch (2015) used German data and found an increase in the probability of labour market exits due to health shocks. Additionally, Jones et al. (2010) using UK data, found that health shocks were key determinants of retirement age. In the same vein, Conley and Thompson (2013) using data from the United States, found an association between health shocks and labour market exits for older American men.

Another area of empirical work that has gained considerable currency relates to the pursuit of the effects of ill-health and health shocks on hours of labour. To this end, Seuring et al. (2019) who used diabetes as a measure of ill-health, found that diabetes decreased hours of work. Similarly, Ettner et al. (1997) showed that psychiatric disorders reduced hours of work while Frijters et al. (2010) observed a negative relationship between mental health and hours worked. Relatedly, Kumara and Samaratunge (2018) showed that non-communicable diseases reduced hours of work in Sri-Lanka while Lindelow and Wagstaff (2005) reported substantial reduction in labour supply in China following a health shock. Gajate-Garrido (2015) also showed a link between household-level health shocks and decreases in hours of agricultural labour participation in Pakistan. In the work assessing the effect of ill-health and health shocks on hours of work it is important to note that although a negative relationship has been a common finding (Shawa et al., 2024), other researchers have found different results. For example, Trevisan and Zantomio (2016) found that a health shock increased hours worked for men, while Lenhart (2018) noted a positive association with hours of work following a mild shock.

In the literature, empirical work analysing the relationship between health and job search is uncommon. The few studies that are citable include the work of Carlier et al. (2014) who showed that individuals with impaired health were less likely to engage in job searching and were less likely to succeed in obtaining a job. Others such as Vuori and Vinokur (2005) observed that despite health challenges such as suffering from poor mental health, finding a job ultimately depended on job search self-efficacy (Carlier et al., 2014; Liu et al., 2021) which are part of job preparedness and inoculation against setbacks. Liu et al. (2021) carried out research to show that job-search self-efficacy significantly positively predicted re-employment willingness.

To the best of my knowledge, there are currently no studies exploring the effects of ill-health or health shocks on probability of employment, hours worked or job seeking in Malawi. The chapter provides an important contribution to the current literature on the (health) determinants of labour supply. First, relationships are investigated using matching methods using a rich individual-level data set drawn from the latest Malawi Integrated Household Surveys including a pooled data set of the surveys. There has been no work on this topic using either the survey data sets, or the pooled data set in Malawi. This study therefore provides original evidence which will support policy interventions. This evidence will also be relevant to other African countries as well as other LMICs. Second, the chapter is of interest as it focuses on an African country that exhibits a significant degree of informality coupled with inadequate social protection systems in its labour market. Hence the original findings of this study are derived from a country whose labour market structure significantly diverges from that of developed countries, yet it serves as an illustrative model for African nations with comparable levels of informality in their labour markets.[10] Third, the study investigates the effects of both ill-health and health shocks. This means that it examines both the effects of different levels of health as well as changes in health, on the labour supply in Malawi. This is relevant as most previous studies have focused either on ill-heath alone (Gaulke, 2021; Harris et al., 2020; Kumara & Samaratunge, 2018) or on health shocks alone (Lenhart, 2018; Trevisan & Zantomio, 2016; Zucchelli et al., 2010). Information on the labour market implications of both heterogenous health levels and unexpected health events might be important to devise more targeted policies aimed at retaining workers in the labour force. Fourth, apart from delving into understanding the effects of ill-health and health shocks on the probability of employment and hours worked, extending this assessment to the probability of job seeking has distinct advantages since it has been a rare pursuit in the literature compared to studies of other aspects of labour supply.

3.2 Data and econometric methods

3.2.1 Data

Individual-level data from three independently collected nationally representative Malawi Integrated Household Surveys (IHS3, IHS4 and IHS5) and a pooled data set of these surveys are exploited. These repeated cross-sectional surveys are drawn from a Living Standards Measurement Study (LSMS) implemented by the Malawi Government's Statistical Office in collaboration with the World Bank and the International Food Policy Research Institute (IFPRI). Primarily, the Integrated Household Survey (IHS)[11] was an instrument to monitor progress of the Millennium Development Goals (MDGs). Currently the survey is used to monitor progress of Sustainable Development Goals (SDGs) and the goals of the Malawi

[10]Malawi has an informality rate of 83 percent (ILO, 2018) and the effective coverage of social protection (population covered by at least one social protection benefit) was only 21.3 percent in 2016 (latest available statistics). See ILOSTA Database for further information: https://ilostat.ilo.org/data/country-profiles/.

[11] IHS 1was technically supported by the International Food Policy Research Institute (IFPRI) and the World Bank (WB). IHS2 was implemented with technical support of the World Bank. IHS3 was then expanded on the agricultural content of IHS2 and supported under the LSMS-ISA initiative. IHS4 was financially supported by Government of Malawi (GoM), WB LSMS-ISA project, and Millennium Challenge Corporation (MCC) while IHS5 was implemented under the LSMS-ISA initiative with financial support from Government of Malawi (GoM), and the United States Agency for International Development (USAID) (see https://blogs.worldbank.org/opendata/malawis-fifth-integrated-household-survey-2019-2020-and-integrated-household-panel-survey).

Growth and Development Strategy (MGDS). Implemented with technical support from the World Bank (WB) and the International Food Policy Research Institute (IFPRI), IHS1 was collected from November 1997 to October 1998. On the other hand, IHS2 was collected from March 2004 to February 2005. Subsequently, in line with the World Bank Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) initiative, the IHS3 broadened the content on agriculture that characterised IHS2. The objective of the LSMS-ISA initiative was to technically and financially support sub-Saharan African governments to implement multi-topic household surveys. IHS3 was collected from March 2010 to March 2011, the IHS4 was collected from April 2016 to April 2017, and the IHS5 was collected from April 2019 to April 2020.

Given the focus of this study, three IHS surveys, i.e. IHS3-5 (out of the five surveys currently available, IHS1-5) and a pooled data set of these surveys including comprehensive information on health and employment, are employed. The IHS3 included 52,838 individuals whereas IHS4 and ISH5 included 53,664 and 54,067 individuals respectively. The surveys used four questionnaires each: the household questionnaire; the community questionnaire; the agriculture questionnaire; and the fishery questionnaire. The main source of information used in this study is the household questionnaire which covered relevant variables to our study, spanning economic activities, demographics, welfare as we all as information on health, education, time use, employment, and food security. With the focus of the study on health and labour, it is important to note that at least 60 per cent of disease diagnosis was conducted by a medical worker at a hospital for each of the waves used. This is important in avoiding the biases that characterise self-reported diseases.

3.2.2 Empirical Approach: propensity score matching (PSM)

The empirical approach relies on propensity score matching (PSM) (Garrido et al. 2014: Rosenbaum & Rubin, 2022; Rosenbaum & Rubin, 1983; Rubin & Waterman, 2006). This follows previous studies in the field also exploring the relationship between health and labour such as Lenhart (2019) using UK panel data; Trevisan and Zantomio (2016) for sixteen European countries; Kumara and Samaratunge (2018) for Sri-Lanka; García-Gómez and Lopez-Nicolas (2006) for Spain and Aleksandrova et al. (2021) for Russia.

Advantages of propensity score methods compared to traditional regression methods are well documented in literature. Amoa et al. (2022) argue that propensity score methods have a higher likelihood of achieving similar distributions of observed baseline variables across exposed and unexposed groups compared to regression analysis (Adelson et al, 2017) as well as mimicking better the expectations of a randomised control trial (Guo et al., 2020). This is because propensity score methods allow for the integration of a large number of variables in the process of generating propensity scores. However, preference of one propensity score method to another is not a straightforward matter as there is no clear consensus regarding the optimal propensity score approach. In this regard, Amoa et al. (2020) observed that propensity score matching resulted in adequate balance in the exposed and unexposed groups compared to inverse probability weighting and stratification. Additionally, Elze et al. (2017) showed that while propensity score matching performed well, stratification performed poorly with few outcome events while the inverse probability weighting's estimates were imprecise. Further, Lin et al. (2023) found that the nearest neighbour approach yielded a robust estimation compared to other methods. The thesis uses the propensity score approach with the nearest neighbour algorithm. It is noteworthy, however, that propensity score matching excludes unmatched subjects who may differ systematically from matched subjects. The inverse probability weighting on the other hand, apart from using all eligible subjects can also include multiple comparisons. While this is the case, the inverse probability weighting is said to be less intuitive and has an extreme weight issue. Further for Guo et al. (2020) who used monte carlo methods no single propensity score method reduced bias in all scenarios and concluded that optimal results depend on the fit between assumptions embedded in the model and the process of data generation. Consequently, while this thesis uses the nearest neighbour propensity score matching other approaches including regression adjustment, inverse probability weighting, regression adjustment with probability weighting and the augmented inverse probability weighting have also been utilized (in the case of the pooled data set) to provide comparison with results of the nearest neighbour approach and enhance credibility of results.

Since the occurrence of illness and health shocks might not be entirely random, in this case there may been a need to control for the non-experimental nature of the data (Garcia-Gomez & Lopez-Nicolas, 2006) as well as for potential confounding (Hwa, 2022). Here, PSM allows identifying average treatment effects on the treated of our variables of interest (ill-health and health shocks) by comparing (changes in) the employment outcomes of interest across treated and control groups matched based on their observed characteristics. This ultimately implies that, under specific assumptions, it would be possible to obtain treatment effects from non-experimental data by mimicking a quasi-experiment (Morrish et al., 2022). In addition, having matched treated and control groups (effectively including identical individuals, based on the available observables, with the only difference being whether they have been treated or not) helps minimising potential confounding driven by observed characteristics.

Following work conducted by Heinrich et al. (2010), the impact of ill-health or a health shock (our "treatments") for an individual i, denoted by δ_i, is the difference between the employment outcome (probability of employment, hours of work, and job search) in the presence of ill-health or a health shock and the same employment outcome in the absence of ill-health or health shock.

$$\delta_i = Y_{1i} - Y_{0i} \tag{1}$$

This parameter, which identifies the mean impact of the treatment, is called the Average Treatment Effect (ATE).

$$ATE = E(\delta) = E(Y_1 - Y_0) \tag{2}$$

where $E(.)$ represents the average or expected value. Similarly, the Average Treatment Effect on the Treated (ATET) measuring the impact of ill-health or a health shock on the labour market outcomes on those individuals who experienced ill-health, or a health shock can be estimated (D stands for treatment).

$$ATET = E(Y_1 - Y_0|\mathrm{D}=1) \tag{3}$$

Accordingly, the Average Treatment Effect on the untreated ATU is computed as:

$$ATU = E(Y_1 - Y_0|\mathrm{D}=0) \tag{4}$$

Hence, the ATET can be written as follows:

$$\text{ATET} = E(Y_1|D=1) - E(Y_0|D=1) \tag{5}$$

The second term $E(Y_0|D=1)$ represents the counterfactual, i.e. the average (labour market) outcome that treated individuals (those who experienced ill-health, or a health shock) would have experienced in the absence of treatment (ill-health or health shock), which cannot be directly observed in the data. However, the term $E(Y_0|D=0)$ is observed which is the value of Y_0 for untreated individuals. Thus, the difference between the average employment outcome in the presence of ill-health or health shock and the average labour market outcome in the absence of ill-health or health shock (Δ) can be calculated as follows:

$$\Delta = E(Y_1|D=1) - E(Y_0|D=0) \tag{6}$$

The term $E(Y_0|D=1)$ can be added and subtracted to equation (6) to obtain the following:

$$\Delta = E(Y_1|D=1) - E(Y_0|D=1) + E(Y_0|D=1) - E(Y_0|D=0) \tag{7}$$

$$\Delta = ATET + E(Y_0|D=1) - E(Y_0|D=0) \tag{8}$$

$$\Delta = ATET + SEB \tag{9}$$

where SEB stands for selection bias, that is the difference between the counterfactual for treated individuals (those who experienced ill-health or a health shock) and the observed outcome for the untreated individuals (those who did not experience ill-health or a health shock). If this term equals zero, then the ATET can be represented as the difference between the mean of observed outcomes for treated and untreated individuals.

$$\widehat{ATET} = E(Y|D=1) - E(Y|D=0) \tag{10}$$

However, in most cases it is reasonable to assume that the selection term might not be equal to zero implying a biased estimator of the ATET. Thus, in the context of a non-experimental design, it is essential to consider and adjust for differences between treated and untreated groups to correctly estimate the effects of the treatment (here, ill-health/health shocks) on the outcomes of interest (here, probability of employment, weekly hours of work, and job search).

It is important to highlight that matching relies on the standard assumptions of conditional independence and common support. The conditional independence assumption (Austin, 2011; Caliendo & Kopeinig, 2005; Harris & Horst, 2016) states that for a set of observables, treatment assignment is not dependent on potential outcomes. This implies that only observable characteristics influence selection, and that all variables that simultaneously influence both treatment assignment and potential outcomes are fully observed (Caliendo & Kopeinig, 2005). The common support assumption on the other hand implies an overlap in the distribution of propensity scores for both treated and untreated groups.

Accordingly, matching methods are not without limitations. The major challenge with matching is the failure to account for unobservables (King & Nielsen, 2019). This means that unobserved factors that influence health shocks and ill-health and associated labour market outcomes cannot be accounted for. Thus, as argued by Shadish et al. (2002) controlling for observed variables only, means that any hidden bias due to unobservables may not disappear. In fact, there is even an increased possibility of hidden bias due to bias obtainable from dormant latent confounders unleashed by matching only on observables (Pearl, 2010). Even so, matching needs large data sets to ensure meaningful overlap between treated and untreated groups. This is important because without the overlap, matching would not be possible.

Data used in this paper presents two advantages with respect to the limitations of matching. First, treatments used include variables defining health shocks such as illness/injury in the last fourteen days; and whether the individual was hospitalised in the last twelve months. These treatments are unexpected negative health events. The unexpectedness of (some of) these events might ease potential concerns related to the role of individual level unobservables in the relationship between health and labour supply also reducing the risk of simultaneity or reverse causality issues. Second, the use of individual-level data from a rich and nationally representative dataset, covering key observable variables from a large population might imply that, although matching does not explicitly account for unobservables, the data may include enough relevant observed variables and so might produce a reasonable approximation of the genuine treatment effects of interest.

While some treatments used in the analysis are unexpected negative health events and that a large nationally representative dataset has been employed, results of the PSM may still need to be interpreted with caution. This is because the conditional independence assumption (Rosenbaum & Rubin, 1983) which implies the absence of unobserved confounding variables and that the propensity score model includes all confounders (Emsley et al., 2008; Caliendo & Kopeinig, 2005) is rather strong. Moreover, as argued by Guo and Fraser (2014) this cannot be tested directly owing to the lack of knowledge regarding the distributions of both the treated and untreated groups (Narita et al., 2023). Essentially this means that appropriate covariates can only be identified by theoretical and empirical means.

The implementation of PSM involved three steps (see for example Kumara & Samaratunge, 2018). First, propensity scores were estimated using a logit model with the ill-health and health shock variables as treatment variables and labour market variables as outcome variables. Socio-demographic variables were used for matching. These include - depending on the wave - variables that have the potential to influence health shocks and illness related to such factors as an individual's behaviour and their living conditions. Ultimately, the selection of matching variables was influenced by variables in the survey and informed by previous studies in this field (see for example Aleksandrova et al., 2021; Kumara & Samaratunge, 2018). Second, the algorithm with which to perform the matching was chosen. The nearest neighbour (NN) approach in which individuals from the group that suffered from a health shock or illness and those who did not, are matched using the closest propensity score (Caliendo & Kopeinig, 2005; Harris & Horst, 2016; Heinrich et al., 2010)). The nearest neighbour approach is commonly used and therefore renders itself to comparison with many studies (Harris & Horst 2016). Finally, ATETs with the matched sample were estimated and standard errors calculated. To ensure the comparison group has a distribution of propensity scores like the intervention group, quality of matches (balance)[12] was assessed by using standardised mean differences and variance ratios.[13]

[12] See Appendix 3A for covariance balance summaries (using wave 5 as an example).
[13] Due to being influenced by sample sizes (Austin, 2009; Imai et al., 2008) pairwise t-tests on observables across treated and control groups before and after matching were not undertaken.

3.3 Results

3.3.1 Descriptive statistics

It is noteworthy that the data used is from three separate cross-sections as well as a pooled data set of these three cross-sectional data sets. Although this is the case, it might be useful to check percentages of key variables across all three waves and the pooled data set.

a) Health and Labour Variables

Table 3.1 shows proportions of those who reported an illness/injury, hospitalisation, a chronic illness, those who were involved in wage employment or casual employment, and those who searched for a paid job. The proportion of those who suffered from an illness or injury in the last 14 days was highest in wave 4 (30.3 per cent) and lowest in wave 3 (24.6 per cent). This was 26.1 per cent in the pooled sample. The proportion of those who were hospitalised in the last twelve months was the highest (5.3 per cent) in wave 3 and lowest in wave 4 (3.7 per cent). In the pooled sample this proportion was 4.0 per cent. In terms of the proportion of those who suffered a chronic disease, wave 5 recorded the highest (7.7 per cent) and wave 3 had the lowest (5.5 per cent). This was 6.9 per cent in the pooled sample. There was an increasing trend in the proportion of those who worked for wage employment in the last twelve months from 3.4 per cent in wave 3; to 5.10 per cent in wave 4, reaching 6.4 per cent in wave 5. The pooled sample showed a proportion of 6.9 per cent. Interestingly the proportion of those engaged in casual/part-time work commonly referred to as *ganyu*[14] was always higher than that of wage workers. This was 13.5 per cent compared to only 3.4 per cent of wage workers in wave 3; 16.9 per cent compared to only 5.10 per cent of wage workers in wave 4; and 27.9 per cent compared to only 6.4 per cent of wage workers in wave 5. The proportion was 27.1 per cent in the pooled sample. It is also noteworthy that the proportion of *ganyu* labour also followed an increasing trend. High proportions were observed for those who searched for a paid job in the previous four weeks in the respective waves, with wave 3 registering 32.0 per cent, wave 4 recording 40.9 per cent, wave 5 showing 38.0 per cent, and the pooled sample forming 36.0 per cent of those who searched for a paid job.

[14] Ganyu labour entails "any off-own farm work mostly done by rural people on a casual basis" (see Whiteside, 2000).

Table 3. 1: Health and labour variables

Item	Wave 3	Wave 4	Wave 5	Pooled Sample
Having suffered from an illness or injury in the last 14 days	24.6	30.3	28.7	26.1
Hospitalised in the last 12 months	5.3	3.7	4.4	4.0
Having suffered from a chronic illness	5.5	6.0	7.7	6.9
Worked for wage employment in the last 12 months	3.4	5.10	6.4	6.9
Engaged in casual/part time /ganyu labour in the last 12 months	13.5	16.9	27.9	27.1
Searched for a paid job in the last four weeks	32.0	40.9	38.0	36.0

Note: Values are in percentages.
Note: Values were rounded off to one decimal place.

b) Most common diseases

There was heterogeneity in terms of the most common diseases people suffered from in the different waves (Table 3.2). In wave 3, the majority (42.7 per cent) reported fever and malaria, followed by sore throat and flu (12.3 per cent) and diarrhoea (10.5 per cent). In wave 4, the majority reported fever and malaria (34.1 per cent) followed by a cough (11.8 per cent) and sore throat and flu (9.5 per cent). For wave 5, the majority (45.2 per cent) reported suffering from fever and malaria followed by a sore throat (14.5 per cent) and a headache (9.2 per cent). In the pooled sample, 40.4 per cent of respondents reported fever and malaria as the most common disease or ailment they suffered from. This was followed by having a sore throat and flu at 11.4 per cent. Fever (and malaria) was therefore the topmost disease individuals were perceived to suffer from across the three waves. It is also noticeable that diarrhoea was ranked highly in wave 3 but reduced substantially in waves 4 and 5. The reduction could be a response to programmes promoting awareness and prevention of diseases such as diarrhoea under the Primary Health Care System (Masangwi et al., 2016).

Table 3. 2: Most common diseases

Wave 3		Wave 4		Wave 5		Pooled Sample	
Disease	**Proportion**	**Disease**	**Proportion**	**Disease**	**Proportion**	**Disease**	**Proportion**
Fever and malaria	42.7	Fever and malaria	45.2	Fever and malaria	34.1	Fever and malaria	40.4
Sore throat and flu	12.3	Sore throat	14.5	Cough	11.8	Sore throat and flu	11.4
Diarrhoea	10.9	Headache	9.2	Sore throat and flu	9.5	Headache	8.3
Respiratory infection	7.6	stomach-ache	7.0	Headache	9.0	Stomach-ache	7.3
Headache	6.3	Diarrhoea	3.9	stomach-ache	8.2	Diarrhoea	3.8
-	-	Respiratory infection	0.8	Body and joint pains	4.8	Respiratory infection	2.8
-		-	-	Diarrhoea	3.3	Skin problem	2.0
Other	20.2	Other	19.4	Other	19.3	Other	24.0
Total					**100**		

Note: Values in the table are in percentages.
Note: Values in the table were rounded off to one decimal place.

c) Chronic illnesses

There was also some heterogeneity in the reported chronic illnesses that people suffered from across the waves (Table 3.3). In wave 3 the majority reported to be suffering from asthma (22.3 per cent) followed by arthritis (13.1 per cent) and epilepsy (10.1 per cent). Similarly in wave 4 the majority reported to be suffering from asthma (20.8 per cent), but unlike in wave 3 this was followed by HIV and Aids (18.8 per cent). In wave 5, the majority (23.8 percent) reported HIV and Aids, asthma (20.9 per cent) and stomach disorders (8.0 per cent). In the pooled sample the majority reported asthma (22.8 per cent) followed by HIV/Aids (18.3 per cent). Asthma and HIV/Aids were therefore the most reported chronic diseases across the three surveys and the pooled sample.

d) Diagnosis of chronic illnesses

In terms of who diagnosed chronic illnesses (Table 3.4) the majority in all three waves mentioned a medical worker at a hospital. This constituted 68.5 per cent in wave 3; a lower value of 63.2 per cent in wave 4 and 65.3 per cent in wave 5. Similarly in the pooled sample, the majority (67.3 per cent) reported that their chronic diseases were diagnosed by a medical worker at a hospital. While the majority reported that their diagnosis was done by either a medical worker at hospital or a medical worker at another health facility, there were others who contacted traditional healers or self-diagnosed. Furthermore, only a small proportion used a health surveillance assistant. It is important to understand that traditional healers still play a vital role in Malawi's healthcare system. Harries et al. (2002) noted the likelihood of finding at least one traditional healer per village in Malawi, allowing frequent consultation of traditional healers. Simwaka et al. (2007) observed that about 80 per cent of Malawi's population use traditional healers while Brouwer et al. (1998) found that 37 per cent of 89 tuberculosis patients studied at a public hospital in Malawi utilised traditional healers before they sought regular health care. The seemingly substantial proportion of those who reported self-diagnosis points to the challenges relating to access to health facilities and medical personnel due mainly to the long distances needed to travel to the nearest health centres (Masangwi et al., 2016).

Table 3. 3: Chronic diseases

Wave 3		Wave 4		Wave 5		Pooled Sample	
Disease	**Proportion**	**Disease**	**Proportion**	**Disease**	**Proportion**	**Disease**	**Proportion**
Asthma	22.3	Asthma	20.8	HIV/AIDS	23.8	Asthma	22.8
Arthritis	13.1	HIV/AIDS	18.8	Asthma	20.9	HIV/AIDS	18.3
Epilepsy	10.1	Stomach disorder	5.5	Stomach disorder	8.0	Epilepsy	7.2
TB and HIV	8.8	Epilepsy	5.2	Epilepsy	7.3	Stomach disorder	6.2
Chronic Malaria	6.0	Mental illness	4.0	Chronic malaria/fever	4.1	Arthritis	5.8
-	-	Chronic malaria	3.5	Mental illness	2.9	Chronic malaria	4.9
-		Arthritis/Rheumatism	3.3	Diabetes	2.3	Diabetes	2.5
-	-			TB	1.9	TB	2.2
Other	39.8	Other	38.9	Other	25.2	Other	30.1
Total	**100**			**100**	**100**		**100**

Note: Values in the table are in percentages.
Note: Values in the table were rounded off to one decimal place.

Table 3. 4: Percentage distribution of those who diagnosed chronic diseases

	Wave 3	Wave 4	Wave 5	Pooled Sample
Medical worker at hospital	68.5	63.2	65.3	67.3
Medical worker at other health facility	3.1	20.7	17.8	14.6
Health surveillance assistant	0.2	0.5	0.2	1.6
Traditional healer	2.3	1.5	1.7	1.6
Self	14.3	8.3	8.5	9.4
Other	11.5	5.8	6.5	7.1
Total	**100**	**100**	**100**	**100**

Note: Values in the table are in percentages.
Note: Values in the table were rounded off to 1 decimal place.

3.3.2 Main Results

Average Treatment Effects on the Treated (ATET) were estimated using the nearest neighbour approach under a Mahalanobis distance metric[15] (Rubin, 1980) to examine the effects of ill-health and health shocks on the probability of employment, hours of work, and the probability of job seeking. To capture health shocks – categories of the occurrence of illness or an injury and whether individuals were hospitalised were used. Chronic diseases were used to define ill-health. To the extent possible, socio-demographic variables that influence a person's health and relate to such issues as behaviour, habits, and the environment in which they live were used. Ultimately, the choice of these matching variables was driven by the information available in the surveys and guidance from previous work in the area (see for example Kumara & Samaratunge 2018). Subsequently, depending on the wave, the matching variables included sex, age, religion, education level, marital status, difficulty in seeing, difficulty in hearing, difficulty in walking, difficulty in self-care, relationship to household head, months away from

[15]The Mahalanobis distance metric is a pair-matching technique used to find matches as opposed to propensity scores. See Rubin, D. B. (1980). Bias Reduction Using Mahalanobis-Metric Matching. Biometrics, 36(2), 293. https://doi.org/10.2307/2529981.

home, whether always lived in the location, whether stayed overnight at a traditional healer, ability to read, education level, days the individual ate in the household, and whether or not they attended school.

It is noteworthy that the post-matching diagnostics showed reasonable balance. Stuart et al. (2013) argue that an absolute value of a standardised mean difference of less than 0.1 implies that balance has been achieved. Results of quality of matching (balance) show that all standardised mean differences for the matched samples are less than 0.1, confirming reasonable balance (Zhang et al., 2019). Furthermore, a variance ratio of 1 is indicative of a reasonable matching and this can be stretched to any value below 2 (Zhang et al., 2019). Results indicate that all the variance ratios fall into this category, again confirming reasonable matching quality.

a) Ill-health, health shocks and probability of employment[16]

Table 3.5 shows ATET of the probability of wage employment and casual employment following illness/injury, hospitalisation, and suffering from a chronic disease. To define wage employment the following question was used: "In the last twelve months, did you work as an employee for a wage, salary, commission, or any payment other than *ganyu*, even if this was only for one hour?". For casual employment the following the question was used: "In the last twelve months, did you engage in casual, part-time or *ganyu* labour, even if this was only for one hour?".

Apart from in wave 3 (Table 3.5), suffering from an illness or injury was found to reduce the probability of wage employment in wave 4, 5 and the pooled sample. In waves 4 and 5 the probability of wage employment reduced by 1.0 and 1.2 percentage points respectively and these effects were statistically significant. The pooled sample showed a reduction of 1.5 percentage points. Illness/injury was found to increase the probability of wage employment in wave 3, by 0.8 percentage points. Regarding casual employment, results show that suffering from an illness or injury increased the probability of casual employment by 4.3 percentage

[16] To ensure comparability of results with the nearest neighbour approach, other PSM approaches were used on the pooled data set. These included the regression adjustment, inverse probability weighting, regression adjustment with inverse probability weighting, and the augmented inverse probability weighting. Results reported in Appendix 3B were similar with those obtained using the nearest neighbour approach in terms of signs, coefficient sizes and statistical significance.

points in wave 4, 6.4 percentage points in wave 5, and 6.5 percentage points in the pooled sample. The increased probability of employment for those experiencing illness could be explained by the fact that additional resources were needed to (for example) finance hospital bills, support education, or cover food expenses - and casual employment provided a quick avenue to gain such needed resources in the short run. In general terms, results of this study differ from those of developed countries where individuals when faced with health shocks either exit the labour markets (Conley & Thompson, 2013; Tisch, 2015; Zucchelli 2010) or substantially reduce the probability of employment (Aleksandrova et al., 2021; Garcia-Gomez et al., 2013; Seuring et al., 2015).

Regarding the link between hospitalisation and wage employment, hospitalisation significantly increases the probability of wage employment in waves 3 and 5 by 1.5 and 1.6 percentage points respectively and reduced the probability of wage employment in the pooled sample by 1 percentage point. However, there was no statistically significant effect of hospitalisation on the probability of wage employment in wave 4. Hospitalisation was found to significantly increase the probability of casual employment by 3.4 percentage points in wave 3, reduce the probability of casual employment by 2.8 percentage points in wave 5 and increase the probability of casual employment by 3 percentage points in the pooled sample. The changes in signs associated with hospitalisation may signal that the substitution and income effects are at play in the different waves. Again, in general, these results run contrary to traditional results obtained in developed countries, which emphasises the different structures of the economy of Malawi and perhaps other LMICs too (see for example Garcia-Gomez, 2013).

Apart from wave 3, where suffering from a chronic disease increased both the probability of wage employment (2 percentage points) and casual employment (2.3 percentage points), it is associated with reductions in the probability of both wage and casual employment in waves 4, 5 and the pooled sample with all coefficients being statistically significant. In wave 4 the probability of wage employment reduced by 1.6 percentage points while that of casual employment reduced by 2.5 percentage points. In wave 5 the reduction in the probability of wage employment was much smaller at 0.9 percentage points compared to that of casual employment at 2.6 percentage points. With reference to the literature, several authors have reported the negative link between chronic diseases and employment, including Ebaidalla & Ali (2020); Kumara & Samaratunge (2018); Ward (2015); and Zhang et al. (2009). This heightens the importance of the positive finding in wave 3 where those who are chronically ill still face barriers to leave the labour market to support their survival in the absence of social protection and other social support initiatives. This result might also have been influenced by the types of chronic diseases. Unlike in wave 4 and wave 5 (Table 3), the most common chronic diseases reported were asthma (22.2 per cent); arthritis (13.1 per cent) and epilepsy (10.1 per cent). This may be compared to waves 4 and 5 which had common chronic diseases such as asthma, HIV/AIDS and stomach disorders, although not necessarily in the same order. One may argue that given the government supported free medical schemes for those living with HIV/AIDS, in these cases there is less demand for employment to pay for such medical bills.

Overall, two fundamental issues emerged from the analysis. First, is the wave specificity of some results. For instance, illness/injury increased the probability of wage employment in wave 3 but reduced it in waves 4 and 5. Similarly suffering a chronic disease was associated with increases in the probability of both wage and casual employment in wave 3 but with reductions in these probabilities in waves 4 and 5. One can argue that, in part, this phenomenon could be a reflection of how far apart, chronologically, these surveys are. Wave 3 was conducted between 2010 and 2011, wave 4 between 2016 and 2017 and wave 5 in 2019 and 2020. These periods all had different socio-economic contexts including different economic growth rates. The World Bank[17] data base for Malawi shows differing annual GDP growth rates of 6.9 per cent in 2010; 4.9 per cent in 2011; 2.5 per cent in 2016; 4.0 per cent in 2017; 5.4 per cent in 2019 and, mainly due to the effects of the COVID pandemic, a drop to 0.8 per cent in 2020.

Second, the magnitudes of the effects of ill-health and health shocks on the probability of employment were not particularly large, and most estimated coefficients are below 5 percentage points. This finding appears to align with some of the previous evidence presented. For instance, Aleksandrova et al. (2021) found a 2.1 percentage point decline in probability of employment following a health shock in Russia, and using UK data, Lenhart (2019) found some effects as low as 0.97 percentage points. That said, other studies have reported larger effects such as that conducted by Trevisan and Zantomio (2016) who used data from sixteen European countries. They found effects ranging between 7.2 percentage points to 15.1 percentage points. In general, studies in developed settings have reported higher magnitudes than those reported by the results of this study.

[17] See https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?locations=MW.

Yet, the small magnitude of these effects may conceal important and distinctive features of Malawi's labour market. Unlike developed countries with more established social security systems including unemployment benefits, disability allowance and high formal employment, Malawi has very high informal employment where 8 in 10 people (ILO, 2018) are in informal employment in Malawi. In addition, only 21.3 percent of the population is covered by at least one social protection benefit. This means that though in poor health, there exist barriers to exit from labour markets for most individuals who will continue to work during illness, often informally. Another potential explanation for the comparatively small sizes of the effects might relate to the nature of illnesses and shocks. Reported common illnesses included fever and malaria, sore throats, coughs and headaches with most of them turning out to be less severe illnesses. Chronic illnesses included asthma, arthritis, and HIV-AIDS, and with availability of treatments for such diseases as HIV/AIDS under government support schemes this may mean less pressure to look for resources in the management of these diseases. In this sense one could also argue that the chronic illnesses reported were less severe illnesses. Therefore, most of these illnesses would not greatly impact the probability of employment. In fact, authors such as Lenhart (2019), and Aleksandrova (2021) who categorised health shocks into mild and severe shocks, found that severe shocks were more likely to be associated with larger declines in the probability of employment than mild or less severe shocks.

Table 3. 5: ATET effects on probability of employment following ill-health or a health shock

	Wave 3		Wave 4		Wave 5		Pooled sample	
	(n=26,082)		(n=30,708)		(n=32,894)		(n= 60,188)	
	Wage employment	**Casual employment**	**Wage employment**	**Casual employment**	**Wage employment**	**Casual employment**	**Wage employment**	**Casual employment**
Illness/injury	0.008**	-0.018**	-0.010***	0.043***	-0.012***	0.064***	-0.015***	0.065***
	(0.003)	(0.009)	(0.004)	(0.007)	(0.004)	(0.007)	(0.004)	(0.006)
Hospitalisation	0.015*	0.034**	0.013	0.022	0.016**	-0.028*	-0.010*	0.030***
	(0.008)	(0.015)	(0.009)	(0.016)	(0.008)	(0.016)	(0.006)	(0.011)
Chronic disease	0.020***	0.023**	-0.016**	-0.025**	-0.009*	-0.026***	-0.011**	-0.024***
	(0.010)	(0.011)	(0.007)	(0.011)	(0.005)	(0.009)	(0.005)	(0.009)

Abbreviations: ATET: Average Treatment Effect on the Treated
n = number of observations.
***P<0.01, ** P<0.05, * P<0.1.
Note: The table shows ATET values estimated using nearest neighbour propensity score matching relating to effects of ill-health or health shocks on the probability of employment
Note: Figures in parentheses are standard errors.
Note: Values in the table were rounded off to three decimal places.

c) Ill-health, health shocks and weekly working hours[18]

To assess the effects of ill-health and health shocks on weekly working hours, first the sum of number of hours involving on-farm employment and off-farm employment was determined. On-farm employment was derived from the following question: "How many hours in the last seven days did you spend on household farming activities, whether for sale or for household food?". Regarding off-farm employment we used the following question: "How many hours in the last seven days did you run or do any kind of non-agricultural or non-fishing household business, big or small, for yourself?".

Results show that illness/injury significantly reduced hours worked per week in waves 3, 5 and the pooled sample (Table 3.6). Although the ATET coefficient had a negative sign, there were no statistically significant effects of illness/injury on weekly hours worked in wave 4. Illness/injury was associated with reduction of up to 1.5 hours per week in wave 3, and almost an hour per week in wave 5, and 1.1 hours in the pooled sample.

Hospitalisation was associated with 1.6 hours reduction in wave 3. However, perhaps emphasising the uniqueness of the waves, hospitalisation was found to increase number of hours worked per week in wave 5 by almost an hour. Hospitalisation was associated with a 1.1-hour reduction in the pooled sample. While the negative link between health shocks and hours worked has been established in the literature (Aleksandrova et al., 2021; Cai et al., 2013; Lenhart, 2019;), the positive link between hospitalisation and hours worked per week in wave 5 might be the result of barriers to exit from labour markets faced by individuals with impaired health, re-enforcing the working for survival argument. Nonetheless this result is not entirely surprising. Trevisan and Zantomio (2016) found that following a health shock, men increased the number of hours of work relative to women. Lenhart (2018) also showed that workers increased hours of work after a health shock with mild health shocks and severe health shocks increasing hours worked per week by 0.79 and 1.11 hours, respectively.

[18] To ensure comparability of results with the nearest neighbour approach, other PSM approaches were used on the pooled data set. These included the regression adjustment, inverse probability weighting, regression adjustment with inverse probability weighting, and the augmented inverse probability weighting. Results reported in Appendix 3C were similar with those obtained using the nearest neighbour approach in terms of signs, coefficient sizes and statistical significance.

With reference to the effect of chronic illness on weekly hours of work, there was evidence of reduction in weekly hours worked associated with the occurrence of a chronic illness in wave 5 and in the pooled sample. However, although ATET coefficients in waves 3 and 4 had negative signs, they were not statistically significant. Although the sizes of coefficients may not be substantial owing to the informal nature of work and poor social security systems, our results regarding the negative link between chronic illnesses and hours of work are also in tandem with those of Booker et al., (2020); Gaulke (2021); and Kumara and Samaratunge (2018).

Furthermore, while the reductions in hours worked seem small and fully justified given the nature of labour markets in Malawi, it is noteworthy that findings of this study had coefficients with larger magnitudes than those found by Trevisan and Zantomio (2016) whose findings ranged from -0.072 to -0.151 compared to our findings of -0.515 to -1.55. Moreover, the results of Lenhart (2019) had some values as low as -0.03, much smaller than what the current study found.

Table 3. 6: ATET effects on working hours following an ill-health or a health shock.

	Wave 3	**Wave 4**	**Wave 5**	**Pooled sample**
	(n=21,206)	(n=30,710)	(n=32,894)	(n= 60,188)
	Hours Worked	**Hours Worked**	**Hours Worked**	**Hours Worked**
Illness/injury	-1.527***	-0.132	- 0.953***	-1.135***
	(0.316)	(0.192)	(0.183)	(0.139)
Hospitalization	-1.55***	-0.352	0.889**	-1.117***
	(0.542)	(0.375)	(0.388)	(0.284)
Chronic disease	-0.514	-0.164	-0.515**	-1.014***
	(1.521)	(0.263)	(0.248)	(0.205)

Abbreviations: ATET: Average Treatment Effect on the Treated
n = number of observations.
***P<0.01, ** P<0.05, * P<0.1.
Note: The table shows ATET values estimated using nearest neighbour propensity score matching relating to effects of ill-health or health shocks on weekly hours of work.
Note: Figures in parentheses are standard errors.
Note: Values in the table were rounded off to three decimal places.

c) Ill-health, health shocks and job search[19]

Despite its central role to the functioning of labour markets, a job search is not costless. It is a process that characterises the behaviour of the unemployed but also those wishing to transition between jobs. Related to job search is the phenomenon of the "discouraged worker" effect (Bloemen, 2005) which basically refers to "People who want to work but are not seeking work because they believe no suitable job is available for them" (ILO, 2015). To assess the effects of ill-health and health shocks on the probability of job search, the following question was utilised: "During the last four weeks did you do anything to find a job?".

Illness/injury (Table 3.7) was found to significantly reduce the probability of job search by 2 percentage points in waves 3 and 4; by 1.5 percentage points in wave 5, and by 0.5 percentage points in the pooled sample. Again, the reductions are small, reinforcing the working for survival argument given the circumstances that individuals find themselves in.

Similarly, regarding hospitalisation, the study found evidence of significant reductions in the probability of job search by 5 percentage points and 3.3 percentage points in waves 3 and 5 respectively. The ATET coefficients in wave 4 and the pooled sample have positive signs but are not statistically significant. Reducing the probability of job search seeking may also signal shifts towards searching for casual work as results on probability of casual employment may already have signalled. But it may also entail inactivity through the discouraged worker effect with individuals not seeking employment despite having no jobs. Again, the magnitudes are small, emphasising the dire need to survive and the existing barriers to leave the labour market.

Suffering a chronic disease significantly reduced the probability of job search by 3.2 percentage points in wave 3; but significantly increased the probability of job search by 2.2 percentage points in wave 4, and 2.5 percentage points in wave 5. The pooled sample saw an increase of 1.2 percentage points. As already alluded to, increasing the probability of job search while in poor health points to the lack of alternatives to work, particularly with regards to poor social

[19] To ensure comparability of results with the nearest neighbour approach, other PSM approaches were used on the pooled data set. These included the regression adjustment, inverse probability weighting, regression adjustment with inverse probability weighting, and the augmented inverse probability weighting. Results reported in Appendix 3D were similar with those obtained using the nearest neighbour approach in terms of signs, coefficient sizes and statistical significance.

protections systems. Yet the negative effect in wave 3 and the positive effects in waves 4 and 5 including those in the pooled sample, are a reminder of the uniqueness of the surveys that are indeed far apart underlying different socio-economic circumstances.

Table 3. 7: ATET effects on job search following ill-health and a health shock

	Wave 3	Wave 4	Wave 5	Pooled sample
	(n=21,204)	(n=30,708)	(n=32,894)	(n=60,180)
Illness/injury	-0.020**	-0.020***	-0.015***	-0.005*
	(0.008)	(0.006)	(0.006)	(0.003)
Hospitalization	-0.050***	0.019	-0.034**	0.002
	(0.016)	(0.014)	(0.018)	(0.007)
Chronic disease	-0.032**	0.022**	0.027***	0.012**
	(0.013)	(0.010)	(0.009)	(0.005)

Abbreviations: ATET: Average Treatment Effect on the Treated
n = number of observations.
****P*<0.01, ** *P*<0.05, * *P*<0.1.
Note: The table shows ATET values estimated using nearest neighbour propensity score matching relating to effects of ill-health or health shocks on job search.
Note: Figures in parentheses are standard errors.
Note: Values in the table were rounded off to three decimal places.

d) Synthesis of results

When the effects of ill-health and health shocks on the probability of employment, hours of work, and the probability of job search (Table 3.8), were considered in light of the pooled sample, a number of vital conclusions emerged.

Regarding the effects of illness/injury, hospital admission, and chronic illness on the probability of employment, the following conclusions were drawn from the analysis: a) individuals who reported to have suffered an illness or injury in the last fourteen days significantly reduced their probability of wage employment by 1.5 percentage points but increased the probability of casual employment by 6.5 percentage points; b) individuals who reported to have experienced a hospital admission in the last twelve months significantly reduced their probability of wage employment by 1 percentage point but increased their probability of casual employment by 3 percentage points; and c) individuals who reported that they suffered from a chronic disease significantly reduced their probability of wage employment by 1.1 percentage points and reduced their probability of casual employment by 2.4 percentage points.

In terms of the effects of illness/injury, hospital admission, and chronic illness on weekly hours of work, the following conclusions were discernible from the analysis: a) individuals who reported to have suffered an illness or injury in the last fourteen days significantly reduced their weekly hours of work by 1.14 hours; b) individuals who reported to have experienced a hospital admission in the last twelve months significantly reduced their hours of work by 1.12 hours; and c) individuals who reported that they suffered from a chronic disease significantly reduced their weekly hours of work by 1.0 hours.

Considering the effects of illness/injury, hospital admission, and chronic illness on the probability of job search the following conclusions were discernible from the analysis: a) individuals who reported to have suffered an illness or injury in the last fourteen days significantly reduced their probability of job search by 0.5 percentage points; b) there was no statistically significant effect on the probability of job search for individuals who reported to have experienced a hospital admission in the last twelve months[20]; and c) individuals who reported that they suffered from a chronic disease significantly increased the probability of searching for a job by 1.2 percentage points.

[20] It is important to note that although hospital admission did not seem to have a statistically significant effect on the probability of job search in the pooled sample, hospital admission reduced the probability of job search by 5 percentage points in wave 3 and 3.4 percentage points in wave 5.

Table 3. 8: Summary of results using the Pooled sample

	Wage employment	Effect	Casual employment	Effect	Hours-worked	Effect	Job-search	Effect
Ill/injury	-0.015	-ve (sig)	0.065	+ve (sig)	-1.135	-ve (sig)	-0.005	-ve (sig)
Hospitalisation	-0.010	-ve (sig)	0.030	+ve (sig)	-1.117	-ve (sig)	0.002	+ve (No sig effect)
Chronic disease	-0.011	-ve (sig)	-0.024	-ve (sig)	-1.014	-ve (sig)	0.012	+ve (sig)

Abbreviations: Sig: Statistically Significant, **-ve**: Negative effect; **+ve**: Positive effect
Note: Values were rounded off to three decimal places

3.4. Conclusions and policy recommendations

3.4.1 Conclusions

This chapter examined the effects of ill-health and health shocks on the probability of employment, weekly hours of work, and probability of job search. Three independently collected cross-sectional surveys of the Malawi Integrated Household Survey (IHS3, IHS4, IHS5) were used including a pooled data set of the three surveys. Analysis was at an individual level. A Nearest Neighbour Propensity Score Matching (PSM) approach was employed which ensured that individuals in the treated group (those who suffered ill-health or a health shock) and control group (those who did not suffer ill-health or a health shock) were matched based on key observed characteristics. Health shock and ill-health variables, namely illness/injury, hospitalisation and chronic diseases, were employed as treatment variables. Outcome variables included the probability of employment, hours worked per week, and job seeking. While ultimately, they depended on the variables in the respective surveys, socio-demographic variables, including those that were seen to have an influence on one's poor health, were used for matching.

The analysis provided some important findings. First, regarding the probability of employment, a) individuals who reported to have suffered an illness or injury in the last fourteen days significantly reduced their probability of wage employment but increased the probability of casual employment, b) individuals who reported to have experienced a hospital admission in the last twelve months significantly reduced their probability of wage employment but increased their probability of casual employment; and c) individuals who reported that they suffered from a chronic disease significantly reduced both the probability of wage employment and that of casual employment. In relation to weekly hours of work, individuals who reported to have suffered an illness or injury in the last fourteen days, individuals who reported to have experienced a hospital admission in the last twelve months - as well as individuals who reported that they suffered from a chronic disease - significantly reduced their hours of work. Finally, regarding the probability of job search, individuals who reported to have suffered an illness or injury in the last fourteen days significantly reduced their probability of job seeking, whereas individuals who reported that they suffered from a chronic disease significantly increased the probability of searching. There was no evidence of a significant effect on job for individuals who reported to have experienced a hospital admission in the last twelve months.

These results notwithstanding, two important issues emerged from the analysis. First are the differing effects across waves for some variables. For example, while suffering illness/injury caused reductions in wage employment and increased casual employment in waves 4 and 5, it had the opposite effects in wave 3. Similarly, suffering from a chronic disease increased both wage and casual employment in wave 3 but had negative causal effects in waves 4 and 5. Furthermore, despite decreasing hours worked per week in wave 3 and the pooled sample, hospitalisation increased hours worked per week in wave 5. Additionally, suffering a chronic disease reduced the probability of job search in wave 3 but increased it in wave 4, wave 5 and the pooled sample. The most plausible explanation to this emanates from the timing of the surveys. The waves were quite far apart with wave 3 conducted in 2010, wave 4 in 2016 and wave 5 in 2019. These periods were also experiencing different socio-economic developments unique to their time.

The second important issue emerging is that of the small sizes of ATET coefficients. While it is true that some studies in developed countries have reported similar magnitudes it cannot be generalised for those countries as most studies have tended to report large effects. It can be argued therefore that the small sizes are reflective of the nature of the Malawian economy and other LMICs which are dominated by informal employment and poor social protection systems including lack of unemployment benefits, disability allowance and other social initiatives. This essentially means that even with impaired health, individuals will not exit the labour force because they must survive. Thus, it can be seen that in some instances, individuals in fact increased the probability of employment, hours worked per week, or the probability of paid job search. In relation to this, Goryakin and Suhrcke (2016) established in Russia that workers in rural areas were more likely to continue with work than workers in urban areas because though they were in poor health, there existed barriers for them to exit labour markets that were not faced by those in urban areas. In our case, workers in Malawi and other LMICs face barriers to exit labour markets, that may not be faced by those in developed countries where access to social protection is higher than in developing countries.

Another dimension for the small sizes of coefficients relates to the nature of illnesses. Ultimately the nature and extent of these shocks or illnesses will be important in the net effect on labour markets. In relation to this, Jones et al. (2020) employed the concept of acute health shocks in their analysis; Garcia-Gomez et al. (2012) referred to acute hospitalisations which had significant effects on the probability of employment; and Booker et al. (2020) showed that individuals with more severe or chronic illnesses had more difficulties to remain in employment. The illnesses reported in the three surveys could be regarded as mild.

3.4.2 Policy Recommendations

The results of this work have important policy implications for Malawi which may be generalisable to other LMICs. One obvious challenge when compared to developed countries is the poor social protection systems in LMICs. The fact that workers who have suffered a shock or suffer from a chronic illness found barriers to exit the labour market can easily be explained by the lack of social security. In Africa the effective social protection rate stands at 17.4 per cent (ILO 2020) while in Malawi this figure stands at 21.3 per cent, and persons above retirement age receiving a pension are only 2.3 per cent.[21] Garcia-Gomez (2011) attributed the heterogeneous effects of health shocks on employment among countries in Europe to social security arrangements, emphasising the important role of social protection. In the same light, French (2005) observed that social protection was an important determinant of the labour market for those aged 62 and 65 in the United States. Even so, Candon (2019) showed that when health shocks were evaluated jointly with eligibility for social security, weekly hours reduced substantially. Malawi and other LMICs need to focus on establishing social protection systems that can support optimal labour market transitions.

Furthermore, the affinity to engage in casual employment rather than wage employment, even when in poor health, is revealing of market rigidities or acute barriers to accessing wage employment. It points out to the need to revitalise the priorities regarding job creation through job-rich growth initiatives. This is particularly imperative given the high informal employment in the country. Yet such a job rich strategy will require investments in developing relevant

[21] See ILOSTAT database at https://www.ilo.org/shinyapps/bulkexplorer41/?lang=en&segment=indicator&id=SDG_0131_SEX_SOC_RT_A.

skills, promoting entrepreneurship, and speeding the transition from the informal economy to the formal economy. Again, the slowing down of job points to the discouraged worker phenomenon which will need deliberate efforts to push people back into the labour force.

The health system may need attention too. Self-diagnosis of diseases reported by a large proportion of the population, means access to health centres and medical care is a huge challenge. The health policy in most countries already has important priorities outlined, but these need to be systematically implemented. Strategies to support Universal Health Coverage for essential health services are urgent and need to be deliberately supported by a budgeting process that creates the fiscal space for health.

CHAPTER FOUR

Joint effects of ill-health, health shocks and social protection on the intensive margin of labour supply: Evidence from Malawi

4.1 Introduction

Africa has the lowest levels of access to social protection[22] globally. The ILO (2020) observed that compared with a global average of 46.9 per cent, only 17.4 per cent of Africans are effectively covered by at least one social protection benefit compared to 46.9 per cent of the population globally. The large gap in social protection coverage and the generally poor social protection systems in Africa are correlated with significant underinvestment in social protection. Studies have linked social protection to a reduction in vulnerability to poverty in Africa. Ohrnberger (2022) showed that pro-poor cash transfers were effective at protecting the most vulnerable individuals from the effects of the COVID-19 shock. In the same vein, Atake (2018) found that when health shocks interacted with access to health insurance, household vulnerability to poverty significantly decreased in Burkina Faso, Niger, and Togo. Ouadika (2020) also found that health shocks accentuated the vulnerability to poverty in Congo, calling for social safety net programmes to support households in the event of heath shocks.

Although there has been some work conducted in Africa on the topic of social protection and labour, most evidence comes from countries other than Africa. For instance, Garcia-Gomez (2011) observed that variations in social security arrangements led to heterogeneous effects of ill-health and health shocks on labour market outcomes across European countries. Similarly, Candon (2019) and Coile (2004) found that eligibility for social security or pensions was associated with reduced labour supply. In the same vein, Fialová and Mysíková (2009) showed that access to social protection benefits provided an incentive to exit from labour markets in the Czech Republic. Moreover, Maestas et al. (2013) found that Social Security Disability Insurance reduced employment by 34-35 percentage points, decreased the probability of

[22] In the IHS survey social protection is defined in terms of social safety nets that include any cash, food, or other aid given to a member of household from the government, development partners, or Non-Governmental Organisations (NGOs). It does not include pensions and vouchers for fertilizer and seed given to a member of a household.

engaging in substantial gainful activity by 24-25 percentage points and led to a significant drop in annual earnings. French (2005) showed that in the United States, pensions as well as the social security tax structure partly explained job exits for those aged 62 and 65. Nevertheless, others such as Brauw et al. (2021), found no discernible effects of social protection on the labour supply. Le et al. (2019) reported that the effects of social protection (Universal Health Coverage) on labour markets in terms of increasing incentives or disincentives to work, depend on the design of the system. This is because some systems target only formal employees (such as in Thailand's 2001 reforms), while others target all employees.

Two key issues are apparent from the literature regarding the role of social security in labour markets. First, previous work has focussed mainly on developed countries (see for example Garcia-Gomez, 2011; French, 2005; and Platts, 2015). This calls for additional work in developing countries where socio-economic conditions and social security arrangements are different from those of developed countries, and where specific evidence to support relevant policy interventions is lacking. Second, while there have been studies assessing the effects of ill-health and health shocks on labour markets and, separately, the effects of social protection on labour markets (see for example Le et al., 2019), efforts to assess the joint effect of ill-health or health shocks and social protection on labour market outcomes have been rare. To this end one can cite the work of Candon (2019) who found that when health shocks and eligibility for social security were examined jointly, weekly hours were reduced by three to four hours in the United States.

Apart from the general paucity of studies linking social security and labour market outcomes, no work currently has assessed the joint effects of ill-heath or health shocks and social protection on the intensive margin of labour supply in Malawi. However, in a country with a limited social protection system both in quality and coverage,[23] dominated by cash and in-kind transfers, an understanding of the dynamic interaction between social protection, ill-health, or health shocks and labour intensity might be relevant policy-wise, and there is not much information hitherto available on this topic. The COVID-19 pandemic exposed a major shortfall in social protection support in the country. Generating evidence on the role of social protection in times of ill-health or health shocks may support appropriate investments in social

[23] See https://www.social-protection.org/gimi/gess/ShowCountryProfile.action?iso=MW.

protection. This is particularly important for a country with only 21.3 percent effective coverage of social protection; which spends only 3 per cent of GDP on healthcare; and only 1 per cent of GDP on social protection, irrespective of having a total labour force of almost 8.4 million (ILOSTAT, 2020).

Thus, this chapter contributes to the literature on several fronts. First, this is one of the first papers exploring the effects of health shocks on employment while accounting for the potential role played by the social protection system in an African country. It bridges the gap that exists in the literature regarding the health-labour relationship and the interaction with social protection, because no study has hitherto assessed the interaction of ill-health, health shocks and social protection on the intensive margin of labour supply in Africa. The evidence from this paper might support meaningful interventions in labour markets that consider both ill-health and health shocks on the one hand, and their interaction with social protection on the other hand, in the design of social protection programmes and universal health coverage (UHC) pursuits. Second, by using data from Malawi, the current study might inform potential country-specific policy interventions in a country in which social protection systems are poor and employment is highly informal. Third, the paper exploits the relationship using a pooled sample, which, although not in a panel setting, embodies attributes of the three different survey periods and provides additional information on the nature of the relationship. In this analysis joint effects are assessed through the interaction of ill-health and health shocks with social protection. This implies examining the effects of ill-health and health shocks in the presence of at least some form of social protection in Malawi.

4.2 State of Social Protection in Malawi

Most Malawians (51.7 per cent) live below the poverty line and 22.5 per cent are ultra-poor (UNICEF, 2021). With pervasive poverty, attempts to offer some form of social support to Malawians have been a pre-occupation of government policy since the country attained independence in 1964 (Chinsinga, 2007; Slater & Tsoka, 2007). From 1964 to approximately 2006, four social support phases were distinguished (Slater & Tsoka, 2007). The first is the period between 1964 and the 1980s. This period was characterised by price controls and subsidies dominating social support. These measures were, however, abandoned at the start of structural adjustment programmes (SAPs) championed by the Bretton Woods Institutions, mainly because of fiscal constraints. The second period spanned from 1981 to 1990. With input and output prices decontrolled and subsidies removed, this period targeted nutrition programmes, food transfers and credit schemes (Slater & Tsoka, 2007). The third period was the period 1990-1994. In response to what became known as the Social Dimension of Adjustment (SDA) as vulnerability increased (Chinsinga, 2007), this period saw the re-enforcement of targeted nutritional programmes, food transfers and credit schemes. The fourth period was between 1994 and 2006. During this period more safety nets were introduced, including programmes such as MSME credit schemes, a public works programme, input transfers, food transfers, school feeding programmes, cash transfers, targeted input subsidies, targeted nutrition programmes and integrated livelihood support (Chinsinga, 2007; Slater & Tsoka, 2007).

By 2005, as vulnerability increased and poverty remained widespread, it was clear that the numerous safety net programmes failed to improve livelihoods. This was attributed to poor coordination of these safety net interventions which were mostly *ad hoc* in nature (Chinsinga, 2007). This would prompt the government, the donor community, and the United Nations system to forge a comprehensive systematic plan toward social support in Malawi, prompting the development of a social protection policy whose draft was ready in 2008. With apparently subdued government commitment (Chinsinga, 2007; Devereux et al*.,* 2006; Siachiwena, 2021), the policy could not be finalised. This did not happen until 2012, when the National Social Support Policy (NSSP) was finalised, and it explicitly provided guidance on social protection in Malawi. The NSSP is now the overarching policy instrument that guides social protection in Malawi (UNICEF, 2021). It is well-linked to the Malawi Growth and Development Strategy III of 2017 which is premised, among other things, on, social protection programmes aimed at mitigating adverse effects on development and gender equality (Government of Malawi, 2017). Social protection formed the second theme of the MGDS I and has been given prominence in the Malawi 2063 vision. The vision recognises the role of social protection in the pursuit of supporting human capital development; health and nutrition promotion; as well as facilitation of the adaptation to shocks by vulnerable groups (Government of Malawi, 2020).

Poverty reduction is the main objective of the NSSP. This is achieved through promoting welfare support; providing asset protection and building resilience, nurturing productivity, and ensuring effective synergies with other initiatives (Bharadwaj et al., 2023; ILO, n.d.; Government of Malawi, 2012). To implement the NSSP, the government created the Malawi

National Social Support Programme (MNSSP). The first MNSSP (MNSSP I) ran from 2012 to 2016 while the MNSSP II ran from 2018 to 2023. The MNSSP II includes five priority themes[24], namely supporting consumption, building resilient livelihoods, ensuring synergy between social protection and other programmes, and supporting shock-sensitive social protection systems (Holmes et al*.,* 2018). Principally, the MNSSP is an instrument for monitoring priority programmes, including i) a Social Cash Transfer Programme (SCTP); ii) Public Works Programmes (PWPs); iii) School Meals Programmes (SMPs); iv) Village Savings and Loans Programmes (VSLs); and v) Microfinance Programmes (MF) (Homes et al*.,* 2018; Government of Malawi, 2018).

The Social Cash Transfer Programme (SCTP), locally known as "Mtukula Pakhomo", is a non-conditional safety net programme that serves vulnerable ultra poor Malawians (Government of Malawi, 2021; ILO n.d; Siachiwena, 2021). Over 1.3 million Malawians benefit from the programme yearly (Government of Malawi, 2021). It is expected that these beneficiaries would eventually move out of poverty. Targeting 10 per cent of beneficiaries per district, the recipients must be from both ultra-poor and labour constrained households, with an amount received determined by household size (Government of Malawi, 2021; Otchere & Handa, 2022). With an average of Malawi Kwacha 9000.00 (USD$ 11.0 in 2021)[25] per household, additional amounts are given for every child enrolled in primary school (Government of Malawi, 2021). The Directorate for Social Protection Services (DSPS) in the Ministry of Gender, Children, Disability and Social Welfare (MoGCDSW) leads the SCP programme, which is also supported by developing partners, including the EU, Irish Aid, KfW Germany, and the World Bank (Holmes et al., 2018).

On the other hand, the Labour-Intensive Public Works Programme (PWP) has the objective of transferring income to poor households that are not labour constrained, to reduce chronic or shock-induced poverty and provide social protection (Bharadwaj et al., 2023; ILO n.d.). This is done through the provision of limited employment opportunities. Working as safety nets

[24] According to Holmes et al. (2018), the five key programmes are complemented by the Farm Input Subsidy Programme (FISP); the Malawi Vulnerability Assessment Committee (MVAC) emergency; as well as other livelihoods and resilience-building activities.

[25] This amount was revised in December 2023 to Malawi Kwacha 14,919 (USD$ 8.8) per month per household owing partly to major devaluations of the Malawi Kwacha (https://mtukula.com/content?view=18&pageName=Cash%20Transferssee).

these programmes operate during non-farming seasons when income- generating activities are scarce (Chirwa et al., 2002; Beegle et al., 2017). Construction activities have dominated the PWP programme, and the Malawi Social Action Fun (MASAF) programme can be cited as the most popular PWP in Malawi (Bharadwaj et al., 2023, ILO n.d.). The programme is led by the Ministry of Local Government and Rural Development (MoLGRD) and funded by the World Bank (Homes et al., 2018).

Supported by developing partners such as GIZ, the EU, WFP, and Mary's Meals, the Department of School Health and Nutrition in the Ministry of Education, Science and Technology (MoEST) leads the School Meals Programme (SMP) (Bharadwaj et al., 2023; Holmes et al., 2018). The WFP takes three approaches to support this programme (WFP, 2018; WFP 2019; WFP 2021). First, in what is called a centralised model, WFP distributes food to cater for nutritional needs. This model aims to ease short-term hunger and ensure that learners have a longer attention span during lessons. The second approach is the Homegrown School Meals (HGSM) where the WFP partners with schools to purchase food locally from identified farmer organisations. Third, is through the United Nations Joint Programme for Girls Education (JPGE) where the WFP provides nutritious school meals and take-home rations. The SMP is operational only in the central and southern regions of the country (Holmes et al., 2018; WFP, 2021).

The Village Savings and Loans (VSL) Programmes are managed through the Ministry of Industry and Trade (MoIT). According to Holmes et al. (2018), over 100 different programmes exist with funding from the World Bank, DFID, USAID, Irish Aid, and Norway (ILO n.d.). Other actors include the Ministry of Local Government and Rural Development (MLG&RD), the MoGCDSW, the micro-finance institutions (MFIs), Reserve Bank of Malawi (RBM), village agents, CBOs and NGOs (Holmes et al., 2018).

Using mobile phone companies (MPCs), micro-finance institutions (MFIs), NGOs and CBOs, tertiary training institutions (TTIs), Micro-Finance (MF) Programmes (Holmes et al., 2018) are coordinated through the Reserve Bank of Malawi (RBM). Strengthening the capacity of microfinance institutions (MFIs) is seen as key to supporting financial access (ILO n.d.).

4.3 Data, variables, and model specification

a) Data

A pooled dataset comprising data from IHS3, IHS4 and IHS5 was used. Unlike chapter three in which ATET effects were estimated on the effects of ill-health and health shocks on several employment-related outcomes using matching methods, here emphasis was placed on the intensive margin of labour supply. To achieve this, weekly hours of work were used. Weekly hours of work were constructed by calculating the sum of hours obtained using two questions: “How many hours in the last seven days did you spend on household farming activities whether for sale or for household food?” and “How many hours in the last seven days did you run or do any kind of non-agricultural or non-fishing household business, big or small, for yourself?”. Second, apart from extracting measures of health shocks and ill-health which included illness/injury, hospitalisation, and chronic disease, a measure of social protection was also constructed using the question: “In the last twelve months has any member of your household received cash, food, or other aid from any known programme?”.

The known programmes in the question included a) free maize; b) free food other than maize; c) MASAF public works programme; d) inputs-for-work-programme; e) school feeding programme; f) free distribution of likuni phala to children and mothers (Targeted Nutrition Programme); g) supplementary feeding for malnourished at a nutritional rehabilitation unit; h) scholarships/bursaries for secondary education such as CRECCOM; i) scholarships for tertiary education such as university scholarship, upgrading teachers, tertiary loan schemes such as government loan for university and other tertiary education; j) direct cash transfers from government (mtukula pakhomo); and direct cash transfers from other sources such as development partners, and NGOs. There were other variables in relation to social safety nets including the total assistance received per programme, and whether the assistance was given to the household head or another member of the family. However, these questions were poorly responded to, leading to large missing data cases.[26] Thus, anyone who reported having received assistance in at least one of the programmes was coded as having benefited from social protection. The social protection variable was then used to construct three interaction variables:

[26] The subsequent questions were only answered by 5,405; 6,997; 5,177; and 18,016 out of a total of 469,970 who responded to the question that was used for social protection. Respondents had multiple answers given the possibility of participating in a number of programmes.

an interaction variable of illness/injury and social protection, an interaction variable of social protection and hospitalisation, and an interaction variable of social protection and chronic disease.

b) Variables

The dependent variable was weekly hours of work. This was the sum of the responses given to the following two questions: "How many hours in the last seven days did you spend on household farming activities whether for sale or for household food?"; and "How many hours in the last seven days did you run or do any kind of non-agricultural or non-fishing household business, big or small, for yourself?". To capture the effects of health shocks, two variables were used: **illness/injury** - During the last two weeks have you suffered from an illness or injury? and **Hosp**: During the last twelve months were you hospitalised or have an overnight stay in medical facility? To consider the effects of ill-health, suffering from a chronic disease was used: **chronic -** Do you suffer from a chronic illness? The health shock variables (illness/injury and hospitalisation) capture sudden and unexpected effects while the ill-health variable (chronic illness) captures long-term health effects. As such these variables may have potentially different effects on hours worked.

To consider access to social protection, the following was used: **SP**- In the last twelve months has any member of your household received cash, food, or other aid from any known programme? To assess joint effects the following interaction variables were considered: **ill*SP** - Interaction variable involving questions: During the two weeks have you suffered from an illness or injury?* In the last twelve months has any member of your household received cash, food, or other aid from any known programme?; **hosp*SP**: Interaction variable involving questions: During the last twelve months were you hospitalised or had an overnight stay in a medical facility?* In the last twelve months has any member of your household received cash, food, or other aid from any known programme?; **chronic*SP**: Interaction variable involving questions: Do you suffer from a chronic illness?* In the last twelve months has any member of your household received cash, food, or other aid from any known programme?

The interaction terms captured different effects. **ill*SP** and **hosp*SP** captured how social protection ameliorated the sudden health effects while **chronic*SP** captured how social protection ameliorated long term illness. Some control variables were included in the analysis.

These included: **Sex**- What is your sex?; **Age**- What is your age (years); **Religion**: What religion if any do you practice?; **Marstatus**- What is your present marital status?; and **Edulevel**- What is the highest educational qualification you have acquired? The variables used are described in Table 4.1.

Table 4. 1 Variables used

Variable	Description	Designation
Weekly hours of work	This is the sum of responses from the following two questions: “How many hours in the last seven days did you spend on household farming activities whether for sale or for household food? and “How many hours in the last seven days did you run or do any kind of non-agricultural or non-fishing household business, big or small, for yourself?	Dependent variable
Illness/Injury	During the last 2 weeks have you suffered from an illness or injury?	Independent variable
Hospitalisation	During the last 12 months where you hospitalized or had an overnight stay in medical facility?	Independent variable
Social protection	In the last 12 months has any member of your household received cash, food, or other aid from any known programme?	Independent variable
Chronic disease	Do you suffer from a chronic illness?	Independent variable
Ill*sp	Interaction variable between illness/injury and social protection	Independent variable
Hosp*sp	Interaction variable between hospitalisation and social protection	Independent variable
Chronic*sp	Interaction variable between chronic illness and social protection	Independent variable
Sex	What is your sex?	Control variable
Age	What is your age (years)?	Control variable
Religion	What religion if any do you practice?	Control variable
Marstatus	What is your present marital status?	Control variable
Edulevel	What is the highest educational qualification you have acquired?	Control variable

c) Model specification

In estimating the model, the analysis follows guidance established by Coile (2004) and Candon (2019) who modelled the joint effects of health shocks and social security on labour market outcomes. However, unlike Coile (2004) and Candon (2019) who used eligibility for social security, which essentially included individuals who were 60 years and older to interact with health shock variables, the present analysis uses individuals of any age who reported that they benefited from social protection. They also used longitudinal data drawn from the Health and Retirement Study. However, due to limitations in the panel data sub-sample of the Integrated Household Survey for Malawi, a pooled dataset of cross-sectional data including waves of IHS3, IHS4 and IHS5[27] was used in the current analysis.[28] In terms of health shocks, Candon (2019) used a current diagnosis of lung disease, heart problems, cancer, and strokes. Coile (2004) used three comprehensive sets of measures. The first included new diagnoses of cancer, heart attack, and strokes - dubbed acute health; the second had current diagnosis of diabetes, lung disease, arthritis, and heart failure while the third set encompassed injuries from accidents or falls. The current work used illness/injury and hospital admissions as health shocks and suffering chronic illness as a measure of ill-health. The study also differs from those of Coile (2004) and Candon (2019) who considered only health shocks by using both ill-health and health shocks.[29] The use of health shocks (unexpected health events) might help in the identification of the effects of health on hours of work as some partly exogenous/unexpected changes in health are being exploited.

In terms of labour market outcomes, Coile (2004) used the probability of labour exits and changes in hours worked. Like Candon (2019) the present study focuses on the intensive margin and looks at hours of work. This aligns with the study's interest to assess the effects of ill-health and health shocks on the intensive margin of labour supply, and to build the comprehensive model, six model formulations were used:

$$Hours = \emptyset_0 + \emptyset_1 ill + \emptyset_2 sp + \emptyset_3 (ill * sp) + \varepsilon_t \quad (1)$$

$$Hours = \emptyset_0 + \emptyset_1 ill + \emptyset_2 sp + \emptyset_3 (ill * sp) + \emptyset_i \sum_{i=4}^{n} \mathcal{X}_i + \varepsilon_t \quad (2)$$

---

[27] See the discussion on the data section.

[28] It is important to note that by not using panel data and so not using panel data specifications this analysis is not able to control for individual-level unobserved heterogeneity.

[29] When chronic diseases such as cancer, stroke, heart disease, diabetes are measured in terms of new diagnosis they are considered health shocks and not ill-health.

$$Hours = \emptyset_0 + \emptyset_1 ill + \emptyset_2 hosp + \emptyset_3 sp + \emptyset_4 (ill * sp) + \emptyset_5 (hosp * sp) + \varepsilon_t \tag{3}$$

$$Hours = \emptyset_0 + \emptyset_1 ill + \emptyset_2 hosp + \emptyset_3 sp + \emptyset_4 (ill * sp) + \emptyset_5 (hosp * sp) + \emptyset_i \textstyle\sum_{i=6}^{n} \mathcal{X}_i + \varepsilon_t \tag{4}$$

$$Hours = \emptyset_0 + \emptyset_1 ill + \emptyset_2 hosp + \emptyset_3 chronic + \emptyset_4 sp + \emptyset_5 (ill * sp) + \emptyset_6 (hosp * sp) + \emptyset_7 (chronic * sp) + \varepsilon_t \tag{5}$$

$$Hours = \emptyset_0 + \emptyset_1 ill + \emptyset_2 hosp + \emptyset_3 chronic + \emptyset_4 sp + \emptyset_5 (ill * sp) + \emptyset_6 (hosp * sp) + \emptyset_7 (chronic * sp) + \emptyset_i \textstyle\sum_{i=8}^{n} \mathcal{X}_i + \varepsilon_t \tag{6}$$

where $Hours$ = weekly hours of work, ill = illness/injury, $hosp$ = hospital admission, $chronic$ =chronic disease, sp =social protection; $ill * sp$= interaction between illness/injury and social protection; $hosp * sp$=interaction between hospital admission and social protection and $chronic * sp$= interaction between chronic disease and social protection, $\mathcal{X}$ = a vector of control variables, and ε_t is the error term.

In equation (1) weekly hours are regressed on illness/injury, social protection, and the interaction of social protection and illness/injury. In equation (2) weekly hours are regressed on illness/injury, social protection, and the interaction of social protection and illness/injury and control variables. In equation (3) weekly hours are regressed on illness/injury, hospital admissions, social protection, the interaction between social protection and illness/injury, and the interaction between social protection and hospital admission. In equation (4), weekly hours are regressed on illness/injury, hospital admissions, social protection, the interaction of social protection and illness/injury, and the interaction of social protection and hospital admission and control variables. In equation (5), weekly hours are regressed on illness/injury, hospital admissions, chronic illness, social protection, the interaction between social protection and illness/injury, the interaction between social protection and hospital admission, and the interaction between social protection and chronic illness. In equation (6) weekly hours are regressed on illness/injury, hospital admissions, chronic illness, social protection, the interaction between social protection and illness/injury, the interaction between social protection and hospital admission, and the interaction between social protection and chronic illness and control variables.

4.4 Estimation Methods

Weekly hours of work fall under the category of count data. Such data types have a lower-bound of zero and often are characterised by over-dispersion. Since the outcome is skewed, econometric techniques amenable to such data need to be employed. The present analysis uses five different types of count data models, namely: negative binomial, zero-inflated negative binomial, Poisson, zero-inflated Poisson and a two-part model. A standard OLS model was also estimated to produce some baseline estimates not based on a count data model.

a) Poisson regression

Karazsia and Van Dulmen (2008) observe that the Poisson distribution is skewed positively with a decreasing mean of the response variable, a characteristic that reflects a conventional count data property. The present work follows that conducted by Lukman et al. (2021), Chau et al. (2018), Frome and Checkoway (1985), and Cupal et al. (2014) who utilised the Poisson distribution in their works. A Poisson distribution with parameter $\lambda > 0$ is used to model weekly hours denoted by y_i as follows:

$$P(y) = \frac{e^{-\lambda}\lambda^{y}}{y!}, \quad y = 0, 1,2,3 \ldots \tag{7}$$

A key assumption that underlies the Poisson distribution is the equality of variance and mean:

$$\mathrm{E}(y_i) = \lambda,\ var(y_i) = \lambda \tag{8}$$

Using the sample of weekly hours of work $y_{1,}\ y_2 \ldots y_n,\ y_i$ can be characterised as follows:

$$y_i = E(y_i) + \varepsilon_i, \quad i = 1, 2, 3, \ldots n \tag{9}$$

We then use a link function v to relate the mean of weekly hours worked (y) to a linear predictor as follows:

$$v(\lambda_i) = \eta_i \tag{10}$$

$$v(\lambda_i\,) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k \tag{11}$$

$$v(\lambda_i) = x_i'\beta \tag{12}$$

From (10) λ_i can be characterised as follows:

$$\lambda_i = v^{-1}(\eta_i) \tag{13}$$

$$\lambda_i = v^{-1}(x_i'\beta) \tag{14}$$

It follows that the identity link can be presented as follows:

$$v(\lambda_i) = \lambda_i = x_i'\,\beta \tag{15}$$

The log-link function is presented as follows:

$$v(\lambda_i) = \ln(\lambda_i) = x_i'\beta \tag{16}$$

where $\lambda_i = v^{-1}(x_i'\beta) = \exp(x_i'\beta)$

Although the Poisson regression, developed using the Poisson probability distribution, is arguably the most used model in the analysis of count data (Arora and Chaganty, 2021), it does have some limitations (Weaver et al., 2015). Gurmu and Trivedi (1996) make three observations. The first observation relates to the assumption of equi-dispersion implying equality of variance and mean. This is rarely the case in practice (Hellstrom, 2002). Instead, we have over-dispersion with variance greater than the mean or under-dispersion when variance is less than the mean. The second limitation relates to the possibility of a higher number of zeros than are expected in the Poisson model, called the zero-inflation problem (Arora & Chaganty, 2021; Gurmu & Trivedi 1996; Gupta et al., 1996). Third, events captured by a count data model may not be independent of the preceding occurrence. In this case the conditional independence assumption, does not hold (Gurmu & Trivedi 1996).

b) Negative binomial regression

The Poisson model assumes the equality of the mean and variance. Conversely, the negative binomial model on the other hand relaxes this assumption. In this model, a latent heterogeneity (Greene, 2008; Gourieroux et al*.,* 1984) is introduced into the conditional mean of the Poisson model to yield the following:

$$\mathrm{E}[y_i|\boldsymbol{x}_i, \varepsilon_i] = \exp(\alpha + \boldsymbol{x}_i'\beta + \varepsilon_i) = h_i\lambda_i \tag{17}$$

where $h_i = \exp(\varepsilon_i)$ follows a gamma distribution $G(\theta, \theta)$ with a mean of unity and variance $1/\theta = \kappa$;

$$f(h_i) = \frac{\theta^\theta \exp(-\theta h_i) h_i^{\theta-1}}{\Gamma(\theta)}, h_i \geq 0, \theta > 0 \tag{18}$$

To obtain the marginal negative binomial, h_i is integrated out of (18) to yield the following:

$$Prob\,[Y = y_i|\boldsymbol{x}_i)] = \frac{\Gamma(\theta+y_i) r_i^\theta (1-r_i)^{y_i}}{\Gamma(1+y_i)\Gamma(\theta)}, y_i = 0,1,\dots,\theta > 0, r_i = \theta/(\theta + \lambda_i) \tag{19}$$

The conditional mean is preserved as,

$$\mathrm{E}[y_i|\boldsymbol{x}_i, \varepsilon_i] = \lambda_i \tag{20}$$

However, the overdispersion is induced by the latent heterogeneity,

$$\mathrm{Var}[y_i|\boldsymbol{x}_i]=\lambda_i\left[1+\left({}^{1}/_{\theta}\right)\lambda_i\right]=\lambda_i[1+\kappa\lambda_i] \tag{21}$$

where $\kappa = var(h_i)$

c) Zero-inflated negative binomial model

In the Zero-Inflated Negative Binomial regression there are two distinct data generation processes underpinned on a Bernoulli trial (Fang et al., 2016; Greene, 1994; Yau et al., 2003). The sole possible response associated with the first process is a zero count with probability π_i, corresponding to observation i. The second process with probability $((1-\pi_i)$, which also generates zeros, is associated with a negative binomial with mean λ_i. This means that the zero counts are generated from both the first and second processes. Accordingly, the overall probability of zero counts corresponds to both processes and is given as follows:

$$Prob(Y_i = 0) = \pi_i + (1-\pi_i)(1+\kappa\lambda_i)^{\frac{-1}{\kappa}} \tag{22}$$

$$Prob(Y_i = y_i) = (1-\pi_i)\frac{\Gamma\left((y_i+\frac{1}{\kappa})\right)(\kappa\lambda_i)^{y_i}}{\Gamma(y_i+1)\Gamma\left(\frac{1}{\kappa}\right)(1+\kappa\lambda_i)^{y_i+\frac{1}{\kappa}}} \tag{23}$$

The mean and variance of Y_i are given as follows:

$$\mathrm{E}(Y_i) = (1-\pi_i)\lambda_i \tag{24}$$

$$Var(Y_i) = (1-\pi_i)\lambda_i(1\text{-}\lambda(\pi_i+\kappa)) \tag{25}$$

In this case the mean λ_i is the mean of the inherent negative binomial distribution and κ is the parameter that represents over-dispersion.

Complementing the negative binomial model with the zero-inflated negative binomial model has the advantage that, in the presence of excessive zeros - which is common when modelling hours of work - the zero-inflated negative binomial model undertakes a comprehensive analysis by estimating both the probability of excess zeros relating to hours of work, and the general count distribution, unlike the negative binomial which only provides estimates on account of the general count distribution.

d) The zero-inflated Poisson model (ZIP)

The zero-inflated Poisson model accounts for some of the limitations of a standard Poisson model (see for example Lambert, 1992; Arora & Chaganty, 2021). More specifically, in this model there are two elements that relate to two zero generating processes (Lukusa & Phoa, 2020; Pew et al., 2020). The initial process corresponds to a binary distribution that produces true zeros also called structural zeros. The second process relates to a Poisson distribution that produces counts that could also assume the value zero.

The two model components (see for example Pew et al., 2020; Arora & Chaganty, 2021; Sakthivel & Rajitha, 2018; and Becket et al., 2014) are given as follows:

$$P(y_i = 0) = \pi + (1-\pi)e^{-\lambda} \tag{26}$$

$$P(y_i = \varpi) = (1-\pi)\frac{\lambda^{\varpi}e^{-\lambda}}{\varpi!}, \quad \varpi \in \{1,2,3,\dots\} \tag{27}$$

where $0 \leq \pi \leq 1$ and $\lambda \geq 0$

The mean and variance of the ZIP are given as follows:

$$\mathrm{E}(y_i) = (1-\pi)\lambda\,,\ var(y_i) = \lambda(1-\pi)(1+\pi\lambda). \tag{28}$$

Essentially:

$$ln\,(\lambda) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k \tag{29}$$

$$Logit\,\pi = ln\left(\frac{\pi}{1-\pi}\right) = \emptyset_0 + \emptyset_1 h_1 + \emptyset_2 h_2 + \cdots \emptyset_m h_m \tag{30}$$

where

i) $x_1, \dots, x_k$ are predictors,

ii) $\beta_1, \dots, \beta_k$ are regression coefficients,

iii) $h_1, \dots, h_m$ are the zero-inflated predictors responsible for inflation of the number of zeros in the model, and

iv) $\emptyset_1, \dots, \emptyset_m$ are the zero-inflated coefficients.

Similar to the zero-inflated negative binomial model, complementing the Poisson model with the zero-inflated Poisson model has the advantage that, in the presence of excessive zeros, which is common when modelling hours of work, the zero-inflated Poisson model undertakes a comprehensive analysis by estimating both the probability of excess zeros relating to hours of work and the general count distribution, unlike the Poisson model which only provides estimates on account of the general count distribution.

e) The two-part model

To model weekly hours of work using a two-part model, the analysis followed the methods of Ciminata et al., (2020); Arrospide et al., (2020); and Deb and Norton (2018). This model is used for mixed discrete-continuous outcomes (Belotti et al., 2015). The model consists of two parts: I) a binary choice part, which corresponds to the probability of observing a positive – versus-zero weekly hours worked; II) Then a relevant regression is fit for the positive outcome, conditional on a positive outcome.

To handle the zeros, a model of the following form is used:

$$\psi(y > 0) = P(y > 0/x) = \Gamma(x\upsilon) \tag{31}$$

where x represents a vector of independent variables, υ represents the coefficients to be estimated and Γ is the cumulative function corresponding to the independent and identically distributed error term. The logit or probit distributions are used for this part.

Regarding the second model for a positive outcome, the following formulation is used:

$$\psi(y/y > 0, x) = h(x\alpha) \tag{32}$$

where x represents a vector of independent variables, α is the coefficient vector and h is a relevant density function for $y/y > 0$.

The likelihood contribution associated with an observation is given as follows:

$$\psi(y) = \{1 - \Gamma(x\upsilon)\}^{i(i=0)} * \{\Gamma(x\upsilon)h(x\alpha)\}^{i(y>0)} \tag{33}$$

where $i(.)$ denotes an indicator function.

It follows that the loglikelihood is:

$$ln\{\psi(y)\} = i(i = 0)ln\{1 - \Gamma(x\upsilon)\} + i(i > 0)[ln\{\Gamma(x\upsilon)\} + ln\{h(x\alpha\}] \tag{34}$$

Since υ and α coefficients are additively separable, it is possible to estimate the two parts of the model separately. The overall mean is simply the product of expectations from two parts as follows:

$$\mathrm{E}(y/x) = P(y > 0/x) * \mathrm{E}(y/y > 0, x) \tag{35}$$

Thus, in situations where outcomes, like hours of work, embody two statistical features where hours of work can be positive or zero, and where the observed zeros, are observed multiple times, warranting special analysis, a two-part model presents a better option than single index model (Belotti et al., 2015).

f) Summary of models used

The thesis uses five count models in analysing joint effects of ill-health, health shocks and social protection on the intensive margin of labour supply. Each model has its unique underlying assumptions which are useful in different situations. The Poisson regression model is premised on the equality of variance and mean (Frome & Checkoway,1985; Cupal et al., 2014). However, this is a rarity in practice. The negative binomial model relaxes this equi-dispersion assumption and is used when variance is greater than mean (Stoklosa et al., 2022, Greene, 2008; Gourieroux et al., 1984). This is because ignoring overdispersion can lead to overestimated parameters and affect statistical inference (Stoklosa et al., 2022). Further, although the negative binomial model handles the dispersion problem, both the Poisson and negative binomial models are not well suited in the presence of the zero-inflation problem. To deal with this problem, zero-inflated models are used (Lukusa & Phoa, 2020; Pew et al., 2020). These models assume that excess zeros are not due to random variation but rather to a separate process ((Fang et al., 2016; Greene, 1994; Yau et al., 2003). The thesis uses the zero-inflated binomial model and the zero-inflated Poisson model. They are a two-component mixture model with a binary component that models excess zeros and a count component that models non-zero counts. On the other hand, the two-part model is used in situations of mixed discrete-continuous random variables where a single index model may not be desirable (Belotti, 2015).

4.5 Results

Using the delta method, marginal effects were obtained using the negative binomial model, the zero-inflated negative binomial model, the Poisson model, the zero-inflated Poisson model, and a two-part model to assess the joint impact of ill-health, health shocks and social protection on the intensive margin of labour supply in Malawi. Moreover, a standard OLS model was also estimated to produce some baseline estimates which were not based on a count data model.

4.5.1 The Negative Binomial Model[30]

Results of the negative binomial model are captured in Table 4.2. In the 1st formulation, the marginal effect of illness/injury was negative and statistically significant. The marginal effect of social protection was also negative and statistically significant. However, when illness/injury were interacted with social protection the marginal effect became positive signalling that individuals who were ill or injured increased their weekly hours of work. In the 2nd case when control variables were introduced, the marginal effect of illness/injury remained negative and statistically significant. The marginal effect of social protection became positive but not statistically significant. Additionally, the interaction term of illness/injury and social protection had a negative marginal effect that was statistically insignificant.

In the 3rd formulation, a negative statistically significant marginal effect of illness/injury on weekly hours was found. Hospital admission had a negative marginal effect albeit one which was not statistically significant. The marginal effect of social protection had a negative sign which was highly statistically significant. Although marginal effects of illness/injury and social protection were negative and highly statistically significant, their interaction term produced a positive marginal effect which was only marginally significant. Further, the interaction term between social protection and hospital admission had a positive and highly statistically significant marginal effect. According to the 4th model, the marginal effects of illness/injury and hospital admission were found to be negative and highly statistically significant. Nevertheless, social protection did not exert a significant influence on weekly hours. Moreover, the interaction term between social protection and illness/injury was statistically

[30] Analysis at wave level (wave 3, wave 4, and wave 5) for all models was also done results of which are shown in Appendix 5A.

insignificant. In contrast, the interaction term between hospital admission and social protection had a positive and highly significant marginal effect.

According to the 5th model, the marginal effect of illness/injury was found to be negative and highly statistically significant, the marginal effect of hospital admission was found to be negative but statistically insignificant, the marginal effect of chronic illness was found to be positive and highly significant statistically, and the marginal effect of social protection was found to be negative and highly significant. In terms of interaction variables, both the marginal effect of social protection and illness/injury and that of social protection and hospital admission were found to be positive and highly statistically significant. In the 6th model (the comprehensive model) illness/injury was found to have a negative and statistically significant marginal effect. The marginal effect of hospital admission was negative and only marginally significant. On the other hand, the marginal effects of both chronic illness and social protection were statistically insignificant. The interaction effect between illness/injury and social protection was negative and statistically insignificant. Furthermore, the interaction effect between hospital admission and social protection was positive and highly statistically significant. In addition, the interaction effect between chronic illness and social protection was negative and not statistically different from zero.

Overall, when the comprehensive model was considered, the negative binomial model led to the following conclusions: a) individuals who experienced an illness or injury reduced their hours of work; b) individuals who experienced a hospital admission reduced their hours of work; and c) individuals who experienced a hospital admission and benefited from social protection significantly increased their hours of work. However, there was no significant statistical evidence regarding the effect of chronic illness or social protection on weekly hours of work. Furthermore, the interaction effects between social protection and illness/injury as well as between social protection and chronic illness were not found to be statistically significant.

Table 4. 2: Results of the Negative Binomial Model

Dep var: Weekly hours of work Model: Negative binomial						
Variable	**dy/dx (1st)**	**dy/dx (2nd)**	**dy/dx (3rd)**	**dy/dx (4th)**	**dy/dx (5th)**	**dy/dx (6th)**
Illness/injury	-0.696*** (0.118)	-0.743*** (0.176)	-0.691*** (0.119)	-0.723*** (0.177)	-0.814*** (0.119)	-0.754*** (0.178)
Hospitalisation			-0.129 (0.199)	-0.514*** (0.293)	-0.288 (0.200)	-0.502* (0.294)
Chronic illness					1.680*** (0.206)	0.098 (0.270)
Social protection	-0.293*** (0.093)	0.171 (0.136)	-0.465*** (0.106)	-0.256 (0.157)	-0.481*** (0.107)	-0.206 (0.160)
Illness/Injury*Social protection	0.387** (0.191)	-0.081 (0.280)	0.356* (0.191)	-0.137 (0.280)	0.382*** (0.192)	-0.085 (0.282)
Hospitalisation*Social protection			0.230*** (0.069)	0.533*** (0.099)	0.216*** (0.069)	0.537*** (0.100)
Chronic illness *Social protection					-0.135 (0.313)	-0.648 (0.407)
Control variables		**YES**		**YES**		**YES**
AIC	604,154.7	485,545.6	604,104.3	485,516.7	603,994.4	485,495
BIC	604,204.6	485,753.7	604,111.2	485,743.7	604,084.2	485,741
N	160,268	94,851	160,261	94,856	160,232	94,846

Abbreviations: AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.
N= number of observations.
dy/dx =Marginal effects.
***P<0.01, ** P<0.05, * P<0.1.
Note: The table shows marginal effects estimated by the negative binomial model.
Note: Figures in parentheses are standard errors.
Note: Control variables included sex, age, religion, marital status, and education level.
Note: Values in the table were rounded off to three decimal places.

4.5.2 The Zero-inflated Negative Binomial Model

Results of the zero-inflated negative binomial model are captured in Table 4.3. Similar results were found in the 1st and 2nd versions in which both illness/injury and social protection had negative, highly statistically significant marginal effects and the interaction terms had negative, but not statistically significant marginal effects. According to the 3rd version, the marginal effect of illness/injury was negative and highly statistically significant, while the marginal effect of hospital admission was positive and highly statistically significant. Social protection had a negative effect that was highly statistically significant. However, a positive but insignificant marginal effect for the interaction term between illness/injury and social protection was obtained. On the contrary, a negative and highly statistically significant marginal effect was obtained for the interaction between hospital admission and social protection.

In the 4th formulation of the model, only the marginal effect of illness/injury and that of the interaction between hospital admission and social protection were significantly different from zero. Both had negative signs. In the 5th formulation of the model, statistically significant negative marginal effects were found for illness/injury, social protection, and the interaction term between hospital admission and social protection. The marginal effect of chronic illness had a positive and highly significant marginal effect. The rest of the variables had no significant influence on weekly hours of work. In the comprehensive model (6th), only illness/injury (negative), chronic illness(positive) and the interaction between hospital admission and social protection (negative) had statistically significant marginal effects.

Overall, results of the zero-inflated binomial model (using the comprehensive model) led to the following conclusions: a) individuals who experienced an illness or injury reduced their hours of work; b) individuals who experienced chronic illnesses increased their hours of work; and c) individuals who experienced a hospital admission and benefited from social protection reduced their hours of work. However, there was no statistical significance regarding the effect of hospital admission and social protection on weekly hours of work. Further, interaction terms between social protection and illness/injury as well as between social protection and chronic illness were not statistically significant.

Table 4. 3: Results of the Zero-Inflated Negative Binomial Model

Dep var: Weekly hours of work Model: Zero-inflated Negative binomial						
Variable	**dy/dx (1^{st})**	**dy/dx (2^{nd})**	**dy/dx (3^{rd})**	**dy/dx (4^{th})**	**dy/dx (5^{th})**	**dy/dx (6^{th})**
Illness/injury	-0.217*** (0.068)	-0.542*** (0.068)	-0.227*** (0.068)	-0.544*** (0.100)	-0.274*** (0.069)	-0.567*** (0.101)
Hospitalisation			0.245*** (0.116)	0.024 (0.166)	0.185 (0.116)	-0.001 (0.167)
Chronic illness					0.556*** (0.106)	0.296** (0.152)
Social protection	-0.334*** (0.052)	-0.242*** (0.077)	-0.159*** (0.060)	-0.133 (0.089)	-0.166*** (0.061)	-0.117 (0.091)
Illness/Injury*Social protection	-0.031 (0.108)	-0.130 (0.156)	0.002 (0.108)	-0.114 (0.156)	0.012 (0.109)	-0.092 (0.158)
Hospitalisation*Social protection			-0.224*** (0.038)	-0.134** (0.055)	-0.229*** (0.038)	-0.134** (0.054)
Chronic illness *Social protection					-0.038 (0.160)	-0.250 (0.228)
Control variables		**YES**		**YES**		**YES**
AIC	584,035.9	469,309.6	583,994.3	469,306.3	583,910.8	469,206.1
BIC	584,095.8	469,527.1	584,074.7	469,542.8	584,010.6	469,541.6
N	160,268	94,851	160,261	94,850	160,232	94,846

Abbreviations: AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.
N= number of observations.
dy/dx =Marginal effects.
***P<0.01, ** P<0.05, * P<0.1.
Note: The table shows marginal effects estimated by the zero-inflated negative binomial model.
Note: Figures in parentheses are standard errors.
Note: Control variables included sex, age, religion, marital status, and education level.
Note: Values in the table were rounded off to three decimal places.

4.5.3 The Poisson Model

When the Poisson model (Table 4.4) was used in the 1st model formulation, illness/injury was found to have a negative influence on weekly hours. Similarly, social protection was found to have a negative statistically significant negative effect on hours worked. The interaction variable of social protection and illness/injury had a positive marginal effect that was significant at the 1 per cent level. According to the 2nd model formulation, the marginal effect of illness/injury was negative and highly statistically significant. On the other hand, that of social protection was positive and statistically significant. However, the interaction variable of social protection and illness had a negative and statistically insignificant marginal effect.

In the 3rd model formulation, the marginal effects of illness/injury, hospitalisation, and social protection had highly significant negative marginal effects. Furthermore, the interaction variables of illness/injury and social protection, and hospitalisation and social protection exhibited positive and highly significant marginal effects. In the 4th model, the marginal effects of illness/injury, hospitalisation, and social protection had negative highly significant marginal effects. The interaction variable of illness/injury and social protection exhibited a negative and highly significant marginal effect while that of hospitalisation and social protection had a positive and highly significant marginal effect. In the 5th version of the model, while chronic illness had a positive significant influence on weekly hours; illness/injury, hospitalisation, and social protection had negative and highly statistically significant marginal effects. All interaction variables showed significant effects on weekly hours. The interaction variables of illness/injury and social protection, and hospitalisation and social protection had positive marginal effects while that involving chronic illness and social protection had a negative marginal effect.

In the comprehensive model (6th) illness/injury, hospital admission, and social protection were found to have negative and highly statistically significant marginal effects. The marginal effect of chronic illness was negative but not statistically significant. Regarding interaction variables, illness/injury and social protection had a negative marginal effect which was not statistically significant. However, the interaction term of hospitalisation and social protection had a positive and highly statistically significant marginal effect. Furthermore, the interaction variable of chronic illness and social protection had a negative and statistically significant marginal effect.

Overall the results of the Poisson model led to the following conclusions: a) individuals who experienced an illness or injury reduced their weekly hours of work; b) individuals who experienced hospital admissions reduced their weekly hours of work; c) individuals who benefited from social protection reduced their weekly hours of work; d) individuals who experienced hospital admission and benefited from social protection increased their hours of work; and e) individuals who were chronically ill and benefited from social protection reduced their hours of work. It is noteworthy however that there was no statistically significant effect regarding individuals who experienced chronic illnesses on their hours of work. Furthermore, there was no statistically significant evidence regarding the effect of the interaction variable between social protection and illness/injury on weekly hours of work.

Table 4. 4: Results of the Poisson Model

Dep var: Weekly hours of work Model: Poisson						
Variable	**dy/dx (1st)**	**dy/dx (2nd)**	**dy/dx (3rd)**	**dy/dx (4th)**	**dy/dx (5th)**	**dy/dx (6th)**
Illness/injury	-0.138*** (0.003)	-0.924*** (0.028)	-0.691*** (0.018)	-0.113*** (0.004)	-0.800*** (0.018)	-0.894** (0.029)
Hospitalisation			-0.116*** (0.028)	-0.097*** (0.006)	-0.315*** (0.029)	-0.730*** (0.047)
Chronic illness					1.589*** (0.026)	-0.033 (0.042)
Social protection	-0.058*** (0.021)	0.168*** (0.021)	-0.465*** (0.015)	-0.021*** (0.003)	-0.474*** (0.0157)	-0.117*** (0.026)
Illness/Injury*Social protection	0.077*** (0.006)	-0.070 (0.045)	0.369*** (0.028)	-0.015*** (0.006)	0.349*** (0.029)	-0.056 (0.046)
Hospitalisation*Social protection			0.226*** (0.010)	0.056*** (0.002)	0.210*** (0.010)	0.447*** (0.016)
Chronic illness *Social protection					-0.090** (0.041)	-0.640*** (0.065)
Control variables		**YES**		**YES**		**YES**
AIC	2,623,890	1,646,020	2,623,294	1,645,022	2,617,434	1,644,784
BIC	2,623,930	1,646,218	2,623,354	1,645,240	2,617,514	1,645,020
N	160,248	94,851	160,261	94,850	160,232	94,846

Abbreviations: AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.
N= number of observations.
dy/dx =Marginal effects.
***P<0.01, ** P<0.05, * P<0.1.
Note: The table shows marginal effects estimated by the Poisson model.
Note: Figures in parentheses are standard errors.
Note: Control variables included sex, age, religion, marital status, and education level.
Note: Values in the table were rounded off to three decimal places.

4.5.4 The Zero-inflated Poisson Model

According the Zero-inflated Poisson model (Table 4.5), the 1^{st} and 2^{nd} models produced similar results. Illness/Injury, social protection and their interaction term were all negative and highly significant. However, there were differences in the 3^{rd} and 4^{th} model formulations. In the 3^{rd} model, illness/injury and social protection were found to have negative and highly statistically significant marginal effects while the marginal effect of hospital admission was found to be positive and statistically significant. In terms of interaction effects, the interaction term between illness/injury and social protection had a negative but insignificant marginal effect, while the interaction term between hospital admission and social protection had a negative and highly significant marginal effect.

In the 4^{th} model formulation, all the variables, including interaction terms, had highly negative statistically significant marginal effects with only the marginal effects of hospital admission having a positive and non-significant marginal effect. In the 5^{th} version of the model, illness/injury and social protection had highly negative significant marginal effects while hospital admission and chronic illness had positive and highly significant marginal effects. Out of the three interaction terms, only the term relating to hospital admission and social protection yielded a negative and highly statistically significant marginal effect.

According to the comprehensive model (6^{th}) the marginal effects of illness/injury and social protection were negative and highly statistically significant. The marginal effect of chronic illness was positive and highly statistically significant. The marginal effect of hospital admission was positive but not significant statistically. In this model all the interaction terms had negative signs and were statistically significant.

In summary, the results of the zero-inflated Poisson regression showed the following: a) individuals who experienced an illness or injury reduced their weekly hours of work; b) individuals who experienced chronic illness increased their weekly hours of work; c) individuals who benefited from social protection reduced their weekly hours of work; d) individuals who experienced an illness/injury and benefited from social protection reduced their weekly hours of work; e) Individuals who had a hospital admission and benefited from social protection reduced their weekly hours of work; and g) individuals who were chronically ill and benefited from social protection reduced their weekly hours of work. However, there was no statistically significant evidence regarding the effect of hospital admission on weekly hours of work. It is important however to note that model versions three and five produced positive highly significant marginal effects.

Table 4. 5: Results of the Zero-Inflated Poisson Model

Dep var: Weekly hours of work Model: Zero-inflated Poisson						
Variable	**dy/dx (1st)**	**dy/dx (2nd)**	**dy/dx (3rd)**	**dy/dx (4th)**	**dy/dx (5th)**	**dy/dx (6th)**
Illness/injury	-0.164** (0.018)	-0.538*** (0.027)	-0.174*** (0.018)	-0.540*** (0.027)	-0.211*** (0.018)	-0.558*** (0.027)
Hospitalisation			0.257*** (0.029)	0.022 (0.045)	0.207*** (0.029)	0.002 (0.045)
Chronic illness					0.453*** (0.026)	0.252*** (0.040)
Social protection	-0.319*** (0.013)	-0.245*** (0.021)	-0.124*** (0.015)	-0.124*** (0.024)	-0.130*** (0.016)	-0.112*** (0.024)
Illness/Injury*Social protection	-0.064** (0.028)	-0.116*** (0.043)	-0.028 (0.028)	-0.094*** (0.043)	-0.027 (0.028)	-0.077* (0.044)
Hospitalisation*Social protection			-0.249*** (0.010)	-0.154*** (0.015)	-0.252*** (0.010)	-0.154*** (0.015)
Chronic illness *Social protection					-0.023 (0.040)	-0.194*** (0.061)
Control variables		**YES**		**YES**		**YES**
AIC	997,095	794, 832.8	794,734.8	995,874.1	995,874.1	794, 678.1
BIC	997,145.1	795,040.9	794,961.8	995,964	995,964	794,924
N	160,248	94,851	160,261	94,850	160,232	94,846

Abbreviations: AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.
N= number of observations.
dy/dx =Marginal effects.
***P<0.01, ** P<0.05, * P<0.1.
Note: The table shows marginal effects estimated by the zero-inflated Poisson model.
Note: Figures in parentheses are standard errors.
Note: Control variables included sex, age, religion, marital status, and education level.
Note: Values in the table were rounded off to three decimal places.

4.5.5 The Two-Part Model

In the two-part model (Table 4.6), the marginal effects of illness/injury and social protection were negative and highly statistically significant, in the 1st model formulation. Their interaction terms yielded a positive and highly significant marginal effect. In the 2nd version of the model, illness/injury had a negative significant influence on weekly hours of work, while social protection had a positive effect on weekly hours of work. Their interaction term had a positive non-significant effect. According to the 3rd formulation, illness/injury, and social protection had a negative statistically significant effect on weekly hours of work. On the other hand, hospitalisation had a negative sign which was not statistically significant. In terms of interaction effects, both interaction terms involving social protection and illness and that involving social protection and hospital admission had positive and statistically significant marginal effects.

In the 4th model, illness/injury, hospital admission, and social protection had negative and highly statistically significant marginal effects. The interaction term of hospital admission and social protection was positive and highly significant while that of illness and social protection yielded a negative and statistically insignificant marginal effect. In the 5th model, illness/injury, hospital admission, and social protection had negative highly statistically significant marginal effects. However, chronic illness had a positive and highly statistically significant marginal effect. The interaction terms involving illness/injury and social protection and that involving hospitalisation and social protection had positive significant marginal effects. On the contrary the interaction term social protection and chronic illness was not statistically significant.

In the comprehensive model (6th) illness/injury, hospital admission, and social protection had negative highly statistically significant marginal effects. Although negative, the marginal effect of chronic illness was not statistically significant. The interaction variable involving hospital admission and social protection had a positive statistically significant marginal effect while that involving chronic illness and social protection, had a negative and significant marginal effect. The interaction variable between illness/injury and social protection was not statistically significant.

In summary, the results of the Two-Part Model regression showed the following: a) individuals who experienced an illness or injury reduced their weekly hours of work; b) individuals who experienced hospital admissions reduced their weekly hours of work; c) individuals who benefited from social protection reduced their weekly hours of work; d) individuals who experienced a hospital admission and benefited from social protection increased their hours of work; and e) individuals who were chronically ill and benefited from social protection reduced their weekly hours of work. However, there was no statistically significant evidence regarding the effect of chronic illness on weekly hours of work. Moreover, there was no statistically significant evidence regarding the effect of the interaction between social protection and illness/injury on weekly hours of work.

Table 4. 6: Results of the Two-Part Model

Dep var: Weekly hours of work Model: Two-Part Model						
Variable	**dy/dx (1st)**	**dy/dx (2nd)**	**dy/dx (3rd)**	**dy/dx (4th)**	**dy/dx (5th)**	**dy/dx (6th)**
Illness/injury	-0.687*** (0.084)	-0.906*** (0.123)	-0.680*** (0.084)	-0.878*** (0.124)	-0.793*** (0.084)	-0.882*** (0.124)
Hospitalisation			-0.120 (0.142)	-0.734*** (0.205)	-0.304*** (0.142)	-0.693*** (0.206)
Chronic illness					1.670*** (0.135)	-0.027 (0.189)
Social protection	-0.293*** (0.064)	0.161* (0.095)	-0.470*** (0.074)	-0.240** (0.110)	-0.480*** (0.075)	-0.188* (0.111)
Illness/Injury*Social protection	0.389** (0.133)	0.016 (0.194)	0.381*** (0.133)	-0.027 (0.194)	0.372*** (0.134)	0.046 (0.196)
Hospitalisation*Social protection			0.251*** (0.047)	0.524*** (0.068)	0.237*** (0.047)	0.530*** (0.068)
Chronic illness *Social protection					-0.123 (0.206)	-0.700** (0.283)
Control variables		**YES**		**YES**		**YES**
AIC	619,791.3	492,383	619,494.5	492,108.4	619,161.8	492,053.8
BIC	619,871.2	492,780.3	619,614	492,543.5	619,321.5	492,526.8
N	160,248	94,851	160,261	94,850	160,232	94,846

Abbreviations: AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.
N= number of observations.
dy/dx =Marginal effects.
***P<0.01, ** P<0.05, * P<0.1.
Note: The table shows marginal effects estimated by the two-part model.
Note: Figures in parentheses are standard errors.
Note: Control variables included sex, age, religion, marital status, and education level.
Note: Values in the table were rounded off to three decimal places.

4.5.6 The OLS Model

When the OLS model was considered (Table 4.7), the 1st model formulation yielded negative statistically significant coefficients for illness/injury social protection. The constant term was found to be positive and significant. Moreover, the interaction variable was found to be positive and highly significant. In the 2nd version of the model, illness/injury (negative) and the constant term (positive) were the only significant terms. According to the 3rd model formulation, the coefficients of illness/injury and social protection were negative and highly significant. The coefficient of hospital admission was negative but not statistically significant. The interaction terms involving social protection and illness/injury as well as social protection and hospital admission were both positive and highly statistically significant. The constant term was also significant.

Unlike social protection which had a negative but statistically insignificant coefficient, in the 4th model formulation, illness/injury, and hospital admission had negative and statistically significant coefficients. The interaction term of hospital admission and social protection had a positive and highly statistically significant coefficient while that of illness/injury and social protection had a negative non-significant coefficient. According to the 5th model formulation, illness/injury, hospital admission, and social protection had negative and statistically significant coefficients. Chronic illness had a positive and highly significant coefficient. The interaction terms involving illness/injury and social protection, and hospital admission and social protection had positive and highly significant coefficients. On the other hand, the interaction term involving chronic illness and social protection was negative and not statistically significant. The constant term was statistically significant.

In the comprehensive model, the coefficients of illness/injury, and hospital admission, had negative and highly significant coefficients. The coefficients of chronic illness and social protection were negative but statistically insignificant. While the interaction term involving social protection and illness/and injury did not have a statistically significant coefficient, those of hospital admission and social protection (positive) and chronic illness and social protection (negative) had highly significant coefficients. The constant term was also statistically significant.

Overall, the results of the OLS led to the following conclusions: a) individuals who experienced an illness or injury reduced their weekly hours of work; b) individuals who experienced hospital admissions reduced their weekly hours of work; c) individuals who experienced hospital admission and benefited from social protection increased their weekly hours of work; and d) individuals who were chronically ill and benefited from social protection reduced their weekly hours of work. However, there was no statistically significant evidence regarding the effect of chronic illness on weekly hours of work. Though it is important to note that in the 5^{th} model formulation, chronic illness produced a positive highly significant coefficient. Furthermore, there was no statistically significant evidence regarding the effect of social protection on weekly hours of work. Furthermore, the interaction term between social protection and illness/injury on weekly hours of work was not statistically significant.

Table 4. 7: Results of the OLS Model

Dep var: Weekly hours of work Model: OLS						
Variable	**(1st)**	**(2nd)**	**(3rd)**	**(4th)**	**(5th)**	**(6th)**
Illness/injury	-0.680*** (0.082)	-0.960*** (0.125)	-0.675*** (0.082)	-0.927*** (0.125)	-0.783*** (0.082)	-0.927*** (0.126)
Hospitalisation			-0.115 (0.138)	-0.858*** (0.207)	-0.316** (0.139)	-0.816*** (0.208)
Chronic illness					1.804*** (0.142)	-0.083 (0.192)
Social protection	-0.298*** (0.065)	0.145 (0.096)	-0.462*** (0.074)	-0.670 (0.111)	-0.468*** (0.074)	-0.125 (0.112)
Illness/Injury*Social protection	0.384*** (0.132)	-0.014 (0.198)	0.366*** (0.132)	-0.053 (0.198)	0.350*** (0.133)	0.012 (0.200)
Hospitalisation*Social protection			0.221*** (0.048)	0.409*** (0.070)	0.206*** (0.048)	0.415*** (0.070)
Chronic illness *Social protection					-0.176 (0.218)	-0.614** (0.288)
Constant	5.256*** (0.038)	9.245*** (0.289)	5.260*** (0.038)	9.328*** (0.289)	5.183*** (0.039)	9.302*** (0.290)
Control variables		**YES**		**YES**		**YES**
AIC	1,218,137	747,324.9	1,218,072	747,271.8	1,217,619	747,235.9
BIC	1,218,177	747,523.6	1,218,131	747,489.4	1,217,699	747,472.4
N	160,268	94,851	260,261	94,850	160,232	94,846

Abbreviations: AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.
N= number of observations.
dy/dx =Marginal effects.
***P<0.01, ** P<0.05, * P<0.1.
Note: The table shows coefficients estimated by the standard OL model.
Note: Figures in parentheses are standard errors.
Note: Control variables included sex, age, religion, marital status, and education level.
Note: Values in the table were rounded off to three decimal places.

4.5.7 Results of all models: Comprehensive models

When comprehensive models for all estimation methods (Table 4.8) were considered, important results were observed. First, for all models, the marginal effects of illness/injury were negative and highly statistically significant. Second, though the marginal effects of hospital admission were not statistically significant in the zero-inflated negative binomial and the zero-inflated Poisson models, they were negative and statistically significant in the negative binomial model, the Poisson model, the two-part model, and the OLS model. Third, the marginal effects of chronic illness were positive and significant only in the zero-inflated negative binomial and the zero-inflated Poisson model. Fourth, the marginal effects of social protection were consistently negative in all the models and significant in the Poisson, zero-inflated Poisson, and in the two-part models. Fifth, the interaction term of social protection and illness/injury was negative and statistically insignificant in the negative binomial, zero-inflated binomial, and Poisson models. It was positive and not significant in the two-part and OLS models. However, it was negative and marginally statistically significant in the zero-inflated Poisson model. Furthermore, regarding the interaction variable of hospital admission and social protection all models produced statistically significant results. However, while all the models produced positive marginal effects, the zero-inflated negative binomial and the zero-inflated Poisson produced negative signs. This could be a result of the special attention given to those who reported zero hours under the zero-inflated models as compared to the other count data models that may not necessarily consider the zero-inflation problem. Furthermore, the marginal effects of the interaction term involving chronic illness and social protection was consistently negative and significant in the Poisson, zero-inflated Poisson, two-part, and OLS models.

From the results the following conclusions emerged: a) individuals who reported illness or injury significantly reduced their weekly hours of work; b) individuals who reported hospital admission significantly reduced their weekly hours of work; c) individuals who were chronically ill significantly increased their weekly hours of work; d) individuals who benefited from social protection significantly reduced their weekly hours of work; e) individuals who suffered an illness/injury significantly reduced their weekly hours of work also significantly reduced their hours of work when they benefited from social protection; f) individuals who had a hospital admission significantly reduced their hours of work - when they benefited from social protection, they increased their hours of work; and g) individuals with chronic illnesses who significantly increased their weekly hours significantly reduced their hours of work when they benefited from social protection.

The conclusions above notwithstanding it is important to consider that in the case of the interaction variable between social protection and illness/injury, marginal effects were only marginally significant in the Poisson model while they were not significant in the rest of the comprehensive models. Moreover, marginal effects relating to the interaction term between hospitalisation and social protection, while significant in all models, assumed a negative sign in the zero-inflated models while they maintained a positive sign in all the other models. As stated earlier this could be due to the special attention to the zero-inflation problem attached to the zero-inflated models.

Table 4. 8: Results of the Comprehensive Models

Dep var: Weekly hours of work Model: All models (Comprehensive models)						
Variable	**dy/dx Negative Binomial**	**dy/dx ZINB**	**dy/dx Poisson**	**dy/dx ZIP**	**dy/dx TWOPM**	**OLS**
Illness/injury	-0.754*** (0.178)	-0.567*** (0.101)	-0.894** (0.029)	-0.558*** (0.027)	-0.882*** (0.124)	-0.927*** (0.126)
Hospitalisation	-0.502* (0.294)	-0.001 (0.167)	-0.730*** (0.047)	0.002 (0.045)	-0.693*** (0.206)	-0.816*** (0.208)
Chronic illness	0.098 (0.270)	0.296** (0.152)	-0.033 (0.042)	0.252*** (0.040)	-0.027 (0.189)	-0.083 (0.192)
Social protection	-0.206 (0.160)	-0.117 (0.091)	-0.117*** (0.026)	-0.112*** (0.024)	-0.188* (0.111)	-0.125 (0.112)
Illness/Injury*Social protection	-0.085 (0.282)	-0.092 (0.158)	-0.056 (0.046)	-0.077* (0.044)	0.046 (0.196)	0.012 (0.200)
Hospitalisation*Social protection	0.537*** (0.100)	-0.134** (0.054)	0.447*** (0.016)	-0.154*** (0.015)	0.530*** (0.068)	0.415*** (0.070)
Chronic illness *Social protection	-0.648 (0.407)	-0.250 (0.228)	-0.640*** (0.065)	-0.194*** (0.061)	-0.700** (0.283)	-0.614** (0.288)
Constant						9.302*** (0.290)
Control variables	**YES**	**YES**	**YES**	**YES**	**YES**	**YES**
AIC	485,495	469,206.1	1,644,784	794, 678.1	492,053.8	747,235.9
BIC	485,741	469,541.6	1,645,020	794,924	492,526.8	747,472.4
N	94,846	94,846	94,846	94,846	94,846	94,846

Abbreviations: AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.
N= number of observations.
dy/dx =Marginal effects.
****P*<0.01, ** *P*<0.05, * *P*<0.1.
Note: The table shows marginal effects estimated by the negative binomial model, the zero-inflated binomial model, the Poisson model, the zero-inflated Poisson model, the two-part model, and coefficients from a standard OLS model.
Note: Figures in parentheses are standard errors.
Note: Control variables included sex, age, religion, marital status, and education level.
Note: Values in the table were rounded off to three decimal places.

4.6 Conclusions and policy implications

4.6.1 Conclusions

This chapter sought to examine the joint effects of ill-health, health shocks and social protection on the intensive margin of labour supply. Due to the nature of the data, count data models were employed. These models included the negative binomial, the zero-inflated binomial, the Poisson, the zero-inflated Poisson, and the two-part models. A standard OLS model was also estimated to produce some baseline estimates which were not based on a count data model. The variables used included illness/injury, hospitalisation, chronic disease, and access to social protection. The ill-health and health shock variables were interacted with social protection to examine the joint influence of social protection and those who suffered an illness/injury, social protection and those who were hospitalised, and social protection and those who had a chronic illness, on the intensive margin of labour supply (weekly hours worked).

Regarding joint effects the main results of the negative binomial model was that individuals who experienced a hospital admission and benefited from social protection, significantly increased their hours of work. There were no significant interaction effects involving social protection and illness/injury or social protection and chronic illness on weekly hours of work. From the zero-inflated binomial model it was found that individuals who experienced a hospital admission and benefited from social protection significantly reduced their hours of work. There were no significant interaction effects involving social protection and illness/injury as well as social protection and chronic illness on weekly hours of work. The results of the Poisson model showed that individuals who experienced hospital admission and benefited from social protection significantly increased their hours of work and individuals who were chronically ill and benefited from social protection significantly reduced their hours of work. There were no significant interaction effects involving social protection and illness/injury.

Results of the zero-inflated Poisson regression showed that individuals who experienced an illness/injury and benefited from social protection significantly reduced their weekly hours of work, individuals who had a hospital admission and benefited from social protection significantly reduced their weekly hours of work, and individuals who were chronically ill and benefited from social protection significantly reduced their weekly hours of work. The two-part model regression results showed individuals who experienced a hospital admission and benefited from social protection significantly increased their hours of work and individuals who were chronically ill and benefited from social protection significantly reduced their weekly hours of work. There were no significant interaction effects involving social protection and illness/injury. Similarly, the standard OLS showed the following: while there were no significant effects of the interaction term between illness/injury and social protection, individuals who experienced hospital admission and benefited from social protection significantly increased their weekly hours of work, and individuals who were chronically ill and benefited from social protection significantly reduced their weekly hours of work.

Overall, regarding the joint effects, the following key conclusions were discernible from the analysis of this chapter : a) individuals who suffered an illness/injury and benefited from social protection significantly reduced their hours of work; b) individuals who had experienced a hospital admission and benefited from social protection significantly increased their hours of work; and c) individuals with chronic illnesses who benefited from social protection significantly reduced their weekly hours of work.

4.6.2 Policy implications

The results of this study have important policy implications for health and labour policy in general and social protection. First, the finding that individuals who suffer an illness/injury reduce their weekly hours of work signals the need for better health care. The duration between getting ill and reporting to work will depend, at least in part, on how quickly the sick get medical care. Here two issues are important: access to medical care and quality of care. Reducing hours of work invariably has implications for incomes or earnings and this entrenches the challenges workers face in labour markets. This points to the need for increased access to medical workers, medical facilities, and medicines. While this should certainly be a government priority, creating a conducive environment for private sector participation in healthcare provision might be desirable. The study also revealed that individuals who suffered an illness/injury and benefited from some form of social protection significantly reduced their weekly hours of work. This is an expected result considering that the social protection received, a cash transfer, food, or agricultural input would serve to provide some safety net that would ease the need to go to work for those who were ill. Ensuring that people who are ill are not burdened by work to support their livelihoods is key to maintaining a healthy workforce, and social security seems useful if not vital in this regard.

The chapter also found that individuals who were hospitalised significantly reduced their weekly hours of work. Again, two things are noteworthy here. It is obvious that hospitalisation itself is correlated with absence at work. However, what happens during the post-hospitalisation period is much more important in terms of reducing hours of work. The period of recuperation, in part, will depend on the care the patient receives while at the hospital and when out of the hospital. This, therefore, points to quality of care, quality of diagnosis, and quality of medical personnel but also the quality of home care by family members and caregivers. Investments in primary health care, awareness raising through community action such as community radio programmes for homecare support, might be useful. When individuals who were hospitalised were introduced to social protection, they also significantly reduced their weekly hours worked. Perhaps this implies that individuals were engaged in work even when they were not fully recovered because they had to survive. In that regard, the issue of social security/social support targeting is vital as well.

The analysis revealed that the chronically ill individuals consistently increased their weekly hours of work. Managing chronic illnesses such as diabetes, HIV/AIDS, and arthritis is costly. This requires steady incomes, and increasing weekly hours of work is one avenue for obtaining the needed income. This prompts one to carefully think about targeted government support for chronically ill people. While free medical programmes exist for those living with HIV, this does not seem to be the case for those with other chronic illnesses. Targeting all chronically people irrespective of the disease might be a better approach for inclusivity of support. When individuals with chronic illness benefited from social protection, they significantly reduced their weekly hours of work. This is a clear signal that investments in social protection contribute to useful reductions in labour supply. Candon (2019) has argued that it is presenteeism rather than absenteeism that is associated with greater productivity losses. Additionally, presenteeism implies absences in the future due to sickness but also due to a reduction in self-reported health. Without a cushioning effect through social protection, such individuals will present themselves to work but will essentially not be effective at performing some tasks. This will also translate into a situation like the "added worker effect" (Lundberg, 1985) where other workers will have to take up some work through a reallocation process.

Individuals who benefited from social protection (without interacting with ill-health or health shock) were found to significantly reduce their weekly hours of work. There is evidence that social protection (such as through social transfers) reduces labour supply (Coile, 2004; Coile & Levine, 2007; Fialová, K., & Mysíková, 2009 and Maestas et al., 2013). However, the work of Baird et al. (2018) showed that cash transfers did not change adult labour, particularly when a focus on labour is absent. Orkin et al. (2022) reported similar results of no overall change in hours of work due to cash transfers. Additionally, Vera-Cossio (2021) established that cash transfers increased hours of work in Bolivia. These mixed results point to the reality of different contexts of cash transfers such as whether they are conditional or unconditional, and what their sizes are. For example, Handa et al. (2021) found that when transfer values are in tandem with global practice and are paid regularly, they have more pronounced effects on the intended objectives. Policy-wise, it will be important to consider the contexts and design (Le et al., 2019) of social protection programmes. This includes juggling with the politics of social protection targeting (Pruce, 2022) which can result in unfavourable secondary effects (Burch & Roscioli, 2022).

CHAPTER FIVE

General Conclusions and Policy Recommendations

5. 1 Summary of Findings

The thesis contributes to existing knowledge in the economics of health and human capital by exploring the effects of ill-health and health shocks on labour market outcomes. Central to the research is how the effects of ill-health and health shocks in LMICs differ from the widely known effects in the developed world, using Malawi as the specific case study. These effects relate mainly to hours of work, the probability of employment, and job search.

Chapter two is a systematic review and meta-analysis of the effects ill-health and health shocks on hours worked and the probability of employment. The chapter separately estimates effect sizes relating to hours worked and the probability of employment. The estimation of overall effect sizes or pooled estimates followed a random effects model with results reported through forest plots. Sub-group analyses were undertaken to test statistical significance of sub-group pooled estimates and understand the sources of heterogeneity. Moreover, the sources of heterogeneity were further examined using meta regressions while funnel plots, the Begg's test and trim-and fill analysis both computed to the right and left, were used to test for reporting bias. Key results were discernible from the chapter. First, regarding the effects of ill-health and health shocks on hours worked, a negative statistically significant pooled estimate was found. This result worked to provide credibility to otherwise individual study findings in the literature of the negative effects of ill-health/health shocks on hours of labour worked. The analysis also found statistically significant effect sizes by region (developed vs developing countries). Moreover, statistically significant pooled estimates of the relationship between ill-health and health shocks and hours of work in relation to model type were found. The year of publication of literature was also found to have significant pooled estimate of effect sizes. Overall, considerable heterogeneity was detected among studies. Taken together, geography, model type, sample size and publication year were found to be important sources of heterogeneity. Moreover, using the funnel plots, the Begg's test, as well as the trim and fill methodology, the analysis established no substantial reporting bias regarding the effects of ill-health and health shocks on hours worked.

Second, in terms of the effects of ill-health and health shocks on the probability of employment, the random effects model produced a negative statistically significant overall effect size of the impact of ill-health and health shocks on the probability of employment. Statistically significant pooled estimates were also found relating to developed and developing country groups. Furthermore, the study established statistically significant effect sizes or pooled estimates of sub-groups formed by model type, and by publication year. In relation to heterogeneity, the overall model as well sub-groups exhibited substantial heterogeneity. From sub-group analyses and meta regressions, the sources of heterogeneity were determined as geography, sample size, model type and publication year. Moreover, results of the reporting bias discernible from funnel plots, the Begg's test, and the trim and fill approach showed some level of reporting bias in the analysis of the effects of ill-health and health shocks on probability of employment.

Chapter three goes on to examine the effects of ill-health and health shocks on the probability of employment, weekly hours worked, and job search using nearest-neighbour propensity score matching. While different surveys showed some mixed results, overall conclusions emerged when the pooled dataset was considered. First, in terms of the effects of illness/injury, hospital admission, and chronic illness on the probability of employment, the study found: a) that individuals who reported to have suffered an illness or injury in the last fourteen days significantly reduced their probability of wage employment but increased the probability of casual employment; b) that individuals who reported to have experienced a hospital admission in the last twelve months significantly reduced their probability of wage employment but increased their probability of casual employment; and c) that individuals who reported that they suffered from a chronic disease significantly reduced both their probability of wage employment and that of casual employment. In terms of the effects of illness/injury, hospital admission, and chronic illness on weekly hours of work, the study found that individuals who reported to have suffered an illness or injury in the last fourteen days, individuals who reported to have experienced a hospital admission in the last twelve months, and individuals who reported that they suffered from a chronic disease, all significantly reduced their weekly hours of work. Finally, regarding the effects of illness/injury, hospital admission, and chronic illness on the probability of job search, the following conclusions were discernible from the analysis: a) that individuals who reported to have suffered an illness or injury in the last fourteen days significantly reduced their probability of job search and b) that individuals who reported that they suffered from a chronic disease significantly increased the probability of searching for a job. There was no statistically significant effect on the probability of job search for individuals who reported to have experienced a hospital admission in the last twelve months.

Chapter four moved on to examine the joint effects of ill-health/health shocks and social protection on weekly hours. Using the delta method, marginal effects were obtained using the negative binomial model, the zero-inflated negative binomial model, the Poisson model, the zero-inflated Poisson model, and a two-part model to assess the joint impact of ill-health, health shocks and social protection on the intensive margin of labour supply in Malawi. Moreover, a standard OLS model was also estimated to produce some baseline estimates which were not based on a count data model. Regarding joint effects the main results of the negative binomial model and the zero-inflated binomial model were that individuals who experienced a hospital admission and benefited from social protection significantly increased their hours of work. On the other hand, the Poisson model showed that individuals who experienced hospital admission and benefited from social protection significantly increased their hours of work while individuals who were chronically ill and benefited from social protection significantly reduced their hours of work. The zero-inflated Poisson regression showed that individuals who experienced an illness/injury and benefited from social protection, individuals who had a hospital admission and benefited from social protection and individuals who were chronically ill and benefited from social protection all significantly reduced their weekly hours of work. The two-part model and OLS regression results showed that individuals who experienced a hospital admission and benefited from social protection significantly increased their hours of work, while individuals who were chronically ill and benefited from social protection significantly reduced their weekly hours of work. Overall, the chapter found that that: a) individuals who suffered an illness/injury and benefited from social protection reduced their hours of work; b) individuals who had experienced a hospital admission and benefited from social protection increased their hours of work; and c) individuals with chronic illnesses who benefited from social protection reduced their weekly hours of work.

5. 2 Policy implications

The results of the systematic review and meta-analysis showed that ill-health and health shocks are important explanatory variables of hours of work and impact upon the probability of employment. Overall, the negative and significant estimated effect sizes in the effect of ill-health and health shocks on the two labour market outcomes: hours of labour, and probability of employment signal that ill-health and health shocks play a role in the health-labour relationship. Invariably this implies that policy interventions aimed at containing losses in hours of work and reductions in probability of employment should bear in mind this negative relationship. More importantly this underlines the importance of initiating social protection policies, disability benefits, and unemployment benefits to mitigate losses in working hours and labour market exits. The results also demonstrate the need for further research regarding the effects of health shocks on labour supply in countries with poor social security systems and high prevalence of informal employment, such as Malawi and other LMICs. Often these countries also have poor and dysfunctional health systems in general.

The deeper analysis showing the effects of illness and health shocks on labour supply using nearest neighbour propensity score matching approach in chapter three showed more nuanced results in terms of treatment effects in relation to probability of wage employment, probability of casual employment, hours of work, and job search. The policies emanating from the analysis relate to access to social protection, job creation and health coverage. Policies that support a viable social protection system stem from the realisation that people are forced to work with impaired health. The barriers to exit the labour market point to the fact that people cannot afford not to work given the circumstances they find themselves in. Regarding job creation, lack of wage employment forces many workers to engage in casual employment. The results have shown that while illness/injury reduced wage employment, it increased casual employment. This calls for deliberate efforts to support job-rich growth initiatives. Promoting public employment services might be a useful option, particularly given the high informal employment in the country. Complementary to job-rich growth initiatives are investments in skills, promoting entrepreneurship, and speeding up the transition from the informal economy to the formal economy. Results also revealed that illness and health shocks slowed down the job search process. This emphasises the need for more quality jobs to avoid the discouraged worker phenomenon. Results of chapter three also point to the need for policies to support Universal Health Coverage for essential health services.

The results of chapter four also call for important policy implications for health and labour policy in general and social protection. First the study also found that individuals who suffered an illness/injury and benefited from some form of social protection significantly reduced their weekly hours of work. Ideally a cash transfer, food, or agricultural input would serve to provide some safety net that would ease the need to go to work for those who were ill. Ensuring that those who are ill are not burdened by work to support livelihoods is key to maintaining a healthy workforce, and social security seems useful in this regard. Second, when individuals who were hospitalised were introduced to social protection, they also significantly reduced their weekly hours worked. Perhaps this implies that individuals were engaged in work with impaired health, because they had to work to survive. In that regard, the issue of social security/social support targeting is important as well. Third, as expected, when individuals with chronic illness benefited from social protection, they significantly reduced their weekly hours of work. This is a clear signal that investments in social protection contribute to a useful reduction in labour supply. Working with impaired health is sub-optimal. Candon (2019) has argued that it is presenteeism rather than absenteeism that is associated with greater productivity losses. Additionally, presenteeism implies absences in future due to sickness but also due to reduction in self-reported health. Without a cushioning effect through social protection, such individuals will present themselves to work but will essentially not be effective at performing some tasks. This will also translate into a situation like the "added worker effect" (Lundberg, 1985) where other workers will have to take up some work through a reallocation process.

5.3 Limitations and future work

The analyses of the three chapters have exposed some limitations worth noting. A critical look at these limitations may help shape future research work resulting from this PhD work. Regarding the systematic review and meta-analysis of the effects of ill-health and health shocks on labour market outcomes, three limitations could be identified. First, the analysis suggests the presence of considerable heterogeneity in the effects of ill-health and health shocks on labour markets outcomes. This limitation notwithstanding, the sources of heterogeneity were comprehensively assessed and accounted for. Through subgroup analysis and meta-regressions, factors such as geography, model type, publication year and sample size were found to be the drivers of heterogeneity. Second, when considered together the three tests used to assess reporting bias showed no substantial reporting bias. However, for all outcomes the funnel plot displayed some asymmetry and the case of probability of employment showed some level of reporting bias. This means that results, particularly those involving the effects of ill-health and health shocks on the probability of employment may need to be interpreted with caution. Furthermore, in terms of approach, while the meta-analysis assessed the effects of ill-health and health shocks on labour market outcomes collectively, future meta-analysis may delve to disentangle the effects of ill-health and health shocks and report the effects separately.

Regarding chapter three the first limitation relates to the use of the PSM. This approach may not take into account the effects of unobserved confounding variables, and this means that results have to be interpreted with caution. The second limitation relates to the data used. Three surveys and a pooled data set of the three surveys were used. It would have been useful to use the panel data set that is a sub-set of the IHS. However, the panel data sub-sample had issues with individual identifiers[31] making it difficult to follow individuals over time leading to several missing data issues that limited any meaningful analysis. Not using a panel dataset meant that the dynamics due to time in the data could not be analysed and unobserved individual characteristics could not be accounted for. While not a panel data set, the pooled data set was able to provide average estimates and supported necessary conclusions. It is also important to note that the waves were quite far apart making comparison of results across waves difficult. Wave 3 was conducted between 2010 and 2011, wave 4 between 2016 and 2017 and wave 5 in 2019 and 2020. These periods had different socio-economic contexts including different economic growth rates. The World Bank data base for Malawi shows differing annual GDP growth rates of 6.9 per cent in 2010; 4.9 per cent in 2011; 2.5 per cent in 2016; 4.0 per cent in 2017; 5.4 per cent in 2019 and, mainly because of the COVID pandemic a drop to 0.8 per cent in 2020. The differing socio-economic contexts made comparison over waves difficult. It was clear that the direction of effects regarding ill-health and health shock effects on labour supply was not always the same in the different surveys. Moreover, interpreting the results

[31] Others who have used the panel data sub-sample such as Machira et al. (2023) could only utilise the two-wave panel of 2016 and 2019 neglecting the 2010-2013 perhaps owing to difficulties related to unique identification. However, using only the two-wave panel sub-sample would severely limit the analysis given the data requirements for methods such as the propensity score matching that we utilise.

needed to consider which counteracting effect between the substitution effect and the income effect was dominant.

The third limitation in chapter three relates to the variables available for matching. While the IHS has a module on health the survey is not devoted to detailed data collection on health. This affected the kind of matching variables that could be used in the analysis. Ideally people fall ill owing to genetic propensities, the environment, behaviour, and habits, as such matching should include these characteristics in the PSM analysis. However, limited by available variables in the surveys, there was no luxury to select such variables for matching. Thus, overall, matching variables were influenced by the variables available in the survey. The NSO may need to revise the questionnaire to capture such aspects. Alternatively future work may seek to utilise other relevant data sets in other settings.

The fourth limitation relating to chapter three was the ambiguity in the use of some ill-health and health shock variables. For instance, respondents were asked whether they were ill or injured in the last two weeks, but while the question does ask what the illness/injury was, the severity of the illness/injury is not reported. This made it difficult to classify illness or injuries as moderate, severe, or acute as it has been done in other studies (see for example Booker et al., 2020; Jones et al., 2020; Garcia-Gomez et al., 2012). Similarly, apart from asking whether one was hospitalised in the last twelve months there was no question that would indicate length or how acute the hospitalisation was. This also made it difficult to distinguish the effects of acute hospitalisations from less acute hospitalisations as other studies have done. This could also mean revising the questionnaire to capture those aspects which would be useful in explaining differences in results obtainable in different waves. In future, papers in this area, data permitting, may need to delve into understanding how severe illnesses or acute hospitalisations affect labour markets in relation to less severe illnesses and hospitalisations.

Furthermore, this chapter concentrated on understanding the effects of ill-health and health shocks on the probability of wage employment, the probability of casual employment, hours worked and whether the respondent was job seeking. Future research would analyse such effects on wages or earnings, the effects of spousal shocks including parental health shocks on child labour and devote more work to job seeking which has hitherto not been extensively covered in the available literature. Furthermore, the effects of ill-health and health shocks pertaining to the probability of employment, hours worked, and job seeking were analysed in more general terms. Future research could focus on understanding the direct effect of diseases such as malaria, arthritis, and diabetes as well as the social gradient of health (see for example Lundborg et al., 2015) by looking at these effects in relation to education, those in informal employment, women and youths, among others.

Like in chapter three, the first limitation to chapter four relates to the inability of the study to use panel data as planned, despite the availability of the panel data sub-set. The panel data subset is beset with challenges including those relating to identification and missing information. This posed a real challenge to follow respondents throughout the survey. There is a need for the NSO to look at the way the sub-component is collected and how data is captured to make the panel data set accessible to researchers. Consequently, the present thesis utilised a pooled data set. The second limitation regarding the analysis in chapter four relates to the fact that the analysis could not take care of potential selectivity bias. Individuals who received social protection were used to form interaction terms with those who experienced ill-health or health shock. It is possible that those who received social protection had some unique characteristics different from those that did not receive social protection, and this may have affected the results. Future research needs to disentangle this to be able to obtain a clearer result. Furthermore, in using the variable for social protection a much general definition of social protection was used: whether an individual received cash, food, or other aid from any known programme in the last twelve months. This is because categorised data pertaining to individual social protection programmes were not properly responded to making it difficult to perform other layers of analysis regarding social protection without losing large observations.

The limitations highlight important challenges that exist in the analysis of ill-health and health shocks on labour market outcomes using survey data in LMICs. They are a call for more nuanced data and investment in longitudinal data sets. In the case of Malawi, the partnership between the World Bank, the NSO and IFPRI needs to be enhanced to further improve data quality. There is a need to make the panel data sub-set easily usable.

5.4 Final Conclusions and Policy Implications

The thesis has unravelled important general conclusions which are not the same as the results of developed countries in this area. First, the thesis has found that experiencing ill-health or health shocks reduces the probability of wage employment but increases the probability of casual employment. This not a standard result in developed countries where individuals confronted with this would either reduce the probability of employment considerably or exit the labour market. This is possible because of the presence of efficient social security systems in developed countries which would offer support to those with impaired health who have exited the labour market. This is not the case in LMICs with limited social protection systems. Second, the ill-health and health shocks reduced weekly hours of work. This result would be standard if one did not consider the magnitudes of reduction. Results showed that reduction in weekly hours worked following ill-health or health shocks had smaller magnitudes of reductions compared to what would otherwise characterise results in developed countries. Third, the effects of ill-health and health shocks on the probability of job search was generally negative. However again, the magnitudes of reduction were relatively smaller than those that would be obtained in developed country studies. Fourth, ill-health and health shocks, when interacted with social protection, either reduced or increased weekly hours of work. The results showed that while individuals who suffered an illness/injury and benefited from social protection and individuals with chronic illnesses who benefited from social protection reduced their weekly hours of work, individuals who had experienced a hospital admission and benefited from social protection in fact increased their hours of work.

With poor social protection systems and high informality, increasing hours of work after hospital admission is a survival strategy. Yet, for the reductions in hours of work, the magnitudes were relatively small compared to results that would be obtained in developed countries, again emphasising the differences with developed economies. For instance, Candon (2019) found reductions of up to four hours in the USA. These results mean more empirical work is needed in LMICs, Africa and Malawi. This may be vital in supporting policy decisions in the area of poor health and work. Using standard results that abound in developed countries may lead to misallocation of resources in LMICs since the results obtainable in LMICs are different from those of developed countries.

References

Acuña, C., Héctor. R. A., & Carrasco, D. (2019). Health shocks and the added worker effect: a life cycle approach. *Journal of Applied Economics*, *22*(1), 273–286. https://doi.org/10.1080/15140326.2019.1613089

Adelson, J. L., McCoach, D. B., Rogers, H. J., Adelson, J. A., & Sauer, T. M. (2017). Developing and applying the propensity score to make causal inferences: Variable Selection and Stratification. *Frontiers in Psychology*, *8*(1413). https://doi.org/10.3389/fpsyg.2017.01413

Alam, K., & Mahal, A. (2014). Economic impacts of health shocks on households in low and middle income countries: a review of the literature. *Globalization and Health*, *10*(1), 21. https://doi.org/10.1186/1744-8603-10-21

Alam, S. A. (2015). Parental health shocks, child labour and educational outcomes: Evidence from Tanzania. *Journal of Health Economics*, *44*, 161–175. https://doi.org/10.1016/j.jhealeco.2015.09.004

Alavinia, S. M., & Burdorf, A. (2008). Unemployment and retirement and ill-health: a cross-sectional analysis across European countries. *International Archives of Occupational and Environmental Health*, *82*(1), 39–45. https://doi.org/10.1007/s00420-008-0304-6

Aleksandrova, E., Bagranova, V., & Gerry, C. J. (2021). The effect of health shocks on labour market outcomes in Russia. *Cambridge Journal of Economics*. https://doi.org/10.1093/cje/beab043

Aliyu, A. A., Bello, M. U., Kasim, R., & Martin, D. (2014). Positivist and non-positivist paradigm in social science research: Conflicting Paradigms or Perfect Partners? *Journal of Management and Sustainability*, *4*(3), 79–95. https://doi.org/10.5539/jms.v4n3p79

Amoah, J., Stuart, E. A., Cosgrove, S. E., Harris, A. D., Han, J. H., Lautenbach, E., & Tamma, P. D. (2020). Comparing propensity score methods versus traditional regression analysis for the evaluation of observational Data: A Case Study Evaluating the Treatment of Gram-Negative Bloodstream Infections. *Clinical Infectious Diseases*. https://doi.org/10.1093/cid/ciaa169

Andersen, M. (2015). Heterogeneity and the effect of mental health parity mandates on the laboor market. *Journal of Health Economics*, *43*, 74–84. https://doi.org/10.1016/j.jhealeco.2015.06.008

Arora, M., & Chaganty, N. R. (2021). EM Estimation for zero- and k-inflated Poisson regression model. *Computation*, *9*(9),94.https://doi.org/10.3390/computation9090094

Arrospide, A., Ramos-Goñi, J. M., Pechlivanoglou, P., & Mar, J. (2020). Application of two-part models and Cholesky decomposition to incorporate covariate-adjusted utilities in probabilistic cost-effectiveness models. *Gaceta Sanitaria*, *34*(1), 91–95. https://doi.org/10.1016/j.gaceta.2018.09.003

Atake, E.H. (2018). Health shocks in Sub-Saharan Africa: are the poor and uninsured households more vulnerable? *Health Economics Review*, *8*(1). https://doi.org/10.1186/s13561-018-0210-x

Austin, P. C. (2009). Balance diagnostics for comparing the distribution of baseline covariates between treatment groups in propensity-score matched samples. *Statistics in Medicine,* 28(25), 3083–3107. https://doi.org/10.1002/sim.3697

Austin, P. C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research*, 46(3), 399–424.

Baird, S., McKenzie, D., & Özler, B. (2018). The effects of cash transfers on adult labour market outcomes. *IZA Journal of Development and Migration*, *8*(1). https://doi.org/10.1186/s40176-018-0131-9

Baker, W. L., Michael White, C., Cappelleri, J. C., Kluger, J., & Coleman, C. I. (2009). Understanding heterogeneity in meta-analysis: the role of meta-regression. *International Journal of Clinical Practice*, *63*(10), 1426–1434. https://doi.org/10.1111/j.1742-1241.2009.02168.x

Banerjee, S., Chatterji, P., & Lahiri, K. (2015). Effects of psychiatric disorders on labour market outcomes: A latent variable approach using multiple clinical indicators. *Health Economics*, *26*(2), 184–205. https://doi.org/10.1002/hec.3286

Bates, N., Callander, E., Lindsay, D., & Watt, K. (2018). Labour force participation and the cost of lost productivity due to cancer in Australia. *BMC Public Health*, *18*(1). https://doi.org/10.1186/s12889-018-5297-9

Beegle, K., Galasso, E., & Goldberg, J. (2017). Direct and indirect effects of Malawi’s public works program on food security. *Journal of Development Economics*, *128*, 1–23. https://doi.org/10.1016/j.jdeveco.2017.04.004

Begg, C. B., & Mazumdar, M. (1994). Operating characteristics of a rank correlation test for publication Bias. *Biometrics*, *50*(4), 1088. https://doi.org/10.2307/2533446

Belotti, F., Deb, P., Manning, W. G., & Norton, E. C. (2015). Twopm: Two-part models. *The Stata Journal: Promoting Communications on Statistics and Stata*, *15*(1), 3–20. https://doi.org/10.1177/1536867x1501500102

Bharadwaj, R., Mitchell, T., Karthikeyan, N., Raj, N., Chaliha, S., Abhilashi, R., Chinnaswamy, K., … McCabe, T. (2023*). Delivering Anticipatory Social Protection: Country Readiness Assessment.* IIED, London.

Bloemen, H. G. (2005). Job search, search intensity, and labour market transitions. *Journal of Human Resources*, *XL*(1), 232–269. https://doi.org/10.3368/jhr.xl.1.232., XL(1), 232–269. https://doi.org/10.3368/jhr.xl.1.232

Bloom, D. E., & Canning, D. (2000). The health and wealth of nations. *Science's Compass*, *287: 1207-1209*. . https://doi.org/10.1126/science.287.5456.1207

Bonfrer, I., & Gustafsson-Wright, E. (2016). Health shocks, coping strategies and foregone healthcare among agricultural households in Kenya. *Global Public Health*, *12*(11), 1369–1390. https://doi.org/10.1080/17441692.2015.1130847

Booker, C. L., Andrews, L., Green, G., & Kumari, M. (2020). Impacts of long-standing illness and chronic illness on working hours and household income in a longitudinal UK study. *SSM - Population Health*, *12*, 100684. https://doi.org/10.1016/j.ssmph.2020.100684

Bosu, W. K., Aheto, J. M. K., Zucchelli, E., & Reilly, S. (2017). Prevalence, awareness, and associated risk factors of hypertension in older adults in Africa: a systematic review and meta-analysis protocol. *Systematic Reviews*, *6*(1). https://doi.org/10.1186/s13643-017-0585-5

Bosu, W. K., Aheto, J. M. K., Zucchelli, E., & Reilly, S. T. (2019). Determinants of systemic hypertension in older adults in Africa: a systematic review. *BMC Cardiovascular Disorders*, *19*(1). https://doi.org/10.1186/s12872-019-1147-7

Bosu, W. K., & Bosu, D. K. (2021). Prevalence, awareness and control of hypertension in Ghana: A systematic review and meta-analysis. *PLOS ONE*, *16*(3), e0248137. https://doi.org/10.1371/journal.pone.0248137

Bosu, W. K., Reilly, S. T., Aheto, J. M. K., & Zucchelli, E. (2019). Hypertension in older adults in Africa: A systematic review and meta-analysis. *PLOS ONE*, *14*(4), e0214934. https://doi.org/10.1371/journal.pone.0214934

Bown, M. J., & Sutton, A. J. (2010). Quality control in systematic reviews and meta-analyses. *Journal of Vascular Surgery*, *52*(5), 1424. https://doi.org/10.1016/j.jvs.2010.09.037

Bradley, C. J., Bednarek, H. L., & Neumark, D. (2002). Breast Cancer and Women's Labor Supply. *Health Services Research*, *37*(5), 1309–1327. https://doi.org/10.1111/1475-6773.01041

Bridges, S., & Lawson, D. (2008). A Gender-based investigation into the determinants of labour market outcomes: Evidence from Uganda. *Journal of African Economies*, *18*(3), 461–495. https://doi.org/10.1093/jae/ejn017

Brouwer, J. A., Boeree, M. J., Kager, P., Varkevisser, C. M., & Harries, A. D. (1998). Traditional healers and pulmonary tuberculosis in Malawi. *The International Journal of Tuberculosis and Lung Disease: The Official Journal of the International Union against Tuberculosis and Lung Disease*, *2*(3), 231–234. https://pubmed.ncbi.nlm.nih.gov/9526196/

Bryan, M. L., Rice, N., Roberts, J., & Sechel, C. (2022). Mental health and employment: A bounding approach using panel data. *Oxford Bulletin of Economics and Statistics*, *84*(5), 1018–1051. https://doi.org/10.1111/obes.12489

Cai, L., Mavromaras, K., & Oguzoglu, U. (2013). The effects of health status and health shocks on hours worked. *Health Economics*, *23*(5), 516–528. https://doi.org/10.1002/hec.2931

Caldwell, B. (1980). Positivist Philosophy of Science and the Methodology of Economics. *Journal of Economic Issues*, *14*(1), 53–76. https://doi.org/10.1080/00213624.1980.11503723

Caliendo, M., & Kopeinig, S. (2005). Some practical guidance for the implementation of propensity score matching. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.721907

Candon, D. (2019). The joint effect of health shocks and eligibility for social security on labour supply. *The European Journal of Health Economics*, *20*(7), 969–988. https://doi.org/10.1007/s10198-019-01053-2

Carter, K. N., Gunasekara, F. I., Blakely, T., & Richardson, K. (2013). Health shocks adversely impact participation in the labour force in a working age population: a longitudinal analysis. *Australian and New Zealand Journal of Public Health*, *37*(3), 257–263. https://doi.org/10.1111/1753-6405.12068

Chau, A., Lo, E., Wong, M., & Chu, C. (2018). Interpreting Poisson regression models in dental carries. *Caries Research*, *52*(4), 339–345. https://doi.org/10.1159/000486970

Chicoine, L. (2012). AIDS mortality and its effect on the labor market: Evidence from South Africa. *Journal of Development Economics*, *98*(2), 256–269. https://doi.org/10.1016/j.jdeveco.2011.08.003

Chinnaswamy, K., … McCabe, T. (2023). *Delivering Anticipatory Social Protection: Country Readiness Assessment.* IIED, London.

Chinsinga, B. (2007). The Social Protection Policy in Malawi: Processes, politics and challenges. Discussion Paper. Future Agricultures.

Chirikos, T. N. (1993). The Relationship between Health and Labor Market Status. *Annual Review of Public Health*, *14*(1), 293–312. https://doi.org/10.1146/annurev.pu.14.050193.001453

Chirwa, E. W., Zgovu, E. K., & Mvula, P. M. (2002). Participation and Impact of Poverty-oriented Public Works Projects in Rural Malawi. *Development Policy Review*, *20*(2), 159–176. https://doi.org/10.1111/1467-7679.00163

Ciminata, G., Geue, C., Langhorne, P., & Wu, O. (2020). A two-part model to estimate inpatient, outpatient, prescribing and care home costs associated with atrial fibrillation in Scotland. *BMJ Open*, *10*(3), e028575. https://doi.org/10.1136/bmjopen-2018-028575

Cipollina, M., Cuffaro, N., & D'Agostino, G. (2018). Land inequality and economic growth: A Meta-Analysis. *Sustainability*, *10*(12), 4655. https://doi.org/10.3390/su10124655

Coile, C. C. (2004, October 1). *Health Shocks and Couples' Labor Supply Decisions*. National Bureau of Economic Research. https://doi.org/10.3386/w10810

Coile, C. C., & Levine, P. B. (2007). Labor market shocks and retirement: Do government programs matter? *Journal of Public Economics*, *91*(10), 1902–1919. https://doi.org/10.1016/j.jpubeco.2007.01.005

Conley, D., & Thompson, J. (2013). The effects of health and wealth shocks on retirement decisions. *Review*, *95*(5). https://doi.org/10.20955/r.95.389-404

Cornwell, K., Forbes, C., Inder, B., & Meadows, G. (2009). Mental illness and its effects on labour market outcomes. *The Journal of Mental Health Policy and Economics*, *12*(3), 107–118. https://pubmed.ncbi.nlm.nih.gov/19996474/

Cupal, M., Deev, O., & Linnertova, D. (2015). The Poisson regression analysis for occurrence of floods. *Procedia Economics and Finance*, *23*, 1499–1502. https://doi.org/10.1016/s2212-5671(15)00465-7

Currie, J., and B.C. Madrian. (1999). *Health, health insurance and the labour market*. New York: Elsevier Science.

Crossan, F. (2003). Research philosophy: towards an understanding. *Nurse Researcher*, *11*(1), 46–55.

Dano, A. M. (2005). Road injuries and long-run effects on income and employment. *Health Economics*, *14*(9), 955–970. https://doi.org/10.1002/hec.1045

Datta Gupta, N., Kleinjans, K. J., & Larsen, M. (2015). The effect of a severe health shock on work behaviour: Evidence from different health care regimes. *Social Science & Medicine*, *136-137*, 44–51. https://doi.org/10.1016/j.socscimed.2015.05.008

de Brauw, A., Gilligan, D. O., Hoddinott, J., & Roy, S. (2015). Bolsa Família and Household Labor Supply. *Economic Development and Cultural Change*, *63*(3), 423–457. https://doi.org/10.1086/680092

Deb, P., & Norton, E. C. (2018). Modeling health care expenditures and use. *Annual Review of Public Health*, *39*(1), 489–505. https://doi.org/10.1146/annurev-publhealth-040617-013517

Devereux, S., Baulch, B., Phiri, A., & Sebates-Wheeler, R., (2006), Vulnerability to chronic poverty and malnutrition in Malawi. A Report for DFID Malawi, Lilongwe, Malawi.

Dobkin, C., Finkelstein, A., Kluender, R., & Notowidigdo, M. J. (2018). The economic consequences of hospital admissions. *American Economic Review*, *108*(2), 308–352. https://doi.org/10.1257/aer.20161038

Dworsky, M., & Powell, D. (2022). *The Long-Term Effects of Workplace Injury on Labor Market Outcomes: Evidence from California*. https://www.nber.org/sites/default/files/2023-02/NB19-16%20Dworsky%2C%20Powell%20-%20DRAFT.pdf

Ebaidalla, E. M., & Mustafa Ali, M. E. (2022). Chronic illnesses and labuor market participation in the Arab countries: evidence from Egypt and Tunisia. *Middle East Development Journal*, *14*(2), 303–322. https://doi.org/10.1080/17938120.2022.2143748

Elze, M. C., Gregson, J., Baber, U., Williamson, E., Sartori, S., Mehran, R., Nichols, M., Stone, G. W., & Pocock, S. J. (2017). Comparison of Propensity Score Methods and Covariate Adjustment: Evaluation in 4 Cardiovascular Studies. *Journal of the American College of Cardiology*, *69*(3), 345–357. https://doi.org/10.1016/j.jacc.2016.10.060

Emsley, R., Lunt, M., Pickles, A., & Dunn, G. (2008). Implementing double-robust estimators of causal effects. *The Stata Journal: Promoting Communications on Statistics and Stata*, *8*(3), 334–353. https://doi.org/10.1177/1536867x0800800302

Ettner, S. L., Frank, R. G., & Kessler, R. C. (1997). The Impact of psychiatric disorders on labour market outcomes. *Industrial and Labor Relations Review*, *51*(1), 64. https://doi.org/10.2307/2525035

Fang, R., Wagner, B. D., J. Kirk Harris, & Fillon, S. (2016). Zero-inflated negative binomial mixed model: an application to two microbial organisms important in oesophagitis. *Epidemiology and Infection*, *144*(11), 2447–2455. https://doi.org/10.1017/s0950268816000662

Fialová, K., & Mysíková, M. (2009). Labour market participation: The impact of social benefits in the Czech Republic and selected European Countries. *Prague Economic Papers*, *18*(3), 235–250. https://doi.org/10.18267/j.pep.352

.

French, E. (2005). The effects of health, wealth, and wages on labour supply and retirement behaviour. *The Review of Economic Studies*, *72*(2), 395–427. https://www.jstor.org/stable/3700657

Frijters, P., Johnston, D. W., & Shields, M. A. (2010). Mental health and labour market participation: Evidence from IV Panel Data Models. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1595524

Frome, E. L., & Checkoway, H. (1985). Epidemiologic programs for computers and calculators: use of Poisson regression models in estimating incidence rates and ratios. *Am. J. Epidemiol.; (United States)*, *121*(2). https://www.osti.gov/biblio/5751958

Fu, R., Noguchi, H., Kaneko, S., Kawamura, A., Kang, C., Takahashi, H., & Tamiya, N. (2019). How do cardiovascular diseases harm labor force participation? Evidence of nationally representative survey data from Japan, a super-aged society. *PLOS ONE*, *14*(7), e0219149. https://doi.org/10.1371/journal.pone.0219149

Gajade-Garrido, G. (2015). The impact of household health shocks on female time allocation and agricultural labour participation in rural Pakistan. *IFPRI Discussion Paper 01449*.

García-Gómez, P., & López Nicolás, A. (2006). Health shocks, employment and income in the

Spanish labour market. *Health Economics*, *15*(9), 997–1009. https://doi.org/10.1002/hec.1151

García-Gómez, P. (2011). Institutions, health shocks and labour market outcomes across Europe. *Journal of Health Economics*, 30(1), 200–213. https://doi.org/10.1016/j.jhealeco.2010.11.003

García-Gómez, P., Jones, A. M., & Rice, N. (2010). Health effects on labour market exits and entries. *Labour Economics*, *17*(1), 62–76. https://doi.org/10.1016/j.labeco.2009.04.004

García-Gómez, P., Kippersluis, H. V., & Doorslaer, E. V. (2011). Effects of health on own and spousal employment and income using acute hospital admissions. *SSRN Electronic Journal.*

García-Gómez, P., Kippersluis, H. V., O'Donnell, O., & Doorslaer, E. V. (2013). Long-term and spillover effects of health shocks on employment and income. *Journal of Human Resources*, 48(4), 873-909. https://doi.org/10.1353/jhr.2013.0031

Garrido, M.M., Kelley, A.S., Paris, J., Roza, K., Meier, D.E., Morrison, R.S. and Aldridge, M.D. (2014). Methods for constructing and assessing propensity scores. *Health Services Research*, 49(5), pp.1701–1720. doi:https://doi.org/10.1111/1475-6773.12182

Gaulke, A. (2021). Individual and family labour market impacts of chronic diseases. *IZA World of Labor*. https://doi.org/10.15185/izawol.482

Germinario, G., Amin, V., Flores, C. A., & Flores-Lagunes, A. (2022). What can we learn about the effect of mental health on labor market outcomes under weak assumptions? Evidence from the NLSY79. *Labour Economics*, *79*(102258), 102258. https://doi.org/10.1016/j.labeco.2022.102258

Goryakin, Y., Rocco, L., Suhrcke, M., Roberts, B., & McKee, M. (2014). The effect of health on labour supply in nine former Soviet Union countries. *The European Journal of Health Economics*, *15*(1), 57–68. https://doi.org/10.1007/s10198-012-0455-y

Goryakin, Y., & Suhrcke, M. (2016). The impact of poor adult health on labour supply in the Russian Federation. *The European Journal of Health Economics*, *18*(3), 361–372. https://doi.org/10.1007/s10198-016-0798-x

Government of Malawi (2012), National Social Support Policy, Lilongwe, Malawi.

Government of Malawi (2017), Malawi Growth and Development Strategy III, Lilongwe, Malawi.

Government of Malawi (2018), Malawi National Social Support Programme II (MSSP II), Lilongwe, Malawi.

Government of Malawi (2020), Malawi's Vision: An inclusively wealthy and self-reliant nation, Malawi 2063, National Planning Commission (NPC), Lilongwe, Malawi.

Gourieroux, C., Montfort, A., & Trognon A., (1984). Pseudo maximum likelihood methods: Applications to Poisson models. *Econometrica*, 53(3).

Greene, W. (1994). Accounting for excess zeros and sample selection in Poisson and negative binomial regression models, Department of Economics, Stern School of Business, New York University, New York.

Greene, W. (2008). Functional forms for the negative binomial model for count data. *Economics Letters*, *99*(3), 585–590. https://doi.org/10.1016/j.econlet.2007.10.015

Gupta, S., Montenovo, L., Nguyen, T., Rojas, F. L., Schmutte, I., Simon, K., Weinberg, B., & Wing, C. (2020). Effects of social distancing policy on labour market outcomes. *NBER Working Paper Series*. https://doi.org/10.3386/w27280

Gurmu, S., & Trivedi, P. K. (1996). Excess zeros in count models for recreational trips. *Journal of Business & Economic Statistics*, *14*(4), 469–477. https://ideas.repec.org/a/bes/jnlbes/v14y1996i4p469-77.html

Guo, S., & Fraser, M. W. (2014). *Propensity Score Analysis*. SAGE Publications.

Guo, S., Fraser, M., & Chen, Q. (2020). Propensity score analysis: Recent debate and discussion. *Journal of the Society for Social Work and Research*, *11*(3), 463–482. https://doi.org/10.1086/711393

Handa, S., Otchere, F., & Sirma, P. (2021). More evidence on the impact of government social protection in Sub Saharan Africa: Ghana, Malawi and Zimbabwe. *Development Policy Review*. https://doi.org/10.1111/dpr.12576

Harries, A. D., Banerjee, A., Gausi, F., Nyirenda, T. E., Boeree, M. J., Kwanjana, J., & Salaniponi, F. M. (2002). Traditional healers and their practices in Malawi. *Tropical Doctor*, 32(1), 32–33. https://doi.org/10.1177/004947550203200116

Harris, A. (2009). Diabetes, cardiovascular disease and labour force participation in Australia: An endogenous multivariate probit analysis of clinical prevalence data. *Economic Record*, *85*(271), 472–484. https://doi.org/10.1111/j.1475-4932.2009.00572.x

Harris, H., & Horst, S. J. (2016). A brief guide to decisions at each step of the propensity score matching process. *Practical Assessment, Research and Evaluation*, 21(4),1-12.

Harris, M. N., Zhao, X., & Zucchelli, E. (2020). Ageing workforces, ill-health and multi-state labour market transitions. *Oxford Bulletin of Economics and Statistics*, *80*(1). https://doi.org/10.1111/obes.12379

Hatmi, Z. N. (2021). A Systematic review of systematic reviews on the COVID-19 pandemic. *SN Comprehensive Clinical Medicine*, *3*, 429–436. https://doi.org/10.1007/s42399-021-00749-y

Hausman, D. M. (2000). Realist philosophy and methodology of economics: what is it? *Journal of Economic Methodology*, *7*(1), 127–133. https://doi.org/10.1080/135017800362275

Hayward, S. M., McVilly, K. R., & Stokes, M. A. (2016). Challenges for females with high functioning autism in the workplace: a systematic review. *Disability and Rehabilitation*, *40*(3), 249–258. https://doi.org/10.1080/09638288.2016.1254284

Heath, R., Mansuri, G., & Rijkers, B. (2019). Labour supply responses to health shocks: Evidence from high-frequency labour market data from urban Ghana. *Policy Research Working Papers.* doi:10.1596/1813-9450-9046

Heimberger, P. (2020). Does economic globalisation affect income inequality? A meta-analysis. *The World Economy*, *43*(11), 2960–2982. https://doi.org/10.1111/twec.13007

Heinrich, C., Maffioli, A., & Vazquesz, G. (2010) A primer for applying propensity-score matching, *Inter-American Development Bank*, 1-60.

Helgesson, M., Tinghög, P., Niederkrotenthaler, T., Saboonchi, F., & Mittendorfer-Rutz, E. (2017). Labour-market marginalisation after mental disorders among young natives and immigrants living in Sweden. *BMC Public Health*, *17*(1). https://doi.org/10.1186/s12889-017-4504-4

Higgins, J. P. T. (2008). Commentary: Heterogeneity in meta-analysis should be expected and appropriately quantified. *International Journal of Epidemiology*, *37*(5), 1158–1160. https://doi.org/10.1093/ije/dyn204

Higgins, J. P. T., López-López, J. A., Becker, B. J., Davies, S. R., Dawson, S., Grimshaw, J. M., McGuinness, L. A., Moore, T. H. M., Rehfuess, E. A., Thomas, J., & Caldwell, D. M. (2019). Synthesising quantitative evidence in systematic reviews of complex health interventions. *BMJ Global Health*, *4*(Suppl 1), e000858. https://doi.org/10.1136/bmjgh-2018-000858

Higgins, J. P. T., Thompson, S. G., Deeks, J. J., & Altman, D. G. (2003). Measuring inconsistency in meta-analyses. *BMJ*, *327*(7414), 557–560. https://doi.org/10.1136/bmj.327.7414.557

Ho, D.E., Imai, K., King, G. and Stuart, E.A. (2007). Matching as nonparametric pre-processing for reducing model dependence in parametric causal inference. *Political Analysis*, 15(03), pp.199–236. doi:https://doi.org/10.1093/pan/mpl013

Holmes, R., Scott, L., Both, N., and Chinsinga, B., (2018). Strengthening institutional coordination of social protection in Malawi: An analysis of coordination structures and options. Lilongwe, Malawi.

Hwa, J. K. (2022). Applications of propensity score matching. *Annals of Coloproctology*, 38(6), 398–402. https://doi.org/10.3393/ac.2022.01060.0151

ILO. (2015). National employment policies: A guide for workers' organisations, some key terms and what they mean, Geneva.

ILO. (2016). World Social Protection Data Dashboard, https://www.social-protection.org/gimi/gess/WSPDB.action?id=13

ILO. (2018). Women and men in the informal economy: A statistical picture, Geneva.

ILO. (2020). *World Social Protection Report 2020-22*, Geneva.

ILO. (n.d.). Social protection in Malawi: Assessment based national dialogue brief, Lilongwe.

ILO. (2021, January 25). *ILO Monitor: COVID-19 and the world of work. 7th edition*. Www.ilo.org.ttps://www.ilo.org/global/topics/coronavirus/impacts-and-responses/WCMS_767028/lang--en/index.htm

ILO: ILOSTAT Database, https://ilostat.ilo.org/data/country-profiles/

Imai, K., King, G., & Stuart, E. A. (2008). Misunderstandings between experimentalists and observationalists about causal inference. *Journal of the Royal Statistical Society: Series a (Statistics in Society)*, *171*(2), 481–502. https://doi.org/10.1111/j.1467-985x.2007.00527.x

Jarl, J., Linder, A., Busch, H., Nyberg, A., & Gerdtham, U.G. (2020). Heterogeneity in the associations between common mental disorders and labour outcomes – a population study from southern Sweden. *BMC Public Health*, *20*(1). https://doi.org/10.1186/s12889-020-09348-3

Jones, A. M., Rice, N., & Roberts, J. (2010). Sick of work or too sick to work? Evidence on self-reported health shocks and early retirement from the BHPS. *Economic Modelling*, 27(4), 866–880. https://doi.org/10.1016/j.econmod.2009.10.001

Jones, A. M., Rice, N., & Zantomio, F. (2020). Acute health shocks and labour market outcomes: Evidence from the post-crash era. *Economics & Human Biology*, *36*, 100811. https://doi.org/10.1016/j.ehb.2019.100811

Karazsia, B. T., & van Dulmen, M. H. M. (2008). Regression models for count data: Illustrations using Longitudinal Predictors of Childhood Injury. *Journal of Pediatric Psychology*, *33*(10), 1076–1084. https://doi.org/10.1093/jpepsy/jsn055

King, G., & Nielsen, R. (2019). Why propensity scores should not be used for matching. *Political Analysis*, 27(4), 435–454. https://doi.org/10.1017/pan.2019.11

Koch, S. F., & Thsehla, E. (2022). The impact of diabetes on labour market outcomes. *Development Southern Africa*, *39*(3), 1–33. https://doi.org/10.1080/0376835x.2021.2015291

Kumara, A. S., & Samaratunge, R. (2018). The effects of chronic non-communicable diseases on labour force outcomes: Quasi experimental evidence from Sri Lanka. *Economics & Human Biology*, *31*(31), 40–53. https://doi.org/10.1016/j.ehb.2018.08.002

Lambert, D. (1992). Zero-inflated Poisson regression, with an Application to Defects in Manufacturing. *Technometrics*, *34*(1), 1. https://doi.org/10.2307/1269547

Layard, R. (2013). Mental health: the new frontier for labour economics. *Journal of Labour Policy*, *2*(1), 2. https://doi.org/10.1186/2193-9004-2-2

Le, N., Groot, W., Tomini, S. M., & Tomini, F. (2019). Effects of health insurance on labour supply: a systematic review. *International Journal of Manpower*, *40*(4), 717–767. https://doi.org/10.1108/ijm-02-2018-0038

Leive, A., & Xu, K. (2008). Coping with out-of-pocket health payments: empirical evidence from 15 African countries. *Bulletin of the World Health Organization*, *86*(11), 849–856. https://doi.org/10.2471/blt.07.049403

Lenhart, O. (2018). The effects of health shocks on labour market outcomes: evidence from UK panel data. *The European Journal of Health Economics*, *20*(1), 83–98. https://doi.org/10.1007/s10198-018-0985-z

Levinsohn, J., McLaren, Z. M., Shisana, O., & Zuma, K. (2013). HIV status and labour market participation in South Africa. *Review of Economics and Statistics*, 95(1), 98–108. https://doi.org/10.1162/rest_a_00237

Li, J.W., Han, T.W., Woodward, M., Anderson, C. S., Zhou, H., Chen, Y.-D., & Neal, B. (2020). The impact of 2019 novel coronavirus on heart injury: A Systematic review and Meta-analysis. *Progress in Cardiovascular Diseases*, *63*(4), 518–524. https://doi.org/10.1016/j.pcad.2020.04.008

Li, X., Guan, B., Su, T., Liu, W., Chen, M., Bin Waleed, K., Guan, X., Gary, T., & Zhu, Z. (2020). Impact of cardiovascular disease and cardiac injury on in-hospital mortality in patients with COVID-19: a systematic review and meta-analysis. *Heart*, *106*(15), 1142–1147. https://doi.org/10.1136/heartjnl-2020-317062

Lin, Z., Ding, P., & Han, F. (2023). Estimation based on nearest neighbour matching: From density ratio to average treatment effect. *Econometrica*, *91*(6), 2187–2217. https://doi.org/10.3982/ecta20598

Lindelow, M., & Wagstaff, A. (2005). Health Shocks in China: Are the poor and uninsured less protected? World Bank Policy Research Working Paper 3740. https://documents1.worldbank.org/curated/en/857281468236989022/pdf/wps3740.pdf

Liu, S., Hong, Z., Zhou, W., Fang, Y., & Zhang, L. (2021). Job-search self-efficacy and reemployment willingness among older adults: roles of achievement motivation and age. *BMC Geriatrics*, *21*(1). https://doi.org/10.1186/s12877-021-02645-5

Lukman, A. F., Adewuyi, E., Månsson, K., & Kibria, B. M. G. (2021). A new estimator for the multicollinear Poisson regression model: simulation and application. *Scientific Reports*, *11*(1). https://doi.org/10.1038/s41598-021-82582-w

Lukusa, M. T., & Phoa, F. K. H. (2020). A note on the weighting-type estimations of the zero-inflated Poisson regression model with missing data in covariates. *Statistics & Probability Letters*, *158*, 108654. https://doi.org/10.1016/j.spl.2019.108654

Lundberg, S. (1985). The Added Worker Effect. *Journal of Labour Economics*, 3(1), 11–37. https://www.jstor.org/stable/2535048

Lundborg, P., Nilsson, M., & Vikström, J. (2015). Heterogeneity in the impact of health shocks on labour outcomes: evidence from Swedish workers. *Oxford Economic Papers*, 67(3), 715–739.

Maestas, N., Mullen, K. J., & Strand, A. (2013). Does disability insurance receipt discourage work? Using examiner assignment to estimate causal effects of SSDI receipt. *American Economic Review*, *103*(5), 1797–1829. https://doi.org/10.1257/aer.103.5.1797

Machira, K., Mgomezulu, W. R., & Malata, M. (2023). Understanding poverty dimensions and transitions in Malawi: A panel data approach. *Research in Globalization*, *7*, 100160. https://doi.org/10.1016/j.resglo.2023.100160.

Masangwi, S., Ferguson, N., Grimason, A., Morse, T., & Kazembe, L. (2016). Care-seeking for diarrhoea in southern Malawi: Attitudes, practices and implications for diarrhoea control. *International Journal of Environmental Research and Public Health*, 13(11), 1140. https://doi.org/10.3390/ijerph13111140

McGeary, K. A. (2009). How do health shocks influence retirement decisions? *Review of Economics of the Household*, *7*(3), 307–321. https://doi.org/10.1007/s11150-009-9053-x

Mommaerts, C., Raza, S. H., & Zheng, Y. (2020). The economic consequences of hospitalizations for older workers across countries. *The Journal of the Economics of Ageing*, *16*(1002), 100213. https://doi.org/10.1016/j.jeoa.2019.100213

Morrish, N., Mujica-Mota, R., & Medina-Lara, A. (2022). Understanding the effect of loneliness on unemployment: propensity score matching. *BMC Public Health*, 22(1). https://doi.org/10.1186/s12889-022-13107-x

Narita, K., Tena, J. D., & Detotto, C. (2023). Causal inference with observational data: A tutorial on propensity score analysis. *The Leadership Quarterly*, 101678. https://doi.org/10.1016/j.leaqua.2023.101678

OECD (2021). An assessment of the impact of COVID-19 on job and skills demand using online job vacancy data. *OECD*. https://www.oecd.org/coronavirus/policy-responses/an-assessment-of-the-impact-of-covid-19-on-job-and-skills-demand-using-online-job-vacancy-data-20fff09e/

OECD/EU (2016), Health at a Glance: Europe 2016 – State of health in the EU Cycle. *OECD Publishing*, Paris. http://dx.doi.org/10.1787/9789264265592-en

Ohrnberger, J. (2022). Economic shocks, health, and social protection: The effect of COVID-19 income shocks on health and mitigation through cash transfers in South Africa. *Health Economics*, *31*. https://doi.org/10.1002/hec.4592

Orkin, K., Grabowska, M., Kreft, B., Cahill, A., Garlick, R., & Bekkouche, Y. (2022). *Designing Social Protection to Improve Employment, Earnings and Productivity in Lower-and Middle- Income Countries i*. https://mbrg.bsg.ox.ac.uk/sites/default/files/2022-02/cash-policy-2.2.pdf

Otchere, F., & Handa, S. (2022). Building resilience through social protection: Evidence from Malawi. *The Journal of Development Studies*, 1–23. https://doi.org/10.1080/00220388.2022.2075733

Ouadika, S. A. B. (2020). Health shocks and vulnerability to poverty in Congo. *Humanities and Social Sciences Communications*, *7*(1). https://doi.org/10.1057/s41599-020-00674-w

Park, Y. S., Konge, L., & Artino, A. R. (2020). The positivism paradigm of research. *Academic Medicine*, *95*(5), 690–694. Researchgate. https://doi.org/10.1097/ACM.0000000000003093

Parro, F., & Pohl, R. V. (2021). The effect of accidents on labour market outcomes: Evidence from Chile. *Health Economics*, *30*(5), 1015–1032. https://doi.org/10.1002/hec.4230

Pearl, J. (2010). *Causality: models, reasoning, and inference*. Cambridge University Press.

Pedersen, J., Gerds, T. A., Bjorner, J. B., & Christensen, K. B. (2014). Prediction of future labour market outcome in a cohort of long-term sick- listed Danes. *BMC Public Health*, *14*(1). https://doi.org/10.1186/1471-2458-14-494.

Pedron, S., Emmert-Fees, K., Laxy, M., & Schwettmann, L. (2019). The impact of diabetes on labour market participation: a systematic review of results and methods. *BMC Public Health*, *19*(1). https://doi.org/10.1186/s12889-018-6324-6

Petitti, D. B. (2000). *Meta-analysis, decision analysis, and cost-effectiveness analysis: methods for quantitative synthesis in medicine*. Oxford University Press.

Pew, T., Warr, R. L., Schultz, G. G., & Heaton, M. (2020). Justification for considering zero-inflated models in crash frequency analysis. *Transportation Research Interdisciplinary Perspectives*, *8*, 100249. https://doi.org/10.1016/j.trip.2020.100249

Pintor, M. P., Fumagalli, E., & Suhrcke, M. (2024). The impact of health on labour market outcomes: a rapid systematic review. *Health Policy*, 105057. https://doi.org/10.1016/j.healthpol.2024.105057

Platts, L. G. (2015). A prospective analysis of labour market status and self-rated health in the UK and Russia. *Economics of Transition*, *23*(2), 343–370. https://doi.org/10.1111/ecot.12065

Preston, N. J., Farquhar, M. C., Walshe, C. E., Stevinson, C., Ewing, G., Calman, L. A., Burden, S., Brown Wilson, C., Hopkinson, J. B., & Todd, C. (2016). Strategies designed to help healthcare professionals to recruit participants to research studies. *Cochrane Database of Systematic Reviews*, *2*(2). https://doi.org/10.1002/14651858.mr000036.pub2

Pruce, K. (2022). The politics of who gets what and why: Learning from the targeting of social cash transfers in Zambia. *The European Journal of Development Research*, *35*, 820–839. https://doi.org/10.1057/s41287-022-00540-2

Psaki, S. R., Chuang, E. K., Melnikas, A. J., Wilson, D. B., & Mensch, B. S. (2019). Causal effects of education on sexual and reproductive health in low and middle-income countries: A systematic review and meta-analysis. *SSM - Population Health*, *8*, 100386. https://doi.org/10.1016/j.ssmph.2019.100386

Rees, D. I., & Sabia, J. J. (2014). Migraine headache and labour market outcomes. *Health Economics*, *24*(6), 659–671. https://doi.org/10.1002/hec.3052.

Rellstab, S., Bakx, P., García-Gómez, P., & van Doorslaer, E. (2020). The kids are alright - labour market effects of unexpected parental hospitalisations in the Netherlands. *Journal of Health Economics*, *69*(102275), 102275. https://doi.org/10.1016/j.jhealeco.2019.102275

Rocco, L., Tanabe, K., Suhrcke, M., & Fumagalli, E. (2011). Chronic diseases and labour market outcomes in Egypt. *Policy Research Working Papers*. https://doi.org/10.1596/1813- 9450-5575

Rodríguez-Sánchez, B., & Cantarero-Prieto, D. (2017). Performance of people with diabetes in the labour market: An empirical approach controlling for complications. *Economics & Human Biology*, *27*, 102–113. https://doi.org/10.1016/j.ehb.2017.05.005

Rosenbaum, p. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Rosenbaum, P. R., & Rubin, D. B. (2022). Propensity scores in the design of observational studies for causal effects. *Biometrika*. https://doi.org/10.1093/biomet/asac054.

Rubin, D. B. (1980). Bias reduction using mahalanobis-metric matching. *Biometrics,* 36(2), 293. https://doi.org/10.2307/2529981

Rubin, D. B., & Waterman, R. P. (2006). Estimating the causal effects of marketing interventions using propensity score methodology. *Statistical Science*, 21(2). https://doi.org/10.1214/088342306000000259

Ryan, A. B. (2024). Post-Positivist Approaches to Research - MURAL - Maynooth University Research Archive Library. *Maynoothuniversity.ie*. https://mural.maynoothuniversity.ie/id/eprint/874/1/post-positivist_approaches_to_research.pdf

Schofield, D. J., Callander, E. J., Shrestha, R. N., Passey, M E., Percival, R., & Kelly, S. J. (2013). Multiple chronic health conditions and their link with labour force participation and economic status. *PLoS ONE*, *8*(11), e79108. https://doi.org/10.1371/journal.pone.0079108

Schrag, F. (1992). In defense of positivist research paradigms. *Educational Researcher*, *21*(5), 5–8.

Scotland, J. (2012). Exploring the philosophical underpinnings of research: Relating ontology and epistemology to the methodology and methods of the scientific, interpretive, and critical research paradigms. *English Language Teaching*, *5*(9), 9–16. https://files.eric.ed.gov/fulltext/EJ1080001.pdf

Schuring, M., Robroek, S. J., Otten, F. W., Arts, C. H., & Burdorf, A. (2013). The effect of ill health and socioeconomic status on labour force exit and re-employment: a prospective study with ten years follow-up in the Netherlands. *Scandinavian Journal of Work, Environment & Health*, *39*(2), 134–143. https://doi.org/10.5271/sjweh.3321

Seuring, T., Goryakin, Y., & Suhrcke, M. (2015). The impact of diabetes on employment in Mexico. *Economics & Human Biology*, 18, 85-100.

Seuring, T., Serneels, P., & Suhrcke, M. (2019). The impact of diabetes on labour market outcomes in Mexico: A panel data and biomarker analysis. *Social Science & Medicine*, *233*, 252–261. https://doi.org/10.1016/j.socscimed.2019.05.051

Shadish, W. R., Cook, T. D., & Donald T. C. (2002). *Experimental and Quasi-experimental Designs for Generalized Causal Inference*. Cengage Learning.

Shawa, K., Hollingsworth, B., & Zucchelli, E. (2024). A systematic review and meta-analysis on the effects of ill health and health shocks on labour supply. *Systematic Reviews*, *13*(1). https://doi.org/10.1186/s13643-024-02454-y

Shen, Z., Zheng, X., & Tan, Y. (2019). The spillover effects of spousal chronic diseases on married couples' labour supply: Evidence from China. *International Journal of Environmental Research and Public Health*, *16*(21), 4214. https://doi.org/10.3390/ijerph16214214

Siachiwena, H. (2022). International donors, domestic politics, and the expansion of social cash transfers in Malawi. *Development Policy Review*. https://doi.org/10.1111/dpr.12660

Simwaka, A., Peltzer, K., & Maluwa-Banda, D. (2007). Indigenous healing practices in Malawi. *Journal of Psychology in Africa,* 17(1-2), 155–161. https://doi.org/10.1080/14330237.2007.10820162

Slater, R., & Tsoka, M. (2007). Social protection in Malawi: A status report. Centre for Social Research and Overseas Development Institute.

Smith, J. (2005, August 1). *Consequences and Predictors of New Health Events*. National Bureau of Economic Research; University of Chicago Press. http://www.nber.org/chapters/c10362

Song, F. (1999). Exploring heterogeneity in meta-analysis. *Journal of Clinical Epidemiology*, *52*(8), 725–730. https://doi.org/10.1016/s0895-4356(99)00066-9

Song, F., Sheldon, T. A., Sutton, A. J., Abrams, K. R., & Jones, D. R. (2001). Methods for exploring heterogeneity in meta-analysis. *Evaluation & the Health Professions*, *24*(2), 126–151. https://doi.org/10.1177/01632780122034849

Stabridis, O., & van Gameren, E. (2018). Exposure to firewood: Consequences for health and labour force participation in Mexico. *World Development*, *107*, 382–395. https://doi.org/10.1016/j.worlddev.2018.03.009

Stuart, E. A., Lee, B. K., & Leacy, F. P. (2013). Prognostic score–based balance measures can be a useful diagnostic for propensity score methods in comparative effectiveness research. *Journal of Clinical Epidemiology*, *66*(8), S84-S90.e1. https://doi.org/10.1016/j.jclinepi.2013.01.013

Stoklosa, J., Blakey, R. V., & Hui, F. K. C. (2022). An overview of modern applications of negative binomial modeling in ecology and biodiversity. *Diversity*, *14*(5), 320. https://doi.org/10.3390/d14050320

Sutton, A. J. (2000). *Methods for Meta-Analysis in Medical Research*. John Wiley & Sons.

Timbie, J. W., Horvitz-Lennon, M., Frank, R. G., & Normand, S.-L. T. (2006). A Meta-analysis of labour supply effects of interventions for major depressive disorder. *Psychiatric Services*, *57*(2), 212–218. https://doi.org/10.1176/appi.ps.57.2.212

Tisch, A. (2015). Health, work ability and work motivation: determinants of labour market exit among German employees born in 1959 and 1965. *Journal for Labour Market Research*, *48*(3), 233–245. https://doi.org/10.1007/s12651-015-0186-5

Trevisan, E., & Zantomio, F. (2016). The impact of acute health shocks on the labour supply of older workers: Evidence from sixteen European countries. *Labour Economics*, *43*, 171–185. https://doi.org/10.1016/j.labeco.2016.04.002

Tunceli, K., Bradley, C. J., Nerenz, D., Williams, L. K., Pladevall, M., & Elston Lafata, J. (2005). The impact of diabetes on employment and work productivity. *Diabetes Care*, *28*(11), 2662–2667. https://doi.org/10.2337/diacare.28.11.2662

UNICEF (2021), Malawi Annual Report 2021. Lilongwe, Malawi

van den Berg, T., Schuring, M., Avendano, M., Mackenbach, J., & Burdorf, A. (2010). The impact of ill health on exit from paid employment in Europe among older workers. *Occupational and Environmental Medicine*, *67*(12), 845–852. https://doi.org/10.1136/oem.2009.051730

Vera-Cossio, D. A. (2021). Dependence or constraints? Cash transfers and labour supply. *Economic Development and Cultural Change*, *70*(4). https://doi.org/10.1086/714010

Vuori, J., & Vinokur, A. D. (2005). Job-search preparedness as a mediator of the effects of the Työhön job search intervention on re-employment and mental health. *Journal of Organizational Behavior*, *26*(3), 275–291. https://doi.org/10.1002/job.308

Wagstaff, A. (2007). The economic consequences of health shocks: Evidence from Vietnam. *Journal of Health Economics*, *26*(1), 82–100. https://doi.org/10.1016/j.jhealeco.2006.07.001

Wagstaff, A., & Lindelow, M. (2013). Are health shocks different? Evidence from a multi-shock survey in Laos. *Health Economics*, *23*(6), 706–718. https://doi.org/10.1002/hec.2944

Wang, X., Guo, J., Zhang, X., Qu, Z., Tian, D., & Ma, S.S. (2014). The effects of depression and chronic diseases on the work outcomes of employees: a prospective study in Northwest China. *Public Health*, *128*(8), 734–742. https://doi.org/10.1016/j.puhe.2014.06.007

Ward, B. W. (2015). Multiple chronic conditions and labor force outcomes: A population study of U.S. adults. *American Journal of Industrial Medicine*, 58(9), 943-954. https://doi.org/10.1002/ajim.22439

WFP (2018). Social Meals Programme. www.wfp.org/countries/Malawi

WFP (2019). Social Feeding Factsheet. www.wfp.org/countries/Malawi

WFP (2021). Social Meals Programme. www.wfp.org/countries/Malawi

Whiteside, M. (2000). Ganyu labour in Malawi and its implications for livelihood security interventions -an analysis of recent literature and implications for poverty alleviation. Agricultural Research & Extension Network: ODI. https://cdn.odi.org/media/documents/8256.pdf

WHO (2023). Health Statistics 20203: Monitoring health for the SDGs, Geneva.

Yau, K. K. W., Wang, K., & Lee, A. H. (2003). Zero-inflated negative binomial mixed regression modelling of over-dispersed count data with extra zeros. *Biometrical Journal*, *45*(4), 437–452. https://doi.org/10.1002/bimj.200390024

Zhang, X., Zhao, X., & Harris, A. (2009). Chronic diseases and labour force participation in Australia. *Journal of Health Economics*, *28*(1), 91–108. https://doi.org/10.1016/j.jhealeco.2008.08.001

Zhang, Z., Kim, H. J., Lonjon, G., Zhu, Y. (2019). Balance diagnostics after propensity score matching. *Annals of Translational Medicine*, 7(1), 16–16. https://doi.org/10.21037/atm.2018.12.10

Zhao, P., Li, K., & Coyte, P. C. (2023). The impact of non-communicable chronic diseases on the earned income of working age Chinese residents. *Humanities and Social Sciences Communications*, *10*(1), 1–9. https://doi.org/10.1057/s41599-023-01961-y

Zimmer, D. M. (2013). Employment effects of health shocks: The role of fringe benefits. *Bulletin of Economic Research*, *67*(4), 346–358. https://doi.org/10.1111/boer.12010

Zucchelli, E., Jones, A. M., & Rice, N. (2010). Health shocks and labour market exits evidence from the HILDA Survey. *Australian Journal of Labour Economics,* 13(2), 191-218.

CHAPTER TWO: Appendices

Appendix 2A: Adapted Data Extraction form

https://wiki.joannabriggs.org/display/MANUAL/5.5.7+Data+extraction

1. STUDY DETAILS	DETAILS	COMMENTS
1.1 Reviewer ID		
1.2 Study ID		
1.3 Date of extraction		
1.4 Study Title		
1.5 Author		
1.6 Year of Publication		
1.7 Journal		
2. STUDY METHODS		
2.1 Study aims		
2.2 Study design		
2.3 Study setting		
2.4 Participants' recruitment		
2.5 Follow up/Study duration		
2.6 Study characteristics		
2.7 Outcome Variable(s)		
2.8 How labour market outcomes were measured		
2.9 Exposure of interest		
2.10 Ethical approval		
2.11 Methods of data analysis		
3. RESULTS		
3.1 summary of descriptive statistics		
3.2 Details of regression coefficients, correlation coefficients., their signs, Standard errors, confidence intervals, p-values		
3.3 Diagnostic tests undertaken, Robust checks and sensitivity analysis		
4. POLICY IMPLICATIONS		
4.1 Key policy recommendations		
5. REVIEWERS COMMENTS		
5.1 Key critical comments by Reviewer		

Appendix 2B: Conversion Formulae for Partial Correlation Coefficients

- **Linear models with either Continuous or Dichotomous IVs**
  - Equation 1.1:
    - Equations:
      - $t = \frac{B}{se_B}$, where t refers to the t-statistic
      - $r = \frac{t}{\sqrt{t^2+df}}$
    - Data needed:
      - T-statistic (t)or Unstandardized Regression Coefficient and Standard Error (B, se_B)
      - Residual Degrees of Freedom (sample size minus the number of predictors) (df)

Dichotomous DV

- **Logit Models**
- Equation 2.1: Logit models with dichotomous IV and dichotomous DV
  - Equations:
    - $B = \log(OR)$
    - $d = B(\frac{\sqrt{3}}{\pi})$, where d refers to Cohen's d
    - $r = \frac{d}{\sqrt{4+d^2}}$
  - Data needed:
    - Unstandardized Regression Coefficient or Odds Ratio (B or OR)
- **Linear models with dichotomous IVs**
- Equation 2.2.1: Linear models with dichotomous IV and dichotomous DV (if control group success proportion is presented)
  - Equations:
    - $a = n_{treat}(p_{control} + B)$
    - $b = n_{treat}(1 - (p_{control} + B))$
    - $c = n_{control} * p_{control}$
    - $d = n_{control}(1 - p_{control})$
    - $r = \frac{(ad)-(bc)}{\sqrt{(a+b)(c+d)(a+c)(b+d)}}$
  - Data needed:
    - Unstandardized Regression Coefficient (B)
    - Control group sample size (n_{treat})
    - Treatment group sample size $(n_{control})$
    - Control group success proportion (i.e. mean) of DV $(p_{control})$
- Equation 2.2.2: Linear models with dichotomous IV and dichotomous DV (if only overall success proportion is presented)
  - Equations:
    - $a = n_{treat}(p + .5B)$
    - $b = n_{treat}(1 - (p + .5B))$
    - $c = n_{control}(p - .5B)$
    - $d = n_{control}(1 - (p - .5B))$
    - $r = \frac{(ad)-(bc)}{\sqrt{(a+b)(c+d)(a+c)(b+d)}}$

- Data needed:
  - Unstandardized Regression Coefficient (B)
  - Control group sample size ($n_{control}$)
  - Treatment group sample size (n_{treat})
  - Overall success proportion (i.e. mean) of DV (p)

- **Probit Models**
  - Imputed 0 if regression coefficient=0, otherwise:
  - Equation 2.3: Probit models
    - Equation:
      - $d = \frac{B}{SD_x}$
      - $r = \frac{d}{\sqrt{r+d^2}}$
    - Data needed:
      - Unstandardized Regression Coefficient (B)
      - Standard Deviation of IV (either for the entire analytical sample or disaggregated by treatment and control groups) (SD_x)

Standard errors and Confidence Intervals

- **Standard errors**
  - If only the standard error of the coefficient is available:
    - Equation 3.1:
      - $se_r = \frac{r * se_B}{B}$, where se_r refers to the standard error of the Partial correlation
    - Data needed
      - Unstandardized Regression Coefficient (B)
      - Standard Error of the Unstandardized Regression Coefficient (se_B)
  - If only the 95% confidence intervals for the coefficient are available:
    - Equation 3.2:
      - $se_B = \frac{CI_{upper} - CI_{lower}}{1.96}$, where se_B refers to the standard error of the unstandardized regression coefficient
      - $se_r = \frac{r * se_B}{B}$, where se_r refers to the standard error of the Partial correlation
    - Data needed
      - Unstandardized Regression Coefficient (B)
    - Confidence intervals of the Unstandardized Regression Coefficient (CI_{upper}, CI_{lower})
- **Confidence intervals**
  - The equation below can apply to either regression coefficients as well as partial correlations:
    - Equation 3.3
      - $CI = B \pm se_B \cdot 1.96$

Appendix 3A: Covariance balance summaries (using wave 5 as an example)

a) Covariate balance summary wage employment and illness/injury

	Raw	Matched
Number of obs =	32,895	16,942
Treated obs =	8,471	8,471
Control obs =	24,424	8,471

	Standardized differences Raw	Standardized differences Matched	Variance ratio Raw	Variance ratio Matched
Sex	-.1254667	.0032256	.9796066	1.000952
Age	.3565433	.0301079	1.46106	1.069979
Read	-.1596009	-.0014434	1.219654	1.001491
Religion				
TRADITIONAL	.0745929	.0054238	1.922765	1.040916
CHRISTIANITY	-.01986	-.0299081	1.038589	1.05917
ISLAM	.0001094	.0302089	1.000349	1.080603
OTHER RELIGION	-.013588	.0004352	.8673952	1.004745
Marstatus				
POLYGAMOUS M~L	.0330032	.0065529	1.203891	1.035911
SEPARATED	.0625353	.0048524	1.381941	1.023236
DIVORCED	.0783543	.0095648	1.415863	1.039334
WIDOW OR WID~R	.2056893	.0068593	2.1462	1.019933
NEVER MARRIED	-.3140814	-.0085639	.8272476	.9918757
Edulevel				
PSLC	-.0132912	.0103106	.9573374	1.035412
JCE	-.0666927	.0111071	.7562628	1.052751
MSCE/GCSE	-.0530995	.0049055	.8210955	1.019708
A-LEVEL	-.0395607	0	.502656	1
DIPLOMA	-.071051	.0027015	.4541725	1.037389
DEGREE	-.0187636	0	.7842992	1
MASTERS	-.0266835	0	.3329448	1
PhD	-.004419	0	.8239321	1
DON'T KNOW	.0989087	.0250321	1.308638	1.064827
Difficulty in seeing				
YES, SOME DI~Y	.2434946	.0275653	2.383289	1.077301
YES, A LOT O~Y	.1180869	.0094739	3.426179	1.073727
CANNOT PERFO~L	.027831	0	2.274163	1
Difficulty in hearing				
YES, SOME DI~Y	.1290541	.0116868	2.120698	1.056956
YES, A LOT O~Y	.0484987	.0042054	1.957477	1.050473
CANNOT PERFO~L	-.0191949	.0044361	.4327218	1.285613
Difficulty in walking or climbing steps				
YES, SOME DI~Y	.2201506	.0115882	2.614031	1.038161
YES, A LOT O~Y	.1304518	.0075433	3.49562	1.05275
CANNOT PERFO~L	.045976	.0060935	3.288887	1.124645
Difficulty in remembering or concentrating				
YES, SOME DI~Y	.1788016	.0127269	2.693934	1.054459
YES, A LOT O~Y	.0762399	.0024409	2.763407	1.025072
CANNOT PERFO~L	.0250893	3.77e-18	3.362096	1

b) Covariate balance summary wage employment and hospitalisation

	Raw	Matched
Number of obs =	32,895	62,928
Treated obs =	31,464	31,464
Control obs =	1,431	31,464

	Standardized differences Raw	Standardized differences Matched	Variance ratio Raw	Variance ratio Matched
Sex	.3557632	.0744258	1.165845	1.011098
Age	-.1695252	.0907328	.9887575	1.249535
Received ss	-.0149138	.0254871	.9950147	1.00849
Read	.0175951	-.0724738	.9763327	1.111411
Religion				
TRADITIONAL	-.0308677	.0029283	.7645287	1.027794
CHRISTIANITY	-.0161218	-.0737342	1.031243	1.164668
ISLAM	.0091689	.0816429	1.02259	1.247765
OTHER RELIGION	.0439271	.0035775	1.669597	1.037461
Marstatus				
POLYGAMOUS M~L	-.047184	.0131725	.774764	1.08108
SEPARATED	-.1001255	.0139323	.6205118	1.080719
DIVORCED	-.0328202	.0119947	.8636089	1.058281
WIDOW OR WID~R	-.0910635	.0303841	.7177882	1.136112
NEVER MARRIED	.4542616	.0306965	1.506624	1.013298
Edulevel				
PSLC	-.0012956	.0371418	.9951236	1.134826
JCE	-.0011411	.0256304	.9947909	1.111684
MSCE/GCSE	.0353654	.0309269	1.140459	1.121717
A-LEVEL	.0103446	.0318014	1.180949	1.771914
DIPLOMA	-.0015066	.0005508	.9849068	1.005357
DEGREE	.0298684	.0284288	1.511715	1.479247
MASTERS	.0067818	.035111	1.272363	8.348514
PhD	-.006369	.027562	.7727762	8.699567
DON'T KNOW	-.1170375	.0346594	.7410317	1.109015
Difficulty in seeing				
YES, SOME DI~Y	-.1474466	.0389595	.6109023	1.174437
YES, A LOT O~Y	-.1170054	.0037379	.3569206	1.043707
CANNOT PERFO~L	-.0425796	.0179115	.3415062	2.006474
Difficulty in hearing				
YES, SOME DI~Y	-.0815349	.0132083	.6362053	1.08841
YES, A LOT O~Y	-.0565453	.0047896	.4917533	1.075367
CANNOT PERFO~L	-.0395475	.021566	.303445	3.241817
Difficulty in walking or climbing				
YES, SOME DI~Y	-.1779357	.0155124	.500007	1.079121
YES, A LOT O~Y	-.1249683	.0056018	.363213	1.060957
CANNOT PERFO~L	-.0760579	.0066369	.2111404	1.225689
Difficulty in remembering or concentrating				
YES, SOME DI~Y	-.1304404	.0131447	.5188679	1.084381
YES, A LOT O~Y	-.0585961	.0065922	.4926805	1.101697
CANNOT PERFO~L	-.0354686	.0178807	.2502385	4.072999

c) Covariate balance summary wage employment and chronic disease

	Raw	Matched
Number of obs =	32,895	6,884
Treated obs =	3,442	3,442
Control obs =	29,453	3,442

	Standardized differences Raw	Standardized differences Matched	Variance ratio Raw	Variance ratio Matched

Sex	-.1400094	.0019581	.970593	1.000705
Age	.5880787	.0453429	1.330246	1.036513
Read	-.2649613	-.0118876	1.328617	1.009098
Religion				
TRADITIONAL	.0424741	.0028731	1.441767	1.022789
CHRISTIANITY	-.0744836	-.0480674	1.1449	1.088531
ISLAM	.0566075	.0459202	1.144488	1.114116
OTHER RELIGION	.0205102	.0050005	1.224818	1.048532
Marstatus				
POLYGAMOUS M~L	.0368827	.0120412	1.225451	1.065762
SEPARATED	.0654361	.0043719	1.387932	1.020175
DIVORCED	.1601002	.0113828	1.906555	1.038316
WIDOW OR WID~R	.3145142	.0129132	2.733678	1.028926
NEVER MARRIED	-.4141085	.0013464	.7177059	1.001784
Edulevel				
PSLC	-.0578254	.0269772	.8195808	1.108034
JCE	-.0576459	.0216505	.7828009	1.107558
MSCE/GCSE	-.0462319	.0227212	.8407382	1.097324
A-LEVEL	-.0111651	0	.8356165	1
DIPLOMA	-.0516369	.0033513	.5661485	1.043928
DEGREE	-.0022957	0	.9717541	1
MASTERS	-.0003775	0	.9876041	1
PhD	.0240111	0	2.443788	1
DON'T KNOW	.055016	.0195007	1.16161	1.052358
Difficulty in seeing				
YES, SOME DI~Y	.2524253	.0322427	2.241268	1.082008
YES, A LOT O~Y	.1471155	.0101999	3.774886	1.066103
CANNOT PERFO~L	.0291033	-.0048816	2.216555	.9002038
Difficulty in hearing				
YES, SOME DI~Y	.1147049	.0252199	1.874059	1.125984
YES, A LOT O~Y	.0977304	.0073836	3.316433	1.068188
CANNOT PERFO~L	.0069169	.0069603	1.283624	1.285465
Difficulty in walking or climbing steps				
YES, SOME DI~Y	.2327675	.0241172	2.47309	1.073314
YES, A LOT O~Y	.1857119	.0154947	4.572908	1.086779
CANNOT PERFO~L	.0821487	.0089777	6.225725	1.131716
Difficulty in remembering or concentrating				
YES, SOME DI~Y	.1795939	.0166889	2.451805	1.06648
YES, A LOT O~Y	.1524619	.004819	5.756907	1.034416
CANNOT PERFO~L	.0610691	.0251885	13.66511	1.844185

d) Covariate balance summary: casual employment and illness/injury

	Raw	Matched
Number of obs =	32,894	16,942
Treated obs =	8,471	8,471
Control obs =	24,423	8,471

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
Sex	-.1254248	.0032256	.9796082	1.000952
Age	.3565653	.0300641	1.461025	1.069884
Read	-.1596821	-.001532	1.219799	1.001583
Religion				
TRADITIONAL	.0745892	.0054238	1.922687	1.040916
CHRISTIANITY	-.0198427	-.0299081	1.038554	1.05917
ISLAM	.000095	.0302089	1.000313	1.080603
OTHER RELIGION	-.013592	.0004352	.86736	1.004745
Marstatus				
POLYGAMOUS M~L	.0329965	.0065529	1.203843	1.035911
SEPARATED	.0625284	.0048524	1.381886	1.023236
DIVORCED	.0783463	.0095648	1.415807	1.039334
WIDOW OR WID~R	.2056814	.0068593	2.146116	1.019933

NEVER MARRIED	-.3141179	-.0085639	.8272395	.9918757
Edulevel				
PSLC	-.0133028	.0103106	.9573014	1.035412
JCE	-.0667027	.0111071	.7562336	1.052751
MSCE/GCSE	-.0531104	.0049055	.8210643	1.019708
A-LEVEL	-.0395634	0	.5026355	1
DIPLOMA	-.0710553	.0027015	.4541541	1.037389
DEGREE	-.018767	0	.7842673	1
MASTERS	-.0266847	0	.3329312	1
PhD	-.00442	0	.8238984	1
DON'T KNOW	.0988964	.0250321	1.308589	1.064827
Difficulty in seeing				
YES, SOME DI~Y	.2434868	.0275653	2.383196	1.077301
YES, A LOT O~Y	.1180843	.0094739	3.42604	1.073727
CANNOT PERFO~L	.0278299	0	2.27407	1
Difficulty in hearing				
YES, SOME DI~Y	.1290488	.0116868	2.120613	1.056956
YES, A LOT O~Y	.0484964	.0042054	1.957397	1.050473
CANNOT PERFO~L	-.019196	.0044361	.4327041	1.285613
Difficulty in walking or climbing steps				
YES, SOME DI~Y	.2201442	.0115882	2.613927	1.038161
YES, A LOT O~Y	.1304491	.0075433	3.495477	1.05275
CANNOT PERFO~L	.045975	.0060935	3.288752	1.124645
Difficulty in remembering or concentrating				
YES, SOME DI~Y	.1787965	.0127269	2.693826	1.054459
YES, A LOT O~Y	.0762377	.0024409	2.763294	1.025072
CANNOT PERFO~L	.0250887	3.77e-18	3.361958	1

e) Covariate balance summary casual employment and hospitalisation

	Raw	Matched
Number of obs =	32,894	62,926
Treated obs =	31,463	31,463
Control obs =	1,431	31,463

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
Sex	.3557293	.1004986	1.165842	1.017697
Age	-.1695405	.0938321	.9887806	1.283704
Received ss	-.0148865	.0216035	.995023	1.007104
Read	.0176549	-.0899636	.9762541	1.142946
Religion				
TRADITIONAL	-.0308643	.0026257	.7645527	1.024868
CHRISTIANITY	-.0161354	-.0920151	1.031269	1.213958
ISLAM	.0091801	.0916629	1.022619	1.285735
OTHER RELIGION	.0439301	.0349758	1.669649	1.485333
Marstatus				
POLYGAMOUS M~L	-.0471787	.0118303	.7747879	1.072355
SEPARATED	-.1001199	.0115386	.6205309	1.066136
DIVORCED	-.0328137	.0152291	.8636352	1.074926
WIDOW OR WID~R	-.0910561	.0335761	.7178098	1.152145
NEVER MARRIED	.4542888	.0437461	1.50664	1.019612
Edulevel				
PSLC	-.0012866	.0293387	.9951527	1.104052
JCE	-.0011336	.0228599	.9948208	1.098653
MSCE/GCSE	.0353737	.0264762	1.140492	1.10273
A-LEVEL	.0103467	.043986	1.180987	2.354843
DIPLOMA	-.0015034	.000515	.9849377	1.005008
DEGREE	.0298709	.0447904	1.511763	1.944347
MASTERS	.0067827	.037092	1.272403	11.79786
PhD	-.0063682	.0290156	.7728007	12.18058
DON'T KNOW	-.1170275	.0334861	.7410529	1.10499

Difficulty in seeing				
YES, SOME DI~Y	-.1474392	.0483948	.6109206	1.224231
YES, A LOT O~Y	-.1170029	.0010779	.3569319	1.012314
CANNOT PERFO~L	-.0425787	.0239394	.341517	2.770225
Difficult in hearing				
YES, SOME DI~Y	-.08153	.0141663	.636225	1.095291
YES, A LOT O~Y	-.0565433	.0116882	.4917689	1.200138
CANNOT PERFO~L	-.0395468	.0249948	.3034546	4.452319
Difficulty in walking or climbing steps				
YES, SOME DI~Y	-.1779296	.022053	.5000222	1.115506
YES, A LOT O~Y	-.1249656	-.003518	.3632244	.9643981
CANNOT PERFO~L	-.0760571	.0141077	.2111471	1.589356
Difficulty in remembering or concentrating				
YES, SOME DI~Y	-.1304354	.0137389	.518884	1.088454
YES, A LOT O~Y	-.058594	.0076928	.4926961	1.120201
CANNOT PERFO~L	-.0354681	.0200942	.2502465	5.679115

f) Covariate balance summary casual employment and chronic disease

	Raw	Matched
Number of obs =	32,894	6,882
Treated obs =	3,441	3,441
Control obs =	29,453	3,441

	Standardized differences Raw	Matched	Variance ratio Raw	Matched
Sex	-.1403582	.0071781	.9704724	1.00263
Age	.588042	.0280694	1.330632	1.025978
Read	-.2645374	-.0027216	1.3282	1.00205
Religion				
TRADITIONAL	.0425103	.0015634	1.44218	1.012301
CHRISTIANITY	-.0746189	-.0331769	1.14516	1.059344
ISLAM	.0567181	.03127	1.144772	1.075152
OTHER RELIGION	.0205408	.0044958	1.225171	1.043465
Marstatus				
POLYGAMOUS M~L	.0369366	.0092724	1.225795	1.05004
SEPARATED	.0654967	.0024092	1.388317	1.011036
DIVORCED	.1601801	.0038647	1.907065	1.012736
WIDOW OR WID~R	.3146227	.0057185	2.734352	1.012613
NEVER MARRIED	-.4139478	.0008709	.7178542	1.001153
Edulevel				
PSLC	-.0577517	.0160513	.8198036	1.062055
JCE	-.0575855	.0177722	.7830185	1.086953
MSCE/GCSE	-.046163	.0175244	.8409688	1.073729
A-LEVEL	-.0111479	0	.8358585	1
DIPLOMA	-.0516148	.0025071	.5663121	1.032586
DEGREE	-.0022729	0	.9720349	1
MASTERS	-.0003689	0	.9878909	1
PhD	.0240204	0	2.444498	1
DON'T KNOW	.0551158	-.0013373	1.161908	.996582
Difficulty in seeing				
YES, SOME DI~Y	.2525285	.0215703	2.241832	1.053521
YES, A LOT O~Y	.1471568	.0018884	3.775955	1.011747
CANNOT PERFO~L	.0291158	0	2.217198	1
Difficulty in hearing				
YES, SOME DI~Y	.1147643	.0092262	1.874579	1.043341
YES, A LOT O~Y	.0977601	.0070846	3.317385	1.06528
CANNOT PERFO~L	.0069254	.0241139	1.283996	2.998256
Difficulty in walking or climbing steps				
YES, SOME DI~Y	.232855	.0139897	2.473738	1.041417
YES, A LOT O~Y	.1857591	.0038235	4.574192	1.020369
CANNOT PERFO~L	.0821668	.0080562	6.227525	1.116994

Difficulty in remembering or concentrating				
YES, SOME DI~Y	.1796625	.0085552	2.452474	1.033197
YES, A LOT O~Y	.1524968	.0035265	5.758547	1.025004
CANNOT PERFO~L	.06108	9.00e-18	13.66908	1

g) Covariate balance summary: working hours and illness/injury

	Raw	Matched
Number of obs =	32,894	16,942
Treated obs =	8,471	8,471
Control obs =	24,423	8,471

	Standardized differences Raw	Standardized differences Matched	Variance ratio Raw	Variance ratio Matched
Whether always lived in the location	.0496364	.0667309	1.06024	1.083389
Sex	-.1254248	-.0236381	.9796082	.9936915
Age	.3566679	.0739178	1.461475	1.152499
Received ss	.0689033	.022902	1.018882	1.005136
Read	-.1595802	-.0409358	1.219616	1.045319
Religion				
TRADITIONAL	.0745892	.0134547	1.922687	1.106424
CHRISTIANITY	-.0198427	-.0713811	1.038554	1.153892
ISLAM	.000095	.0696958	1.000313	1.205155
OTHER RELIGION	-.013592	.0017469	.86736	1.019256
Marstatus				
POLYGAMOUS M~L	.0329965	.0195437	1.203843	1.113395
SEPARATED	.0625284	.0198072	1.381886	1.100535
DIVORCED	.0783463	.022658	1.415807	1.097409
WIDOW OR WID~R	.2056814	.0237612	2.146116	1.072118
NEVER MARRIED	-.3141179	-.0346229	.8272395	.9686217
Edulevel				
PSLC	-.0133028	.0191343	.9573014	1.067421
JCE	-.0667027	.0214249	.7562336	1.105858
MSCE/GCSE	-.0531104	.0138313	.8210643	1.05723
A-LEVEL	-.0395634	0	.5026355	1
DIPLOMA	-.0710553	.0074107	.4541541	1.107842
DEGREE	-.018767	.0022062	.7842673	1.031087
MASTERS	-.0266847	0	.3329312	1
PhD	-.00442	0	.8238984	1
DON'T KNOW	.0988964	.0629003	1.308589	1.17859
Difficulty in seeing				
YES, SOME DI~Y	.2434868	.0773022	2.383196	1.246769
YES, A LOT O~Y	.1180843	.0258294	3.42604	1.222505
CANNOT PERFO~L	.0278299	0	2.27407	1
Difficulty in hearing				
YES, SOME DI~Y	.1290488	.034941	2.120613	1.186944
YES, A LOT O~Y	.0484964	.0104678	1.957397	1.133158
CANNOT PERFO~L	-.019196	.0044361	.4327041	1.285613
Difficulty in walking or climbing steps				
YES, SOME DI~Y	.2201442	.0466919	2.613927	1.170212
YES, A LOT O~Y	.1304491	.022045	3.495477	1.16712
CANNOT PERFO~L	.045975	.0060935	3.288752	1.124645
Difficulty in remembering or concentrating				
YES, SOME DI~Y	.1787965	.0433548	2.693826	1.207191
YES, A LOT O~Y	.0762377	.0091017	2.763294	1.098587
CANNOT PERFO~L	.0250887	3.77e-18	3.361958	1
Relationship to head				
WIFE/HUSBAND	.070687	-.0009785	1.093331	.9988628
CHILD/ADOPTE~D	-.263477	-.0444011	.7773818	.9465739
GRANDCHILD	-.0678675	.0066076	.7418563	1.032582
NIECE/NEPHEW	-.0877619	.0065586	.4848773	1.068239
FATHER/MOTHER	.0471713	.0040851	1.73578	1.042504
SISTER/BROTHER	-.055631	.014315	.6259012	1.151455

SON/DAUGHTER~W	-.04068	.0015234	.5154127	1.029769
BROTHER/SIST~W	-.0301051	.0020038	.6373302	1.03436
GRANDFATHER/~R	.0205733	0	1.591959	1
FATHER/MOTHE~W	.0313289	.0023461	2.111561	1.047495
OTHER RELATIVE	-.032961	.0053285	.6178533	1.093772
SERVANT OR S~E	-.0267252	0	.4995753	1
LODGER/LODGE~E	-.0127979	.	0	.
OTHER NON-RE~E	-.021152	0	.5315321	1
OTHER (SPECI~)	-.000436	0	.9611223	1
Months away from home				
1	.0289276	.0165066	1.204191	1.109136
2	.0232495	.0115809	1.235806	1.107808
3	.0068927	.0073228	1.072453	1.077152
4	-.0230615	.0070373	.716725	1.120392
5	.0180242	.0025148	1.271762	1.032263
6	-.0201263	.0113949	.7735449	1.175529
7	.0060084	.0034017	1.090546	1.049751
8	-.0035105	.0021573	.9544537	1.029688
9	-.0108939	.0037547	.8694361	1.051947
10	-.0334543	.0045078	.5280174	1.108477
11	-.0068716	.0018273	.903031	1.02845
12	.0047854	.0019094	1.08094	1.031128
Days ate in household in the past 7 days				
1	-.0080909	0	.8616394	1
2	.0294964	.0026723	1.554569	1.03656
3	.0201243	.0105196	1.268796	1.128184
4	.0457443	.0173679	1.577781	1.173176
5	.033245	.0090912	1.358366	1.081945
6	.0288907	.006705	1.353137	1.068104
7	-.0015925	-.0258031	1.004908	1.083501
Place of birth				
OTHER VILLAG~T	.0326554	.0410122	1.046306	1.058937
VILLAGE IN O~T	-.0077397	.0364835	.9862235	1.071175
THIS TOWN OR~E	-.0637355	.0070057	.5300572	1.087032
OTHER TOWN O~T	-.019633	.0057969	.7781449	1.083887
TOWN OR URBA~I	-.0093111	.0213112	.9467471	1.14126
OUTSIDE MALAWI	.0362399	.0127523	1.362785	1.108442

h) Covariate balance summary: working hours and hospitalization

	Raw	Matched
Number of obs =	32,894	62,926
Treated obs =	31,463	31,463
Control obs =	1,431	31,463

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
Whether always lived in the location				
	-.1794736	.0504309	.8353969	1.06788
Sex	.3557293	.1106138	1.165842	1.020643
Age	-.1696131	.0905508	.9885856	1.265958
Received ss	-.0149508	.0323601	.9950034	1.011025
Read	.0175782	-.0897263	.976355	1.14248
Religion				
TRADITIONAL	-.0308643	.0141576	.7645527	1.146156
CHRISTIANITY	-.0161354	-.1119655	1.031269	1.272461
ISLAM	.0091801	.1112241	1.022619	1.366008
OTHER RELIGION	.0439301	.0076216	1.669649	1.082444
Marstatus				
POLYGAMOUS M~L	-.0471787	.0393102	.7747879	1.276061
SEPARATED	-.1001199	.0416099	.6205309	1.275095
DIVORCED	-.0328137	.0576614	.8636352	1.338974
WIDOW OR WID~R	-.0910561	.0381491	.7178098	1.175769
NEVER MARRIED	.4542888	.0898253	1.50664	1.04524
Edulevel				

PSLC	-.0012866	.0736894	.9951527	1.300201
JCE	-.0011336	.0503578	.9948208	1.240049
MSCE/GCSE	.0353737	.0753446	1.140492	1.345208
A-LEVEL	.0103467	.0009948	1.180987	1.01556
DIPLOMA	-.0015034	.0228131	.9849377	1.265091
DEGREE	.0298709	.0083451	1.511763	1.112449
MASTERS	.0067827	.0243662	1.272403	2.99822
PhD	-.0063682	.0189832	.7728007	2.998919
DON'T KNOW	-.1170275	.0695873	.7410529	1.241371
Difficulty in seeing				
YES, SOME DI~Y	-.1474392	.0558002	.6109206	1.265783
YES, A LOT O~Y	-.1170029	.0124889	.3569319	1.158196
CANNOT PERFO~L	-.0425787	.0028091	.341517	1.097468
Difficulty in hearing				
YES, SOME DI~Y	-.08153	.0342343	.636225	1.256755
YES, A LOT O~Y	-.0565433	.007026	.4917689	1.113549
CANNOT PERFO~L	-.0395468	.0050834	.3034546	1.236963
Difficulty in walking or climbing steps				
YES, SOME DI~Y	-.1779296	.0214264	.5000222	1.111936
YES, A LOT O~Y	-.1249656	.0160282	.3632244	1.190672
CANNOT PERFO~L	-.0760571	.0041415	.2111471	1.132497
Difficulty in remembering or concentrating				
YES, SOME DI~Y	-.1304354	.0474107	.518884	1.365761
YES, A LOT O~Y	-.058594	.0131782	.4926961	1.219959
CANNOT PERFO~L	-.0354681	.0075179	.2502465	1.571229
Relationship to head				
WIFE/HUSBAND	-.3612153	-.1468118	.724343	.844064
CHILD/ADOPTE~D	.3475094	.0447932	1.517631	1.037152
GRANDCHILD	.1626821	.0624027	2.397748	1.323486
NIECE/NEPHEW	.0584442	.0302071	1.616164	1.26092
FATHER/MOTHER	-.0143417	.0133403	.8439436	1.187122
SISTER/BROTHER	.0688216	.0366187	1.883182	1.360461
SON/DAUGHTER~W	-.0492949	.0042039	.5323741	1.065695
BROTHER/SIST~W	-.0078269	.0009398	.8981836	1.013294
GRANDFATHER/~R	-.0567224	.0007862	.3387399	1.019575
FATHER/MOTHE~W	-.0514331	.0066605	.3494183	1.199707
OTHER RELATIVE	.0871355	.0648027	7.91533	3.31089
SERVANT OR S~E	.0334947	.0359256	2.723802	3.028977
LODGER/LODGE~E	.0112755	.0112755	.	.
OTHER NON-RE~E	.0535211	.0535211	.	.
OTHER (SPECI~)	-.0302839	.0079731	.1364373	2.999809
Months away from home				
1	-.0759055	.0370354	.6387169	1.303491
2	-.0874388	.0130996	.4967015	1.137957
3	-.051876	.0049841	.6203602	1.053758
4	.0045238	.0050905	1.064524	1.073847
5	-.0399142	.0049854	.6118198	1.072956
6	-.0386917	.0071046	.6483193	1.094806
7	-.0137829	.0012571	.8246247	1.018649
8	-.0266138	.0053814	.7205251	1.075865
9	-.0015675	.0064925	.9798573	1.087306
10	-.0026871	-.0003668	.954635	.993712
11	-.0147209	-.0057594	.8133025	.9202758
12	-.0086004	.0014126	.8716272	1.023652
Days ate in household in past 7 days				
1	.0361933	.0220447	2.223301	1.554643
2	-.0324178	.0044564	.6327445	1.074201
3	-.0363448	.0056268	.6677384	1.072818
4	-.0428114	.0140025	.6656415	1.165652
5	.0412674	.0167965	1.54837	1.180031
6	-.0562001	.0104577	.5829594	1.125623
7	.0119374	-.0793526	.9642534	1.301703
Place of birth				
OTHER VILLAG~T	-.0753698	.0855584	.9055429	1.141913
VILLAGE IN O~T	-.0223189	.0645772	.9608506	1.13207
THIS TOWN OR~E	.037549	.0194731	1.445125	1.1994
OTHER TOWN O~T	-.0155303	.0097302	.8316125	1.132601
TOWN OR URBA~I	-.0063163	.0587403	.9634606	1.46591
OUTSIDE MALAWI	-.0268844	.0168051	.7979383	1.168108

i) **Covariate balance summary: working hours and chronic disease**

	Raw	Matched
Number of obs =	32,894	6,884
Treated obs =	3,442	3,442
Control obs =	29,452	3,442

	Standardized differences Raw	Standardized differences Matched	Variance ratio Raw	Variance ratio Matched
Whether always lived in the location	.0806365	.0844044	1.095198	1.100039
Sex	-.139974	-.023926	.9705955	.9920616
Age	.5881901	.1216991	1.330528	1.030222
Received ss	.1371527	.075497	1.027304	1.010064
Read	-.2649437	-.0580937	1.328584	1.048507
Religion				
TRADITIONAL	.0424705	.0133094	1.441719	1.112674
CHRISTIANITY	-.0744693	-.0952093	1.144868	1.19292
ISLAM	.0565957	.0848839	1.144454	1.231432
OTHER RELIGION	.020507	.0173734	1.224777	1.185411
Marstatus				
POLYGAMOUS M~L	.0368771	.02637	1.225411	1.153365
SEPARATED	.0654301	.022716	1.387886	1.112368
DIVORCED	.1600938	.0352484	1.906492	1.127176
WIDOW OR WID~R	.3145075	.0273325	2.733589	1.063163
NEVER MARRIED	-.414138	-.0386947	.7176987	.9521403
Edulevel				
PSLC	-.057835	.0387281	.8195552	1.161244
JCE	-.057654	.0260195	.7827758	1.131512
MSCE/GCSE	-.0462408	.0429349	.8407116	1.197598
A-LEVEL	-.0111672	0	.8355882	1
DIPLOMA	-.0516403	.0116112	.5661295	1.165644
DEGREE	-.0022984	.0102774	.9717213	1.144562
MASTERS	-.0003785	0	.9875706	1
PhD	.0240104	0	2.443705	1
DON'T KNOW	.0550053	.0539836	1.161575	1.157877
Difficulty in seeing				
YES, SOME DI~Y	.252418	.0823956	2.241196	1.236763
YES, A LOT O~Y	.1471132	.0172634	3.774758	1.115967
CANNOT PERFO~L	.0291023	-.0052205	2.21648	.8938339
Difficulty in hearing				
YES, SOME DI~Y	.1146999	.0363841	1.873996	1.190084
YES, A LOT O~Y	.0977286	.0116264	3.316321	1.110653
CANNOT PERFO~L	.006916	.0033763	1.28358	1.124891
Difficulty in walking or climbing steps				
YES, SOME DI~Y	.2327615	.0567988	2.473009	1.188689
YES, A LOT O~Y	.1857096	.0310549	4.572754	1.186544
CANNOT PERFO~L	.0821479	.0115451	6.225514	1.174286
Difficulty in remembering or concentrating				
YES, SOME DI~Y	.1795891	.0495022	2.451724	1.220435
YES, A LOT O~Y	.1524604	.0168587	5.756712	1.12888
CANNOT PERFO~L	.0610689	.0140547	13.66465	1.370564
Relationship to head				
WIFE/HUSBAND	.0604029	-.0007633	1.07817	.9991163
CHILD/ADOPTE~D	-.3466871	-.0545893	.6720651	.9183389
GRANDCHILD	-.0983935	.0274081	.6293302	1.166471
NIECE/NEPHEW	-.1110418	0	.352243	1
FATHER/MOTHER	.0867763	.0151788	2.504558	1.137523
SISTER/BROTHER	-.0207684	.024424	.8451905	1.245507
SON/DAUGHTER~W	-.030889	0	.6038964	1
BROTHER/SIST~W	-.0374248	.0084167	.5499632	1.175957
GRANDFATHER/~R	.0375541	.005034	2.1811	1.090591
FATHER/MOTHE~W	.0256088	-.009071	1.789315	.8441598

OTHER RELATIVE	-.0418857	.0103808	.5170094	1.223836
SERVANT OR S~E	-.029148	0	.443186	1
LODGER/LODGE~E	-.0116541	.	0	.
OTHER NON-RE~E	-.0163675	0	.6116858	1
OTHER (SPECI~)	-.016482	.	0	.
Months away from home				
1	.0137526	.0226985	1.092925	1.160326
2	.0284811	.0153443	1.28779	1.14084
3	.0098742	.0340963	1.104307	1.443685
4	.0049268	.0151202	1.06947	1.237805
5	.0167115	.003687	1.2454	1.047313
6	-.0181294	.009	.7911542	1.136123
7	-.0495477	0	.4115614	1
8	-.0015606	.0053212	.9797418	1.075053
9	-.0229998	.002877	.7335615	1.043275
10	.0081436	.004011	1.146506	1.068234
11	-.0038858	0	.9442371	1
12	-.0407386	0	.4475176	1
Days ate in household in past 7 days				
1	.0142082	0	1.277853	1
2	.0363561	.0006087	1.676834	1.007584
3	.0334584	.0056296	1.460271	1.060203
4	.046912	.020707	1.567084	1.202467
5	.0245934	.0177096	1.251195	1.171614
6	.0212004	.022662	1.245624	1.265584
7	-.0244492	-.0455557	1.075508	1.148428
Place of birth				
OTHER VILLAG~T	.0347393	.0394022	1.048891	1.055616
VILLAGE IN O~T	.0290651	.0509838	1.052598	1.095817
THIS TOWN OR~E	-.0039973	.0169022	.9647994	1.174399
OTHER TOWN O~T	.0072365	.0101946	1.091971	1.132919
TOWN OR URBA~I	.0063334	.0419945	1.037645	1.295756
OUTSIDE MALAWI	.0471014	.0305316	1.471455	1.271707

j) Covariate balance summary job search and illness/injury

	Raw	Matched
Number of obs =	32,895	16,942
Treated obs =	8,471	8,471
Control obs =	24,424	8,471

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
Sex	-.1254667	-.0235846	.9796066	.9937045
Age	.3565433	.0653329	1.46106	1.134864
Read	-.1596009	-.0380331	1.219654	1.041889
Religion				
TRADITIONAL	.0745929	.0131414	1.922765	1.10375
CHRISTIANITY	-.01986	-.0663242	1.038589	1.14146
ISLAM	.0001094	.0636823	1.000349	1.184578
OTHER RELIGION	-.013588	.0017469	.8673952	1.019256
Marstatus				
POLYGAMOUS M~L	.0330032	.0186004	1.203891	1.107465
SEPARATED	.0625353	.0207037	1.381941	1.105463
DIVORCED	.0783543	.0225203	1.415863	1.096771
WIDOW OR WID~R	.2056893	.023534	2.1462	1.071386
NEVER MARRIED	-.3140814	-.0314007	.8272476	.9713809
Edulevel				
PSLC	-.0132912	.0144589	.9573374	1.050257
JCE	-.0666927	.020654	.7562628	1.101743
MSCE/GCSE	-.0530995	.0107581	.8210955	1.044061
A-LEVEL	-.0395607	0	.502656	1
DIPLOMA	-.071051	.0079748	.4541725	1.116768
DEGREE	-.0187636	.0022062	.7842992	1.031087
MASTERS	-.0266835	0	.3329448	1

PhD	-.004419	0	.8239321	1
DON'T KNOW	.0989087	.0566218	1.308638	1.158257
Difficulty in seeing				
YES, SOME DI~Y	.2434946	.0743397	2.383289	1.235395
YES, A LOT O~Y	.1180869	.0251686	3.426179	1.215885
CANNOT PERFO~L	.027831	0	2.274163	1
Difficulty in hearing				
YES, SOME DI~Y	.1290541	.0346699	2.120698	1.185284
YES, A LOT O~Y	.0484987	.0099779	1.957477	1.126335
CANNOT PERFO~L	-.0191949	.0044361	.4327218	1.285613
Difficulty in walking or climbing steps				
YES, SOME DI~Y	.2201506	.043366	2.614031	1.156514
YES, A LOT O~Y	.1304518	.0223426	3.49562	1.169667
CANNOT PERFO~L	.045976	.0060935	3.288887	1.124645
Difficulty on remembering or concentrating				
YES, SOME DI~Y	.1788016	.0420886	2.693934	1.200181
YES, A LOT O~Y	.0762399	.0091017	2.763407	1.098587
CANNOT PERFO~L	.0250893	3.77e-18	3.362096	1
Relationship to head				
WIFE/HUSBAND	.0707087	.0018494	1.093363	1.00216
CHILD/ADOPTE~D	-.2634468	-.0392391	.7773968	.9523699
GRANDCHILD	-.0678579	.0062955	.7418849	1.031005
NIECE/NEPHEW	-.0877562	.0056376	.4848967	1.058235
FATHER/MOTHER	.0471743	.0044983	1.735851	1.046956
SISTER/BROTHER	-.0556256	.0142128	.6259264	1.150252
SON/DAUGHTER~W	-.0406771	.0015234	.5154337	1.029769
BROTHER/SIST~W	-.0301021	.0020038	.6373562	1.03436
GRANDFATHER/~R	.0205749	0	1.592024	1
FATHER/MOTHE~W	.0313303	.0023461	2.111648	1.047495
OTHER RELATIVE	-.0329579	.0060114	.6178785	1.106749
SERVANT OR S~E	-.0267234	0	.4995957	1
LODGER/LODGE~E	-.0127977	.	0	.
OTHER NON-RE~E	-.0211504	0	.5315538	1
OTHER (SPECI~)	-.0004356	0	.9611616	1
Months away from home				
1	.0289335	.0159094	1.20424	1.104869
2	.0232537	.0108512	1.235856	1.100498
3	.0068966	.0074264	1.072497	1.078308
4	-.0230585	.0070373	.7167542	1.120392
5	.0180271	.0020086	1.271814	1.025644
6	-.0201229	.0113949	.7735764	1.175529
7	.0060112	.0034017	1.09059	1.049751
8	-.0035074	.0021573	.9544925	1.029688
9	-.0108906	.0037547	.8694715	1.051947
10	-.0334518	.0045078	.528039	1.108477
11	-.0068688	.0018273	.9030678	1.02845
12	.0047879	.0019094	1.080984	1.031128
Days ate in household in the last 7 days				
1	-.0080886	0	.8616746	1
2	.0294988	.0026723	1.554632	1.03656
3	.0201275	.0105196	1.268847	1.128184
4	.0457478	.0173679	1.577845	1.173176
5	.033249	.009448	1.358421	1.08537
6	.0288943	.006705	1.353192	1.068104
7	-.0016048	-.0249879	1.004945	1.080683
Place of birth				
OTHER VILLAG~T	.0326764	.028129	1.046337	1.039497
VILLAGE IN O~T	-.0077214	.0308006	.9862558	1.059411
THIS TOWN OR~E	-.0637308	.0074913	.5300786	1.093488
OTHER TOWN O~T	-.0196296	.0062199	.7781765	1.090424
TOWN OR URBA~I	-.0093042	.0205188	.9467848	1.135461
OUTSIDE MALAWI	.0362442	.0128362	1.36284	1.109214

.

k) Covariate balance summary: job search and hospitalization

	Raw	Matched
Number of obs =	32,895	62,928
Treated obs =	31,464	31,464
Control obs =	1,431	31,464

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
Sex	.3557632	.0831721	1.165845	1.01315
Age	-.1695252	.0788151	.9887575	1.202886
Read	.0175951	-.0892958	.9763327	1.141686
Religion				
TRADITIONAL	-.0308677	.0140497	.7645287	1.144924
CHRISTIANITY	-.0161218	-.1047931	1.031243	1.250835
ISLAM	.0091689	.10306	1.02259	1.331475
OTHER RELIGION	.0439271	.0077358	1.669597	1.083759
Marstatus				
POLYGAMOUS M~L	-.047184	.0352512	.774764	1.242293
SEPARATED	-.1001255	.0466187	.6205118	1.316219
DIVORCED	-.0328202	.056248	.8636089	1.328563
WIDOW OR WID~R	-.0910635	.033643	.7177882	1.152489
NEVER MARRIED	.4542616	.0695249	1.506624	1.0333
Edulevel				
PSLC	-.0012956	.0676	.9951236	1.269941
JCE	-.0011411	.0502388	.9947909	1.239379
MSCE/GCSE	.0353654	.0865651	1.140459	1.413545
A-LEVEL	.0103446	.0007453	1.180949	1.011625
DIPLOMA	-.0015066	.0217021	.9849068	1.24978
DEGREE	.0298684	.0092605	1.511715	1.12595
MASTERS	.0067818	.017469	1.272363	2.023185
PhD	-.006369	.0139792	.7727762	2.072591
DON'T KNOW	-.1170375	.0611292	.7410317	1.206921
Difficulty in seeing				
YES, SOME DI~Y	-.1474466	.0401087	.6109023	1.180324
YES, A LOT O~Y	-.1170054	.0113157	.3569206	1.14176
CANNOT PERFO~L	-.0425796	.0042635	.3415062	1.153699
Difficulty in hearing				
YES, SOME DI~Y	-.0815349	.028645	.6362053	1.208203
YES, A LOT O~Y	-.0565453	.0066071	.4917533	1.106243
CANNOT PERFO~L	-.0395475	-.0036487	.303445	.8696482
Difficulty in walking or climbing steps				
YES, SOME DI~Y	-.1779357	.0168667	.500007	1.086499
YES, A LOT O~Y	-.1249683	.0145079	.363213	1.170285
CANNOT PERFO~L	-.0760579	.0038138	.2111404	1.121069
Difficulty in remembering or concentrating				
YES, SOME DI~Y	-.1304404	.0446952	.5188679	1.339443
YES, A LOT O~Y	-.0585961	.012757	.4926805	1.211826
CANNOT PERFO~L	-.0354686	.0026417	.2502385	1.15784
Relationship to head				
WIFE/HUSBAND	-.3612325	-.1210762	.7243265	.8659449
CHILD/ADOPTE~D	.3474871	.023913	1.517606	1.019074
GRANDCHILD	.1626752	.0600229	2.397675	1.308175
NIECE/NEPHEW	.05844	.0297644	1.616113	1.256362
FATHER/MOTHER	-.0143442	.0127675	.843917	1.178023
SISTER/BROTHER	.0688177	.0350577	1.883123	1.341186
SON/DAUGHTER~W	-.0492969	.0036301	.5323573	1.056351
BROTHER/SIST~W	-.0078291	.000676	.8981552	1.009536
GRANDFATHER/~R	-.0567236	.0007862	.3387291	1.019575
FATHER/MOTHE~W	-.0514341	.0060574	.3494072	1.179224
OTHER RELATIVE	.0871335	.0497623	7.91508	2.286793
SERVANT OR S~E	.0334935	.0271341	2.723716	2.134329
LODGER/LODGE~E	.0112753	.0112753	.	.
OTHER NON-RE~E	.0535203	.0535203	.	.
OTHER (SPECI~)	-.0302841	.006768	.136433	2.399867

Months away from home				
1	-.0759101	.0358684	.6386971	1.291828
2	-.087442	.0127698	.4966859	1.134136
3	-.051879	.0036119	.6203407	1.038527
4	.0045215	.0056248	1.06449	1.082076
5	-.0399164	.0049853	.6118005	1.072956
6	-.0386942	.0073841	.6482988	1.098815
7	-.013785	.0014151	.8245986	1.021029
8	-.0266161	.0052333	.7205023	1.073662
9	-.00157	.0068453	.9798263	1.092381
10	-.002689	-.0005498	.9546047	.9905976
11	-.014723	-.0096157	.8132768	.8720954
12	-.0086023	.0018575	.8715996	1.031275
Days ate in household in past 7 days				
1	.0361916	.0005718	2.223231	1.010277
2	-.0324198	.0043692	.6327245	1.07267
3	-.0363474	.0076846	.6677174	1.101481
4	-.0428143	.0141244	.6656205	1.167279
5	.0412641	.016575	1.548321	1.177343
6	-.0562029	.0103949	.582941	1.124801
7	.0119469	-.0726594	.9642255	1.270567
Place of birth				
OTHER VILLAG~T	-.0753863	.0548604	.9055218	1.08587
VILLAGE IN O~T	-.022333	.0433373	.9608261	1.08487
THIS TOWN OR~E	.0375455	.0181058	1.445079	1.183474
OTHER TOWN O~T	-.0155328	.0094477	.8315862	1.128383
TOWN OR URBA~I	-.0063216	.0622767	.9634308	1.50461
OUTSIDE MALAWI	-.0268879	.0178986	.7979133	1.180536

l) Covariate balance summary: job search and chronic disease

	Raw	Matched
Number of obs =	32,895	6,884
Treated obs =	3,442	3,442
Control obs =	29,453	3,442

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
Sex	-.1400094	-.0049161	.970593	.9982676
Age	.5880787	.0730139	1.330246	1.022355
Read	-.2649613	-.028578	1.328617	1.022573
Religion				
TRADITIONAL	.0424741	.0111487	1.441767	1.093089
CHRISTIANITY	-.0744836	-.073055	1.1449	1.141431
ISLAM	.0566075	.0677374	1.144488	1.177157
OTHER RELIGION	.0205102	.0114217	1.224818	1.116335
Marstatus				
POLYGAMOUS M~L	.0368827	.0233292	1.225451	1.133843
SEPARATED	.0654361	.0106993	1.387932	1.050547
DIVORCED	.1601002	.0151879	1.906555	1.05168
WIDOW OR WID~R	.3145142	.0180069	2.733678	1.040779
NEVER MARRIED	-.4141085	-.0102378	.7177059	.9867029
Edulevel				
PSLC	-.0578254	.0210853	.8195808	1.082848
JCE	-.0576459	.0230937	.7828009	1.11538
MSCE/GCSE	-.0462319	.038474	.8407382	1.174218
A-LEVEL	-.0111651	0	.8356165	1
DIPLOMA	-.0516369	0	.5661485	1
DEGREE	-.0022957	.0076439	.9717541	1.104617
MASTERS	-.0003775	0	.9876041	1
PhD	.0240111	0	2.443788	1
DON'T KNOW	.055016	.0298552	1.16161	1.082194
Difficulty in seeing				
YES, SOME DI~Y	.2524253	.0534249	2.241268	1.142868
YES, A LOT O~Y	.1471155	.0124749	3.774886	1.081777

CANNOT PERFO~L	.0291033	0	2.216555	1
Difficulty in hearing				
YES, SOME DI~Y	.1147049	.0236934	1.874059	1.117651
YES, A LOT O~Y	.0977304	.0079848	3.316433	1.074052
CANNOT PERFO~L	.0069169	.0170486	1.283624	1.999128
Difficulty in walking or climbing steps				
YES, SOME DI~Y	.2327675	.0369446	2.47309	1.116201
YES, A LOT O~Y	.1857119	.0118667	4.572908	1.065423
CANNOT PERFO~L	.0821487	.008055	6.225725	1.116994
Difficulty in remembering or concentrating				
YES, SOME DI~Y	.1795939	.030684	2.451805	1.128013
YES, A LOT O~Y	.1524619	.0107111	5.756907	1.079047
CANNOT PERFO~L	.0610691	0	13.66511	1
Relationship to head				
WIFE/HUSBAND	.0604211	-.0092644	1.078196	.9894299
CHILD/ADOPTE~D	-.3466627	-.0214007	.6720766	.9660461
GRANDCHILD	-.0983857	.0276755	.6293505	1.168306
NIECE/NEPHEW	-.1110374	0	.3522547	1
FATHER/MOTHER	.0867786	.0037063	2.504643	1.031123
SISTER/BROTHER	-.0207641	.0143436	.8452188	1.133966
SON/DAUGHTER~W	-.0308867	0	.6039168	1
BROTHER/SIST~W	-.0374224	.0113767	.5499818	1.249272
GRANDFATHER/~R	.0375554	.005034	2.181174	1.090591
FATHER/MOTHE~W	.0256101	-.0133281	1.789376	.783179
OTHER RELATIVE	-.0418833	.0084167	.5170268	1.175957
SERVANT OR S~E	-.0291466	0	.443201	1
LODGER/LODGE~E	-.0116539	.	0	.
OTHER NON-RE~E	-.0163663	0	.6117066	1
OTHER (SPECI~)	-.0164817	.	0	.
Months away from home				
1	.0137576	.0107189	1.092961	1.071095
2	.0284846	.0075489	1.287834	1.065725
3	.0098775	.0246002	1.104345	1.29326
4	.0049292	.008055	1.069506	1.116994
5	.0167139	.0018329	1.245442	1.023106
6	-.0181266	.0082874	.7911809	1.124343
7	-.0495454	0	.4115753	1
8	-.0015581	.0019733	.9797749	1.026877
9	-.0229971	0	.7335862	1
10	.0081456	.0048291	1.146545	1.083017
11	-.0038835	0	.944269	1
12	-.0407366	0	.4475328	1
Days ate in household in the past 7 days				
1	.0142101	0	1.277896	1
2	.0363581	0	1.67689	1
3	.0334611	.0045939	1.46032	1.048719
4	.0469151	.0116692	1.567137	1.106967
5	.0245969	.0118031	1.251237	1.109641
6	.0212035	.0150187	1.245666	1.164957
7	-.0244594	-.0268894	1.075542	1.083283
Place of birth				
OTHER VILLAG~T	.0347569	.0208934	1.048917	1.028531
VILLAGE IN O~T	.0290802	.0396656	1.052627	1.072903
THIS TOWN OR~E	-.0039936	.0169022	.9648318	1.174399
OTHER TOWN O~T	.0072392	.0089624	1.092008	1.115463
TOWN OR URBA~I	.006339	.0265782	1.037679	1.172832
OUTSIDE MALAWI	.0471051	.0231674	1.471505	1.196462

Appendix 3B: ATET effects on probability of employment following ill-health or a health shock

	Nearest neighbour		Regression adjustment		Inverse-probability weighting (IPW)		Regression adjustment with IPW		Augmented inverse-probability weighting (AIPW)	
	Wage employment	Casual employment	Wage employment	Casual employment	Wage employment	Casual employment	Wage employment	Casual employment	Wage employment	Casual employment
Illness/injury	-0.015*** (0.004)	0.065*** (0.004)	-0.017*** (0.003)	0.055** (0.004)	-0.005* (0.002)	0.055** (0.004)	-0.005** (0.002)	0.055*** (0.004)	-0.005** (0.002)	0.055** (0.004)
Hospitalisation	-0.010* (0.006)	0.030*** (0.011)	-0.018*** (0.005)	0.012 (0.009)	-0.011** (0.005)	0.014 (0.009)	-0.011** (0.005)	0.014 (0.009)	-0.011** (0.005)	0.014 (0.009)
Chronic disease	-0.011** (0.009)	-0.024*** (0.009)	-0.008* (0.005)	0.001 (0.006)	-0.005 (0.004)	0.010 (0.009)	-0.006 0.005)	0.008 (0.006)	-0.005* (0.003)	0.009* (0.005)

Abbreviations: ATET: Average Treatment Effect on the Treated
n = number of observations.
***P<0.01, ** P<0.05, * P<0.1.
Note: The table shows ATET values estimated using nearest neighbour propensity score matching relating to effects of ill-health or health shocks on the probability of employment
Note: Figures in parentheses are standard errors.
Note: Values in the table were rounded off to three decimal places.

Appendix 3C: ATET effects on working hours following an ill-health or a health shock.

	Nearest neighbour	Regression adjustment	Inverse-probability weighting (IPW)	Regression adjustment with IPW	Augmented inverse-probability weighting (AIPW)
Illness/injury	-1.135*** (0.139)	-0.914*** (0.111)	-0.878*** (0.110)	-0.880*** (0.111)	-0.884*** (0.113)
Hospitalisation	-1.117*** (0.284)	-0.859*** (0.241)	-0.819*** (0.240)	-0.819*** (0.241)	-0.820*** (0.239)
Chronic disease	-1.014*** (0.205)	-0.292 (0.181)	-0.074 (0.180)	-0.074 (0.180)	-0.059 (0.150)

Abbreviations: ATET: Average Treatment Effect on the Treated
n = number of observations.
***P<0.01, ** P<0.05, * P<0.1.
Note: The table shows ATET values estimated using nearest neighbour propensity score matching relating to effects of ill-health or health shocks on weekly hours of work.
Note: Figures in parentheses are standard errors.
Note: Values in the table were rounded off to three decimal places.

Appendix 3D: ATET effects on job search following ill-health and a health shock

	Nearest neighbour	Regression adjustment	Inverse-probability weighting (IPW)	Regression adjustment with IPW	Augmented inverse-probability weighting (AIPW)
Illness/injury	-0.005* (0.003)	-0.005* (0.003)	-0.006* (0.004)	-0.006* (0.004)	-0.005* (0.003)
Hospitalisation	0.002 (0.007)	0.003 (0.006)	0.003 (0.007)	0.002 (0.007)	0.004 (0.008)
Chronic disease	0.012** (0.005)	0.013** (0.006)	0.013** (0.006)	0.016** (0.007)	0.015** (0.008)

Abbreviations: ATET: Average Treatment Effect on the Treated
n = number of observations.
***P<0.01, ** P<0.05, * P<0.1.
Note: The table shows ATET values estimated using nearest neighbour propensity score matching relating to effects of ill-health or health shocks on job search.
Note: Figures in parentheses are standard errors.
Note: Values in the table were rounded off to three decimal places.

CHAPTER FIVE: Appendices

Appendix 5A Model Results for Wave 3, Wave 4, and Wave 5

	WAVE 3 dy/dx						WAVE 4 dy/dx						WAVE 5 dy/dx					
Variable	**NBin**	**ZINB**	**PSN**	**ZIP**	**TPM**	**OLS**	**NBin**	**ZINB**	**PSN**	**ZIP**	**TPM**	**OLS**	**NBin**	**ZINB**	**PSN**	**ZIP**	**TPM**	**OLS**
Ill/injury	-1.532*** (0.259)	-0.227 (0.232)	-0.940*** (0.063)	-0.151** (0.061)	-0.912*** (0.266)	-0.958*** (0.267)	0.203 (0.125)	-0.045 (0.108)	0.047 (0.032)	-0.137*** (0.144)	-0.070 (0.144)	0.122 (0.146)	-0.436 (0.279)	-0.787*** (0.163)	-0.730*** (0.047)	-0.124*** (0.006)	-0.758*** (0.201)	-0.770*** (0.205)
Hosp	-1.774*** (0.487)	-0.738* (0.441)	-1.572*** (0.121)	-0.691*** (0.118)	-1.515*** (0.499)	-1.561*** (0.494)	0.371 (0.284)	0.541** (0.245)	0.700*** (0.071)	0.424*** (0.331)	0.765** (0.331)	0.708** (0.347)	1.093* (0.591)	0.283 (0.360)	1.350*** (0.104)	0.035*** (0.014)	1.160*** (0.436)	1.450*** (0.433)
Chronic	-0.913** (0.379)	0.856** (0.339)	0.112 (0.089)	0.808*** (0.087)	0.140 (0.389)	0.098 (0.388)	-0.702*** (0.204)	-0.240 (0.175)	-0.748*** (0.052)	-0.253*** (0.048)	-0.754*** (0.237)	-0.870*** (0.250)	0.385 (0.414)	0.378 (0.241)	0.272*** (0.067)	0.046*** (0.009)	0.225 (0.298)	0.224 (0.304)
SP	0.321 (0.237)	0.609*** (0.219)	0.607*** (0.057)	0.612*** (0.056)	0.554** (0.252)	0.609** (0.252)	1.456*** (0.091)	-0.152** (0.078)	0.832*** (0.023)	-0.273*** (0.022)	0.784*** (0.103)	-0.869*** (0.105)	2.807 (1.777)	1.327 (1.043)	2.964*** (0.298)	0.175*** (0.039)	2.802** (1.284)	3.087** (1.306)
Ill*SP	-1.156** 0.592	-0.609 (0.528)	-1.174*** (0.144)	-0.591*** (0.140)	-1.054* (0.603)	-1.083* (0.597)	-0.555*** (0.173)	-0.172 (0.149)	-0.487*** (0.045)	-0.044 (0.042)	-0.442** (0.202)	-0.479** (0.211)	-0.306 (0.420)	-0.043 (0.240)	-0.126* (0.070)	0.012 (0.009)	0.031 (0.298)	-0.097 (0.308)
Hosp*SP	0.389 (1.195)	1.084 (1.076)	1.213*** (0.282)	1.323*** (0.275)	1.117 (1.215)	1.238 (1.188)	-0.530 (0.393)	-0.074 (0.337)	-0.417** (0.099)	0.031 (0.091)	-0.415 (0.463)	-0.369 (0.493)	-0972 (0.895)	-0.698 (0.525)	-1.080*** (0.150)	-0.099*** (0.020)	-1.019 (0.647)	-1.153* (0.657)
Chronic*SP	-1.261 (0.824)	-1.857** (0.736)	-2.055*** (0.202)	-1.794*** (0.196)	-2. 000** (0.836)	-1.965** (0.830)	-0.238 (0.267)	0.420* (0.230)	0.288** (0.068)	0.531*** (0.063)	0.370 (0.316)	0.511 (0.341)	-1.080* (0.595)	-0.545 (0.342)	-1.050*** (0.097)	-0.063*** (0.013)	-1.054** (0.424)	-1.048** (0.437)
Constant						11.047*** (0.641)						-1.264*** (0.162)						5.758*** (0.980)
Control variables	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
AIC	165835.6	161912.1	536451.8	287690	168430.6	222947	156813.6	154611	632732.3	250512.1	159736.3	342126.8	169336.5	164085.2	542636.9	274265.9	174228.8	256632.6
BIC	166049.2	162133.9	536657.2	287903	168841.3	223152.4	156927.3	154733.4	632837.3	250625.8	159946.2	342231.7	169580.2	164337.3	542872.1	274509.5	174699.3	256867.8
N	27306	27306	27306	27306	27306	27306	46440	46440	46440	46440	46440	46440	32896	32896	32896	32896	32896	32896