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

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## Abstract

**Background** There is sparse evidence on the joint effects of ill-health, health shocks and social protection on the intensive margin of labour supply, particularly in developing countries. We interact ill-health and health shocks with access to social protection and estimate their joint effects on weekly hours of work.

**Methods** We employ a zero-inflated Poisson model to assess joint effects of ill-health, health shocks and social protection on weekly hours of work exploiting pooled repeated cross-sectional data from Malawi.

**Results** We find that overall, individuals who suffered from ill-health or a health shock, including an illness/injury, a hospital admission or a chronic illness and benefited from social protection, reduced their weekly hours of work.

**Conclusions** The study provides novel empirical evidence on the potential joint effects of ill-health, health shocks and social protection on the intensive margin of labour supply, shedding light on the role social protection can play in developing countries.

**Keywords** Ill-health, Health shocks, Count data, Pooled data, Social protection, Malawi, Hours of work, Intensive margin of labour supply

## Background

Africa has the lowest levels of access to social protection globally. The International Labour Organization (ILO) observed that only 17.4% of Africans are effectively covered by at least one social protection benefit compared to 46.9% globally [1]. The huge gap in social protection coverage and the generally poor social protection systems in Africa are correlated with significant underinvestment in social protection. Some studies have linked social protection to a reduction in vulnerability to poverty in Africa. For instance, Ohrnberger [2] showed that pro-poor cash transfers were effective in protecting the most vulnerable from the effects of the COVID-19 shock. Also, Atake [3] found that when health shocks were interacted with access to health insurance, household vulnerability to poverty was significantly reduced in Burkina Faso, Niger, and Togo. Related to this, Ouadika [4] found that health shocks increased vulnerability to poverty in Congo and called for social safety nets programmes to support households in the event of such shocks.

While there has been some work in Africa on the topic of social protection and employment, most evidence comes from countries outside Africa. For instance, Garcia-Gomez [5] observed that variations

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in social security arrangements led to heterogeneous effects of ill-health and health shocks on labour market outcomes across several European countries. Similarly, Candon [6] and Coile [7] found that eligibility for social security or pension was associated with reduced labour supply in the US. Fialova and Mysikova [8] showed that access to social benefits provided an incentive to exit from labour markets in the Czech Republic. Moreover, Maestas et al. [9] found that Social Security Disability Insurance reduced employment by 34–35% points and led to a significant drop in annual earnings. In addition, French [10] 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. Nevertheless, other studies such as de Brauw et al. [11] found no discernible effects of social protection on labour supply. Le et al. [12] report that the effects of Universal Health Coverage on labour markets, in terms of increasing incentives or disincentives to work, depend on the specific design of the system, especially whether systems target only formal employees (such as in Thailand's 2001 reforms) or all types of employees (formal and informal).

Two key issues emerge from the literature regarding the role of social security in labour markets. First, previous work has mainly focused on developed countries [5, 10, 13]. This underlines the need to provide evidence for emerging and developing countries where socioeconomic conditions as well as social security arrangements are different from those of developed countries, to support relevant policy interventions. Second, while there have been studies assessing the effects of ill-health and health shocks on labour markets and, separately, effects of social protection on labour markets [12], less is known on the joint effects of ill-health or health shocks and social protection on labour outcomes. One of the very few studies on the latter is the one by Candon [6] who found that when health shocks and eligibility for social security were examined jointly, weekly hours of work were reduced by three to four hours in the United States.

Apart from the general lack of studies linking social security to labour market outcomes in Low- and Middle-Income Countries (LMICs), no previous work has assessed the joint effects of ill-heath or health shocks and social protection on the intensive margin of labour supply in Malawi. In a country with limited social protection systems both in quality and coverage [14] 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. Moreover, the COVID-19 pandemic revealed significant deficiencies in social protection within the country, highlighting the need for evidence-based policy interventions to address these gaps. Such evidence is critical for a country with only 21.3% effective coverage of social protection; that spends only 3% on healthcare and only 1% on social protection, irrespective of having a total labour force of almost 8.4 million [15].

This paper contributes to the literature in several important ways. First, this is one of the first papers exploring the effects of ill-health and health shocks on employment while accounting for the social protection system in an African country. As such, our paper bridges the gap that exists in Africa regarding the health-labour relationship and its interaction with social protection. The evidence from this paper will help support meaningful interventions in labour markets that consider both ill-health and health shocks on one hand, and their interaction with social protection on the other, in the design of social protection programmes and universal health coverage (UHC) pursuits in Malawi, Africa and other developing countries. Second, by using data from Malawi, the current study provides novel evidence that could inform country-specific policy interventions in a country in which social protection systems are poor and employment is highly informal. Third, the paper exploits pooled repeated cross-sections which, although not in a panel setting, combine comprehensive information from three different survey periods.

## State of social protection in Malawi

Most Malawians (51.7%) live below the poverty line while 22.5% can be defined as ultra-poor[1] [16, 17]. With pervasive poverty, attempts to offer some form of social support to people living in Malawi has been a pre-occupation of government policy since attaining independence in 1964 [18, 19]. From 1964 to about 2006, four social support phases are distinguishable [19]. First, the period between 1964 and the 1980s was characterised by price controls and subsidies, the latter being the most common form of social support during that phase. These measures were however abandoned at the start of structural adjustment programmes (SAPs) championed by the Bretton Woods Institutions, mainly on account of fiscal constraints [18, 19]. The second period spanned 1981 to 1990. With input and output prices deregulated and subsidies removed, targeted nutrition programmes, food transfers as well as credit schemes were the largest programmes of social

[1] Ultra poverty relates to the inability to meet the most basic needs including food. Such households have a total per capita expenditure below the food poverty line (See Malawi Poverty Report, 2020).

support in this period [19]. Third, was the period 1990–1994. In response to what became known as the Social Dimension of Adjustment (SDA) after increases in vulnerability [18], this period saw the re-enforcement of targeted nutritional programmes, food transfers and credit schemes. Finally, the fourth period was between 1994 and 2006. The period saw more safety nets introduced including such programmes as Micro-Small and Medium Enterprises (MSME) credit schemes, public works programmes, input transfers, food transfers, school feeding programmes, cash transfers, targeted input subsidies, targeted nutrition programmes and integrated livelihood support [18, 19].

By 2005, as vulnerability increased and poverty remained widespread, it was clear that the numerous safety net programmes failed to improve livelihoods. This was largely blamed on poor coordination of these safety net interventions which were mostly ad hoc in nature [18]. This prompted government, the donor community, and the United Nations systems to forge a comprehensive and systematic plan towards social support in Malawi, fostering the development of a social protection policy - a draft was ready in 2008. With apparent subdued government commitment [18, 20] the policy could not be finalised. It was in 2012 that the National Social Support Policy (NSSP) was finalised and explicitly provided guidance on social protection in Malawi. The NSSP is now the overarching policy instrument that guides social protection in Malawi. It is linked to the Malawi Growth and Development Strategy III of 2017 that is premised, among other things, on social protection programmes aimed at mitigating adverse effects on development and gender equality [21]. 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 [22].

Poverty reduction is the main objective of the NSSP. This is to be achieved through promoting welfare support; asset protection and building resilience; nurturing productivity; and ensuring effective synergies with other initiatives [23–25]. 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[2]advanced five priority themes including supporting consumption; building resilient livelihoods; ensuring synergy between social protection and other programmes; and supporting shock-sensitive social protection systems [26]. Principally the MNSSP is an instrument to monitor 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) [26, 27].

The Social Cash Transfer Programme (SCTP) locally known as "Mtukula Pakhomo" is a non-conditional safety net programme that serves vulnerable ultra poor Malawians [20, 24, 28]. Over 1.3 million Malawians benefit from this programme [28]. It is expected that these beneficiaries would eventually move out of poverty. Targeting 10% of beneficiaries per district, the recipients must be both ultra-poor and labour-constrained households with the amount received determined by household size [28, 29]. With an average amount of MWK9000.00[3]per household, additional amounts are given for every child enrolled in a primary school or secondary school [28]. The Directorate for Social Protection Services (DSPS) in the Ministry of Gender, Children, Disability and Social Welfare (MoGCDSW) leads the SCTP programme which is also supported by developing partners including the EU, Irish Aid, KfW Germany, and World Bank [26].

On the other hand, the Labour-Intensive Public Works Programme (PWP) had an objective of transferring income to poor households who are not labour constrained to reduce chronic or shock-induced poverty and provide social protection [23, 24]. This is done through the provisions of limited employment opportunities. Working as safety nets these seasonal programmes operate during non-farming seasons when income generating activities are scarce [30]. Construction activities have dominated the PWP programme and the MASAF programme can be cited as the most popular PWP in Malawi [23, 24]. The programme is led by the Ministry of Local Government and Rural Development (MoLGRD) and funded by World Bank [26].

Supported by developing partners such as GIZ, EU, WFP, and Mary's Meals, the Department of School Health and Nutrition in the Ministry of Education, Science and Technology (MoEST) leads the implementation of the School Meals Programme (SMP) [23, 26]. In support of this programme, the WFP takes three approaches to support this programme [31–33]. First, in what is called a centralised model, WFP distributes

[2] According to Holmes et al. [26], 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.

[3] 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.

in-kind food commodities to provide daily nutrition meals of corn soya blend plus (CSB+). This model aims to reduce short-term hunger and improve attention span in class. 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 [26, 33].

The Village Savings and Loans (VSL) Programmes are coordinated through the Ministry of Industry and Trade (MoIT). According to [26] over 100 different programmes exist with funding from DFID, Irish Aid, Norway, World Bank, USAID (ILO n.d). Other actors include MoGCDSW, Ministry of Local Government and Rural Development (MLG&RD), Reserve Bank of Malawi (RBM), MFIs, NGOs and CBOs, and Village Agents.

Run through Micro-Finance Institutions (MFIs), Mobile Phone Companies (MPCs), NGOs and CBOs, Tertiary Training Institutions (TTIs), Micro-Finance (MF) Programmes [26] are coordinated through Reserve Bank of Malawi (RBM). Strengthening the capacity of microfinance institutions (MFIs) is seen as key to supporting financial access [24].

## Methods

### Data

We exploit a pooled data set obtained by combining three independently collected nationally representative Malawi Integrated Household Surveys (IHS3, IHS4 and IHS5). While these surveys collected data at both household and individual level, the unit of analysis in our study is the individual. Implemented by the Malawi Government's Statistical Office in collaboration with the World Bank, the Integrated Household Survey (IHS)[4] is primarily used in the monitoring of the progress of the Sustainable Development Goals (SDGs). The survey also serves as a tool to monitor the implementation of the Malawi Growth and Development Strategy (MGDS). Data collection for IHS3 started in March 2010 and ended in March 2011. Data for the IHS4 were collected from April 2016 to April 2017. Finally, data collection for the IHS5 was conducted from April 2019 to April 2020. The surveys collected information using four questionnaires: the community questionnaire; the household questionnaire; the agriculture questionnaire; and the fishery questionnaire. Our study utilised the household questionnaire which covered relevant variables that included information on health, education, time use, and employment. The surveys use a stratified two-stage sampling design. The IHS3 strata had 31 districts while both the IHS4 and IHS5 strata had 32 districts each. Based on the listing information and cartography from the Malawi Population and Housing Census (PHC) the sampling frame for IHS encompasses three broad regions (North, Center and South). The IHS3 targeted 12,271 households. The IHS4 had a target of 12,447 households while for the IHS5 12,288 households. For representativeness [34], during our analysis, each sample household was weighted using the inverse of its probability of selection, using the weights already included in the surveys for this purpose[5]. No imputation was needed for missing values as variables with large proportions of missing information were not considered in the analysis to avoid any bias. There was no evidence of a systematic occurrence of missing values.

### Variables

The dependent variable was weekly hours of work. Independent variables included illness/injury, hospital admission, chronic illness, social protection, the interaction term of illness/injury and social protection, the interaction term of hospital admission and social protection, and the interaction term of chronic illness and social protection. Control variables used included sex, age, religion, marital status, and education level. Variables used are described in Table 1.

### Model specification

In estimating the model, the study follows Candon [6] and Coile [7] who modelled joint effects of health shocks and social security on labour market outcomes. However, unlike Coile [7] and Candon [6] who used eligibility for social security which essentially included individuals who were 60 years and older to interact with health shock variables, the present study only uses individuals who reported that they benefited from social protection.

[4] 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).

[5] A detailed discussion regarding weight is given in the Basic Information Document that accompanies each survey. For example the Basic Information Document for the Fourth Integrated Household Survey (IHS4) 2016–2017 can be obtained on https://microdata.worldbank.org/index.php/catalog/2936/related-materials.

**Table 1** Description of the dependent, independent and control variables

| 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[a] | 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 |
| Illness/injury*social protection | Interaction variable between illness/injury and social protection | Independent variable |
| Hospitalisation*social protection | Interaction variable between hospitalisation and social protection | Independent variable |
| Chronic illness*social protection | 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 |
| Marital status | What is your present marital status? | Control variable |
| Education level | What is the highest educational qualification you have acquired? | Control variable |

[a] 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

This is relevant as our analysis focuses on actual use of the social protection system, and not just eligibility. Moreover, they used longitudinal data drawn from the Health and Retirement study while mainly due to limitations in the panel data sub-sample of the Integrated Household Survey for Malawi, a pooled data set of cross-sectional data including waves of IHS3, IHS4 and IHS5 is used in the current analysis. In terms of health shocks, Candon [6] used current diagnoses of lung disease, heart problems, cancer, and stroke. Coile [7] used three comprehensive sets of measures. The first included new diagnoses of cancer, heart attack, and stroke dubbed acute health; the second had current diagnoses 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 [7] and Candon [6] who only considered variables describing health shocks. Here we use both health shock variables (illness/injury and hospital admission) as well as an ill-health variable (chronic illness).

In terms of labour market outcomes, Coile [7] used the probability of labour exits and changes in hours worked. Like Candon [6] the present study focuses on the intensive margin and looks at hours of work. In line with this study's interest in assessing the effects of ill-health and health shocks on the intensive margin of labour supply the following model formulation is used:

$$Hours = \varnothing_0 + \varnothing_1 ill + \varnothing_2 hosp + \varnothing_3 chronic + \varnothing_4 sp + \varnothing_5 (ill * sp) + \varnothing_6 (hosp * sp) + \varnothing_7 (chronic * sp) + \varnothing_i \sum_{i=8}^{n} \mathcal{X}_i + \epsilon_t \quad (1)$$

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 $\epsilon_t$ is the error term. Thus, in Eq. (1) weekly hours are regressed on illness/injury, hospital admissions, chronic illness, social protection as well as three interaction terms: i.e., the interaction between social protection and illness/injury; the interaction of social protection and hospital admission; and the one between social protection and chronic illness; in addition to a range of control variables.

As weekly hours of work include a series of positive integers measured on a continuous scale, it can be considered a count variable. Such variables often present skewed distributions, over-dispersion, and excess zeros and are more appropriately modelled by econometric specifications accounting for these features. Accordingly, the present analysis uses two widely used count data models, namely: Poisson and zero-inflated Poisson models, accounting for the count data nature of the dependent variable. However, the choice of our preferred model is informed by comparing values of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), two common tests assessing model fitness.

Regarding the Poisson model, Karazsia and Van Dulmen [35] 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. [36], Chau et al. [37], Frome and Checkoway [38], and Cupal et al. [39] 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:

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

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

$$\mathrm{E}(y_i) = \lambda\,,\ \ var(y_i) = \lambda \tag{3}$$

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

$$y_i = E(y_i) + \epsilon_i, \quad i = 1,\ 2,\ 3,\ldots\ n \tag{4}$$

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

$$\nu(\lambda_i) = \eta_i \tag{5}$$

$$\nu(\lambda_i\ ) = \beta_0 + \beta_1 x_1 + \ldots\ + \beta_k x_k \tag{6}$$

$$\nu(\lambda_i) =\ x_i'\beta \tag{7}$$

From (6) $\lambda_{\ i}$ can be characterised as follows:

$$\lambda_i = \nu^{-1}(\eta_i) \tag{8}$$

$$\lambda_i = \nu^{-1}(x_i'\beta) \tag{9}$$

It follows that the identity link can be presented as:

$$\nu(\lambda_i) = \lambda_i = x_i' \tag{10}$$

With the log-link function presented as:

$$\nu(\lambda_i) = \ln(\lambda_i) = x_i'\beta \tag{11}$$

Where $\lambda_i = \nu^{-1}(x_i'\beta) = \exp(x_i'\beta)$

Given weekly hours of work $y_{1,}\ y_2 \ldots\ y_n$ estimation of parameters follows a maximum likelihood approach with the following likelihood function:

$$L(y,\lambda) = \prod_{i=1}^{n} P_i(y_i) \tag{12}$$

$$L(y,\lambda) = \prod_{i=1}^{n} \frac{\exp(-\lambda_i)\lambda_i^{y_i}}{y_i!} \tag{13}$$

$$L(y,\lambda) = \frac{\left(\prod_{i=1}^{n}\lambda_i^{\mu_i}\right)\left(exp\left(-\sum_{i=1}^{n}\lambda_i\right)\right)}{\prod_{i=1}^{n} y_i!} \tag{14}$$

In logarithmic form we represent (13) as:

$$lnL(y,\lambda) = \sum_{1=1}^{n} y_i ln(\lambda_i) - \sum_{i=1}^{n}\lambda_i - \sum_{i=1}^{n}\ln(y_i!) \tag{15}$$

where $\lambda_i$ is related to the $\beta's$ through the link function

$$\lambda_i = \nu^{-1}(x_i'\beta) \tag{16}$$

Our estimated Poisson regression model is then presented as:

$$\widehat{y} = \nu^{-1}\left(x_i^{'}\,\widehat{\beta}\,\right) \tag{17}$$

Utilising the identity link, we get:

$$\widehat{y}_i = \nu^{-1}\left(x_i'\widehat{\beta}\right) = \exp(x_i'\widehat{\beta}) \tag{18}$$

Although the Poisson regression, developed using the Poisson probability distribution, is arguably the most commonly used model in the analysis of count data [40], it does have some limitations [41]. Gurmu and Trivedi [42] 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 [43]. 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 [40, 42, 44]. 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 [42].

The zero-inflated Poisson model is said to correct the challenges of the standard Poisson model [40, 45]. In this model, there are two elements that relate to two zero-generating processes [46, 47]. 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 which could also assume the value zero.

The two model components [40, 47–49] are given as follows:

$$P(y_i = 0) = \pi + (1 - \pi)e^{-\lambda} \tag{19}$$

$$P\left(y_i = \varpi\right) = (1 - \pi)\frac{\lambda^{\varpi} e^{-\lambda}}{\varpi !}, \quad \varpi \in \{1,2,3,\dots\} \tag{20}$$

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

The mean and variance of ZIP are given as follows:

$$\mathrm{E}\left(y_i\right) = (1 - \pi)\lambda \ , \ var\left(y_i\right) = \lambda\,(1 - \pi)(1 + \pi\,\lambda). \tag{21}$$

Essentially:

$$ln\,(\lambda) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k \tag{22}$$

$$Logit\,\pi = ln\left(\frac{\pi}{1-\pi}\right) = \varnothing_0 + \varnothing_1 h_1 + \varnothing_2 h_2 + \dots\ \varnothing_m h_m \tag{23}$$

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) $\varnothing_1, \dots, \varnothing_m$ are the zero-inflated coefficients.

Comparing the Poisson model with the zero-inflated Poisson model has the advantage that, in the presence of excess 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.

## Results

We start reporting our results by presenting the descriptive statistics of our sample which we report in Table 2. The table shows that the average total weekly working hours were around 8 hours. Further, the table shows that individuals who suffered an illness/injury represented 23% of the sample, those who had a hospital admission represented 4%, those who had a chronic illness were 9 per cent of the sample, and 37 per cent of individuals accessed some form of social protection. The table also shows that 9% of the sample who suffered an illness/injury had accessed some form of social protection, 3% who had a hospital admission accessed some form of social protection, while 4% who reported a chronic illness accessed some form of social protection. With respect to demographic variables, the average age of the sample is around 33 years, and the sample is almost evenly split by gender. Moreover 85% of the sample reports being Christian, 50% of the sample was married and at least 10% of the sample held the Primary School Leaving Certificate.

### Choice of model

In this section, we present results of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) for model selection. Information displayed in Table 3 indicates that the zero-inflated Poisson regression model presents lower AIC and BIC values. Given these results, we conclude that in this case, a zero-inflated Poisson model provides a better fit compared to the standard Poisson model. Accordingly, our paper focuses on the results produced by the zero-inflated Poisson model.

### Regression results

Our results (Table 4) show that individuals who reported an illness/injury significantly reduced their hours of work as shown by a highly statistically significant marginal effect. The marginal effect of hospitalisation was positive but not statistically significant. Results further showed that individuals who were chronically ill significantly increased their hours of work as their marginal effect was positive and highly statistically significant. In terms of the effects of access to social protection, the analysis revealed that individuals who benefited from social protection were associated with a negative highly statistically significant marginal effect.

We found a negative and significant marginal effect for individuals who were ill or suffered an injury and received some social protection. Similarly, individuals who had a hospital admission and benefited from social protection, were associated with a negative and highly

**Table 2** Summary statistics

| | Mean | S.D | Min | Max | Obs |
|---|---|---|---|---|---|
| **Outcome Variable** | | | | | |
| Weekly hours worked | 7.90 | 12.90 | 0 | 38 | 94,846 |
| **Independent Variables** | | | | | |
| Illness/injury | 0.23 | 0.42 | 0 | 1 | 94,846 |
| Hospital admission | 0.04 | 0.20 | 0 | 1 | 94,846 |
| Chronically ill | 0.09 | 0.29 | 0 | 1 | 94,846 |
| Social protection | 0.37 | 0.48 | 0 | 1 | 94,846 |
| Illness/injury*social protection | 0.09 | 0.29 | 0 | 1 | 94,846 |
| Hospitalisation*social protection | 0.03 | 0.17 | 0 | 1 | 94,846 |
| Chronic illness*social protection | 0.04 | 0.19 | 0 | 1 | 94,846 |
| **Demographics** | | | | | |
| Sex | 0.47 | 0.50 | 0 | 1 | 94,846 |
| Age | 32.44 | 17.24 | 12 | 78 | 94,846 |
| Religion | | | | | |
| None | 0.03 | 0.16 | 0 | 1 | 94,846 |
| Traditional | 0.01 | 0.09 | 0 | 1 | 94,846 |
| Christianity | 0.85 | 0.36 | 0 | 1 | 94,846 |
| Islam | 0.11 | 0.31 | 0 | 1 | 94,846 |
| Other religion | 0.01 | 0.08 | 0 | 1 | 94,846 |
| Marital Status | | | | | |
| Married (Monogamous) | 0.47 | 0.50 | 0 | 1 | 94,846 |
| Married (Polygamous) | 0.03 | 0.18 | 0 | 1 | 94,846 |
| Separated | 0.03 | 0.18 | 0 | 1 | 94,846 |
| Divorced | 0.03 | 0.18 | 0 | 1 | 94,846 |
| Widow | 0.06 | 0.23 | 0 | 1 | 94,846 |
| Never married | 0.33 | 0.47 | 0 | 1 | 94,846 |
| Education Level | | | | | |
| Primary | 0.10 | 0.30 | 0 | 1 | 94,846 |
| Junior certificate | 0. 05 | 0.21 | 0 | 1 | 94,846 |
| MSCE | 0.06 | 0.23 | 0 | 1 | 94,846 |
| Non-university | 0.01 | 0.09 | 0 | 1 | 94,846 |
| University diploma/degree | 0.01 | 0.09 | 0 | 1 | 94,846 |
| Post graduate | 0.00 | 0.06 | 0 | 1 | 94,846 |

*S.D* Standard deviation, *Min* Minimum value, *Max* Maximum value, *Obs* Observations

The table reports summary statistics of variables used in the study

Values have been rounded to 2 decimal places

**Table 3** AIC and BIC values for the models

| Criterion | Poisson Model | Zero-Inflated Poisson Model |
|---|---|---|
| AIC | 1,644,784 | 794,678 |
| BIC | 1,645,020 | 794,924 |

*AIC* Akaike Information Criterion, *BIC* Bayesian Information Criterion

significant marginal effect. Finally, when the chronically ill received social protection, they significantly reduced their hours of work as their marginal effect was highly statistically significant.

In summary regression results showed that individuals who experienced an illness or injury reduced their weekly hours of work, individuals who experienced chronic illness increased their weekly hours of work, and individuals who benefited from social protection reduced their weekly hours of work. There was no significant statistical evidence regarding the effect of hospital admission on weekly hours of work. In terms of interaction between health variables and social protection, results showed negative statistically significant evidence regarding the effect of the interaction between social protection and illness/injury on weekly hours of work, the interaction between social protection and hospital admission on weekly hours of work, and effect of the interaction between social protection and chronic illness on weekly hours of work.

## Discussion

We contribute to the literature on the health-labour relationship by investigating the combined effects of ill-health and health shocks with social protection on weekly hours of work in Malawi. We exploit rich pooled repeated cross-sectional data from the Integrated Health Survey and provide estimates of the correlations between the occurrence of a series of health conditions, including illness/injury, hospitalisation, and chronic illness, on hours of work.

Our results suggest a statistically significant joint effect of illness/injury and social protection. When considered separately individuals who reported an illness/injury significantly reduced their hours of work. When these individuals accessed social protection, they also reduced their hours of work. This may be so because social protection provides a cushioning effect in terms of income or through in-kind support which in turn provides an incentive for individuals suffering and illness/injury not to work long hours with impaired health.

Results also suggest a statistically significant joint effect of hospitalisation and social protection on weekly hours. This may signal the disincentive to work more hours with impaired health or at least before full recovery when (health) needs are covered by social protection. Despite a positive sign, the effects of hospital admissions on hours worked were not statistically significant.

While suffering from a chronic disease is associated with an increase in weekly hours of work as our results suggest, when such individuals access social protection, they reduced their hours of work. One potential

**Table 4** Regression results of the zero-inflated Poisson model[a]

| Variables | dy/dxb[b] | SE | Z | P>\|Z\| | 95%CI |
|---|---|---|---|---|---|
| Illness/Injury | -0.558*** | 0.027 | -20.47 | 0.000 | -0.612, -0.505 |
| Hospitalisation | 0.002 | 0.045 | 0.04 | 0.972 | -0.086,0.090 |
| Chronic illness | 0.252*** | 0.040 | 6.33 | 0.000 | 0.174,0.33 |
| Social protection | -0.112*** | 0.024 | -4.56 | 0.000 | -0.159,-0.064 |
| Illness/Injury*Social protection | -0.077* | 0.044 | -1.76 | 0.078 | -0.162, 0.009 |
| Hospitalisation *Social protection | -0.154*** | 0.015 | -10.02 | 0.000 | -0.184,-0.123 |
| Chronic illness*Social protection | -0.194*** | 0.061 | -3.17 | 0.002 | -0.314,-0.074 |
| Control Variables | YES | | | | |

*N* (number of observations)= 94,846

*dy/dx* Marginal effects

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

The table shows marginal effects estimated by the zero-inflated Poisson model

Figures in parentheses are standard errors

Control variables included sex, age, religion, marital status, and education level

Values in the table were rounded off to three decimal places

[a] Results of the zero-inflated negative binomial model and those of a standard OLS are presented in Table 5 in Appendix A. Unlike the OLS results of, the result of the zero-inflated negative binomial model mimicked the results of the zero-inflated Poisson model that we report in this study

[b] In our analysis and discussion, we use marginal effects owing to the non-linear nature of the zero-inflated Poisson model. We present coefficients of the regression model in Table 6 in Appendix B

interpretation might be that chronic illness may trigger increases in out-of-pocket expenditure, unpaid hospital bills as well as bankruptcy. To compensate for these, individuals suffering from chronic diseases may need extra income, and one way to earn such income is to increase working hours. For instance, managing chronic illnesses such as diabetes, HIV/AIDS, and arthritis is costly. This requires steady incomes and increasing weekly hours of work would be one way to produce the needed increased income. However, when social protection provides support, individuals seem to reduce their hours of work.

When assessed separately, individuals who benefited from social protection were found to significantly reduce their weekly hours of work[6]. There is evidence that social protection (such as through social transfers) reduces labour supply [7–9, 50]. Yet, the work of Baird et al. [51] showed that cash transfers did not change adult labour, particularly when interventions were not specifically designed to increase labour supply. Orkin et al. [52] reported similar results of no overall change in hours of work due to cash transfers. Additionally, Vera-Cossio [53] 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, but also their sizes. For example, Handa et al. [54] found that when transfer values are in tandem with global practice and are paid regularly, they have more pronounced effects on the intended objectives. Moreover, results showing a negative link between illness/injury and labour supply are supported by the literature [55]. Yet, findings showing a positive link between chronic illness and hours of work seem unique to Malawi or LMICs, mainly because of the need to survive owing to accumulated medical bills as well as other catastrophic expenditures. In general, the literature focused on developed countries has found that chronic illnesses reduce labour supply [56–58]. Overall, the result that joint effects of ill-health as well as health shocks and social protection are associated with reduction in hours of work are supported by previous evidence on the health-labour relationship (see Candon [6]).

Our results highlight the importance of social protection in potentially improving the health of economically active individuals, ensuring that individuals in ill-health do not continue working while suffering from a health condition or a health shock. Indeed, Candon [6] has argued that it is presenteeism rather than absenteeism that is associated with greater productivity losses. Additionally, presenteeism might also imply future frequent absences due to sickness often proxied by lower levels of self-reported health. Without a cushioning effect through social protection, such individuals will continue working but will likely be less productive. This will potentially lead to a "added worker effect" [59] where other workers will have to compensate for the loss of productivity via additional work or a reallocation process.

[6] This relates to when social protection is used as a separate independent variable and not interacted with any of the health variables.

## Conclusions and policy implications

The paper examined the joint effects of ill-health, health shocks and social protection on the intensive margin of labour supply in Malawi. Due to the nature of the data, a count data model was explored. 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 on weekly hours worked. The results showed that individuals who suffered from an illness/injury and benefited from social protection reduced their hours of work. Similarly, individuals who had experienced a hospital admission or with chronic illnesses who also benefited from social protection, reduced their hours of work. The analysis also showed a negative association between illness/injury and weekly hours of work, a positive link between chronic illness and weekly hours of work, and a negative relationship between access to social protection and weekly hours of work.

Results of this study might suggest three possible policy recommendations. A first recommendation relates to the finding that individuals who suffered an illness/injury and benefited from some form of social protection significantly reduced their weekly hours of work. Efforts to increase access to social protection may be an appropriate policy because it reduces the number of people reporting to work with impaired health. In addition, due to the importance of work for income stability, ensuring that the injured return to work in good health may be key to pursue. This calls for better access to both medical care and quality of care. This could be achieved by increased access to medical workers, medical facilities, and availability of medicines. While this should certainly be a government's priority, creating a conducive environment for private sector participation in healthcare provision would also be desirable.

A second recommendation relates to the finding that when individuals who had a hospital admission were introduced to social protection, they also significantly reduced weekly hours worked. Perhaps this implies that individuals were engaged in work, before accessing social protection, even when they were not fully recovered because they had to maintain some level of income to survive. In that regard, the issue of social security/social support targeting is vital as well. Increasing access to social security needs to be entrenched with the understanding that the period of recuperation for an individual, in part, depends on the care the patient received while at hospital, as well as that received when out of hospital. This therefore points to quality of diagnosis, quality of care, quality of medical personnel but perhaps more importantly, the quality of home care by family members and caregivers. As such investments in primary health care, creating awareness such as through community trainings and community radio programmes on home-care support may be useful.

Finally, the finding that individuals who suffered from a chronic disease, although they increased their hours of work, reduced their hours of work after accessing social protection also emphasises the role of social protection in the health and labour discourse. The results are a call for targeted government support to the chronically ill in Malawi. While free medical programmes exist for those living with HIV, it does not seem to be the case with other chronic illnesses. Targeted health care spending for those with diabetes, arthritis, and other chronic illnesses may be a good endeavour for the Government of Malawi.

Over and above the three policy strands, a potentially useful strategy is to consider the contexts and design [12] of social protection programmes. This includes juggling with the politics of social protection targeting [60] which can result into unfavourable secondary effects [61]. As usual, there may be potential limitations to our work. The first relates to the potential endogeneity in the relationship between health and labour outcomes which might be linked to different types of biases such as reporting bias, justification bias as well as simultaneity issues between health and work status [55, 62]. However, one of the reasons why we used variables defining health shocks (that is, sudden negative health events) is that some of the endogeneity in the relationship between health and labour supply might be removed by the randomness of the timing of these events. For instance, whereas injuries or hospitalisations might be at least in part anticipated and/or correlated with health behaviours, their timing might be considered random. Although this did not remove the full extent of the potential endogeneity in our models, it may have helped ease endogeneity concerns. This also follows a long tradition of studies relying on these types of measures to look at the relationship between health and employment (e.g. Kumara and Samaratunge [63]; Garcia-Gomez et al. [64]). Secondly, we are aware that this approach can only identify correlations and cannot be interpreted in a causal way. Yet, given data challenges in countries like Malawi, the lack of evidence on these issues, and this being the first-ever analysis on this data, we believe our findings provide some useful initial evidence on the effects of health shocks on hours worked in this context. This is a limitation in many LMICs to be addressed by more comprehensive data collection in future to allow a more precise analysis, while also acknowledging the marginal benefit of the extra information we can offer policy makers to help with decision making at present, given the costs and time delays of collecting more data this may help in an area where currently guidance is very limited.

## Appendix A

**Table 5** Results of the zero-inflated negative binomial and the OLS

| Variables | ZINB (dy/dx) | OLS |
|---|---|---|
| Illness/Injury | -0.567*** | -0.927*** |
| | (0.101) | (0.126) |
| Hospitalisation | -0.001 | -0.816*** |
| | (0.167) | (0.208) |
| Chronic illness | 0.296** | -0.083 |
| | (0.152) | (0.112) |
| Social protection | -0.117 | -0.125 |
| | (0.091) | (0.112) |
| Illness/Injury*Social protection | -0.092 | 0.012 |
| | (0.158) | (0.200) |
| Hospitalisation *Social protection | -0.134** | 0.415*** |
| | (0.054) | (0.070) |
| Chronic illness*Social protection | -0.250 | -0.614** |
| | (0.228) | (0.288) |
| Constant | | 9.302*** |
| | | (0.290) |
| Control Variables | YES | |

N (number of observations) =94,846

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

Figures in parentheses are standard errors

Control variables included sex, age, religion, marital status, and education level

Values in the table were rounded off to three decimal places

## Appendix B

**Table 6** Regression results of the zero-inflated poisson model

| Variables | Coefficient | SE | P>\|Z\| | P>\|Z\| | 95%CI |
|---|---|---|---|---|---|
| Illness/Injury | -0.074*** | 0.004 | -20.52 | 0.000 | -0.081, -0.067 |
| Hospitalisation | 0.000 | 0.006 | 0.04 | 0.972 | -0.011,0.011 |
| Chronic illness | 0.034*** | 0.005 | 6.33 | 0.000 | 0.023,0.044 |
| Social protection | -0.015*** | 0.003 | -4.56 | 0.000 | -0.021,-0.008 |
| Illness/ Injury*Social protection | -0.010* | 0.006 | -1.76 | 0.078 | -0.021,-0.001 |
| Hospitalisation *Social protection | -0.020*** | 0.002 | -10.04 | 0.000 | -0.024,-0.016 |
| Chronic illness*Social protection | -0.026*** | 0.008 | -3.17 | 0.002 | -0.041,-0.010 |
| Control Variables | YES | | | | |

N (number of observations) =94,846

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

The table shows coefficients estimated by the zero-inflated Poisson model

Figures in parentheses are standard errors

Control variables included sex, age, religion, marital status, and education level

Values in the table were rounded off to three decimal places

**Authors' contributions**
KCS conceptualised the idea, analysed data, and is the main author of the manuscript. BH reviewed the manuscript and provided critical comments, direction and guidance in the process of data analysis, and writing. EZ: reviewed the manuscript and provided critical comments, direction and guidance in the process of data analysis, and writing. All authors read and approved the final manuscript.

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**Availability of data and materials**
Data upon which analysis was based are publicly available obtainable on https://microdata.worldbank.org/.

## Declarations

**Competing interests**
The authors declare no competing interests.

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## Publisher's note