MODELLING CATASTROPHIC HEALTH EXPENDITURES AND ITS IMPLICATION FOR HOUSEHOLD WELFARE IN MALAWI: A SPATIAL MULTILEVEL APPROACH

DOCTOR OF PHILOSPHY IN APPLIED STATISTICS THESIS

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DECLARATION

I, Atupele Ngina Mulaga, declare that this thesis is based on my own work. It is submitted in fulfillment of the requirements for a Doctor of Philosophy in Applied Statistics at the University of Malawi, The Polytechnic. This thesis has not been submitted for any degree or examination at any other university or college.

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CERTIFICATE OF APPROVAL

We, the undersigned, hereby certify that we have read and approve for examination by the University of Malawi, The Polytechnic this thesis entitled *“Modelling Catastrophic Health Expenditures and Its Implication for Household Welfare in Malawi: A Spatial Multilevel Approach”*.

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DEDICATION

The thesis is dedicated to my parents, my husband Masutano, my siblings, my children: Shalom and Nathan

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ABSTRACT

Understanding characteristics of population groups vulnerable to catastrophic health expenditures and impoverishment due to health expenditures is important for designing financial protection programs and policies. This thesis developed a model for assessing the effect of household and neighborhood characteristics on the extent of catastrophic health expenditures and impoverishment due to health expenditures. The study used data from a cross-sectional survey conducted between April 2016 to April 2017 among 12447 households in Malawi. The outcome variables were the incidence of catastrophic health expenditures and impoverishment effects of health expenditures. Descriptive statistics such as proportions and means were used to describe characteristics of the sampled households. Moran I statistic was used to test for spatial dependence in impoverishment. Multilevel logistic model was developed to assess the effects of household and neighborhood characteristics on catastrophic health expenditures. Spatial multilevel logistic model was developed to assess the effects of household and neighborhood characteristics on impoverishment. Decomposition analysis was used to decompose socio-economic inequality in catastrophic health expenditures into its determinants. The thesis used simulation analysis to compare spatial multilevel model to multilevel and single level models in terms of overall model fit and performance of the parameter estimates. The analysis showed that 1.37% of the households incurred catastrophic expenditures. Visiting mission health facility, hospitalization, larger household size, higher socioeconomic status, living in central region and rural areas increased the odds of facing catastrophic expenditures. Majority of inequality in catastrophic expenditures is due to income, urban-rural and regional inequalities. 1.6% of Malawians were impoverished due to health expenditures. Lower socio-economic status, hospitalizations, chronic illnesses, residency in rural area increased the odds of impoverishment. There were significant spatial variations in impoverishment with higher spatial effects clustering in central region districts. Multilevel logistic model and spatial multilevel models provided the best fit to the data and unbiased estimated parameters. There is need design better prepayment mechanisms to protect vulnerable population groups and ensure progress towards universal health coverage. Policies aiming to reduce inequalities in health expenditures should simultaneously aim to reduce income, urban-rural and regional inequalities. Researchers using data from complex survey design in modelling health expenditures and its implications on household welfare should account for neighborhood and spatial dependence in the data.

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2. **Mulaga, A. N**., Kamndaya, M. S., & Masangwi, S. J. (2022). Decomposing socio-economic inequality in catastrophic out-of-pocket health expenditures in Malawi. PLOS Glob Public Health, 2(2), 1–13. https://doi.org/10.1371/journal.pgph.0000182

3. **Mulaga, A. N.,** Kamndaya, M. S., & Masangwi, S. J. (2022). Spatial disparities in impoverishing effects of out-of-pocket health expenditures in Malawi. Global Health Action,15(1),1-11. https://doi.org/10.1080/16549716.2022.2047465

4. **Mulaga ,A.N.,** Kamndaya, M.S., & Masangwi,S.J.(2022). Comparison of spatial multilevel model to multilevel and single level logistic models when assessing factors associated with impoverishing effects of out-of-pocket health expenditures. In progress.

ABBREVIATIONS AND ACRONYMS

AIDs	Acquired Immunodeficiency Syndrome
ANC	Antenatal Care
CHAM	Christian Health Association of Malawi
CHE	Catastrophic Health Expenditures
DIC	Deviance Information Criterion
EHP	Essential Health Package
GDP	Gross Domestic Product
HDI	Human Development Index
HIV	Human Immunodeficiency virus
IHS	Integrated Household Survey
IMF	International Monetary Fund
IPTp	Intermittent Preventative Treatment during pregnant
IRS	Indoor Residual Spraying
ITNs	Insecticides Treated Nets
LSMS	Living Standards Measurements Study
MDGs	Millennium Development Goals
MDHS	Malawi Demographic Health Survey
MWK	Malawi Kwacha
NCRSH	National Committee on Research in the Social Sciences and Humanities
NCST	National Commission for Science and Technology
NGOs	Non-Governmental Organizations
NSO	National Statistical Office
SGDs	Sustainable Development Goals
SLAs	Service Level Agreements
T/As	Traditional Authorities

UHC	Universal Health Coverage
USD	United States Dollars
WHO	World Health Organization

CHAPTER 1: INTRODUCTION

1.1 General introduction

The goal of health care financing system is to protect households from the financial risk due to illnesses, ensure equity in utilization of health care services and health financing. This goal is well articulated in the World Health Organization (WHO) 2010 report as the Universal health coverage goal. The Universal Health Coverage (UHC) goal ensures that all people have access to health services and do not face financial hardship due out-of-pocket payments of the services (World Health Organizatio [WHO], 2010). One way in which health systems can protect households from financial burden due to out-of-pocket payments is through prepayment financing and risk pooling mechanisms. However, in most low-and middle-income countries (LMICs) health prepayment financing and risk pooling mechanisms are not well developed, and households rely on out-of-pocket health payments to access health services. Such reliance on out-of-pocket health payments places financial burden on households and leads to catastrophic out-of-pocket expenditures, impoverishment and prevent households from accessing health care making the attainment of the universal health coverage difficult (WHO, 2010).

Catastrophic health expenditure (CHE) occurs when out-of-pocket health payments as a share of household's income or capacity to pay exceeds a predetermined threshold level and impoverishment due to health payments arises when non poor households and those already poor are pushed into poverty after paying for health services (Wagstaff & Doorslaer, 2003; Xu et al., 2003; Xu et al., 2003). CHE pushes households into poverty and leaves households in a vicious cycle of poverty and ill health (Li et al., 2013; Tomini et al., 2013). These effects are common in low -and middle - income countries where many households rely on out-of-pocket for payment of health care services. Multi-country studies showed that an estimated 118.7 and 531.1 million people from Africa and Asia respectively incurred CHEs and 14.9 and 79 million people respectively were impoverished due to health payments by 2010 (Wagstaff et al., 2018; Wagstaff et al., 2018). African and Asian countries accounted for 3.3 % of the population impoverished by out-of-pocket health payments (Wagstaff et al., 2018). Another multi country analysis also reported that catastrophic health expenditure is more common in low- and middle-income countries and countries in transition (Xu et al., 2003) . Thus, advancing a need to understand the extent of catastrophic expenditures and its associated risk factors in low- and middle-income countries including Malawi at national level.

Malawian health system is mainly publicly financed through general tax revenues and receives substantial funding from external donors (Government of the republic of Malawi, 2017a). A minimum package of health services is provided for free in all public health facilities through the essential health package (EHP). This acts as a priority setting tool and includes key public health priority areas and cost effective intervention to address the major causes of mortality and morbidity (Chansa et al., 2018). Total health expenditure in Malawi increased by 14.7 % from MWK429.1 billion to MWK502.8 billion over the period 2015-2018 and the average total per capita expenditure over the period was US$39.8 slightly higher than US$ 39.2 reported over the 2012-2015 period. The total per capita expenditure US$39.8 reported is similar to the average total per capita expenditure of US$41 in other low income countries but 2 times lower than the recommended total per capita expenditures of US$80 per year by WHO to strengthen health systems and implement a minimum set of essential health interventions (Jowett et al., 2016; Ministry of Health (MoH), 2020). Further to that the per capita expenditures is 5 times lower than the Southern Africa Development Cooperation (SADC) average of USD$ 209 in 2018 (UNICEF, 2019) . Such low total per capita expenditures may hinder the country to provide a minimum essential health service and consequently hinder its progress toward Universal Health Coverage. Over the 2015-2018 period external donors contributed 58.6% of total health expenditures while government and private health expenditures represented 23.9% and 17.5% of total health expenditures respectively. Out of 17.5% of private health expenditures 12.6% were from household's out-of-pocket expenditures (Ministry of Health(MoH), 2020). This shows there was an increased in private health expenditures from 13.4% in 2012-2015 period to 17.5% of total expenditures mainly due to the rise in out-of-pocket expenditures from 8.6% of total health expenditures to 12.6% in the 2015-2018 period.

While access to health services in public facilities is free at point of use, households still contribute to total health expenditure through out-of-pocket payments in Malawi. Two main factors could explain this phenomenon. Firstly, the health system face many bottlenecks such as shortage of drugs, skilled medical personnel, poor quality of services and inaccessibility of facilities (World Bank, 2015). These bottlenecks force households to seek care in private health facilities with better quality services and skilled medical personnel where they incur higher out-of-pocket health payments. Shortage of drugs may also force households to purchase drugs at private pharmacies where they incur higher out-of-pocket payments. Secondly, in Malawi prepayment and risk pooling mechanisms for health financing are underdeveloped. Malawi has no social health insurance or health fund and for the private health insurance coverage is low and only accessible to those in the formal employment sector (National Statistical Office[NSO] & ICF, 2017). For instance, 1% of women and 2% of men aged 15-49 in the formal employment sector have health insurance coverage (NSO & ICF, 2017). These low percentages suggest that higher costs of private health insurance leave many in the formal employment sector and those in the informal sector at a risk of catastrophic health expenditure, impoverishment and constrained when accessing health care.

According to previous studies, out-of-pocket health payments expose households to the risk of CHEs and impoverishment (Amaya-lara, 2016; Barasa et al, 2017; Brinda et al, 2014; Gotsadze et al, 2009; Li et al., 2013; Li et al., 2012; Masiye et al, 2016). These studies also show that households in rural areas, in lower socioeconomic status, with chronically ill members, with children, with elderly members and with a larger household size are at an increased risk of incurring CHEs.

A study by Mchenga et al. (2017) showed that 0.73% to 9.73% of households faced CHEs in Malawi. The same study found that out-of-pocket expenditures increases the incidence of CHE and pushes households into poverty (Mchenga et al., 2017). However, existing research in Malawi has paid limited attention to examining factors associated with CHEs and impoverishing effects of out-of-pocket health payments as such it is unclear as to which population groups are vulnerable.

In addition, existing research has focused on the household level factors associated with catastrophic health payments and impoverishing effects of out-of-pocket health payments using single level regression models which neglects the hierarchical structure and spatial dependence inherent in complex survey data used in most of the analysis. This methodological gap implies that the relative importance of geographic space or place is neglected. Neglecting the relative importance of geographic space may lead to wrong inferences and conclusions on the factors associated with catastrophic health payments and impoverishing effects of health payments. As Malawi tackles the challenges of health financing with plans to introduce a national health fund and health insurance to achieve Universal Health Coverage (Government of the republic of Malawi, 2017a) there is need for research to understand the extent of catastrophic out-of-pocket health payments, impoverishing effects of health payments and identify population groups vulnerable to the negative consequences of out-of-pocket health payments.

1.2 Problem statement

While research has focused on understanding household level factors associated with the risk of CHEs and impoverishing effects of out-of-pocket health payments limited evidence exists on the contextual effects on the risk of catastrophic health expenditure and impoverishment. Few studies have explored the effects of contextual level factors on the risk of CHEs using multilevel models (Li et al., 2013; Mohanty et al., 2018; Shi et al., 2011; Yazdi-feyzabadi et al., 2018). Multilevel models account for within neighborhood correlation in the observations due to the hierarchical structure of the data. However, for geographically referenced and hierarchical data multiple dependence in the observations such as within and between neighborhood dependence may exist simultaneously which can lead to incorrect inferences if unaccounted for (Arcaya et al., 2012; Ma et al., 2018). Hence, the multilevel models commonly used in previous studies fail to provide comprehensive information on the contextual effects on the risk of CHEs and impoverishing effects of health expenditures as spatial dependence in the observations is not properly accounted for. Consequently, this shortfall leads to incorrect inferences on the parameters due to underestimation of standard errors and wrong conclusions.

The present study seeks to examine the use of multilevel spatial models that accounts for both spatial dependence and within neighborhood dependence in examining the risk factors associated with catastrophic health expenditures and impoverishing effects of out-of-pocket health payments consequently provides correct inferences on contextual effects and understanding of the variations in catastrophic health expenditures and impoverishment. This study also seeks to develop spatial risk maps for identifying areas at risk of impoverishing effects of out-of-pocket health expenditures.

Spatial and within neighbourhood correlations in impoverishing effects of out-of-pocket health payments and catastrophic health expenditures may reflect geographical variations in disease burden across districts (Chirombo et al., 2014; Kazembe et al., 2007; Kazembe & Kamndaya, 2016; Kazembe & Namangale, 2007; Ngwira & Kazembe, 2015; Nutor et al, 2020), district economic status (IFPRI, 2019), district health funding levels (Borghi et al, 2017), type of health provider utilized (Kazembe et al., 2007) and availability of health services (Malawi Government, 2020). For example, in terms of economic status poverty levels vary across districts with districts in the southern region experiencing higher incidence of poverty than districts in the northern and central region (IFPRI, 2019). The Malawi harmonized health facility assessment survey also observed substantial variations across districts in terms of availability and quality of health services (Ministry of Health, 2019). Moreover, another study in Malawi observed significant variations in total per capita health expenditures and levels of expenditures by sources across districts (Borghi et al., 2017). Consequently, impoverishment due to health payments and catastrophic health expenditures may vary from district to district. Use of statistical models that account for spatial and within neighborhood correlations will help to provide correct inferences on the characteristics of households and help to identify households at greatest risk for targeted interventions.

1.3 Aims and objectives

1.3.1 Main aim

The aim of this study is to examine the use of the logistic regression, multilevel regression, and spatial multilevel models in assessing factors associated with catastrophic out-of-pocket health payments and impoverishing effects of health payments.

1.3.2 Specific objectives

The specific objectives of the study are to:

i. Assess the extent of catastrophic health expenditures and its associated risk factors.
ii. Decompose inequality in catastrophic health expenditures into its determinants.
iii. Assess the extent of impoverishing effects of out-of-pocket health expenditures on households and its associated risk factors.

iv. Compare the performance of multilevel spatial logistic regression model with multilevel logistic and ordinary logistic regression models when assessing factors on impoverishing effects of out-of-pocket health expenditures.

1.4 Research questions

The study addresses the following research questions:

i. What is the extent of catastrophic out-of-pocket health expenditures and impoverishment due to out-of-pocket expenditures in Malawi?
ii. What factors are associated with catastrophic out-of-pocket payments and impoverishing effects of health payments accounting for contextual effects?
iii. What factors contribute to inequality in catastrophic out-of-pocket payments?
iv. Are there spatial variations in impoverishing effects of health payments?
v. Which geographical areas in Malawi are at risk of incurring catastrophic out-of-pocket health payments and impoverishing effects of health payments?
vi. Which statistical model performs well when assessing the factors associated with impoverishing effects of health expenditures using complex survey data?

1.5 Research hypotheses

In line with the specific research objectives, the literature and the theories that were reviewed specifically theory of demand for health care and the behavioural model for health care utilization, hypotheses were set out. The following are the hypotheses:

i. Household socio-economic status is associated with catastrophic health expenditures.
ii. Household socio-economic status is associated with impoverishing effects of health expenditure.
iii. Having hospitalised members in the household is associated with catastrophic health expenditures.
iv. Having hospitalized members in the household is associated with impoverishing effects of health expenditure.
v. Residency in rural location is associated with catastrophic health expenditures.

vi. Residency in rural location is associated with impoverishing effects of health expenditure.

1.6 Significance of the research

This study on catastrophic health expenditures and impoverishing effects of out-of-pocket health expenditures is important for designing policies and programs for making progress towards achieving Universal Health Coverage which falls under Sustainable Development Goal (SDG) 3 target 3.8 and also under enabler 5 of the Malawi's vision 2063 (National Planning Commission, 2020). It also provides evidence relevant for designing programs towards achieving Sustainable Development Goal 10 in terms of reducing inequalities in health expenditures.

Understanding the factors associated with the risk of incurring catastrophic health expenditures and impoverishing effects of health expenditures is important for designing financial protection programs and policies to better protect the most vulnerable households and consequently move towards achieving Universal Health Coverage (UHC) goal. Malawi's vision 2063 enabler 5 on human capital development specifically health seeks to attain Universal Health Coverage accomplished by a comprehensive health care system with interventions to addresses the challenges of the healthcare system (National Planning Commission[NPC],2020). Moving towards Universal Health Coverage requires that priority is given to financially protect the most vulnerable groups (Ranson, 2018) hence a need to identify such vulnerable groups. More importantly identifying households at greatest risk would provide evidence for policy on targeted interventions for the most vulnerable and improving access to health care services regardless of household geographic location. The study provide evidence on financial protection to Malawi government health policy makers which is relevant in their plans to design a health fund and a national health insurance scheme as stipulated in the Malawi health sector plan 2017-2022 (Government of Malawi, 2017a). Furthermore, this study provides evidence on socio-economic inequality and the causes of inequality in catastrophic health expenditures which is important for designing programs for reducing inequality and inequity in health expenditures.

1.7 Ethical approval

The study is based on secondary data from the National Statistical Office of Malawi (NSO). The data that is made publicly available has no identification of the survey participants to respect confidentiality of the survey participants. The data is available upon request from the Commissioner of Statistics or by completing a simple registration at the World Bank website for the Living Standards Measurement Study (LSMS) data portal for the Malawi Fourth Integrated Household Survey. Ethical clearance for this study based on secondary reanalysis of the data was obtained from National Committee on Research in the Social Sciences and Humanities (NCRSH) reference No. P.10/19/434 (Appendix 1). The National Statistical Office of Malawi enumerators obtained verbal informed consent from the survey participants and this was recorded on the questionnaire and upon agreement to participate in the survey the enumerators proceeded with the interview.

1.8 Structure of the thesis

The rest of the thesis is structured as follows:

Chapter two provides the profile description of Malawi giving the context in which we can understand out-of-pocket health payments, catastrophic health expenditures and the impoverishing effects of out-of-pocket health expenditures. It discusses the political and administrative systems, demographic and socio-economic characteristics, health status indicators, disease burden, the health systems and health care financing mechanisms. The last section summarises the chapter.

Chapter three evaluates and discusses the literature related to catastrophic health expenditures and impoverishing effects of health expenditure. The first section introduces the chapter followed by a section on the search strategy that was used in the literature search then a section on how the literature review is organised. The fourth section discusses the concepts, theoretical perspectives and presents the conceptual framework for the study. Fifth section evaluates empirical studies on the factors associated with catastrophic out-of-pocket health payments and impoverishing effects of health expenditures. Sixth section discusses and evaluates literature on inequality in catastrophic health payments followed by literature on statistical models in analysing risk factors associated with catastrophic expenditures and impoverishing effects of health expenditures. Section eight evaluates literature on the incidence of catastrophic out-of-pocket health payments and impoverishment due to health expenditures followed by the research gaps identified from the review. The last section summarizes the literature review.

Chapter four describes the research methodology used in addressing the research questions. The chapter include a section on the research philosophy, approach, strategy, choice and design. The section on research techniques and procedure gives the description on the data sources, operational definitions of the key concepts used in the study, description of the main of the main variables and the data analysis. The data analysis section includes measurements of catastrophic health payments and impoverishing impact of out-of-pocket health payments, the multilevel binary logistic regression model, measurement of inequality in catastrophic expenditures and decomposition analysis methods for inequality and discussion on the Bayesian spatial multilevel logistic regression model used in the study to assess the factors associated with impoverishing effects of out-of-pocket health expenditures.

Chapter five presents and discusses findings on the extent of catastrophic health expenditure and the factors associated with catastrophic health payments examined using multilevel logistic model.

Chapter six presents and discusses findings on socio-economic inequality and decomposing inequality in catastrophic health expenditures into its determinants.
Chapter seven presents and discusses findings on the extent of impoverishing effects of out-of-pocket health expenditures and factors associated with impoverishment examined using a spatial multilevel regression model.

Chapter eight presents and discusses findings on the comparison in terms of performance of the spatial multilevel models to the standard multilevel and single level logistic models in examining risk factors associated with impoverishing effects of health expenditures. The comparison of performance of the models was based on both a simulation analysis and the actual data on impoverishing effects of health payments.

Chapter nine concludes by giving the key findings, the key contributions of the study to knowledge, limitations of the study, recommendations to policy makers, researchers, and recommendations for further research.

CHAPTER 2: MALAWI COUNTRY PROFILE

2.1 Introduction

This chapter provides the profile description of Malawi. It provides the context in which we can better understand out-of-pocket health expenditures in Malawi. The chapter specifically describes Malawi's political and administrative systems, demographic and socio-economic characteristics, health status indicators, disease burden, health systems and health care financing.

2.2 Geographical location, political and administration system

Malawi is a landlocked low income country located in southern Africa and it shares borders with Tanzania to the north eastern, Zambia to the north western and Mozambique to the central eastern part (Conticini, 2004; Government of Malawi, 2017a). Malawi is divided into three administrative regions including the northern, central, and southern region. The regions comprise 28 districts which are further divided into traditional authorities(T/As) and are ruled by chiefs. The T/As are further sub divided into villages which form the smallest administrative units (Conticini, 2004; Government of Malawi, 2017a). The districts are also divided into constituencies represented by members of parliament in the National Assembly and these constituencies are divided into wards represented by local councilors who work under district councils (Tostensen, 2017).

In terms of political and governance system, Malawi is a democratic republic with an elected government. The governance system comprises three arms which includes a legislature, a judiciary and an executive (Tostensen, 2017). The elected head of state who is the president has powers to choose cabinet members and together form the executive arm of government (Centre for Social Research (CSR) and Chr.Michelsen Institute(CMI), 2007) . The legislature arm of government consists of members of parliament. The role of the legislature is to formulate laws, represent the people in parliament and provide checks and balance on issues presented by the executive arm. The Judiciary is an independent arm of government headed by the chief justice. The role of the Judiciary is to interpret the laws and resolve issues among citizens or institutions (CSR and CMI, 2007). These three institutions make major decisions on political, economic and social issues affecting citizens according to their mandates or in agreement as defined by the law (Tostensen, 2017).

2.3 Demographic characteristics

Malawi's population is estimated at 18.1 million as of 2018 (National Statistical Office of Malawi[NSO], 2019). Malawi has a predominantly youthful population with about 49% of the total population under the age of 18 years while only 4% is aged 65 years or older and 3% is aged less than one year (NSO, 2019). Over the years the population growth rate has remained high in Malawi. Between the 2008 and 2018 census, the population increased by 35% representing a 2.9% growth rate. The 2018 population census projected that the current population estimate will double in 2042 (NSO, 2019). In terms of distribution by region, the southern region comprises 44% of the total population, the central comprise 43% and the northern region comprise of 13% of the population. Majority of the population is rural with the 2018 census estimating 84% of the population as rural and 16% of the population as urban (NSO, 2019).

2.4 Socio-economic characteristics

The GDP per capita for Malawi was estimated at USD406.35 in 2020 and with this GDP per capita is ranked as one of the least developed countries in the world ranking at 183 out of 186 countries (Foreign Commonweath & Development Office (FCDO) Economics and Evaluation Directorate, 2021). The economy grew from 3.2% in 2018 to 4.5% in 2019; however due to shocks such as May 2019 post-election protests ,bad weather conditions and COVID-19 pandemic the gains that were realized in 2019 were lost as the economic growth fell from 4.5% to 0.6% in 2020 (Foreign Commonweath and Development Office (FCDO) Economics and Evaluation Directorate, 2021). Economic growth picked again in 2021 and the economy grew by 2.2% and the International Monetary Fund(IMF) forecasted that the economy will grow by 6.5% in 2022 (Foreign Commonweath & Development Office(FCDO) Economics and Evaluation Directorate, 2021).

Malawi 's economy is mainly dependent on agriculture and the agriculture sector employs about 64% of the labor force (JICA, 2020). Agriculture, forestry and fisheries contributes 26% of the GDP, industry contributes 13% while services industry contributes 54% of the GDP (Foreign Commonweath & Development Office(FCDO) Economics and Evaluation Directorate, 2021). Due to high dependency on rain fed agriculture the economy is vulnerable to weather shocks such as droughts and floods consequently the country and households at constant risk of food insecurity (JICA , 2020; UNICEF, 2019).

The Gini coefficient for wealthy inequality with wealth measured by household ownership of durable assets was estimated at 0.431 in 2004 and it increased to 0.564 in 2011 and it slightly decreased to 0.447 in 2016 (Mussa & Masanjala, 2015). This increase in the Gini coefficient over the years shows the worsening gap of wealth between the rich and poor with richer households having larger total income than poor households (Mussa & Masanjala, 2015). Although data from household surveys indicate that poverty levels slightly decreased from 52.4% in 2004 to 51.5% of the population below the poverty line in 2016 (Malawi IFPRI, 2019), Inequality over the period worsened. Consumption inequality as measured by the Gini coefficient of per capita consumption was estimated at 0.390 in 2004 and it increased to 0.452 in 2011 indicating worsening in economic inequality in the country (Mussa & Masanjala, 2015).

Malawi falls among countries in the low human development category. The Human Development Index (HDI) was estimated at 0.483 in 2019 ranking the country on 174 out of 189 countries in terms of Human development (Foreign Commonweath & Development Office (FCDO) Economics and Evaluation Directorate, 2021; UNDP, 2020). The HDI for Malawi was low compared to the HDI of neighboring Zambia estimated at 0.583 but higher than that of Mali estimated at 0.434 (UNDP, 2020). In terms of literacy, the Malawi Demographic Health Survey (MDHS) estimated that more men aged 15-49 years are literate (83%) than women (72%) in Malawi (National Statistical Office (NSO) & ICF, 2017). This shows that in Malawi there are gender disparities in schooling which has economic and health implications on the women. In comparison to other African countries. The mean years of schooling for Malawi is estimated at 4.7 years which is higher compared to Mali(2.4 years) but lower compared to Zambia (7.2 years) and the rest of sub Saharan Africa (5.8 years) (UNDP, 2020).

2.5 Health status indicators for Malawi

2.5.1 Maternal mortality

Maternal mortality features under goal number 3 of the Sustainable Development Goals (SDGs) adopted by the United Nations member states in 2015.Target 3.1 under Sustainable Development Goal 3 of health and well-being aims to reduce maternal mortality to less than 70 deaths per 100,000 live births by 2030 (United Nations, 2016). Globally the trend in maternal mortality have been declining. Maternal mortality declined from 342 deaths per 100,000 live births in 2000 to 211 deaths per 100,000 live births in 2017(United Nations & Department of Economic and Social Affairs Population Division, 2019). However 67% of all the estimated 295,000 deaths in 2017 were from countries in the sub Saharan Africa region where maternal mortality was estimated at 542 deaths per 100,000 live births (United Nations & Department of Economic and Social Affairs Population Division, 2019). Thus, countries in the sub-Saharan Africa region bear a larger burden of maternal mortality.

Malawi is among the countries recording the highest maternal mortality worldwide (National Planning Commission, 2021; UNICEF Malawi, 2018). Maternal mortality rate was estimated at 349 deaths per 100,000 live births in 2017 (WHO, UNICEF, UNFPA, & World Bank and United Nations Population Division, 2019) which was higher compared with 213 deaths per 100,000 live births in Zambia and 289 deaths per 100,000 live births in Mozambique but it was lower than the maternal mortality in Tanzania estimated at 524 per 100,000 live births and the maternal mortality of countries in sub Saharan Africa region estimated at 542 deaths per 100,000 live births (United Nations & Department of Economic and Social Affairs Population Division, 2019).

The causes of maternal mortality in Malawi are similar to the causes of maternal mortality globally. Most of the maternal deaths in Malawi are due to direct causes as a result of obstetric complications such as Hemorrhage, Sepsis, Eclampsia, obstructed labor and unsafe abortions (Geubbels, 2006). These complications can be prevented and treated however prevention of such causes depends on availability of care, accessibility of care and quality of care (National Planning Commission, 2021). Indicators of maternal health care in Malawi show progress in providing maternal health care services. For example, the proportion of women who received antenatal care (ANC) from a skilled provider was estimated at 95% in 2016 (NSO & ICF, 2017). This estimate is an increase from 90% in 1992 representing a 5% increase in women who received antenatal care over the 23-year period. Estimate of women who received antenatal care in the first trimester also increased from 9% in 1992 to 24% in 2016 while institutional deliveries increased from 55% to 91% representing a 65% increase over the 23-year period (NSO & ICF, 2017).

Although there have been improvements in indicators of accessibility and availability of maternal health care, maternal mortality ratio in Malawi remains one of the highest globally. This is because accessibility and availability of maternal health care does not usually translate to high quality of maternal health care which could consequently reduce mortality (Leslie et al., 2016; National Planning Commission [NPC], 2021) . For example, a multi country study reported higher mortality in countries with high to very high maternal mortality ratio despite high coverage of essential interventions which implied that high coverage of intervention did not reduce maternal mortality (Souza et al., 2013)**.** On the other hand, another study estimated reductions in maternal deaths by 28% assuming improvement in quality of care among those seeking care (Chou et al., 2020). Moreover, in Malawi a previous qualitative study on perception of quality of maternal health care found that although women perceived quality of prenatal care to be better perception on the quality of post-natal care was poor (Machira & Palamuleni, 2018). This poor perception on quality of maternal care may affect access and utilization of post-natal services consequently negatively impact on maternal health outcomes (Kambala et al., 2015). Poor quality of maternal health care in Malawi is attributed to inadequate funding to the health sector and this inadequate funding results in challenges such as shortage of health personnel and constant drug stock outs (National Planning Commission[NPC], 2021).

2.5.2 Infant and child mortality

Malawi is among a few countries in sub Saharan Africa region that has made tremendous progress in improving child survival and achieving the Millennium Development Goal (MDG) 4 of reducing under five mortality by two thirds between 1990-2015 (Kanyuka et al., 2016). Under five mortality declined by 73% from 234 deaths per 1000 live births in 1992 to 63 deaths per 1000 live births in 2015-16 (NSO & ICF, 2017). This success in the reduction of child mortality and achievement of Millennium Development Goal 4 is attributed to the scale up of interventions such as treatment of illnesses that are regarded as the major causes of child deaths, programs to improve child nutrition and prevent mother-to-child HIV transmission (Kanyuka et al., 2016). There are also differentials in under five mortality rates by place of residence, region and socioeconomic status. Under five mortality rates has been consistently higher in rural areas than in urban areas from 2000 to 2015-16. In 2000 under five mortality was estimated at 210 deaths per 1000 live births in rural areas and 148 deaths in urban areas while in 2015-16 the estimates were 77 deaths per 1000 live births in rural areas and 60 deaths in urban areas (NSO & ICF, 2017). The MDHS 2015-16 (NSO & ICF, 2017) also reports regional disparities in under 5 mortality with a higher under 5 mortality estimated at 81 deaths in central region and the lowest was in northern region estimated at 57 deaths.

While under five mortality declined tremendously from 1990-2015 evidence show that the decline in neonatal mortality was slow over the same period. Neonatal mortality declined with an annual rate of 3.3% from 50 deaths per 1000 live births to 23 deaths over the period which was slow compared to an annual decline rate of 5.4% in under five mortality over the same period (Kanyuka et al., 2016). Despite the progress achieved in improving under five mortality the slow decline in neonatal mortality indicates the need for investments in interventions to improve neonatal care(National Planning Commission, 2021).

Most of the causes of neonatal deaths are preventable and can be reduced by improving quality of newborn care. In 2019, neonatal disorders represented the second leading cause of all deaths in Malawi (Centre for Disease Control and Prevention, 2019). The major causes of neonatal deaths in Malawi are prematurity (33%), births asphyxia and trauma (25.8%), Sepsis (18.5%) and Acute respiratory infections (6%). Other causes include injuries, Tetanus ,HIV/AIDs and diarrhoeal diseases (UNICEF, 2014). In Malawi facility quality of newborn care falls considerably below the international standards of care despite increased accessibility and utilization in institutional deliveries (Kawaza et al., 2020; Leslie et al., 2016). This poor quality of newborn care puts both the life of the mother and newborn child at a risk of death. A previous study in Malawi reported that higher quality facilities were associated with 2.3 percentage point lower neonatal deaths than other facilities (Leslie et al., 2016). This indicates that improving quality of neonatal care through interventions such as infection control, neonatal resuscitation and kangaroo care for preterm births could greatly reduce neonatal deaths among women seeking care at facilities (Leslie et al., 2016; NPC, 2021). Consequently, improving quality of new born care may require greater investments in skilled health personnel, infrastructure and resources (NPC, 2021).

2.6 Disease burden

2.6.1 Malaria burden in Malawi

Globally Malaria cases and deaths are declining however Malaria remains a major public health problem. In 2018, an estimated 228 million malaria cases and 405,000 malaria deaths were reported globally. Of all the global Malaria cases and deaths, 93% of the cases and 94% of the deaths were from African region(World Health Organizatio [WHO], 2019). About half of all Malaria cases globally were attributed to six countries in Africa with Nigeria accounting for 25%, Democratic Republic of Congo (12%), Uganda (5%), Cote d'Ivoire (4%), Mozambique (4%) and Niger (4%). This indicates that countries in African region bear a proportionally huge burden of malaria morbidity and mortality.

Malaria is highly endemic in Malawi and places a huge burden on the population. It is one of the major leading causes of deaths in Malawi (Centre for Disease Control and Prevention , 2019). In 2018, Malaria cases were estimated at 3,876,121 in Malawi which represented 2% of all the estimated cases globally and malaria deaths also accounted for 2% of the total Malaria deaths globally (WHO, 2019). In Malawi ,95% of the population is at risk Malaria infections (USAID, 2018). However, pregnant women and children under age of five remain the main population groups vulnerable to the risk of Malaria infections (NSO & ICF, 2017). Malaria in pregnancy has serious repercussions on the mother and the newborn baby. These effects include Malaria related anemia which puts pregnant women at a substantial risk of death before or after child birth (WHO, 2019). It can also lead to preterm and low birthweight babies who are at an increased risk of death due to problems of child development and cognitive development.

Malawi has made tremendous efforts in reducing the burden of Malaria in children under age of five (Malaria Impact Evaluation Group, 2016; National Malaria Control Programme [NMCP] & ICF, 2018). Estimates of malaria prevalence among children under age of five show a declining trend during the scale up of the interventions. The national prevalence of Malaria among children under the age of five was estimated at 43 % in 2010 and this declined to 28% in 2012 and further declined to 24 % in 2017 representing a 44% decrease in prevalence over the seven-year period (NMCP & ICF, 2018). This decline is attributed to the malaria control interventions such mass distribution of insectides treated nets(ITNs), indoor residual spraying (IRS) and intermittent preventive treatment during pregnant(IPTp) which were scaled up in the early 2000 (NSO & ICF, 2017). For example, there was an increase in access, ownership, and use of ITNs in the whole population over the period 2004 to 2016. Access to ITNs was estimated at 19% in 2004 and this increased to 38% in 2016 while use was estimated at 12% in 2004 and increased to 29% in 2010 and further increased to 34 % in 2016 representing a 17% increase in use of ITNs over the six year period (NSO & ICF, 2017). A similar pattern was also observed on the access, use and ownership of ITNs among pregnant women and children under age of five. An evaluation study on the impact of malaria intervention measures implemented in the early 2000 found that these interventions reduced the cause of child mortality by 41% during the period of malaria control scale up and that ownership of ITNs was associated with decreased risk of mortality among children under age of five (Malaria Impact Evaluation Group, 2016). Another study also found that transmission intensity of malaria decreased over the period 2000 to 2020 in which Malawi scaled up the implementation of malaria control interventions (Chipeta et al., 2019). Huge investments in the scale up of malaria control interventions have been associated with the decrease in malaria morbidity and mortality in Malawi. This highlights the importance of increased health funding to reducing disease burden and the need to maintain consistent funding to sustain reduction in morbidity and mortality in the population.

2.6.2 HIV/AIDs burden in Malawi

HIV/AIDs related deaths continue to decline globally mainly due to the increased access to antiretroviral therapy (UNAIDS, 2020). Despite this decline, HIV/AIDs remains one of the major causes of deaths globally (Institute for Health Metrics and Evaluation [IHME], 2018). Globally, HIV/AIDs related deaths declined from 1.2 million deaths in 2010 to 690 000 in 2020 representing a 42% decrease in deaths over the period (UNAIDS, 2021). Although this was a tremendous decline it lagged behind the 2020 target of less than 500,000 AIDs related deaths set by the United Nations Member States in 2016 (UNAIDS, 2020). Over 66% of the estimated global deaths due to HIV/AIDs were from sub Saharan

African countries (UNAIDS, 2021). This indicates that sub–Saharan African countries bear a large morbidity and Mortality burden due to HIV/AIDs.

In Malawi, the trends in the prevalence of HIV infections and death due to AIDs related illnesses also continues to decline (NSO & ICF, 2017;WHO), 2017). This decline is attributed to the decrease in the incidence of HIV and people with HIV/ AIDS living longer as a result of successful scale up of implementation of ART programme (National AIDS Commission [NAC], 2014). Despite this decline HIV/AIDs remains the major leading cause of deaths in Malawi (US Centre for Disease Control and Prevention Malawi, 2019). In 2019, there were 13,000 estimated deaths due AIDs and this represented 2% of all the deaths globally(Avert, 2020; UNAIDS, 2021). The national HIV prevalence among 15-49 years old adults was estimated at 8.8% 2016 (NSO & ICF, 2017). In Malawi, HIV prevalence varies considerably by gender, age, geographic region and socioeconomic status (NAC, 2014;NSO& ICF, 2017). Prevalence was higher among women (10.8%) than men (6.4%). In terms of geographic location prevalence was 2 times higher in urban areas (14.6%) than rural areas (7.4%) and regionally HIV prevalence is higher in southern region (12.8%) compared to Northern region (5.1%) and central region (5.6%) (NSO & ICF, 2017).

2.7 Health systems and health care financing

In Malawi, health services are mainly provided by the public, private for profit and private not for profit sector (Government of Malawi, 2017a; Ministry of Health(MoH) & ICF International, 2014). The public sector facilities include all public health facilities and health services at these facilities are provided for free. The private for profit sector includes all private hospitals and clinics while the private not for profit sector includes NGOs, religious or mission facilities and company facilities. These private for profit sectors charge user fees for health services (Government of Malawi, 2017a). In terms of ownership of the facilities; the government operates about 48% of the facilities which are mostly located in urban areas (Chansa & Pattnaik, 2018; Government of Malawi, 2017a; Ministry of Health(MoH) & ICF International, 2014). The Christian Health Association of Malawi (CHAM) is the umbrella body that oversees most of the religious or mission facilities and operates 16% of the facilities which are mostly located in rural areas while the private sector, NGOs, and companies operate 24%,6% and 7% respectively (Government of Malawi, 2017a; Ministry of Health(MoH) & ICF International, 2014). In 2014,CHAM health facilities were serving about 40% of Malawi's population and it is estimated that they were providing 75% of health services in rural areas (Chansa & Pattnaik, 2018).

The health system in Malawi follows a four tier system; the community, the primary, secondary and tertiary levels which are linked to each other through an organised referral system (Government of Malawi, 2017a, 2017b). The community level includes health posts, village clinics, dispensaries and maternity clinics. The services at community level are mainly preventive health care. The primary level includes health centres and community hospitals. At primary level the services include outpatient, inpatient services and minor procedures. The secondary level consists of district hospitals. These hospital provide referral services to facilities at primary level in addition to providing inpatient and outpatient services to the communities in their districts (Government of Malawi, 2017a; Ministry of Health(MoH) & ICF International, 2014). The primary and secondary health care systems are managed by the district health management teams under district councils. The district health management team in consultation with communities and service providers develop the implementation plan, the annual plan for delivery of health services and the annual budget. Annual allocation of public resources across districts is based on a formula which takes into account disease burden, population size, costs of treatment and variation of costs across districts (World Bank Health Nutrition and Population Team Malawi, 2021). However, this method of allocating resources for health across districts is not being used instead resources are allocated based on previous year's allocations (World Bank Health Nutrition and Population Team Malawi, 2021). This method of resource allocation results in substantial variations in total per capita health expenditures and levels of expenditures from different sources of health financing across districts (Borghi et al., 2017; World Bank Health Nutrition and Population Team Malawi, 2021). The tertiary level consists of central hospitals. These hospitals provide specialised health services and referral services to districts hospitals within the region in which the tertiary hospitals are located. Tertiary level health system is managed by hospital directors under the Ministry of Health (Government of Malawi, 2017a).

Malawian health system is mainly publicly financed through tax revenues and receives substantial funding from external donors (Government of Malawi, 2017a). A minimum package of health services is provided for free in all public health facilities through the Essential Health Package (EHP). This acts as a priority setting tool and includes key public health priority areas and cost effective intervention to address the major causes of mortality and morbidity (Chansa et al., 2018). In terms of health expenditure, total health expenditure in Malawi increased by 14.7 % from MWK429.1 billion to MWK502.8 billion over the period 2015-2018 and the average total per capita expenditure over the period was US $39.8 slightly higher than US$ 39.2 reported over the 2012-2015 period. The total per capita expenditure US$39.8 reported is similar to the average total per capita expenditure of US$41 in other low income countries but 2 times lower than the recommended total per capita expenditures of US$ 80 per year by WHO to strengthen health systems and implement a minimum set of essential health interventions (Jowett et al., 2016; Ministry of Health(MoH), 2020). Further to that the per capita expenditures is 5 times lower than the Southern Africa Development cooperation average of USD$ 209 in 2018 (UNICEF, 2019). Such low total per capita expenditures may hinder the country to provide minimum essential health services and consequently hinder its progress towards universal health coverage.

Over the 2015-2018 period external donors contributed 58.6% of total health expenditures while Government and private health expenditures represented 23.9% and 17.5% of total health expenditures respectively. Out of 17.5% of private health expenditures 12.6% were from household's out-of-pocket expenditures(Ministry of Health(MoH), 2020). This shows there was an increased in private health expenditures from 13.4% in 2012-2015 period to 17.5% of total expenditures mainly due to the rise in out-of-pocket expenditures from 8.6% of total health expenditures to 12.6% in the 2015-2018 period.

Over the years the Government of Malawi through the Ministry of Health has undertaken health sector reforms to ensure its commitment of financial protection from risk of illnesses among its population. Two of the major health sector reforms undertaken from 2004 to 2010 were the Emergency human resources program and the Service Level Agreements (SLAs) with Christian Health Services Association of Malawi (CHAM). The emergency human resource program was implemented to curb shortage of health human resources in the early 2000’s as a result of core health workers migrating out of the country due to low salaries (Chansa & Pattnaik, 2018). On the other hand SLAs with CHAM health facilities which were signed in 2006 were to ensure free access of health services in CHAM facilities by the population in areas where government facilities are out of reach (Chansa & Pattnaik, 2018). Evidence show that SLAs increased utilization of maternal health services (Manthalu, Yi, Farrar, & Nkhoma, 2016) and have a potential to improve health and financial protection from out-of-pocket health payments (Chirwa, Kazanga, Faedo, & Thomas, 2013).

2.8 Summary

Malawi is a low income country in sub–Saharan Africa with an estimated population of 18.1 million which is predominantly youthful. The GDP per capita for Malawi was estimated at USD 406.35 in 2020 and with this GDP per capita it is ranked as one of the poorest countries in the world ranking 183 out of 185 countries. The economy grew from 3.2% in 2018 to 4.5% in 2019 however due to the COVID-19 pandemic, bad weather conditions and the May 2019 post-elections violence the gains achieved in 2019 were lost as the economic growth declined from 4.5% in 2019 to 0.6% in 2020 and slowly picked to 2.2% in 2021 and is forecasted to grow by 6.5% in 2022.

While the economy has been growing the Gini coefficient of wealthy inequality over the period 2004 to 2011 show a worsening gap in wealth between the rich and poor with richer households having larger total income than poor households. Similarly, the Gini coefficient of per capita consumption increased from 2004 to 2011 indicating a worsening in consumption inequality over the period. Thus, consumption and wealth inequality increased from 2004 to 2016 despite decrease in poverty levels from 52.4% in 2004 to 51.5% in 2016.

In terms of health status indicators, Malawi is among countries recording highest Maternal mortality ratio despite high coverage of maternal health services this is mainly due to poor quality of maternal health services. However, Malawi has made tremendous efforts in terms of child mortality as it was recorded as one of the countries that achieved the Millennium Development Goal 4 of reducing child mortality by two thirds**.** This achievement was attributed to scale up interventions such treatment of illnesses regarded as major causes of child deaths, programs to improve nutrition and prevention of mother to child HIV transmission.

The key providers of health services in Malawi are public, private for profit and private not for profit sectors. Government through the Ministry of Health owns all public health facilities. Government operates 48% of health facilities and health services in public facilities are provided for free. Most of the public health facilities are in urban areas. The Christian Health Association of Malawi which oversees most religious, or mission facilities operates 16% of health facilities which are mostly located in rural areas, while NGOs, private sector and companies operates about 36% of health facilities.

Malawian health system is mainly financed by external donors and the public through tax revenue. External donors contribute a substantial amount to total health expenditures which was estimated at 58.6% of total health expenditure over the 2015-2018 period while government and private contributed 23.9% and 17.5% respectively over the same period. Out of the 17.5% private contributions to total health expenditures 12.6% were from out-of-pocket health expenditures. This indicates that despite free health services households contributes a significant proportion to total health expenditures through out-of-pocket expenditures in Malawi.

The health expenditure over the 2015-2018 period increased by 14.7% and the total per capita health expenditure was US$39.8 which was slightly higher than US$39.2 reported over the 2012-2015 period. However, Malawi's total per capita health expenditures is 2 times lower than the WHO recommended total per capita expenditure to strengthen health systems and implement a set of essential health interventions. Such inadequate funding to the health system creates challenges such as constant stock out of medicines, inadequate medical equipment, inadequate trained medical personnel, and poor quality of health services.

CHAPTER 3: LITERATURE REVIEW

3.1 Introduction

This chapter evaluates and discusses the literature for the study. The first section of the chapter presents the literature search strategy that was used in the search for literature. The second section evaluates and discusses the key concepts, theoretical perspectives, and the conceptual framework. Section three evaluates and discusses empirical evidence on the factors associated with catastrophic health expenditures, followed by section discussing empirical evidence on socio-economic inequality in catastrophic health expenditures. Section five evaluates and discusses literature on the statistical models used to assess factors associated with catastrophic health expenditures followed by section on the incidence of catastrophic health expenditures and impoverishment effects of health payments in sub–Saharan Africa. Section seven presents the gaps in the literature and the last section gives the summary of the literature review.

3.2 Literature search strategy

The purpose of the review is to evaluate and discuss literature on the factors associated with CHEs, incidence of CHEs and impoverishment due to health payments, inequality in catastrophic health expenditures and statistical models used to study factors associated with CHEs. The review also aims at identifying research gaps for further investigation.

Comprehensive search of electronic databases such as PubMed, Science Direct and Google scholar was conducted using a combination of key words. The keywords included catastrophic health expenditures, impoverishment, out-of-pocket payments, financial burden, cost of illness, financial catastrophe, and inequality in catastrophic health expenditures. The inclusion criteria were limited to studies focusing on catastrophic expenditure, impoverishment, factors associated with CHE and financial burden of illnesses. The review includes papers published in English from 2003 onwards. Hospital based patient studies were excluded from the review. The identified papers were screened, papers that met the inclusion criteria were included in the literature review.

3.3 Structure of the literature review

The review is structured into sections that discusses key concepts, theoretical perspectives and the conceptual framework, empirical evidence on the factors associated with CHEs, empirical evidence on inequality in CHEs, statistical models used to assess factors associated with CHEs, incidence of CHEs and impoverishment in sub–Saharan Africa and the summary.

3.4 Concepts, theoretical perspectives, and conceptual framework

3.4.1 Out-of-pocket health payments

Financial protection of households from negative consequences of out-of-pocket health payments is one of the key policy objectives of a country's health systems. Out-of-pocket health payments are payments made by households at the point of use of health services (Wagstaff et al., 2018; Xu, 2005; Xu et al., 2003). These payments include direct costs of treatment such as doctor consultation fees, hospital charges, purchases of medications and does not include reimbursement from health insurance schemes. Out-of-pocket health payments also includes payments on traditional medicine however other costs related to seeking care such as transportation to the health facility are usually excluded from out-of-pocket health payments. Although, the definition of out-of-pocket payments excludes the cost of transportation, other empirical studies have included such costs when measuring out-of-pocket payments while others have used two separate measures with the other measure defined as costs of transportation plus direct costs of services (Barasa et al., 2017; Ekman, 2007). This inclusion of transportation costs in defining out-of-pocket health payments is based on findings that in other contexts transportation costs contributes a substantial amount to out-of-pocket health payments. However such methodologies are not standard ways in which out-of-pocket health payment is measured (Saksena et al., 2014).

3.4.2 Catastrophic health payments

Two measures used in the literature to assess household financial protection are financial catastrophe and impoverishment. Catastrophic health payments occur when out-of-pocket payment for health services as a share of household total income or ability to pay is equal to or more than a specified fraction or threshold level (Wagstaff & Doorslaer, 2003) .

Household income is defined as total household consumption expenditures and household ability to pay is the total household consumption expenditures remaining after spending on food and other provisions. To measure financial catastrophe, Wagstaff and Doorslaer (2003) proposed measures of incidence and intensity of catastrophic health payments. The incidence of catastrophic health payment is assessed using catastrophic payment headcount which is the proportion of a sample whose out-of-pocket payments as a share of household income exceeds a specified threshold. While catastrophic headcount measures the incidence it fails to capture the amount by which out-of-pocket payments exceeds a specified threshold (Wagstaff & Doorslaer, 2003) . Thus, catastrophic payment gap measures the magnitude by which out-of-pocket payments as a proportion of household income exceeds a specified threshold. The threshold levels used in defining catastrophic health payments are arbitrary (Xu et al., 2003) and depends on how income is defined. For example, lower threshold levels ranging from 10% to 25% have been used in the literature when income is defined in terms of total household consumption expenditures (Wagstaff et al., 2018) and higher threshold levels have been used when income is defined as capacity to pay as proposed by the World Health Organization (WHO) (Xu et al., 2003) .

WHO researchers define catastrophic out-of-pocket payment as health spending that exceeds 40% of household capacity to pay (Xu et al., 2003). Capacity to pay is measured as household consumption expenditures remaining after basic subsistence spending have been met. If households report lower food expenditures than subsistence expenditure capacity to pay is defined as total consumption expenditures remaining after deducting food expenditures (Xu, 2005).

3.4.3 Impoverishment due to health payments

Impoverishment occurs when non-poor households fall into poverty and those already poor are pushed deeper into poverty due to out-of-pocket payments for health services (Wagstaff & Doorslaer, 2003; Xu, 2005). While the measures of incidence and intensity of catastrophic payments provide one approach to assess financial protection, the measures fail to capture the impoverishment effects of out-of-pocket payments on households. Wagstaff and Doorslaer (2003) proposed measures to assess the impoverishment effects of out-of-pocket health payments. These measures examine the impact of out-of-pocket health payments on poverty measures such as the poverty headcount and gap. Poverty headcount is the fraction of households below the poverty line and poverty gap refers to the total of all consumption shortfalls from the poverty line (Chuma & Maina, 2012a). Thus the impoverishing effects of out-of-pocket health payments is obtained by calculating estimates of the poverty measures before and after out-of-pocket health payments and comparing the estimates with a poverty line (Wagstaff & Doorslaer, 2003). WHO researchers (Xu, 2005) define households to be impoverished by health spending when they fall below the poverty line after paying for health services. A household is impoverished if total consumption expenditure is equal to and greater than subsistence (nonfood expenditures) and when consumption expenditure minus out-of-pocket expenditure is lower than subsistence expenditure.

3.4.4 Theoretical perspectives and conceptual framework

3.4.4.1 Equity in health and theory of social justice

Equity in health underpins the two outcomes of universal health coverage goal which are: to provide all people with access to needed health services and ensure people do not face financial hardship due to use of these services (World Health Organizatio [WHO], 2010) . In fact the universal coverage goal agrees with the concepts of equity (Ranson, 2018). According to Whitehead (1992) inequity in health is defined as differences which are not only unnecessary and avoidable but they are also unjust and unfair. Thus, according to this definition of inequity judgement of what constitutes unfair and unjust health differences is subjective and may change from place to place and time to time. One way of judging health differences as unfair is through the degree of choice involved in that situation. Whitehead has identified seven influencing factors of differences in health which could be helpful in judging whether health differences are unfair or unavoidable. The author points that differences in health arising from natural biological variations, health damaging behaviors freely chosen such as risk sporting activities and health advantage of one group over another when they are the first to adopt a health promoting behavior are not considered as inequities. On the other hand, health differences arising from insufficient access to needed health services, health damaging behavior where opportunities for a better lifestyle are limited, exposure to unhealthy, poor living and working conditions and change of social class down to lower social class due to sickness are considered to be inequities (Whitehead, 1992).

Although Whitehead definition of equity in health has been widely accepted and adopted there is less consensus as to what constitutes equity (Braveman & Gruskin, 2003; Braveman, 2006; Wagstaff et al., 1989). This is because the concept of equity is based on judgment of moral and ethical values that varies from place to place and time to time as such not all people subscribe to the same concept. For example, not all people agree that the concept of equity means equality. However, Braveman and Gruskin, (2003) have argued that although equity and equality are not synonyms ;equality is necessary for a better definition of equity. According to Braveman and Gruskin (2003) the definition of equity by Whitehead poses a problem to measurement due to the subjective interpretation of what constitute fair and unjust health differences. Peter (2001) also points that this definition is not clear as to how we can go about making judgements of unfairness and injustice. Thus, Braveman and Gruskin (2003) have proposed a definition of equity in health to guide measurement of equity and for tracking the effects of actions taken towards progress to equity. Braveman & Gruskin (2003) define equity in health as “The absence of disparities in health and its social determinants that are systematically associated with social advantage or disadvantage” (pp 256). This definition implies that assessing equity in health necessitates comparison of health outcomes and its social determinants among those in disadvantaged social group to those in more advantaged groups. Such comparison allows assessment of whether any policies or programs leads towards reducing inequities and may help to understand social injustices underlying social processes in a society (Braveman & Gruskin, 2003; Braveman, 2006; Peter, 2001). Our study adopts the definition of equity in health as proposed by Braveman & Gruskin (2003) as we intend to examine financial protection as measured by catastrophic out-of-pocket expenditures ,impoverishing effects of out-of-pocket expenditures among different social groups and inequality in financial protection.

While there is less consensus on how equity is defined due to problems in interpreting what constitute unfair and unjust health differences researchers agree that the theory of social justice underpins the principles of equity (Braveman, 2006; Peter, 2001; Wagstaff et al., 1989; Whitehead, 1992). One such theory is the Rawls’s theory of justice which views justice as fairness. According to the theory a system should be established to ensure that primary social goods are distributed fairly based principles of justice (Ekmekci & Arda, 2016). This system should have established institutions that distribute social goods in line with principles of justice (Ekmekci & Arda, 2016). According to Rawls, justice consists of basic principles which rational individuals could agrees with. These two basic principles are that each person should have equal rights and that social inequalities are considered to be fair if and only if these inequalities favor the worse off (Ekmekci & Arda, 2016). While Rawls's theory (Ekmekci & Arda, 2016; Peter, 2001) does not address health issues because health issues occur randomly in a society, Peter (Peter, 2001) argues that the concepts of justice as fairness developed in the theory could be used to provide guidelines to assess social inequalities in health. Moreover, the theory is considered a reflection of the egalitarian ethical theory that emphasizes more on achieving fairness in distribution rather than total equity in distribution (Ekmekci & Arda, 2016).

The two most common views of social justice theory that underpins equity in health care finance are the egalitarian and the libertarian view. The egalitarian view which stem from the concept of distribution according to need emphasizes a sense of societal collectiveness and unity among people (Wagstaff et al., 1989). For example, Egalitarians view health care as a societal good which should be distributed equally and that each individual has a right to access health care regardless of their income or wealth (Ruger, 2006; Wagstaff et al., 1989). Such a view of social justice suggests a more publicly financed health system where health care is distributed according to need and an obligation for the society to provide health care to its citizens. From an egalitarian point of view, a health financing system is equitable when payment is positively related to ability to pay. Such that those that can pay more should be allowed to do so. This is referred to as vertical equity in finance which implies that those that are different in terms of ability to pay should be treated differently and on the other end horizontal equity requires that those with equal ability to pay be treated equally regardless of geographical location ,gender, age ,place of residence and other characteristics (Wagstaff et al., 1989) .

On the other hand, the libertarian view emphasizes on individual freedom and that the role of government is to protect the rights of individuals (Pauly, MacKinnon, & Varcoe, 2009; Ruger, 2006; Wagstaff et al., 1989). This view entails that individuals can freely choose to purchase health care according to willingness and ability to pay. Thus, libertarian view posits that health care should be distributed according to willingness and ability to pay. Such a view regards health care as a commodity that should freely react to market mechanisms. For example, those that have the ability to pay for better health care should be allowed to do so and that is not deemed as unjust but a manifestation of market forces (Pauly et al., 2009; Ruger, 2006). This view holds when the health care systems is dominated by the private health sector with only little involvement by the government such that government only provides a minimum standard of care (Pauly et al., 2009; Wagstaff et al., 1989). The less strict libertarian view of equity in health financing suggests that there should be income transfers from the rich to the poor through free or subsidized health care (Pauly et al., 2009; Ruger, 2006; Wagstaff et al., 1989).

In this study the egalitarian view of equity in health finance is adopted. The Malawian health financing systems goals clearly reflects the egalitarian view of equity goals where paying for health care is directly related to ability to pay and the health financing systems is predominantly funded by public taxes. As reflected in the Malawi health sector strategic plan (Government of the republic of Malawi, 2017a) the policy goals of the Malawi health systems is to achieve universal health coverage of quality, equitable and affordable health care for all with the aim of improving health outcomes and financial risk protection. Achieving universal coverage and reducing inequalities or inequities in financial burden of health payments require not only monitoring financial protection but also tackling the related determinants of financial protection. Thus, examining the determinants of financial protection may help to understand the unjust social processes behind the observed inequalities or inequities among different subpopulation groups, determine which groups are vulnerable to financial risk due to health payments and track whether different policies put in place achieve its intended purposes.

3.4.4.2 Theory of the demand for health

The 1972 seminal work by Grossman (Grossman, 1972) on the demand for health which resulted into theory of demand for health largely draws from the neoclassical traditional theory for demand of goods. The traditional demand theory assumes that consumers have a preference function that allows them to rank the alternative combinations that maximizes their preference function of goods and services purchased in the market economy

(Grossman, 1999). The Grossman model of demand for health posits that healthcare or medical care is a commodity that individuals consume as an input in a health production function to produce health with the implication that demand for healthcare is derived from the demand for health (Grossman, 1972). That is when individuals demand for health care services they are not demanding for these services per se but they are demanding for better health (Grossman, 1972).

According to Wagstaff simplified version of the Grossman's model (Wagstaff, 1986a, 1986b) the demand for health can be viewed from an economics approach. This approach emphasizes the importance of economic factors in shaping individual's health behavior. The theory of demand for health is based on four assumptions (Wagstaff, 1986b, 1986a). It assumes that health is a desirable commodity demanded by individuals but it is not the only desired commodity, health is determined by health inputs such as health care, food, housing conditions and other equally important factors. These factors enter into the health production function to produce health, health inputs have a positive cost and individuals have a constrained budget to finance the costs of health inputs (Wagstaff, 1986a, 1986b). These four assumptions help to understand an individual's behavior on demand for health.

Wagstaff (1986a) argue that health is desirable and being in good health permits individuals to continue with their social life, to work and to do other things. However, it is clear from individuals' behaviors that health may not be the only desirable commodity. For example, despite health being a desirable commodity individuals may choose to allocate resources to other areas which they consider to be equally important (Wagstaff, 1986a). Moreover, Wagstaff (1986a) argue that if individuals considered health as a commodity above other commodities, they could not engage in behaviors such as smoking, over eating, excess alcohol drinking which are detrimental to their health (Wagstaff, 1986a). From such behaviors it is clear that although individuals consider health as desirable it is not valued above all other commodities. This may explain why individuals may forgo or delay healthcare consumption in preference to commodities which they consider as equally important. This delay in health care seeking has detrimental effects on the individuals' health and affects their welfare in the long run.

The assumption that health is determined by individuals' health inputs provides another way of understanding demand for health. This assumption clearly indicates that individuals have greater control over their health as they affect their consumptions, health care utilization and environment which they live (Wagstaff, 1986a). For example, increased health care utilization by individuals may lead to improved health. Moreover, good health is not a function of health inputs alone but also individuals' knowledge over time. Investments in knowledge has an implication on the production of good health. It is assumed that better educated individuals are better producers of health as they have an efficient way of synthesizing health information and may demand more health care than poorly educated individuals (Grossman, 1999; Wagstaff, 1986a, 1993). Better educated individuals have a better understanding on avoiding risk behaviors such as over eating, smoking, excess alcohol drinking that are detrimental to their health hence they are better producers of health. Thus, individuals' health may be determined by their education.

While health inputs and other consumption activities are important in producing health; there are not without costs (Wagstaff, 1986a). Health inputs like health care, nutritional food, housing conditions will cost money. Individuals have several ways in which they allocate their limited available income to finance health production and consumption activities. This allocation of resources for health production shape the demand for health amongst different individuals and may entail how much health inputs individuals will use which has a subsequent effect on their health (Wagstaff, 1986a).

In summary the theory of demand for health identifies three economic factors including income, prices and health production opportunities which interact to produce health. These factors give an ideal combination of health production and consumption to produce health (Wagstaff, 1986a). For example, individuals with low income may have less to spend on health care consequently this affects health expenditures and health status. Low income may mean a reduction in the quantity of health inputs that enters a health production function to produce health resulting in a decline in health. On the other hand, reducing prices of health inputs may mean an increased utilization of health care consequently improved health status for individuals. The theory of demand for health provides a framework to predict the determinants of health outcomes such as health expenditures and health status.

3.4.4.3 The Andersen's behavioral model for health services use

The Andersen's behavioral model of health care utilization model provides a framework with which to understand health services use. The model was developed in the 1960's with the aim of understanding health services use, measuring equitable access to health care and to help in developing policies that improve equity in access (Andersen, 1995). Andersen's model suggests that health services use is a function of predisposing, enabling and need factors (Andersen, 1995). These factors together help in predicting and understanding health services use. Andersen acknowledges that when the model was developed in the 1960's it was intended to understand health services use as that was the main policy goal rather than understanding cost of using health services (Andersen, 1995). However, the model has been modified and used by several authors to help in understanding health care costs (Du et al., 2019; Dwivedi & Pradhan, 2017; Lehnert et al., 2011)

According to the Andersen model (Andersen, 1995) the predisposing factors include demographic characteristics such as gender and age; social structure measures such as education, occupation, ethnicity and health beliefs all of which may explain how individuals use health services. The enabling factors that may explain health services use include individual personal resources such as income and community resources such as presence of health facilities in the community. These enabling factors influence use of health services in that accessible health facilities with better trained medical personnel must be available in communities where people live and individuals must have income to use health services in those facilities. To use these facilities individuals must have a need. The need factors that are considered include individuals perceived health status, their attitudes and knowledge on health issues. These need factors may indicate individuals' health seeking behavior and consequently explain health services use and health expenditures. The other goal of the model is to measure equitable access to health services. In this case Andersen defines access as inequitable if health services use vary with individuals' income and social structure (Andersen, 1995).

While the Andersen model (Andersen, 1995) was developed to understand health services use it has been adopted in this study together with the demand for health theory and the theory that underpins equity concepts to understand health expenditures. Health expenditures cannot occur without health services utilization as such the Andersen model provide an equally important framework to understand health care expenditure consequently the effects of these expenditures on individuals. In this study the unit of analysis is the household and the predisposing factors included household head demographic characteristics such as the gender, age, education; household composition such as number of children and number of elderly members. Enabling factors included household income measured by household total annual consumption expenditures, distance to the nearest health facility which indicates availability of facilities in the community where people live and work, location of the household whether it is rural or urban. The need factors included presence of chronic illnesses in the household which is an important factor to health services use consequently health expenditures.

Figure 1 displays the conceptual framework that will guide the study. According to Braveman & Gruskin (2003) assessing equity in health requires comparing health outcomes and its determinants among different social groups. Such comparisons allow an assessment of whether policies put in place are leading towards reducing inequalities and inequities as intended. To observe health expenditures; health services use must occur. The Andersen’s behavioral model for health care utilization help to understand how health services use occur. Using the Andersen’s model several household characteristics have been identified in the literature as determinants of health services use consequently health expenditures and financial protection. According to the model health services use is a function of predisposing, enabling and need factors. The predisposing factors include: household age composition such as number of children and elder members in the household, age and gender of household head. For health services utilization to occur as depicted in figure 1, enabling resources such as income, accessible health facilities and well trained health personnel must be available. Enabling factors such as income may reflect household’s ability to pay consequently health services use and payments. Predisposing factors such as health beliefs, social structure together with enabling and need factors such as illnesses or injury influence use of health services consequently health expenditures.

As depicted in figure 1, health shocks in form of illnesses or diseases in the household trigger utilization of formal and informal health care services including inpatient or outpatient care. Utilization of health care services may cause households to incur out-of-pocket payments which are directs costs of illness such as paying for consultation fees, purchases of medication, hospital charges made at point of use of health services. Households may also face other directs costs related to seeking care such as transportation costs to the health facility and special dietary for patients. When out-of-pocket health payments exceed a certain threshold of total consumption expenditure or capacity to pay, the household faces catastrophic health expenditure and impoverishment. The household may also face indirect costs such as loss of income and loss of time by the patient and caregivers which can also lead to impoverishment.

Studies on factors associated with catastrophic health payments and impoverishment have focused on the comparison of financial protection by household factors and neglected the influence of contextual factors such as disparities in economic deprivation status of a region, accessibility of health facilities, health funding levels, disease burden (Borghi et al., 2017; Chirombo et al., 2014; Kazembe & Kamndaya, 2016; Kazembe & Namangale, 2007; Malawi IFPRI, 2019; Mohanty et al., 2018; Ngwira & Kazembe, 2015; Shi et al., 2011). Such contextual factors are the enabling factors to health services use consequently health payments. This study will investigate the impact of household and contextual factors on catastrophic health expenditures and impoverishment to understand how contextual characteristics influence financial protection.

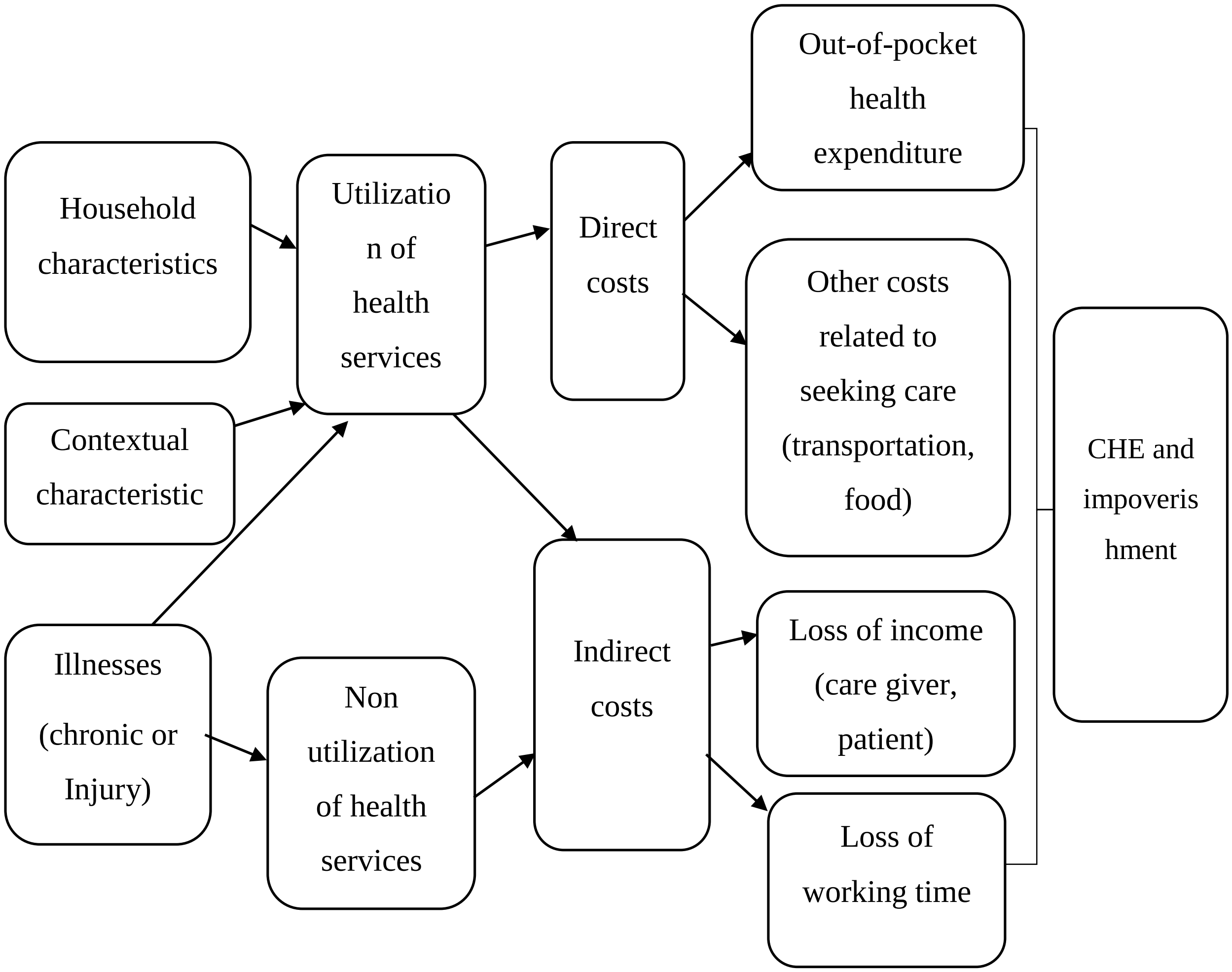

Figure 1: Conceptual framework of the impact of household and contextual factors on CHEs and impoverishment.

Source: Adapted from Mcintyre, Thiede, and Whitehead (2006).

3.5 Empirical evidence on factors associated with catastrophic health expenditures

3.5.1 Catastrophic health expenditures and Household size

Household size is expected to increase the risk of incurring catastrophic health expenditures (CHEs) since a larger household may mean more health care needs for the household. Evidence on the association between household size and CHEs is contradictory. While studies in low income countries mostly sub-Saharan Africa show that larger household size increase the likelihood of incurring CHEs studies in middle income countries show that larger household size has a protective effect. Li et al. (2012)

investigated the factors influencing CHE in China using logistic regression analysis. They found that having a larger family size decreases the likelihood of facing CHEs. Similar findings are also reported by other studies in China by Xu et al. (2015) and Gu et al. (2017). However, studies by Li et al. (2012), Xu et al. (2015) and Gu et al.(2017) did not account for the hierarchical structure of the data in the analysis which may have led to incorrect inference in the parameter estimate. Ignoring the hierarchical structure of the data may result in unbiased estimates as the assumption of independence of the observations is violated (Yazdi-feyzabadi et al., 2018) . Using multilevel logistic analysis to account for the hierarchical structure of the data Shi et al.(2011) and Li et al.(2013) found that an estimated odds of incurring CHE decrease with having a larger family size. Even when the hierarchical structure of the data is accounted for the findings show that larger family size has a protective effect from CHEs. However, in hierarchical and georeferenced data multiple dependencies in the data exists which may not be completely accounted for with multilevel models (Arcaya et al., 2012).

Studies from other middle-income countries provide similar findings that larger family size has a protective effect from CHEs. For example, Minh et al. (2013) examined socio-economic factors associated with CHEs and impoverishment in Vietnam. The authors showed that having a larger family size was significantly associated with lower rates of incurring catastrophic expenditure. Similarly, using logistic regression analysis Ahmed et al. (2018) investigated the association between economic and environmental shocks and observed that a larger family size reduces the probability of facing catastrophic expenditures in Vietnam. Hajizadeh and Nghiem (2011) examined determinants of CHEs for hospital services in Iran using ordered Probit selection model. They showed that the probability of facing higher CHEs decrease with increase in household size. While Hajizadeh and Nghiem (2011) argue that increasing household size increase household income and savings such an assumptions may not be true if many members in the household do not increase the welfare of the household. Rashad and Sharaf (2015) also showed that compared to small household size, large households had a reduced risk of facing CHEs in Egypt. Similarly, Rashad and Sharaf (2015) argue that this result may be due to economies of scale where larger households have more working members and increased income. Nevertheless, the studies by Rashad and Sharaf (2015) and Hajizadeh and Nghiem (2011) did not include a variable in their models to examine whether such an assumption reduces the risk of facing CHEs. Moreover, Amaya-lara and Gómez (2011) showed that the probability of facing CHEs increase with increase in percentage of household working members. Although these studies used hierarchical structured survey data the statistical analysis did not account for hierarchical structure of the data.

On the contrary, studies conducted in low income countries mostly in sub-Saharan Africa show that having a larger family size increase the risk of incurring CHEs. Su et al. (2006) used logistic regression analysis to determine the factors associated with CHEs for 800 households in Burkina Faso. Household size increased the probability of incurring CHEs. Although the association was significant, it was weak which may have been due to small sample size used. Using logistic regression analysis and a nationally representative sample, Barasa et al.(2017) examined the factors related with CHEs in Kenya. The authors showed that having a larger household size increased the estimated odds of incurring CHE. In Tanzania, Brinda et al. (2014) also found that a larger household size was significantly associated with greater likelihood of catastrophic health expenditures. Similarly using a linear probability model Edoka et al. (2017) found that increasing household size increased the likelihood of facing CHE by almost 14 percentage points in Serra Leone. Similar findings are also reported in Botswana and Lesotho by Akinkugbe et al. (2013), in Rwanda by Lu et al.(2012), Mussa (2015a) in Malawi, Zeng et al.(2018) in Zimbabwe and Aryeetey et al. (2016) in Ghana.

From the foregoing, our findings on the relationship between CHEs and household size among studies conducted in low-income sub-Saharan African countries and middle-income countries are inconsistent. Several reasons may explain these inconsistencies. Firstly, the inconsistent in the findings may be due to differences in statistical analysis used in the studies. Although most studies use hierarchical structured survey data; the statistical analysis used does not account for the structure of the data to capture the dependencies in the observations due to the hierarchical structure of the data which may led to incorrect inferences (Chaix et al., 2005). Secondly while larger household size may imply large proportion of household members who work and lower likelihood of facing CHEs through increased income in middle income countries; this may not be true in low-income countries in sub–Saharan African countries where the proportion of household working members is low due to few opportunities. Moreover, a multi country analysis of 15 African countries found that a larger household size increase the likelihood of selling of assets and borrowing when faced with health shocks (Leive & Xu, 2008). Such household coping strategies when faced with health shocks may result in catastrophic health expenditures and impoverishment. In addition, most studies do not account for the number of households working members in the analysis. The review show that only one study by Amaya-lara and Gómez (2011) included this variable together with household size in the analysis and found that increasing the proportion of working household members increases the likelihood of facing CHE. However, when the variable of proportion of household working members is included without the variable household size the analysis showed that increasing proportion of household working members reduced the probability of facing CHE (Amaya-lara, 2016; Buigut et al., 2015).

Thirdly, the mixed findings may be due to different methods and threshold levels used in defining CHEs. For example, Atake and Amendah (2018) found that the likelihood of facing CHEs increased with a larger household size when a lower threshold level was used in defining CHEs and the association was reversed when a higher threshold level was used. Lastly, the conflicting findings may be attributed to household dependency ratios. For example, household dependency ratio is high in most sub-Saharan Africa countries compared to middle- and high-income countries such as China which has a one child policy. These differences imply that for countries with low dependency ratios having a larger household size may mean more working adults and hence more household income (Rashad & Sharaf, 2015).

3.5.2 Catastrophic expenditures and household age composition.

Children under the age of five years and older members of the household are usually more vulnerable to diseases. Such vulnerability places high demand for health care on the household and is likely to increase health expenditure. In an analysis of out-of-pocket health payments and catastrophic health expenditure by age composition in India, Pandey et al. (2018) found that the estimated odds of incurring CHE was 3.26 times greater among households with older people than those with no children or older people after adjusting for other covariates. Similarly, Pal (2012) found that the presence of the elderly and children in the household significantly increased the likelihood of facing catastrophic health expenditure in India. Yardim et al. (2010) examined factors associated with CHE using logistic regression. The authors found that households with members older than 65 years were more likely to face catastrophic expenditures than those with younger children. Similarly, using logistic regression analysis Li et al. (2012) showed that having older members increased the risk of CHE while having younger children decreased the risk. Furthermore, using a sample survey conducted in western and central China and multilevel logistic analysis Shi et al. (2011) found that having a large proportion of members older than 65 years old in the household increased the likelihood of facing CHE. In another study that compared catastrophic health expenses in twelve Caribbean and Latin American countries, Knaul et al. (2011) found that in all the countries households with the elderly had a higher likelihood of incurring catastrophic health expenditure.

While studies found that having younger children under five years protects households from incurring CHEs (Li et al., 2012; Yardim et al., 2010) other studies reported contradicting findings (Amaya-lara, 2016; Ghimire et al., 2018; Li et al., 2013; Minh et al., 2013). Using a sample survey in eastern China and multilevel logistic regression, Li et al. (2013) found that households with younger children under five years old were at an increased risk of CHEs. This result contradicts the findings by Li et al. (2012) and such contradiction may be due to methodological differences . While Li et al. (2012) used a nationally representative sample and did not account for clustering within region Li et al.(2013) used a sample from three provinces and accounted for clustering within region. Using logistic regression, Minh et al.(2013) investigated socioeconomic factors associated with CHEs in Vietnam and found that having younger children was significantly associated with an increased risk of CHE. Similarly, using Probit regression analysis another study showed that having younger children under five years increased the probability of incurring CHEs in Columbia (Amaya-lara, 2016). On the other hand, using logistic regression Ghimire et al. (2018) found that having members less than five years was not significantly associated with probability of facing CHEs in Nepal.

Furthermore, studies conducted in African countries showed that having younger children and the elderly increased the risk of facing CHEs while other studies did not find a significant association. For example, using Tobit regression Séne & Cissé (2015) showed that having children under five years old increased the risk of CHEs in Senegal. In Egypt, Rashad and Sharaf (2015) reported an increased risk of CHEs in households having children less than five years of age and similar findings are also reported by Ayadi and Zouari (2017) in Tunisia. On the contrary, Akinkugbe et al. (2013) using logistic regression found no significant association between CHEs and having children under five years old. In Uganda, Xu et al. (2006) found that the presence of elderly members in the household increased the risk of facing catastrophic health expenditures even after abolition of user fees. while evidence show that households with older members were more likely to face CHEs evidence on the relationship between CHEs and having children under five years old is mixed. These mixed findings may be due to differences in methodologies used in the analysis, socioeconomic context and the health systems financing policies. For example, child and maternal health policies that allow children and women in child bearing age group to access health services for free at point of use may result in lower likelihood of facing CHEs in households with children.

3.5.3 Catastrophic health expenditures and place of residence.

Studies on factors associated with CHEs show that household location is an important predictor of CHEs. Differences in socioeconomic development, disease patterns and accessibility of health facilities between regions may result in variations in income and use of health services consequently ability to pay for health services (Yazdi-feyzabadi et al., 2018). For example, Pandey et al. (2018) found substantial variations in CHE across states grouped according epidemiological transition levels in India. Ghosh(2011) also reported substantial variations in the incidence of catastrophic health expenditure across states in India, though contradictory the study showed that more developed states had higher incidence of catastrophic health expenditures. This finding may indicate the high ability to pay for more expensive services among the more developed states. In India, the results of the poverty impact of health payments also indicated considerable variations in poverty due to health payments across states with wealthier states having larger proportions of households falling into poverty (Berman, Ahuja, & Bhandari, 2010). Similarly, in an assessment of catastrophic health spending by region of residence in Brazil, Barros et al. (2011) showed that there were regional differences in the incidence of catastrophic health expenditures with higher proportions of households in wealthier regions facing catastrophic health expenditures. However, the authors observed that the regional differences did not follow socioeconomic development of the regions as the proportion of households incurring catastrophic health expenditures in other wealthier regions was low.

In a review of catastrophic health expenditures and impoverishment in sub Saharan African countries Njagi et al. (2018) observed that the importance of location of residence as a predictor of CHEs varies with the study setting. Similarly, a systematic review by Azzani et al (2019) found that place of residence is related to catastrophic health expenditure and that households in rural areas were at an increased risk of catastrophic health expenditure. Other Studies have shown that households in rural areas and less developed regions are more likely to incur CHEs than households in urban areas and more developed regions. For example, using Probit regression analysis Amaya-lara (2016) examined the relationship between household geographical location and CHEs in Colombia. The findings showed that regions with more households in rural areas have a higher probability of incurring CHEs. Similarly, Li et al. (2012) found that households in rural areas were at an increased risk of financial catastrophe. Although the descriptive analysis showed that households in wealthier regions had lower probability of facing CHEs, region was not included in the logistic regression analysis. A study by Ghimire et al. (2018) included region in the logistic regression analysis and found that households from well-developed regions were less likely to face CHEs in Nepal. Such geographic disparities within countries may indicate clustering in CHE within regions due to contextual effects such as differences in economic development among regions, disease pattern and accessibility of health facilities. However, these studies did not use statistical models that adjust for clustering of households within regions to account for the effect of contextual factors.

Using multilevel logistic model to account for clustering of households within region, Li et al.(2013) showed that region is significantly associated with probability of incurring CHE. The findings showed variations in CHEs within regions and households in low income areas were at an increased risk. Furthermore, another study using multilevel logistic regression to account for clustering of households in urban and rural areas in Bangladesh, showed that households in rural areas have a higher probability of facing CHEs than households in urban areas (Khan et al., 2017b).

While other studies show that households in rural and less developed regions are more likely to face CHEs findings by other studies are contradictory. For example, using logistic regression analysis a study in Georgia showed that households in the capital city had a higher probability of facing CHEs than households in western and eastern region of Georgia (Gotsadze et al., 2009). However, the study did not adjust for clustering of households within regions. Similar counterintuitive findings are reported by a study in Iran (Yazdi-feyzabadi et al., 2018). Yazdi-feyzabadi et al. (2018) investigated the main factors influencing the likelihood of facing CHEs and used logistic random effects model to adjust for households clustering within provinces. The authors found that households in less developed regions had lower rates of CHEs while the rate was higher in developed regions. On the other hand, another study using a multilevel logistic regression found that CHE was equally higher in more developed and less developed regions in India (Mohanty et al., 2018). Thus, even when clustering of household location is accounted for the findings on the relationship between catastrophic expenditures and its associated factors are mixed. A plausible explanation may be multiple clustering effects in complex survey data. For geographically clustered surveys spatial clustering effects may exist which is not accounted for when standard multilevel logistic regression models are used and result in biased parameter estimates (Ma et al., 2018). Thus, in addition to adjusting for clustering within regions there is need to account for spatial clustering effects inherent in complex surveys used in analysis of risk factors of catastrophic expenditures and impoverishment.

Studies conducted in African settings have also reported within country geographic disparities in catastrophic health expenditures (McIntyre et al., 2018). Evidence show that households in rural and less developed regions have an increased probability of facing CHE (Akinkugbe et al., 2013; Barasa et al., 2017; Mussa, 2015b; Séne & Cissé, 2015). For example, using tobit regression analysis a study in Senegal showed that catastrophic health expenditures is significantly greater in rural areas than urban areas (Séne & Cissé, 2015). Similarly, a study in Kenya showed that households located in marginalized region of the country were at an increased risk of incurring CHE (Barasa et al., 2017). On the contrary, a study in Zimbabwe showed that households in urban areas were more likely to face catastrophic health expenditures (Zeng et al., 2018) and in Ghana households in a less deprived district had a greater risk of facing catastrophic health expenditures (Nguyen et al., 2011). This result in Ghana was attributed to more private and mission health facilities in the district which may have resulted into higher prices (Nguyen et al., 2011). Despite that these studies use nationally representative sample data which naturally introduce geographical clustering of observations within regions none of the studies in the African setting adjusted for clustering in the models. Such geographic disparities in CHE within countries may require further investigation of the effect of geographic location on CHE by adjusting for within neighborhood and spatial effects in the statistical models.

3.5.4 Catastrophic health expenditures and economic status

There is more evidence on the relationship between economic status and catastrophic expenditure. Evidence shows that households in higher income groups are less likely to face CHEs. Economic status determines household capacity to pay for health services this can influence household expenditure behavior consequently CHEs. Although households in higher income group have higher health expenditure the incidence of CHEs is higher in lower income groups indicating low capacity to pay for such groups (Su et al., 2006). Gotsadze et al.(2009) showed that households in the richest income group were less likely to incur CHEs than households in the poorest income group. Similarly, Li et al. (2012) found an inverse association between economic status and catastrophic expenditure. This finding is also observed by other studies in China (Li et al., 2013; Shi et al., 2011). Using Probit regression analysis Amaya-lara & Gómez (2011) observed that households in lower income group had a higher probability of incurring CHEs. Furthermore, using multilevel logistic analysis another study in Bangladesh found that higher socioeconomic status reduced the likelihood of facing CHE (Khan et al., 2017b). In Nepal, Ghimire et al.(2018) showed that households in lower income groups were more likely to face CHEs than households in higher income groups. Another study observed that households in the poorest income quintile were more than 4 times more likely to incur catastrophic health expenditures compared with households in the richest income quintile (Rahman et al., 2013). In Myanmar Myint et al. (2019) also found that higher income decreased the risk of facing CHEs. However, this contradicts their bivariate findings on the incidence of catastrophic health expenditures in which incidence of CHE was lower in households in poorest quintile. This may be due to failure of most studies on catastrophic health expenditures to captures households which forgo seeking care thereby underestimating the incidence of CHE among households in poorest income group. Moreover, the study used a subnational sample which was mainly rural and such poor rural households may forgo seeking care to avoid incurring catastrophic expenditure and being impoverished.

Similar findings are reported in studies conducted in African countries. Most studies in the African setting found that increasing household income reduced the likelihood of incurring CHEs. For example, Su et al.(2006) found that the odds of facing catastrophic expenditure was higher among households in lower income groups. Onwujekwe et al.(2012) showed that incidence of catastrophic health spending decreased with increase in household socioeconomic status and Onoka, Onwujekwe et al. (2011) found significant differences in catastrophic health expenditures across socioeconomic status with large proportion of households in poorest income incurring catastrophic expenditures. Similarly, Ekman (2007) found that increasing household income reduced the risk of facing CHEs. Similar finding are also reported by Barasa et al. (2017), Rashad and Sharaf (2015) , Akinkugbe et al. (2013) and Masiye et al.(2016).

Studies conducted in developed countries also reported that household income is negatively associated with CHE. Using logistic regression analysis Kronenberg and Pita (2014) showed that increase in income reduced the probability of incurring catastrophic health expenditures. Although the impact of income was smaller which indicates smaller differences across income groups it was significant. Similarly, Habicht et al. (2006) and Qosaj et al. (2018) found that the probability of facing CHE increased with lower household income in Estonia and Kosovo respectively. On the contrary, Chantzaras and Yfantopoulos (2018) found that households in higher income groups were at an increased risk of incurring CHE in Greece during the economic crisis. This counterintuitive finding may be because of health expenditures on more advanced treatments among higher income households and failure of lower income groups to access care during the economic crisis.

These results of the negative association between CHEs and expenditure quintile provide a need for targeting of the vulnerable poor who are at greater risk of facing CHEs. However, the problem is always on how we can identify the vulnerable poor who are at greatest risk of CHEs. Targeting households at risk may require the use of spatial statistical models which may help to identify areas and consequently households at risk of catastrophic health expenditures.

3.5.5 Catastrophic health expenditure, chronic illnesses, and hospitalizations

The growing burden of chronic illnesses pose a significant financial risk to households. Households with chronically ill members constantly seek for health care resulting in higher health expenditures. A review by Kankeu et al. (2013) found that households in LMICs spend a significant amount of household resources on chronic non communicable chronic diseases (NCDs) resulting in financial catastrophe and impoverishment. Li et al. (2012) found that households with at least one member with chronic non communicable illness had a higher probability of incurring CHEs in China. Similarly, Li et al.(2013), showed that the probability of facing CHE increased with increase in number of chronically ill members in the household. In a study that looked at a sample of households with chronic illnesses such as diabetes ,tumors, hypertension and chronic pulmonary diseases; Jiang et al. (2012) showed that catastrophic health expenditures were greater in households with chronic illnesses. Similarly, another study analyzed a sample of patients with chronic diseases by health insurance status and found that a lower proportion of insured families incurred catastrophic expenditures due to chronic diseases than noninsured families (Sun et al., 2009).

These findings agree with findings from other countries. For example, in Georgia Gotsadze et al.(2009) found that households that incurred expenditure due to chronic illnesses were 40% more likely to incur catastrophic expenditure than households without chronic illnesses. In Nepal, Saito et al. (2014) found that households with one or more episodes of non-communicable diseases such as diabetes were at a higher risk of facing catastrophic health expenditures. Another study in Nepal also showed that households having at least one member with chronic illness were 48% more likely to face catastrophic expenditure (Ghimire et al., 2018). A study in one rural district in Vietnam on the financial burden of non-communicable diseases found that the risk of catastrophic health expenditure was greater in households with at least one member with chronic disease (Minh & Xuan, 2012). In Thailand, Somkotra and Lagrada (2009) found that households with chronically ill members were more likely to incur catastrophic health expenditures even after the implementation of the national universal health coverage policy. In Korea a study on the association between chronic diseases and catastrophic health expenditure found that households with members suffering from chronic diseases such as kidney failures had an increased probability of incurring CHE (Choi et al, 2015). Similarly, Datta et al. (2019) in a study on the association between costs of diabetes, hypertension and catastrophic expenditures found that households with members who were diabetic and with hypertension had higher health expenditures and incidence of catastrophic expenditures in Pakistan. A multicounty study assessing the financial impact of having diabetic individuals in 35 developing countries also showed that individuals with diabetes had higher out-of-pocket expenditures and probability of incurring catastrophic health expenditures than similar non diabetic individuals (Spangler et al, 2012). In Serbia, Arsenijevic et al. (2013) found that households with members having chronic illnesses such as diabetes and cardiovascular diseases were more likely to be impoverished and had a higher risk of facing catastrophic health expenditures.

Chronic illnesses place a burden on households as they constantly seek for health care, this results in high health expenditures that are catastrophic and impoverishing. Even with high universal coverage to protect households from financial risk due to illnesses, chronic illnesses play an important role on the risk of incurring catastrophic health expenditures and impoverishment (Dugee et al, 2019) . This finding entails the need to consider the growing burden of non-communicable chronic illnesses and its impact on households when designing financial protection mechanisms.

Studies focusing on the elderly, a sub population group in which chronic illnesses are more prevalent have also reported similar findings. Jacobs et al. (2016) found that the incidence of illnesses was greater among older people and that older people spent more on health in Cambodia. Moreover, the authors found that chronic illnesses significantly increased the risk of incurring catastrophic health expenditure among older people. Another study also showed that the incidence of catastrophic health expenditures was significantly greater in households with chronically ill patients among the sample of older people in China (Wang et al., 2015). Similarly, Arsenijevic et al. (2016) found that chronic illnesses such as cardiovascular diseases and diabetes mellitus increased the risk of incurring catastrophic health expenditures among older people in 15 European countries. In India, Brinda et al.

(2015) also showed that chronic illnesses had a substantial financial burden among older people. The authors in India found that chronic illnesses such as diabetes mellitus, hypertension, stroke, and chronic pulmonary disease increased the probability of incurring catastrophic health expenditures among older people. Older people have more health care needs since chronic illnesses are more prevalent among this population group. This puts a financial burden among households resulting in CHE and impoverishment.

Studies conducted in African countries report similar findings. Using a cross sectional sample from one district in Burkina Faso Su et al.(2006) found that households with chronically ill members were more likely to incur catastrophic expenditure than those without chronically ill members. Although the study did not use a nationally representative sample and the sample size was small studies that have used nationally representative sample and a larger sample report similar finding. For example, studies by Barasa et al.(2017), Rashad and Sharaf (2015) and Mussa (2015a) found that households with a chronically members were at an increased risk of incurring catastrophic expenditure. A study on the financial burden of chronic non communicable diseases in rural Malawi also showed that a larger proportion of households faced catastrophic health expenditures and impoverishment due to chronic non communicable diseases (Wang et al., 2016). Thus, chronic illness puts a financial burden on households as they constantly seek care resulting to financial catastrophe and impoverishment.

In addition, hospitalization is another important risk factor for CHEs. Hospitalization in the household could lead to household welfare loss due to loss of productive time and loss of income by care givers. Households with hospitalized members may sell assets, use savings, and hire external labor as a coping mechanism. A study on coping with out-of-pocket payments in 15 African countries found that households with inpatients expenditures are more likely to sell assets and borrow as a means of coping with bills due to hospitalization (Leive & Xu, 2008) .This puts pressure on the household limited resources and leads to catastrophic expenditures and poverty.

A review of evidence in LMICs on the impact of out-of-pocket payments and indirect cost of illness also found use of available cash and savings as the immediate coping strategy used by households when faced with illnesses which required hospitalizations (Mcintyre et al., 2006). Moreover, a study on the drivers of catastrophic health expenditure in 51 countries showed that a larger proportion of households with out-of-pocket expenditures on hospitalization incurred catastrophic health expenditures (Saksena et al., 2010). A study in Georgia also showed that households that incurred a cost of hospitalization were at an increased risk of facing CHEs (Gotsadze et al., 2009). Similarly, Li et al.(2013) found that the odds of facing CHEs increased with an increase in hospitalizations and Amaya-lara(2016) also showed that households that required inpatient services were at an increased risk of facing CHEs. In another, study in Argentina Cavagnero et al.(2006) showed that households with inpatient expenditures were at an increased risk of catastrophic health expenditure and the impact of inpatient expenditures was greater than outpatient expenditures. Similarly, Oudmane et al.(2019) also found that the impact of expenses due to hospitalizations on the risk of incurring catastrophic expenditures was greater. Thus, although hospitalization is an important risk factor for catastrophic expenditures only a few studies have included it in the analysis.

3.6 Inequality in catastrophic health expenditures

Inequality in CHEs is a major concern, especially when households in lower income quintile face CHE more than richer households (Akazili et al., 2017). CHEs may reflect social inequality in access to and cost of health care and lack of effective prepayment financing mechanisms such as social insurance scheme (Li et al., 2013; Shi et al., 2011). These inequalities exist due to economic factors such as income levels and geographic factors such as accessibility of health services (Akazili et al., 2017). Evidence shows that inequality in CHEs is concentrated in households with lower socioeconomic status and socio-economic status accounts for a large proportion of inequality in CHE (Akazili et al., 2017; Akinkugbe et al., 2013; Gu et al., 2017; Islam et al., 2017; Kavosi et al., 2012; Xu et al., 2015) .

Hajizadeh and Nghiem (2011) found that inequality in CHE was concentrated among households in lower income group in Iran. However, the analysis did not include decomposing inequality of CHE into its determinants to understand the contribution of each factor to inequality. Kavosi et al. (2012) in a longitudinal study of one district in Iran examined inequality in CHEs using a concentration index. The concentration index of inequality was decomposed into determinants of CHEs based on logistic regression model. The authors found that the concentration indices were negative indicating greater likelihood of incurring CHEs among poor households. It was observed that economic status account for a large proportion of inequality in CHEs. However, the sample was small and not nationally representative which prevents generalization of the results. In another study in Iran, Moradi et al. (2018) examined inequality in CHE using a nationally representative sample. The corrected concentration index was used to examine inequality and decomposition of inequality was based on logistic regression model. The authors reported income as the major contributor to inequality in CHE in urban and rural households and inequality was concentrated among poor households.

Another study examined the change in inequality in CHE using concentration index for inequality and decomposition of the index into determinants of CHE was based on the logistic regression model (Xu et al., 2015) . Similarly, this study observed that inequality in CHE was more concentrated among poor households and that economic status and household size accounted for a large proportion of inequality in CHE (Xu et al., 2015).

There is a consensus among studies conducted in African setting that CHE is concentrated in poor households. Chuma and Maina (2012b) measured the distribution of catastrophic expenditure in relation to household income using concentration indices in Kenya. The authors found that the concentration indices were negative indicating CHEs was higher in poor households and observed larger inequalities between highest and lowest income households. Similarly, Akinkugbe et al. (2013) assessed inequality in CHEs in relation to income quintile in Lesotho and Botswana using concentration curves. CHEs was concentrated among the poor in Botswana and in Lesotho there was no difference in CHEs between the rich and the poor. Although there is an agreement in these studies; our review found that no study within sub–Saharan Africa that included a decomposition analysis of inequality in CHEs into its determinants.

3.7 Statistical models for analyzing factors associated with catastrophic health payments and impoverishing effects of health payments

While multilevel models provide an approach to account for variations in catastrophic health expenditures (CHEs) due to both household and contextual level factors when examining factors associated with CHE, the models fail to account for the variations completely. Using a multilevel logistic model, Li et al. (2013) examined areal and household level factors influencing CHEs. The authors found that in addition to household level factors regional location of the household was significantly associated with CHEs. This implied dependence in catastrophic health expenditures for households within the same region providing evidence for the need to account for areal level factors when examining factors associated with CHEs. Much as the multilevel model was appropriate to account for variations in CHEs due to the different level of factors the model may have underestimated the regression coefficients standard errors leading to incorrect inference as the standard errors are adjusted for non-independence of catastrophic expenditures within the same region and not spatial dependence in the regions. These findings are consistent with another study by Shi et al. (2011). Using a multilevel logistic model, Shi et al. (2011) investigated the effect of village and household level factors on CHEs and impoverishment and showed that village level factors such as village deprivation level and adult literacy level were significantly associated with CHEs. However, a comparison of the multilevel logistic model and ordinary logistic model showed similar results of parameter estimates indicating that the multilevel model may have partially accounted for the variations in CHEs. Thus, multilevel models partially account for variations in CHEs.

Multilevel model may partially account for variation in CHEs because it assumes that observations are correlated within broad areas such as village, region, state or districts and not over a continuous geographic space (Ma et al., 2018, 2017). Chaix et al. (2005) compared a spatial model that assumes correlation of outcome variables such as CHEs over a continuous geographic space and a multilevel model. Using health care utilization as the outcome variable, they showed that in comparison to the spatial model; spatial variation was unaccounted for in the multilevel model even though the model showed a significant variation in health care utilization. This resulted in overestimation of the significance of the effect of contextual factors on the outcome variable leading to wrong inferences. Thus, using spatial models that account for the correlation of outcome variables over continuous geographic space provide complete information on the spatial distribution of the outcome variables.

Although the studies by Li et al. (2013) and Shi et al. (2011) provide evidence that multilevel models account for the variation in CHE due to household and contextual factors they fail to provide complete information on the variation in catastrophic expenditures and impoverishing effects of health expenditure as spatial dependence in the data is not accounted for. This offers the need to explore variation due to contextual and household factors in CHEs and impoverishment due to health payments using multilevel spatial models.

3.8 Incidence of catastrophic expenditure and impoverishment

Studies conducted in sub–Saharan Africa show that the incidence of CHEs vary depending on threshold levels and measures of household expenditure used in defining CHEs. Other studies have used threshold levels defined in terms of total household expenditures while others used household nonfood expenditures. For example, using threshold of 40% of household nonfood expenditure Su et al. (2006) found that the 8.66% of households incurred catastrophic expenditure in Burkina Faso. In Kenya, Chuma and Maina (2012b) found that 4.6% of households incurred CHEs while using more recent similar data Barasa et al.(2017) found that the estimated incidence was 4.52%. Akinkugbe et al. (2013) estimated the incidence of CHEs in Botswana and Lesotho at 7.43% and 1.25% respectively. In Swaziland, Ngcamphalala and Ataguba (2018) found that 2.7% of households faced catastrophic expenditures. Similarly, in Ghana Akazili et al.(2017) found that 2.43% of households incurred catastrophic expenditures. At a threshold level of 40% of household nonfood expenditure Rashad and Sharaf (2015) reported an estimated incidence of 6% in Egypt and in Malawi, Mchenga et al.(2017) found that 0.73% of the households incurred CHE. Thus, our review show that the incidence of catastrophic spending at 40% threshold level in African countries is between 0% and 7.43%. These low incidences in CHEs may not necessarily indicate financial protection from risk of illness as health systems in most of the countries face challenges such health funding and lack of well-trained medical personnel. It should be observed that there are limitations in the literature regarding measurements of CHEs. One such limitation is that the definition of CHEs fails to capture households that forgo seeking care due to high costs which leads to underestimation of CHEs. It is possible that in most African countries' households forgo care due to high costs. Thus, the lower incidences in CHEs may not necessarily mean financial protection.

Estimates of the impact of health expenditures on poverty from studies conducted in Africa show that households are pushed into poverty due to health payments. For example, Rashad and Sharaf (2015) found that an additional 7.4% of the population was impoverished due to health payments in Egypt. In Uganda Kwesiga et al. (2015) showed that 4.2% of the population is impoverished due to health payments. In Kenya, the incidence of impoverishment decreased from 2.7% in 2012 (Chuma & Maina, 2012b) to 1.17 % in 2017 (Barasa et al., 2017) when more recent data was used.

Other countries have also reported low incidence of impoverishment. For example, Ngcamphalala and Ataguba (2018) showed that only 1.0% of the population in Swaziland was impoverished and Mchenga et al. (2017) found that only 0.93% of the population was impoverished due to health payments in Malawi. Such low estimated incidence does not mean that a larger proportion of the population is protected from financial risk. This is because in most African countries prepayment financing mechanism is not well developed as such many households may forgo seeking care to avoid being impoverished. Thus, from the forgoing review, estimated incidence of impoverishment range between 0% to 7.4% in African countries.

3.9 Research gaps

Although ordinary logistic regression models are used to account for variation in catastrophic health expenditures and impoverishment they fail to account for the hierarchical structure of the data. Variations in catastrophic expenditures and impoverishment due to health payments are mostly attributed to household income, urban, rural and regional differences, chronic diseases, utilization of healthcare services and age composition of the household (Ahmed et al., 2018; Barasa et al., 2017; Li et al., 2013; Li et al, 2012; Mohanty et al., 2018; Shi et al., 2011). For example, using logistic models' majority of these studies found that households in rural and poor regions are at a risk of catastrophic health expenditures. These significant urban, rural and regional variations may mean that catastrophic expenditures vary within urban areas, rural areas and regionally because of context related factors such as health seeking behavior, disparities in disease burden, regional economic disparities, disparities in availability and access to health services (Shi et al., 2011; Yazdi-feyzabadi et al., 2018). Nevertheless, ordinary logistic regression models fail to account for variations due to contextual related factors. This is because ordinary logistic regression models do not account for hierarchical structure of the complex survey data mostly used in the analysis of risk factors of catastrophic health expenditures.

Multilevel models provide an approach to account for contextual factors in examining factors associated with CHEs and impoverishment when using complex survey data. The models account for the hierarchical structure of the data where for example households are nested within villages, districts or states (Li et al., 2013; Mohanty et al., 2018; Shi et al., 2011; Yazdi-feyzabadi et al., 2018) .In such cases, the assumption is that observations for households within the same neighborhood are correlated. Using single level ordinary logistics regression for such hierarchical data results in biased standard errors for the parameter estimates (Li et al., 2013) which leads to incorrect inferences and wrong conclusions. Previous studies that have used multilevel logistic regression models to account for the relative importance of contextual factors influencing CHEs and impoverishment found large significant variation between and within regions which are neglected when using ordinary models (Chaix et al, 2005; Khan et al, 2017a; Li et al., 2013; Shi et al., 2011; Yazdi-feyzabadi et al., 2018). For example, Mohanty et al. (2018) using multilevel models to examine the relative importance of states, districts and village in the variation of CHEs found large significant differences in CHEs between and within states. The authors argue that such variations cannot be attributed to household level factors alone but to contextual factors such as differences in cost of medication, type and utilization of health services, availability of health infrastructures and disease pattern at village and state level. In addition, Mohanty et al.(2018) and Yazdi-feyzabadi et al. (2018) provided maps to illustrate spatial clustering and patterns of catastrophic expenditures and identify households at greatest need of protection from financial catastrophe.

Although multilevel models account for contextual level variations, they fail to provide complete information since such models do not account for spatial dependence in the data. Multilevel models account for contextual variations by assuming that observations within the same neighborhood are correlated. However, observations in neighborhoods which are in close geographical proximity may also be correlated (Chaix et al., 2005; Ma et al., 2017) . Consequently, the need to utilize spatial models that provide complete information on the spatial distribution of CHEs and impoverishment due to health payments. Such models allow the relationship between CHEs, impoverishment due to health payments and other variables to vary across continuous geographic space by assuming correlation in CHEs between neighborhood (Brunsdon et al., 1998; LeSage, 1999; Ma et al., 2018, 2017). Using multilevel spatial models will also help to map areas at risk and understand the spatial patterns in the association between catastrophic health expenditure and its risk factors. This could be useful in designing targeted interventions for financial risk protection.

Socioeconomic inequality in catastrophic out-of-pocket expenditures is a major concern, especially when households in lower income quintile face catastrophic expenditures more than richer households (Guo et al., 2016). Catastrophic out-of-pocket health expenditures may reflect social inequality in access to and cost of health care and lack of effective social insurance scheme(Li et al., 2013; Shi et al., 2011). These inequalities exist due to economic factors such as income levels and geographic factors such as accessibility of health services (Akazili et al., 2017). Evidence shows that socio-inequality in catastrophic expenditures is concentrated in households with a lower socioeconomic status and household socio-economic status accounts for a large proportion of inequality in catastrophic expenditures(Akazili et al., 2017; Akinkugbe et al., 2013; Guo et al., 2016; Islam et al., 2017; Kavosi et al., 2012; Xu et al., 2015). However only a few studies in Africa (Akinkugbe et al., 2013; Barasa et al., 2017; Chuma & Maina, 2012a) have investigated inequality in CHE and these studies did not decompose inequality in CHE into its determinants. As such, the extent and contribution of determinants to inequality remains unclear. This study will fill the gap by investigating inequality and decomposing inequality in CHE into its determinants. Measuring and decomposing inequality in catastrophic expenditures may help to quantify the existing inequalities, explain the contribution of each determinant to inequality and design policies towards reducing such inequalities.

3.10 Chapter summary

Studies on factors associated with CHEs, incidence of catastrophic out-of-pocket expenditures and its impoverishment, statistical models used to study the risk factors of CHEs, impoverishment and inequality in CHEs have been discussed. Firstly, Evidence show that several household factors are associated with CHEs. However, the evidence on the effect of factors such as household size, having children under five years old, and household location is inconsistent. For example, while other studies find that a large household size decrease the risk of CHE (Hajizadeh & Nghiem, 2011; Li et al, 2012; Minh et al., 2013; Rashad & Sharaf, 2015; Shi et al., 2011; Xu et al., 2015) others find that a large household size increase the risk of facing CHE (Akinkugbe et al., 2013; Barasa et al., 2017; Edoka et al., 2017; Su et al., 2006).

Secondly, the review found that most studies use logistic regression models to study effects of risk factors associated with CHEs. Although contextual factors are included in the analysis and studies use complex survey data with hierarchical structure they fail to account for the hierarchical structure of the data. Using ordinary logistic regression model when the data is hierarchical may fail to properly account for the effect of contextual factors. Only a few studies have accounted for the hierarchical structure of the data in examining the effect of contextual factors on CHEs using multilevel models. However, multilevel models may fail to completely account for the effect of contextual factors as standard errors in such models are adjusted for non-independence of observations within the same region or neighborhood and not spatial dependence in the observations (Chaix et al., 2005). This may lead to incorrect inferences, hence the major focus of this study is explore the use spatial multilevel models, evidence shows that such models provide complete information on the effect of contextual factors (Chaix et al., 2005; Xu, 2014b). This literature review found no study in sub Saharan Africa and in Malawi that has accounted for the hierarchical structure of the data and examined the effects of contextual factors on CHE. Mussa,(2015a) examined factors associated with CHE in Malawi using beta inflated regression model, although region was included in the analysis the model used does not account for the hierarchical structure of the data. Moreover, the effect of contextual factors was not studied.

Thirdly, the review found consistent evidence that inequality in CHE is concentrated among poor households. However only few studies have decomposed inequality in CHE into its determinants to understand how each factor contribute to inequality. For example, Kavosi, et al.(2012) and Moradi et al. (2018) show that economic status account for a large proportion of inequality in CHE in Iran. In China, Xu et al. (2015) show that household size and economic status are the factors that accounts for a large proportion of inequality. While evidence from two studies in African setting show that inequality is concentrated among poor households (Akinkugbe et al., 2013; Chuma & Maina, 2012b), at the time of the review there was no study that had decomposed inequality in CHEs into its determinants. Thus, further decomposition analysis of inequality in CHEs is needed to understand factors contributing to inequality.

CHAPTER 4: RESEARCH METHODOLOGY

4.1 Introduction

The thesis comprises of four specific objectives related to the main objective as presented in chapter one. This chapter describes how the research methodology used to address each of the four specific objectives ultimately the main objective was constructed. Section 4.2 describes the research philosophy, approach, strategy, data choice and design. Section 4.3 describes the research techniques and procedures including description of the secondary data source that was used in the thesis, detailed description of the sampling designs and sample size, the survey instruments and detailed information collected by the survey. Section 4.3 also gives the definition of the key concepts and the description and level of measurements of the variables subsequently used in the data analysis. Lastly the section describes the data analysis techniques used for each specific objective including measurements of the outcome variables and how the outcome variables were estimated.

In constructing the research methodology for the study, the research onion model developed by Saunders and colleagues (Saunders et al., 2007) was adopted. According to the model an effective research methodology should be constructed based on six steps which the authors refer to as layers synonymous with layers in an onion. These steps are the research philosophy, approach, strategy, choice, time horizon, techniques, and procedures. The sections that follow describe these steps which are linked together to give a detailed research methodology that was used in this study.

4.2 Research philosophy, approach, strategy, choice, and design

Two philosophical views underpin a research process. These views are ontological and epistemological views. Ontology views reality of knowledge as something that is different from person to person and that there is no single reality while epistemology views reality as one single thing that does not change from person to person and that there is acceptable reality of knowledge (Saunders et al., 2007). These philosophical assumptions about reality of knowledge affects how research is conducted as these determines the research approach, strategy and design that is adopted (Creswell, 2014; Melnikovas, 2018; Saunders et al., 2007) The research philosophies that are based on the epistemological view are positivism and realism while those based on ontological view are constructivism or interpretivism, pragmatism and transformative (Creswell, 2014). The study adopted an epistemological philosophical view specifically a positivism research philosophy to understand catastrophic health expenditures, impoverishing effects of health expenditures and the associated factors. It involved applying methods to determine and assess factors associated with catastrophic health expenditures, impoverishment due to health expenditures. According to Creswell positivism research philosophy is a deterministic philosophy in which researchers believe that causes determine outcomes (Creswell, 2014). A positivist tries to be objective by carefully constructing measures of what is considered to be acceptable knowledge and is concerned with developing knowledge on relationships between the measured variables (Creswell, 2014; Saunders et al., 2007).

In line with positivism research philosophy, the study adopted a deductive quantitative approach. It uses quantitative data from a cross sectional survey design where data for the sampled population were collected at one point in time. The study uses secondary data from a nationally representative observational survey.

4.3 Research techniques and procedures

4.3.1 Data source

The thesis used data from the fourth Malawi integrated household survey (IHS4) collected by National Statistical Office of Malawi (NSO) from April 2016 to April 2017. The thesis also used district boundary data obtained from NSO to compute the spatial weight matrix which provided information on how the districts are connected to each other in the subsequent spatial analysis. The NSO is a government institution mandated by the statistics act of parliament to collect data for purposes of national planning and evidence based policy formulation. The integrated household surveys are repeated cross sectional design surveys conducted every five years. The first integrated household survey IHS1 was conducted in 1997/98, IHS2 in 2004/05, IHS3 in 2010/11 and the most recent IHS4 at the time of writing this thesis was conducted in 2016/17. These surveys provide representative samples at national, district, urban and rural level which provide reliable estimates at these levels. The aim of the fourth integrated household survey was to provide standard poverty and socioeconomic indicators to support evidence based policy formulation and monitor progress towards achieving goals set in the Malawi growth development strategy and the

Sustainable Development Goals (SDGs) and to provide an understanding of the living standards of the population in Malawi (NSO, 2017). The IHS4 was implemented in partnership with World Bank and Millennium Challenge Account which provided financial support and technical assistance.

4.3.2 Sampling designs and sample size

The IHS4 used a stratified two stage sampling design. In the first stage,780 enumeration areas stratified by urban and rural strata were selected with probability proportional to size. The second stage used a random systematic sampling to select 16 primary households and 5 replacement households from the household listing in each sample enumeration area. A total of 12480 households were interviewed and data for 33 households were lost during data management. Data for a total sample of 12,447 households covering 53,885 individuals were collected and this represented a 99.7% response rate. The unit of analysis in this study is a household and the analysis used data for all the 12,447 households on which data is available.

4.3.3 Data collection and instruments

The fourth integrated household survey collected data using questionnaires through computer assisted personal interviews. Four types of questionnaires were used: the household, agriculture, fisheries, and community questionnaires. This study used data from the household questionnaire. The household questionnaire collected information on households' economic activities, demographics, welfare, and other household characteristics. The questionnaire covered several topics which mainly assessed the poverty dynamics of households which included consumption expenditure, savings, income, food security, assets, vulnerability, social protection, education, and health. Particularly, data on the health module collected information on health spending on illnesses and injury over one-month recall period, expenditures on hospitalizations at a health facility and at a traditional healer over twelve months' recall period, chronic illnesses, and diagnosis source of illnesses. The consumption expenditure module collected information on food expenditures and nonfood expenditures. The food consumption expenditures information collected over a one-week recall period included expenditures on items such as cereals, roots, tubers, nuts, pulses, vegetables, meat, fish, meat products, milk, milk products, fruits, sugar, fats, oils beverages and other miscellaneous items. For the nonfood consumption expenditure different recall periods were used for different items. Expenditures for items such as public transport, charcoal, kerosene, cigarettes, newspapers, and magazines were collected over one-week recall period. Expenditures for items including groceries, wages paid to servants, motor vehicle service, mortgage, repairs to household item were collected over one-month recall period and clothing over three-month period. Expenditures for items such as carpets, rugs, linen, sleeping mats, construction materials, council rates, funeral and marriage ceremony costs were collected over twelve months' period. The aggregated data for all consumption expenditures were annualized and for consistency in this study the findings for annual consumptions expenditures are reported. More detailed information on the other items collected in the household questionnaire are provided in the Malawi fourth Integrated household Survey report (NSO, 2017).

4.3.4 Operational definitions of the key concepts

4.3.5 Out-of-pocket health payments

In this study out-of-pocket health payments are defined as payments made at a point of use of health services (Xu et al., 2003) and estimated as total annual health payments on consultation fees, diagnostic tests, medicines, outpatient and hospitalization or inpatient fees. These also include payments on traditional medicine and inpatient fee for staying at traditional healers however it excludes other costs incurred when seeking health care services such as transportation, accommodation, and food costs.

4.3.6 Total household income

We used total annual household consumption expenditure as a measure of household income. Household consumption expenditure is less prone to fluctuations than income which is usually underreported when collecting data using surveys in developing countries (Deaton & Zaidi, 2002).

4.3.7 Household capacity to pay

This is defined as total household income remaining after basic subsistence needs have been met (Wagstaff & Doorslaer, 2003; Xu et al., 2003). In this study capacity to pay is defined as the difference between total annual household consumption expenditure and household annual food expenditure.

4.3.8 Catastrophic health payments

Catastrophic health payments occur when household out-of-pocket health payments as a share of household consumption expenditure exceeds a specified threshold level causing disruptions in household's living standards (Wagstaff & Doorslaer, 2003; Xu et al., 2003). In this study a household incur catastrophic health payments if out-of-pocket health payments as share of consumption expenditure exceeds a threshold level of 10% of total consumption expenditures and 40% of nonfood expenditures. The choice of threshold levels is arbitrary however in the literature threshold levels of 40% of household capacity to pay and 10% of total consumption expenditures have been used (O O'Donnell & Doorslaer, 2007).

4.3.9 Impoverishing effects of out-of-pocket health payments

Impoverishing effects of health payments occur when the non-poor population are pushed into poverty and those already poor are pushed deeper into poverty due to health payments (O O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003). In this study impoverishing effect of out-of-pocket health payments was defined based on the Malawi national poverty line of 137425 MWK which was estimated using 2016 prices (The National Statistical Office of Malawi & The World Bank Poverty and Equity Global Practice, 2018). Impoverishment occurred if a household fall below the national poverty line due to health payments. Impoverishment due to health payments was also based on the international poverty lines of US$1.90 and US$ 3.20 per person per day at Purchasing Power Parity (PPP) in 2011 prices. It occurred if a household fall below the international poverty lines US$1.90 and US$3.20 per person per day at PPP in 2011 prices. Detailed discussion on measurement of impoverishing effects of out-of-pocket health payments is given in section 4.3.13.

4.3.10 Description and level of measurements of the variables

The main outcome variables used in the study are catastrophic health expenditures and impoverishing effects of out-of-pocket health expenditures. Catastrophic health expenditure is constructed as a binary variable which takes the value 1 if a household faced catastrophic expenditures and zero otherwise. Similarly, impoverishing effects of out-of-pocket health expenditures is binary and takes the value 1 if a household faced impoverishment and zero otherwise.

The outcome variable catastrophic health expenditure was used to fit a multilevel binary logistic regression model. The model accounts for clustering due to hierarchical structure of the survey data where the households are nested in districts. The model was used to assess the factors associated with catastrophic health expenditures adjusting for the districts' random effects. The outcome variable impoverishing effects of health expenditures was used to fit a spatial multilevel binary logistic regression model to assess the factors associated with impoverishment adjusting for districts spatial effects in impoverishment. Our initial descriptive exploratory analysis of the data indicated spatial clustering in impoverishing effects of out-of-pocket health expenditures. To account for both spatial and neighborhood clustering the spatial multilevel model was used. Table 1 gives the description of the covariates or independent variables used in the study, the type of variable and level of measurement of the variables. The regression models in the study included as covariates those variables identified in the literature as predictors of catastrophic health expenditures (Akinkugbe et al., 2013; Amaya-lara, 2016; Atake & Amendah, 2018; Barasa et al., 2017; Brinda et al., 2014; Gotsadze et al., 2009; Li et al., 2013; Li et al, 2012; Masiye et al., 2016; McIntyre et al., 2018; Oudmane et al., 2019; Séne & Cissé, 2015) and impoverishing effects of out-of-pocket health payments (Minh et al., 2013; Minh & Xuan, 2012; Obse & Ataguba, 2020; Shi et al., 2011).

Table 1: Description of the variables, type and level of measurement of the variables

Variable	Description	Type of variable	Measurement
Age	Age of the household head	Continuous variable	Ratio
Sex	Sex of the household head	Binary variable: 1=male ,2=female	Nominal
Employment status	Employment status of the household head	Binary variable :1=yes ,2=no	Nominal

Variable	Description	Type of variable	Measurement
Education level	Highest education level of the household head	Categorical variable: 1=none ,2=primary ,3=junior secondary ,4=senior secondary,5=diploma ,6=degree,7=post graduate degree	Nominal
Social safety nets	Whether a household head received direct cash transfers from government in the last 12 months	Binary variable :1=yes ,2=no	Nominal
Consumption expenditure quintile	Household consumption expenditure quintile derived from total annual consumption expenditure per capita	Categorical variable: 1 =poorest ,2=poor,3=middle ,4 =rich ,5=richest	Ordinal
Household size	Number of people living in a household	Continuous variable	
Presence of at least one chronically ill member	Presence of at least one chronically ill member in the household	Binary variable :1= yes ,2=no	Nominal
Presence of at least one child	Presence of at least one child in the household	Binary variable :1= yes ,2=no	Nominal
Presence of at least one elderly member	Presence of at least one elderly member in the household	Binary variable :1= yes ,2=no	Nominal
Presence of at least one hospitalized member	Presence of at least one member hospitalized in the household	Binary variable :1= yes ,2=no	Nominal
Household location	Area in which the household is located	Binary variable :1= urban ,2=rural	Nominal
Region	Region in which the household is located	Categorical variable :1=northern	Nominal

Variable	Description	Type of variable	Measurement
		,2=central,3=southern	
Out-of-pocket health expenditure	Household's annual expenditures on consultation fees, diagnostic tests, medicines, outpatient and hospitalization fees.	Continuous	Ratio
Total household consumption expenditure	Household consumption expenditures on food and nonfood items.	Continuous	Ratio
Impoverishing effects of out-of-pocket health payments	When a non-poor household fall below the national poverty or international poverty line due to health payments	Binary:1=impoverished due to health payments,2=0 not impoverished due to health payments	Nominal
Catastrophic health expenditures	When household out-of-pocket health expenditures as a share of total expenditures that exceeds a predetermined threshold level.	Binary:1=household incurred catastrophic health expenditures ,2=0 did not incur catastrophic health expenditures	

4.3.11 Data analysis

This section describes how catastrophic health expenditures and impoverishing effects of out-of-pocket health expenditures were measured and subsequently used to examine the extent of catastrophic health expenditures, impoverishment effects of health expenditures and to analyze the factors associated with catastrophic health expenditures and impoverishment effects of health expenditures. The section also describes the multilevel binary logistic regression model, the Bayesian spatial multilevel binary logistic model used in the analysis. It further describes the measurement of inequality and decomposition analysis which was used to decompose inequality in catastrophic health expenditures.

4.3.12 Measuring incidence and intensity of catastrophic health expenditures

To assess catastrophic health expenditures (CHEs) the study used measures proposed by Wagstaff and Doorslaer (2003). Wagstaff and Doorslaer (2003) proposed two indicators for measuring catastrophic health payments; these are catastrophic payment head count which measures the incidence and catastrophic payment overshoot which measures the intensity of catastrophic health payments. The incidence of catastrophic health expenditures is estimated as the proportion of the sample with out-of-pocket health expenditures as a share of total expenditures that exceeds a predetermined threshold level.

Catastrophic health expenditure E was defined as (O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003) :

$$E = \begin{cases} 1, if \ \frac{T}{x-f(x)} > Z \\ 0, \ otherwise \end{cases} \tag{1}$$

Where x is the total annual household's consumption expenditure, Z is the threshold level where out-of-pocket health expenditures as a share of household resources is considered to cause a disruption in living standards, T is the total annual household's out-of-pocket health payments and $f(x)$ is the total annual household's food expenditures.

Catastrophic payment head count denoted by H_{cata} was estimated as (O O'Donnell & Doorslaer, 2007) :

$$H_{cata} = \frac{1}{N} \sum_{i=1}^{N} E_i = \mu_E \tag{2}$$

where N is the sample size.

While the catastrophic payment head count gives the proportion of the sample households whose out-of-pocket health expenditures as a share of total expenditure exceeds the predetermined threshold level it fails to give the amount by which the households exceeding the threshold level exceeds it (O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003). The intensity of catastrophic health expenditures as measured by catastrophic payment overshoot gives the extent by which households whose out-of-pocket expenditures as a share of total expenditures exceeds the predetermined threshold level (Wagstaff & Doorslaer, 2003). Suppose we let the catastrophic payment overshoot be defined as $O_i = E_i\left[\left(\frac{T}{x-f(x)}\right) - Z\right]$ (O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003).

Therefore, average catastrophic payment overshoot was estimated as (O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003):

$$O_{cata} = \frac{1}{N}\sum_i^N O_i = \mu_O \qquad (3)$$

where N is the sample size and the average overshoot in (3) measures the intensity of catastrophic health payments. The catastrophic mean positive gap(overshoot) denoted by MPG relates the incidence and intensity of catastrophic health expenditures and was estimated as:

$$MPG_{cata} = \frac{O_{cata}}{H_{cata}} = \frac{\mu_O}{\mu_E} \qquad (4)$$

One of the problems with measures of catastrophic health expenditures is that they are insensitive to income distribution as such they do not reflect whether it is the worse-off or the better off who tend to exceed the threshold level or overshoot (O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003). As such measures of catastrophic health expenditures must be rank weighted to reflect whether it is the better-off or worse-off who are affected more by health expenditures. Thus, the income distribution in catastrophic health expenditures is measured using the concentration indices for E_i and O_i denoted by C_E and C_O respectively. A positive value of C_E indicates that the better-off are more likely to exceed the threshold while a negative value indicates that the worse-off. Similarly a positive value of C_O indicates that overshoot is more common among the better-off while a negative value indicates it is more common among the worse off (O'Donnell & Doorslaer, 2007). To account for income distribution the measures of catastrophic health expenditures are adjusted by multiplying the measures to the complement of the concentration indices and the weighted catastrophic payment headcount and overshoot were estimated as (O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003):

$$H_{cata}^W = H_{cata}(1 - C_E) \qquad (5)$$

$$O_{cata}^W = O_{cata}(1 - C_O) \qquad (6)$$

If the worse off tend to exceed the threshold more, the concentration indices of catastrophic payment headcount are negative hence $H_{cata}^{W} > H_{cata}$. Similarly, if the worse off tend to overshoot the concentration index of catastrophic overshoot is negative hence $O_{cata}^{W} > O_{cata}$. This suggests that the problem of catastrophic health payments is worse and cannot be described by simply looking at the fraction that exceeds a threshold as it ignores that worse-off tend to exceed the threshold more than the better-off (Wagstaff & Doorslaer, 2003).

In this study households incurred CHEs if out-of-pocket health expenditures as a share of household's capacity to pay exceed 40% threshold level, where household's capacity to pay was defined as annual household consumption expenditures remaining after food expenditures (Xu, Evans, et al., 2003) and we also defined CHEs based on 10% threshold level of total consumption expenditures (Wagstaff & Doorslaer, 2003). Although the choice of threshold levels is arbitrary in the literature threshold levels have been defined depending on whether total consumption expenditures or capacity to pay is used as the denominator when estimating the share of out-of-pocket health expenditures from household resources. The threshold levels of 40% and 10% have been used when capacity to pay and total consumption expenditure are used as a denominators respectively (O'Donnell & Doorslaer, 2007). In addition, CHEs defined based on 10% of total consumption expenditures is the official indicator for monitoring universal health coverage financial protection which is one of the indicators of universal health coverage of the Sustainable Development Goals (SDGs indicator 3.8.2) (Wagstaff et al., 2018; World Health Organization and International Bank for Reconstruction and Development /The World Bank, 2020). For comparison of results, we also reported findings on the incidence and intensity of CHEs for the threshold levels 20%, 25% and 30%.

4.3.13 Measuring impoverishing effects of health expenditures on households

Impoverishing effects of out-of-pocket health expenditures occurs when non poor households become poor after paying for health services and those that are poor are pushed deeper into poverty (Wagstaff & Doorslaer, 2003). To assess the impoverishing effects of out-of-pocket health expenditures the study examined the effects of health expenditures on two commonly used poverty measures; these are poverty headcount ratio and poverty gap

(O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003). The study estimated impoverishment impact due to health expenditures as the difference between post-payment poverty head count ratio and pre-payment poverty headcount ratio. The study also estimated the difference between the post-payment poverty gap and pre-payment poverty gap to assess the poverty effects of health payments. Poverty head count ratio gives the proportion of population with total consumption expenditures below the poverty line and poverty gap gives the extent by which the average total consumptions expenditures of the poor fall below the poverty line. The study used the 2016 Malawi national poverty line of MWK137425 per person per year as provided in the methodology for poverty measurements in Malawi (2016/17) document (The National Statistical Office of Malawi & The World Bank Poverty and Equity Global Practice, 2018). The study also used the international poverty lines of US$1.90 and US$3.20 per person per day at Purchasing Power Parity (PPP) in 2011 prices to examine the impoverishing effects of out-of-pocket payments. These international poverty lines converted to MWK526.2 and MWK886.2 per person per day using 2016 prices respectively as provided in the poverty and equity brief document (World Bank Group, 2020). The international poverty lines were used to allow comparisons of the computed estimates with estimates from other countries.

Suppose we define $P_i^{pre} = \begin{cases} 1, if \ \ x_i < PL \\ 0, \quad otherwise \end{cases}$ where PL denotes the poverty line and x_i is the total annual household consumption expenditure per capita for household i; as the individual household i poverty before out-of-pocket health payments. Then the average pre-payment poverty headcount was estimated as (O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003) :

$$H_{poverty}^{pre} = \frac{1}{N}\sum_{i=1}^{N} P_i^{pre} = \mu_{p^{pre}} \qquad (7)$$

where N is the sample size. The poverty gap before out-of-pocket health payments for each individual household i was defined as $g_i^{pre} = P_i^{pre}(PL - x_i)$. Hence the average prepayment poverty gap was estimated as (O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003) :

$$G_{poverty}^{pre} = \frac{1}{N}\sum_{i=1}^{N} g_i^{pre} = \mu_{g^{pre}} \qquad (8)$$

Where N is the sample size. The normalized poverty gap before health payments was estimated as:

$$NGap^{pre} = \frac{G^{pre}_{poverty}}{PL} \tag{9}$$

Similar measures are obtained for the post payment poverty head count and gap after subtracting total annual household's out-of-pocket expenditure per capita from total annual household's consumption expenditure per capita. Define poverty head count after out-of-pocket health payments as

$P_i^{post} = \begin{cases} 1, if \ \ (x_i - T_i) < PL \\ 0, \quad otherwise \end{cases}$. Then the average post payment poverty headcount was estimated as (O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003):

$$H^{post}_{poverty} = \frac{1}{N}\sum_{i=1}^{N} P_i^{post} = \mu_{p^{post}} \tag{10}$$

Where N is the sample size. Define poverty gap after out-of-pocket health payments as $g_i^{post} = P_i^{post}\,(PL - (x_i - T_i)$. Then the average post payment poverty gap was estimated as (O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003)

$$G^{post}_{poverty} = \frac{1}{N}\sum_{i=1}^{N} g_i^{post} = \mu_{g^{post}} \tag{11}$$

Where N is the sample size. The normalized poverty gap after health payments was estimated as

$$NGap^{post} = \frac{G^{post}_{poverty}}{PL} \tag{12}$$

The difference between the corresponding post and pre poverty measures gives the impoverishing effects of out-of-pocket health payments on households. For example, we estimated the impoverishing effects of out-of-pocket payments on poverty head count ratio and gap using the differences:

$$PI_{headcount} = H^{post}_{poverty} - H^{pre}_{poverty} \quad \text{and} \quad PI_{gap} = G^{post}_{poverty} - G^{pre}_{poverty} \tag{13}$$

4.3.14 Multilevel binary logistic regression model

A multilevel binary logistic regression was used to assess the factors associated with catastrophic health expenditures. This regression model was used to account for the nested structure of the survey data where households are nested in districts and to ensure correct estimation of standard errors and statistical inference of the model parameters. This binary regression was also used to account for our main outcome variable which takes the value of 1 if a household incurred catastrophic health expenditure and zero otherwise. The study estimated two models; model 1 was estimated with CHEs defined based on 40% of household nonfood consumption expenditures and model 2 with CHEs based on 10% of household total consumption expenditures.

Let Y_{ij} be the outcome of catastrophic health expenditures for the i^{th} household in j^{th} district, π_{ij} be the probability of incurring catastrophic health expenditures and x_{ij} be some household level covariates. We assume Y_{ij} follows a binomial distribution, i.e.,$Y_{ij} \sim Bin(1, \pi_{ij})$. Then, the probability of incurring catastrophic health expenditures π_{ij} is modelled using a logit link function and the random intercept model was specified as:

$$logit(\pi_{ij}) = \beta_0 + \beta x_{ij} + u_j \qquad (14)$$

Where β is a vector of fixed effects regression coefficients of the corresponding household level covariates x_{ij} and u_j is the district level random effects term which captures the unobserved district level effects. The district level random effects term is assumed to be normally distributed with mean of zero i.e. $u_j \sim N(0, \sigma_u^2)$. Due to the nature of the data, we could not include any district level covariates as such all district level covariates were modeled as a nuisance using the district random effects term.

We included as covariates those factors identified in previous literature as determinants of catastrophic health expenditures (Amaya-lara, 2016; Barasa et al., 2017; Brinda et al., 2014; Gotsadze et al., 2009; Li et al., 2013; Li et al., 2012; Masiye et al., 2016). The covariates have been described in detail in section 4.4, Table 1. These covariates included household head characteristics such as age in years, sex, education and other household characteristics such as household size, socioeconomic status, presence of at least one chronically ill member in the household ,presence of at least one elderly member, presence of at least one child, presence of at least one hospitalized member over the past 12 months, location of household, region in which the household is located, distance to the nearest health facility and type of health facility. The measure of socioeconomic status was constructed based on total household consumption expenditure per capita. Total consumption expenditure per capita was categorized into five consumption expenditure quintiles from the poorest to the richest quintile. However, in the analysis to assess factors associated with impoverishing effects of out-of-pocket health expenditures total consumption expenditure per capita was categorized into two consumption expenditure quintile including lower expenditure quintile and higher expenditure quintile.

Descriptive analysis was conducted to describe the characteristics of the sampled households and the extent of catastrophic health expenditures. This descriptive analysis included estimating the mean, standard deviation for continuous variables and proportions for categorical variables. Inferential data analysis to assess the factors associated with catastrophic health expenditures was conducted using multilevel logistic regression modelling. The descriptive and inferential analysis was implemented in Stata 15. All analyses were adjusted for sampling design using survey sample weights and the survey set command in Stata 15. The results were interpreted at 5% significance level.

4.3.15 Spatial analysis of impoverishing effects of health expenditures

The Moran I statistic was used to assess the spatial clustering in impoverishing effects of out-of-pocket health expenditures. This initial descriptive analysis of estimating the Moran I test statistic of no spatial autocorrelation was conducted using R statistical software. The result showed significant spatial dependence in impoverishing effects of out-of-pocket health expenditures across the districts in Malawi (Moran I= 0.179, p-value <0.05). This finding reinforced the need to account for spatial dependence or clustering in examining the association between impoverishment effects of out-of-pocket health expenditures and its associated risk factors.

4.3.16 Bayesian spatial multilevel modeling

A Bayesian spatial multilevel binary logistic regression model was used to assess the factors associated with impoverishing effects of out-of-pocket health expenditures. This regression was used to account for the nested structure of the survey data where households are nested in districts and to account for districts spatial effects. This ensured correct estimation of standard errors and statistical inference of the model parameters in estimating factors associated with impoverishment as the preliminary descriptive analysis indicated significant spatial clustering effects in impoverishing effects of health expenditures. This binary regression was also used to account for our outcome variable which takes the value of 1 if a household was impoverished due to health expenditures and zero otherwise.

Let y_{ij} be a binary response for household i (level 1) in district j (level 2) and assume that y_{ij} follows a binomial distribution i.e., $y_{ij} \sim Bin(1, \pi_{ij})$. Define $y_{ij} = 1$ if household i nested in district j was impoverished due to out-of-pocket health expenditures and $y_{ij} = 0$ otherwise. Then, following Goldstein (2003) and Congdon (2014) a Bayesian standard multilevel logistic regression model with logit link function is specified as:

$$logit(\pi_{ij}) = \alpha + \beta X_{ij} + \gamma Z_j + u_j \qquad (15)$$

$$u_j \sim N(0, \sigma_u^2)$$

$$[\alpha, \beta, \gamma] \sim N(0, b)$$

Such that X_{ij} is a vector of household level covariates with β as a vector of corresponding regression coefficients to be estimated, Z_j is a vector of district level covariates and γ is a vector of corresponding regression coefficients to be estimated. u_j is independently identically distributed and captures the unobserved district level random effects. The Bayesian standard multilevel logistic model (15) accounts for the dependence in observations within the same geographic area such as districts defined by administrative boundaries and fails to capture dependence in observations due to close proximity in geographic space as it assumes no spatial dependence among geographic areas (Chaix et al., 2005; Dong et al., 2015; Dong et al, 2016;Xu, 2014a) . Following our initial finding of significant spatial dependence in impoverishment due to out-of-pocket health expenditures across districts, we assume that the relationship between impoverishment due to out-of-pocket health expenditures and its associated factors is affected by district level random effects u_j and that the random effects are spatially dependent. We therefore used a spatial multilevel model that incorporates u_j as spatially dependent unobserved district level random effects. Following Ma et al. (2017) u_j is modeled using Leroux, Lei and Breslow Conditional autoregressive prior (Leroux et al., 1999) , denoted as LCAR . The LCAR is specified as (Ma et al., 2018, 2017; MacNab, 2011):

$$u_j|u_{-j}, W, \lambda, \tau^2 \sim N\left(\frac{\lambda \sum_{j\sim i} u_i}{1-\lambda+\lambda w_{j+}}, \frac{1}{\tau^2(1-\lambda+\lambda w_{j+})}\right) \quad (16)$$

Where u_{-j} represents random effects different from the j^{th} random effects, W is the neighborhood spatial proximity matrix defined as $w_{ij} = 1$ if districts $j \ and \ i$ share borders (denoted by $j \sim i$) and zero otherwise, w_{j+} represents the number of districts sharing borders with j^{th} district. $\lambda \in (0,1)$ is the spatial correlation parameter and τ^2 is a precision parameter equal to the inverse of the variance $\left(\text{i. e } \tau^2 = \frac{1}{\sigma^2}\right)$.

Equation (16) indicates the conditional expectation of the random effects u_j, $E\left(u_j|u_{-j}\right)$ is the weighted mean of the random effects of its neighbors. The full conditionals of all the J random effects gives a distinctive Gaussian Markov Random Field , $u_j \sim MVN(0, \Omega_{LCAR})$,where Ω_{LCAR} is a $J \times J$ precision matrix equal to $\tau^2[diag\left(1 - \lambda + \lambda w_{j+}\right) - \lambda W)]$ (Ma et al., 2018, 2017; MacNab, 2011). Our Spatial Multilevel logistic regression model for modelling the probability that a household was impoverished due to out-of-pocket health expenditures is specified as a follow:

$$logit\left(\pi_{ij}\right) = \alpha + \beta X_{ij} + \gamma Z_j + u_j \quad (17)$$

$$u_j \sim MVN(0, \Omega_{LCAR}(\lambda, \tau^2))$$

$$[\alpha, \beta, \gamma] \sim N(0, b)$$

When there is no spatial correlation $i.e \ \lambda = 0$ the multilevel spatial model (17) reduces to a standard multilevel logistic model with $u_j \sim N(0, \tau^2)$ (Congdon, 2017).

Estimation of the parameters in model (17) follows an approximate Bayesian approach. The fixed effects regression coefficients were assigned a Gaussian prior $i.e \ \alpha, \beta, \gamma \sim N(0{,}1000)$. The variance components τ^2 in (17) and $\frac{1}{\sigma_u^2}$ in the standard multilevel model (15) were assigned the default minimally informative prior i.e. $\tau^2 \sim logGamma(1{,}5 \times 10^{-5})$. The spatial correlation parameter λ expressed on a logit scale ; logit (λ) was assigned a diffuse normal prior i.e. $logit(\lambda) \sim N(0{,}100)$. Literature shows that choice of hyper prior may affect results of parameter estimates (Blangiardo et al., 2013; Ma et al., 2018; Ugarte & Adin, 2014). To assess the impact of the choice of the hyper priors used for models (15) and (17), sensitivity analysis was carried out with different hyper priors. The following hyper priors were used in the sensitivity analysis:

$\tau^2 \sim logGamma(1,0.01)$,$\tau^2 \sim logGamma\ (1,0.001)$,$\tau^2 \sim logGamma\ (1,0.0001)$, $logit(\lambda) \sim N(0,10)$,$logit(\lambda) \sim N(0,200)$, $logit(\lambda) \sim N(0,1000)$.

The models (15), (17) and the standard single level logistic regression model were implemented using the integrated nested Laplace approximation(INLA) approach through R-INLA package (Blangiardo et al., 2013; Rue et al, 2009). Model comparisons in terms of goodness of fit was done using the deviance information criterion (DIC) which is defined as the sum of twice the effective number of model parameters and the estimated posterior mean deviance (Spiegelhalter et al., 2002). The model with the smallest DIC value was considered as the model with a better fit. This analysis was done using R and Stata 15 statistical software packages. All results were interpreted at 5% significance level.

4.3.17 Measuring inequality in catastrophic health expenditures

The measures of inequalities in health mainly developed from the literature in the field of epidemiology and economics (Kjellsson et al, 2015; Owen O'Donnell, 2009; Regidor, 2004). Literature on inequalities in health identifies several measures of the extent of inequalities in health. The measures are the range, Gini coefficient, index of dissimilarity, slope index, relative index and the concentration index (Kjellsson et al., 2015; Wagstaff, 1991) . According to Wagstaff these measures should satisfy minimum requirements of conditions for them to be reliable without which they may lead to wrong conclusions on the extent of inequalities in health (Wagstaff, 1991). For the measures to be reliable they must take into account the socioeconomic dimension of health inequalities, experiences of the whole population and must be sensitive to changes in the population distribution by socioeconomic groups (O'Donnell, 2009; Wagstaff, 1991).

The range as a measure of health inequalities involves comparing the distribution of the health variable of interest across the lowest and highest socioeconomic group (Kjellsson et al., 2015; O'Donnell, 2009; Regidor, 2004; Wagstaff, 1991) While it gives a simple way of measuring inequality in health its disadvantage is that it does not take into account the distribution of health variables across the entire population. For example it may fail to capture the changes that may take place within the intermediate population groups (Wagstaff, 1991). The range also fails to consider the size of the population groups when it is used to compare inequality between groups. This may lead to wrong results. The Gini coefficient is a measure of inequality derived from the Lorenz curve. This curve plots the cumulative proportion of the population by the cumulative proportion of their health status. The Gini coefficient is obtained as twice the area between the Lorenz curve and the line of equality of the curve (Wagstaff, 1991). While this measure takes into account the experiences of the whole population it fails to account for the socioeconomic dimension of health inequality hence does not clearly indicate how inequalities in health mirror socioeconomic inequalities (Regidor, 2004; Wagstaff, 1991). The index of dissimilarity measures health inequalities by comparing the socioeconomic group's share of the population's health to group's population share (Regidor, 2004; Wagstaff, 1991). Its limitation is that it does not account for the socioeconomic dimension of health inequality.

The relative index of inequality, slope index of inequality and the concentration index are the measures that satisfy the minimum requirements for a reliable measure of inequality in health (Wagstaff, 1991). The slope index of inequality is a health inequality measure based on the regression equation line of health status and socioeconomic status rank (Kjellsson et al., 2015). The slope index of inequality is the slope of the regression line indicating the relationship between health status and its socioeconomic distribution rank (Kjellsson et al., 2015; Wagstaff, 1991). While the slope index of inequality satisfies the minimum requirements it also has another property that it changes with a change in mean health status variable (Wagstaff, 1991). The relative index of inequality is obtained by dividing the slope index of inequality by the mean health status variable. In addition to satisfying the minimum requirements for a reliable measure of inequality in health, the relative index of inequality is not affected by changes in the mean health status variable (Wagstaff, 1991).

The study adopted the concentration index (CI) because it is a more reliable measure of inequalities in health than the range, Gini coefficient and index of dissimilarity (Wagstaff, 1991). While the slope index of inequality and the relative index of inequality are equally reliable, the choice of the concentration index is based on a binary health variable used in this study which cannot be used with the slope index of inequality since the slope index is based on a weighted least squares regression. On the contrary the concentration index can used with a bounded binary health variable such as catastrophic health expenditures (Kjellsson et al., 2015; Wagstaff, 1991, 2005).

The concentration index (CI) is a common measure in the literature to assess income related health inequalities. The concentration index measures the degree in socioeconomic inequality of a health variable of interest and is defined as two times the area between the line of inequality and the concentration curve (Kakwani et al., 1997). The concentration curve plots the cumulative proportion of the health variable on the y-axis against the cumulative proportion of the sample ranked by socioeconomic status from the poorest to the wealthiest on the x-axis (Wagstaff et al., 2003). The index lies between -1 and +1 when the health variable of interest is unbounded. However, for bounded health variables Wagstaff (2005) has shown that the concentration index lies between $\mu - 1$ and $1 - \mu$ for large samples. Positive values of the concentration index indicate that inequality is more concentrated among the better-off and negative values indicate that inequality in more concentrated among the worse-off (O'Donnell & Doorslaer, 2007).

In this study the concentration index for the incidence of catastrophic health expenditures was estimated using the convenient covariance formula as (O'Donnell & Doorslaer, 2007):

$$C = \frac{2}{\mu} cov(y_i, r_i) \quad (18)$$

Where r_i is the fractional rank of i^{th} household across socioeconomic status as measured by consumption expenditure per capita in this study, y_i is the health variable of interest which is the incidence of catastrophic expenditures that is whether a household hold incurred catastrophic health expenditure or not and μ is the mean of y_i.

For a binary health variable of interest Wagstaff (2005) proposed a normalized concentration index obtained by dividing the standard concentration index in equation (18) by either the reciprocal of y_i or the upper bound of the concentration index of y_i . However, Erreygers (2009) has shown that rank dependent measures of socioeconomic inequality such as the Wagstaff concentration index should satisfy four properties . These include; (i) the mirror image property which states that for any given health distribution the index of a health variable is equal in absolute value to the index of ill-health variable with opposite sign, (ii)cardinal invariance property which states that a positive linear transformation of the health variable does not change the value of index, (iii) transfer property which states that any mean preserving change in health distribution in favor of the wealthier result in change in index in favor of the wealthier and this is also true for change in health distribution in favor of the worse-off ,(iv) level of independence property which states that the value of the index does not change with change in health levels of all persons by an equal absolute amount. Whereas the Wagstaff concentration index satisfy properties (i) to (iii) it fails to satisfy the level of independence property. For bounded health variables, Erreygers (2009) proposed a corrected concentration index which satisfies all the properties of rank dependent measures of inequality. The Erreygers corrected concentration index for catastrophic health expenditures was estimated as follows (Erreygers, 2009):

$$EI = \frac{4\mu}{y^{max} - y^{min}} CI \qquad (19)$$

Where μ is the mean of the health variable which is the incidence of catastrophic health expenditures, y^{max} *and* y^{min} are the upper bound and lower bound of the incidence of catastrophic health expenditures respectively and CI is the concentration index as defined in (18). In this study the concentration index was computed to measure socioeconomic inequality in catastrophic health expenditures. The concentration index is used to quantify the extent of socioeconomic inequality in catastrophic health expenditure. Several authors have used the concentration index in (18) to measure socioeconomic inequality in catastrophic health expenditures (Kavosi, et al., 2012; Si et al., 2017; Wang et al., 2015; Xu et al., 2015). Since the health variable of interest in this study is a bounded binary variable the Erreygers corrected concentration index was computed. The conindex command in Stata 15 (Donnell et al, 2016) was used to compute the concentration indices and Stata 15 was also used in decomposing the concentration index of catastrophic expenditures into its determinants.

4.3.18 Decomposing inequality in catastrophic health expenditures

We employed decomposition analysis to further assess the contribution of inequality in each determinant of catastrophic health expenditures to the overall socioeconomic inequality in catastrophic health expenditures. The method proposed by Wagstaff et al.

(2003) was used to decompose socioeconomic inequality in catastrophic health expenditures into its determinants. This method has also been used by other authors to decompose inequality in catastrophic health expenditures (Kavosi et al., 2012; Si et al., 2017; Wang et al., 2015; Xu et al., 2015). Decomposing the concentration index allows us to understand how socio-economic inequality in each determinant of catastrophic health expenditure contributes to the overall socioeconomic inequality in catastrophic health expenditures. The method of decomposing the concentration index as proposed by Wagstaff et al. (2003) is based on the linear regression model that relates a continuous health outcome variable y_i to a set of k determinants x_k ,given as follows:

$$y_i = \alpha + \sum_k \beta_k x_{ki} + \varepsilon_i \qquad (20)$$

Where β_k is the vector of regression coefficients , x_k is a set of k determinants and ε_i is the random error term. Wagstaff et al. (2003) has shown that the concentration index of y,denoted by C_y can be decomposed as follows:

$$C_y = \sum_k \left(\frac{\beta_k \bar{x}_k}{\mu}\right) C_k + \frac{GC_\varepsilon}{\mu} \qquad (21)$$

Where μ is the mean for the outcome variable y, $\bar{x}_k$ is the mean of each determinant**,** C_k is the concentration index for each of the determinants, β_k represents the estimated regression coefficients for each determinant factor obtained from equation (20) and GC_ε is the generalized concentration index for the error term. For the Erreygers corrected concentration index a similar decomposition formula for the index is expressed as follows (Erreygers, 2009):

$$EI = 4(\sum_k \beta_k(\bar{x}_k C_k) + GC_\varepsilon) \qquad (22)$$

Where $\bar{x}_k$ is the mean of each determinant used in the regression analysis (20), C_k is the concentration index for each of the determinants and β_k is the estimated regression coefficient.

The concentration index C_y in (21) and (22) is decomposed into two components. The first component represents the explained inequality due to variation in the explanatory variables across socioeconomic status and the second component represents inequality that cannot be explained by variation in the explanatory variables across socioeconomic status (Hosseinpoor et al., 2006; O'Donnell & Doorslaer, 2007; Wagstaff et al., 2003).

For the decomposition analysis the multilevel binary logistic regression model was used as described in section 4.5.3; since our outcome variable is binary taking the value 1 if a household incurred catastrophic health expenditure and zero otherwise. In addition, the survey data used is hierarchically structured where households are nested in districts hence the multilevel logistic regression account for the nested structure of the data to give correct inference on the estimated parameters of the regression model. Decomposition analysis proposed by Wagstaff et al. (2003) requires that the regression model relating the health outcome variable y_i to a set of k determinants x_k be linear in form . However, the logistic regression model used to assess the association between catastrophic health expenditure and its determinants is nonlinear in form. To deal with this problem the study used the logit linear transformation of the logistic regression model as proposed by other authors (Doorslaer et al., 2004; Hosseinpoor et al., 2006). This enables the decomposition of the concentration index to be implemented in the same way as proposed by Wagstaff et al. (2003) in equation (21). The study employed the logit linear transformation on the logistic regression model and used the marginal effects of the regression coefficients in the decomposition analysis. Other authors have also used linear transformation of the nonlinear models in decomposing inequality in catastrophic health expenditures (Kavosi, et al., 2012; Liu, Gao, & Yan, 2014; Si et al., 2017; Xu et al., 2015).

The multilevel logit linear transformation model used in the decomposition analysis is specified as follows:

$$\ln\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \alpha_{ij} + \sum \beta_i^m x_{ij} + u_j \qquad (23)$$

Where π_{ij} is the probability of incurring catastrophic health expenditure, β_i^m represents the estimated regression marginal effects of the corresponding determinant factors x_{ij} and u_j is the districts level random error term.

4.3.19 Model diagnostics and validation

The study employed binary multilevel logistic and spatial multilevel logistic models for modelling factors associated with catastrophic health expenditures and impoverishing effects of out-of-pocket health expenditures. To validate the use of these models we explored estimates of the random effects at district level and measures of model fit and complexity for the null models without predictors and full models with all predictors of the outcome variables. Model comparison was done using the Deviance Information Criterion which is an overall measure model fit or adequacy (Spiegelhalter et al., 2002). The Deviance Information Criterion DIC is defined as the sum of the posterior mean sample of the saturated deviance $\overline{D}$ which represent the goodness of fit and the effective number of parameters P_D which represent complexity of the model. Small values of $\overline{D}$ and P_D indicate good model fit and less complexity of the model respectively. Small values of DIC indicate a better model fit. Models with differences of DIC of less than 3 compared to the best model are considered indistinguishable in terms of model fit while those with differences between 3 and 7 are distinguishable (Spiegelhalter et al., 2002) .

The first step in model diagnostic and validation was to fit models without predictors to the data. For the outcome variable catastrophic health expenditures, a binary single level logistic model and a multilevel logistic model was fit to the data and the model were compared in terms of model fit. For the outcome variable impoverishing effects of health expenditures, a binary single level logistic, multilevel logistic and spatial multilevel logistic models were compared.

The second step was to conduct a bivariate analysis to examine the relationship between the individual predictor variables identified in the literature and the outcome variables. Predictor variables which were significant at $p \leq 0.20$ at the bivariate analysis step and improved the model fit by reducing the DIC were entered into the final model. After the individual predictor variables were selected full models with all predictor variables were fit to the data and final model was selected based on the Deviance Information Criterion.

The final step involved assessing whether the assumptions of the selected models used in the study were sufficient or not. The study specifically tested the assumption of normality of the higher-level random effects in the multilevel logistic and spatial multilevel logistic models using the normality plot and the Shapiro-Wilk test of normality. If the district random effects are normally distributed the points on the normal plot should be closer to the straight line and the test of normality should be insignificant. The study also tested for spatial autocorrelation in the district random effects and the observed rates of catastrophic health expenditures and impoverishing effects of out-of-pocket health expenditures using the Moran I test of spatial autocorrelation. If the district random effects and the observed rates are spatially clustered the Moran, I statistic should be statistically significant, and this result should validate accounting for spatial autocorrelation in the models. Other model diagnostic tests included the multicollinearity test, tests of linearity of continuous variables, omitted variables bias tests.

CHAPTER 5: EXTENT OF CATASTROPHIC HEALTH EXPENDITURES AND ITS ASSOCIATED RISK FACTORS

5.1 Introduction

This chapter describes the incidence and intensity of catastrophic out-of-pocket health expenditures using the methods proposed by Wagstaff and Doorslaer (2003) as described in chapter 4 section 4.5.1. The chapter further examines the factors associated with catastrophic out-of-pocket health expenditures to understand the characteristics of households at risk of catastrophic out-of-pocket health expenditures using binary multilevel logistic regression model. The multilevel model account for nested structure of the data used in the analysis where the household which is the unit of analysis is nested in districts there by accounting for within district correlation consequently contextual effects on catastrophic health expenditures. This ensures correct inference on the model parameters and conclusions. The chapter begins by providing results of model validation and diagnostics for the binary multilevel logistic, then results from the analyzed data on catastrophic health expenditures are presented, discussed and policy implications are suggested.

5.2 Diagnostics for the binary multilevel logistic model

Table 2 presents result of the model with no predictors. The single level binary logistic regression model has no random effects to account for districts variations while the binary multilevel logistic regression model includes random effects. The single level binary logistic model is less complex but provides poor fit to the data as indicated by effective number of parameter and DIC respectively. The binary multilevel logistic model is more complex but provides a better fit to the data as indicated by the substantial decrease in DIC from 1501.02 to 1411.54 which is a change in DIC by 89 units. This comparison in models with no predictors suggests that the binary multilevel logistic model is the best model among the two. Accounting for district random variations by including random effects provides a significantly improved model. Moreover, the district random effects for the multilevel model are significant at 95% credible interval indicating significant variations in catastrophic health expenditures at district level.

Table 2:Measures of Model fit and estimates of random effects for the null models fitted to data on catastrophic health expenditures

Variables	Single level logistic model		Multilevel logistic model	
	$\boldsymbol{\beta}$	**SE (95% CI)**	$\boldsymbol{\beta}$	**SE (95% CI)**
Intercept	-4.51	0.09(-4.68,-4.34)*	-4.99	0.24(-5.51, -4.56) *
District random effects				
$\boldsymbol{\sigma_u^2}$	___	___	1.13	0.49(0.46,2.39) *
Model fit diagnostics				
$\boldsymbol{\bar{D}}$		1500.02		1388.25
$\boldsymbol{P_D}$		0.999		23.29
$\boldsymbol{DIC}$		1501.02		1411.54

Note: *Statistically significant at 95% credible interval, σ_u^2 is the districts random effects, DIC is the Deviance Information Criterion, P_D is the effective number of parameters indicates model complexity,$\bar{D}$ is the deviance evaluated at posterior mean of parameters and goodness of fit of model. 95% credible interval in parenthesis. β represent the regression posterior mean.

Table 3 shows the results of the single level binary logistic and multilevel logistic models fitted with all predictors of catastrophic health expenditures. The single level logistic model is less complex as indicated by the effective number of parameters but fits the data poorly. The multilevel logistic model is more complex but provides a better fit to the data as indicated by a decrease in the DIC from 1341.50 to 1294.24. Accounting for the district variations by including a random effect in a multilevel model with all predictors provides a significantly improved model. The estimated district random effects for the models with all predictors are significant indicating significant variations in catastrophic health expenditures at district level. Thus, the multilevel logistic model provides the best model for the data compared to the single level logistic model.

Table 3:Measures of model fit, estimates of district random effects and coefficients for the full model fitted to data on catastrophic health expenditures

Variables	Single level logistic model		Multilevel logistic model	
	$\boldsymbol{\beta}$	**SE (95% CI)**	$\boldsymbol{\beta}$	**SE (95% CI)**
Intercept	-8.55	0.680(-9.915,-7.246)*	-9.004	0.830(-10.698,-7.439)*
Age of household head (ref= Over 56 years)				
Less than 26 years	-0.704	0.458(-1.611,0.187)	-0.677	0.464(-1.595,0.225)
26-35 years	-0.414	0.376(-1.136,0.339)	-0.365	0.381(-1.097,0.399)
36-45 years	-0.655	0.371(-1.367,0.090)	-0.617	0.376(-1.339,0.136)
46-55 years	-0.762	0.397(-1.536,0.022)	-0.796	0.402(-1.581,-0.002)
Sex of household head (ref=Male)	0.098	0.205(-0.313,0.493)	0.122	0.208(-0.294,0.522)
Household size	0.185	0.051(0.083,0.284)*	0.192	0.052(0.089,0.293)*
Socio-economic status (ref=Quintile 1(Poorest))				
Quintile 2	0.715	0.308(0.126,1.334)*	0.703	0.310(0.109,1.326)*
Quintile 3	0.912	0.308(0.323,1.532)*	0.989	0.312(0.392,1.616)*
Quintile 4	0.982	0.321(0.366,1.626)*	1.071	0.327(0.443,1.726)*
Quintile 5(Richest)	1.031	0.352(0.346,1.728)*	1.076	0.358(0.380,1.783)*
Presence of at least one child (ref=No)	0.114	0.231(-0.334,0.572)	0.085	0.234(-0.369,0.548)
Presence of at least one elderly member (ref=No)	-0.285	0.350(-0.963,0.409)	-0.305	0.355(-0.994,0.399)
Presence of at least one chronically ill member (ref=No)	0.343	0.193(-0.041,0.717)	0.313	0.196(-0.075,0.0.692)
Presence of a hospitalized member(ref=No)	1`.762	0.185(1.398,2.126)*	1.748	0.188(1.379,2.117)*
Household location (ref=Urban)	1.616	0.390(0.900,2.432)*	1.712	0.530(0.742,2.830)*
Distance to the nearest health facility(KMs)	-0.006	0.006(-0.018,0.004)	-0.005	0.006(-0.017,0.006)
Health facility (ref=government)				
Religious	0.756	0.224(0.305,1.184)*	0.694	0.241(0.211,1.155)*
Private	-0.549	1.012(-2.807,1.150)	-0.271	1.028(-2.560,1.461)
Region(ref=Northern)				
Central	1.254	0.274(0.737,1.815)*	1.712	0.523(0.386,2.461)*
Southern	0.198	0.292(-0.359,0.789)	0.102	0.518(-0.924,1.126)
District random effects				
$\boldsymbol{\sigma_u^2}$	___	___	0.61	0.365(0.24-1.54)*
Model fit diagnostics				
$\boldsymbol{\bar{D}}$		1321.23		1257.72
$\boldsymbol{P_D}$		20.27		36.52
$\boldsymbol{DIC}$		1341.50		1294.24

Note: *Statistically significant at 95% credible interval, σ_u^2 is the districts random effects, DIC is the Deviance Information Criterion, P_D is the effective number of parameters indicates model complexity,$\bar{D}$ is the deviance evaluated at posterior mean of parameters and goodness of fit of model. 95% credible interval in parenthesis. β is the regression posterior mean.

5.3 Model assumptions for the binary multilevel logistic model

To further validate the choice of binary multilevel model for examining factors associated with catastrophic out-of-pocket health expenditures. We assessed the district level random effects from the multilevel model. Figure 2 gives the normal probability plot for the district random effects. The plot shows some deviation from normality at the end of the tails of the distribution but overall, the plot indicates reasonable normality in the distribution of district random effects as the points are close to the normality line. Moreover, the Shapiro test of normality did not indicate evidence of non-normality in the district random effects ($W = 0.962, pvalue = 0.314$). Thus, the assumption of normality of the district random effects is sufficient. Furthermore, the Moran I test of spatial autocorrelation for the district random effects of catastrophic health expenditures ($Moran\ I\ statistic = 0.008, pvalue = 0.359$) and the observed catastrophic health expenditures ($Moran\ I\ statistic = 0.092, pvalue = 0.128$) are insignificant indicating no spatial clustering in catastrophic health expenditures validating the use of binary multilevel logistic model. Thus, the study adopted the binary multilevel model in the analysis of the factors associated with catastrophic health expenditures.

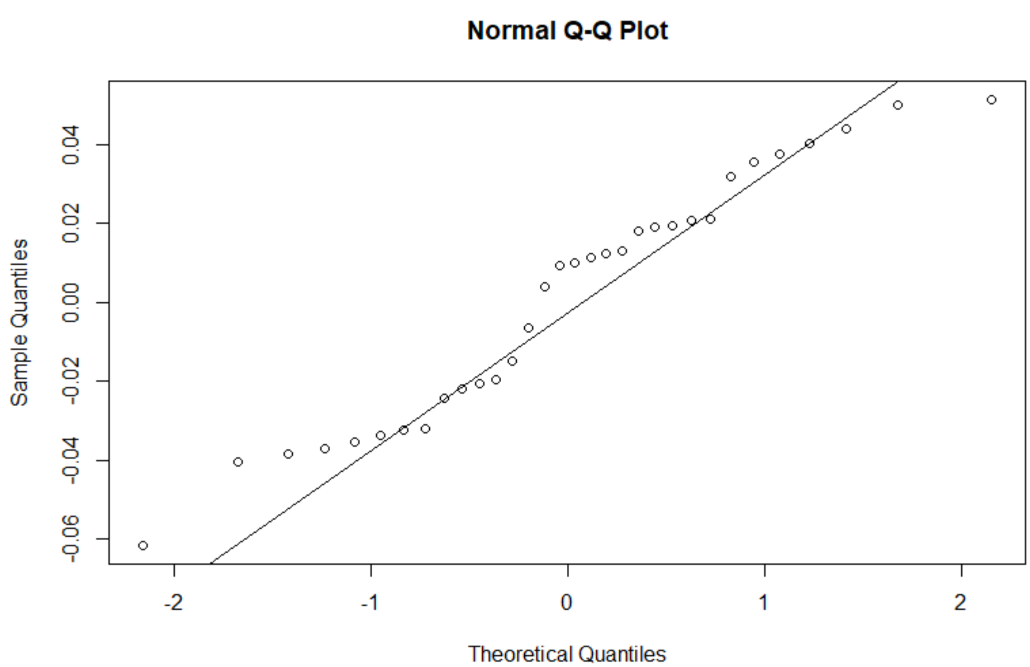

Figure 2:Normal probability plot for random effects from the multilevel model

5.4 Socio-economic and demographic characteristics of the sampled households

Table 4 shows the socio-economic and demographic characteristics of the sampled households. About 27% of the household heads were 26 to 35 years old and a larger majority of the households (71.12%) were male headed. About 63% of the household heads had no formal education ,83.32% were unemployed and only 2.34% received social safety nets from government. A larger proportion (80.95%) of the sampled households was rural. More than half of the households (53.51%) had children under the age of five years old and about 20% of the households had members older than 60 years old. A smaller proportion (13.16%) of the households had at least one member hospitalized and 22.33% had at least one member with chronic illnesses such as diabetes, tuberculosis, HIV/AIDS, and arthritis. The average household size was four. A larger proportion (87.23%) reported having a nearest medical doctor at a government health facility. The average distance to nearest health facility with a medical doctor was 13 kilometers. On average the total annual household consumption expenditure was MWK831433, and the household total annual out-of-pocket health expenditures was MWK15649.

Table 4:Socio-economic and demographic characteristics of sampled households(n=12447)

Variable	Weighted mean (SD)/percentage
Age of household head	
Less than 26 years	12.30
26-35 years	26.66
36-45 years	23.79
46-55 years	15.21
Over 56 years	22.04
Male headed household	71.12
Education level of household head	
None	63.16
Primary	12.60
Secondary	19.80
Tertiary	4.44
Household head Employed	16.68
Household received social safety nets	2.34
Household size (number of members in household)	4.29(2.00)
Presence of at least one child under 5 years	53.52
Presence of at least one elderly member greater than 60 years	19.75
Presence of at least one chronically ill member	22.33
Presence of at least one hospitalized member	13.16
Rural household	80.95
Distance to the nearest health facility (KMs)	13.33(16.85)
Health facility	
Government	87.23
Religious	10.68
Private	2.08
Region	
Northern	9.15
Central	44.32
Southern	46.53
Total annual consumption expenditure (MWK)	831433(94289)

Total annual health expenditure (MWK)	15649(7449853)

Note: MWK is Malawi Kwacha and KMs is Kilometers

More households (32.12%) from the fourth income group, 30.63% of the households from rural and 33% from the central region reported illnesses in the past two weeks preceding the survey as shown in Table 5.

Table 5:Percentage of households reporting illnesses by SES, location and region

Variable	No of households reporting illnesses	Total no. of households	Percentage of households reporting illnesses (95% CI)
Socio-economic status			
Quintile 1(Poorest)	655	2504	26.16 (24.23-28.78)
Quintile 2	724	2473	29.28 (28.23-32.89)
Quintile 3	741	2478	29.90 (28.73-33.28)
Quintile 4	784	2441	32.12 (29.67-34.49)
Quintile 5(Richest)	758	2544	29.44 (28.09-32.79)
Location of household			
Urban	546	2268	24.07 (21.61-27.35)
Rural	3116	10172	30.63(29.99-32.86)
Region			
Northern	582	2488	23.39(20.77-25.08)
Central	1372	4218	32.53(30.66-34.89)
Southern	1708	5734	29.79(27.14-30.81)

Table 6 gives results on out-of-pocket expenditures as a share of total household expenditures per capita by consumption expenditure quintiles and the Kakwani indices to measure progressivity of out-of-pocket payments. Overall, the share of total out-of-pocket health expenditures as percentage of total household expenditure decrease with increase in total expenditures, indicating that out-of-pocket health expenditures are regressive. The share of expenditures on drugs and hospitalizations as a percentage of total household expenditures decrease with increase in total household expenditure indicating that expenditures on drugs and hospitalizations are regressive. Results of the Kakwani index provide similar conclusions. All the Kakwani indices are negative which implies that out-of-pocket health expenditures are regressive as poor households contributes a larger share of their income in paying for health services than rich households.

Table 6:Out-of-pocket payments as share of total household expenditure per capita by expenditure quintiles (%)

Expenditure quintile	Drugs	Outpatients	Hospitalizations	Total health expenditures
Quintile 1(Poorest)	4.70	3.01	1.33	9.04
Quintile 2	4.13	4.04	1.26	9.42
Quintile 3	3.42	4.16	0.87	8.90
Quintile 4	3.23	4.67	0.83	8.73
Quintile 5(Richest)	2.09	4.39	0.78	7.26
Kakwani index	-0.29***	-0.06	-0.19*	-0.16*

Note: *** significant at 1%, * * significant at 5%, * significant at 10%. Kakwani index measures the progressivity in health finance and lies between -2(most regressive financing) and +1(most progressive financing) (O O'Donnell & Doorslaer, 2007).

Table 7 presents household annual out-of-pocket health payments on medicine, out-patient care and hospitalizations by household socio-economic status and location. Overall, the average total annual out-of-pocket health payment for all households was MWK15648.78. The mean total annual out-of-pocket health payment for drugs was MWK5488.84, MWK8412.35 for out-patient services and MWK1747.58 for hospitalizations. A larger amount of a total annual out-of-pocket health payment was spent on out-patient services, this expenditure on out-patient services represented over half (53.75%) of the total out-of-pocket health payments. Households in the richest income quintile spent more on drugs (MWK7745.14), out-patient services (MWK18528.38) and hospitalizations (MWK3427.57) compared to poorest households. Overall, the mean out-of-pocket health spending for richest households was significantly higher (MWK29701.1

Table 7:Households' out-of-pocket health payments by SES, location, region and type of health facility

	Mean annual out-of-pocket health payments in Malawi Kwacha			
Variable	Drugs	Out-patients	Hospitalizations	Total health payments
Socioeconomic status				
Quintile 1(poorest)	3374.11	2185.45	920.89	6480.44
Quintile 2	4548.75	4545.97	1393.13	10487.85
Quintile 3	5085.31	6932.79	1303.59	13321.70
Quintile 4	6692.28	9877.10	1693.99	18263.37
Quintile 5(Richest)	7745.14	18528.38	3427.57	29701.10
Location of household				
Urban	6536.27	13589.04	3166.61	23291.92
Rural	5242.33	7194.05	1413.62	13850.00
Region				
Northern	5570.08	7935.04	1652.61	15157.72
Central	6657.99	11844.20	1748.88	20251.07
Southern	4359.24	5237.40	1765.03	11361.66
Health facility				
Government	5444.23	7995.63	1697.37	15137.21
Mission	5333.54	10212.5	1672.16	17218.19
Private	7895.32	15624.38	3909.86	27424.56
All households	5488.84	8412.35	1747.58	15648.78

5.5 Incidence and intensity of catastrophic health expenditures

Table 8, reports results of the incidence and intensity of catastrophic health expenditures as measured by catastrophic headcount and overshoot respectively. The results are presented using nonfood consumption expenditures and total consumption expenditures as measures of household ability to pay. Incidence and intensity of catastrophic health expenditures decrease with increase in the threshold levels. Overall,4.14% of the households incurred catastrophic health expenditures at 10% of total expenditures in 2016/17. This number decreased to 1.31%, 0.84% ,0.48% and 0.11% of households incurring catastrophic health expenditures at 20% ,25%,30% and 40% of total expenditures respectively. Using nonfood consumption expenditures, 1.34% ,2.84%,5.83% and 14.08% of the households incurred catastrophic health payments at 40%, 30%, 25%, 20 % and 10% threshold levels respectively.

The mean positive overshoot (MPO) was 12.71% at 40% of nonfood expenditures and 8.54% at 10% of total expenditures. Households that incurred catastrophic health payments at 40% of nonfood expenditures, on average spent over half (52.71%) of total nonfood expenditure on health care and those that incurred catastrophic health expenditures at 10% of total expenditures spent 18.54% of the total expenditures on health care.

Table 5 also shows results of the weighted catastrophic health expenditure measures based on the threshold level 40% of nonfood expenditures and 10% of total expenditures. These weighted measures indicate whether it is the better-off or worse-off who tend to exceed the threshold level or overshoot thus they account for the income distribution of those making health payments. The results show that regardless of the threshold level and denominator used in defining the catastrophic health expenditure measures; the incidence of catastrophic health expenditure is more concentrated among the better-off and the better-off tend to overshoot the threshold level more than the worse-off. The positive concentration index of catastrophic payment headcount indicates that the rich tend to exceed the threshold level of 40% of nonfood expenditure more, this decreases the weighted headcount below the unweighted headcount. Similarly, for the threshold level of 10% of total expenditure the positive concentration index of the head count shows that the rich tend to exceed the threshold more and this decreases the weighted headcount below the unweighted headcount. Thus, the unweighted catastrophic health expenditures headcount slightly overstates the problem of catastrophic health expenditures in the case of

Malawi since it is the better-off who tend to exceed the threshold levels more than the worse-off.

Table 8:Incidence and intensity of catastrophic health expenditures

Catastrophic health expenditures measures	**Threshold levels z (%)**				
Out-of-pocket health payments as share of non-food expenditures	**10%**	**20%**	**25%**	**30%**	**40%**
Headcount (H)	14.08	5.83	3.99	2.84	1.34
Standard error for H	0.62	0.40	0.32	0.27	0.18
C_E	0.02	0.003	0.01	0.01	0.004
H^W_{cata}	13.79	5.81	3.95	2.81	1.33
Overshoot (O)	1.68	0.78	0.54	0.37	0.17
Standard error for O	0.12	0.08	0.06	0.05	0.03
C_O	0.003	0.002	0.002	0.002	0.001
O^W_{cata}	1.67	0.78	0.54	0.37	0.17
Mean positive Overshoot (MPO)	11.96	13.42	13.58	13.16	12.71
Standard error	0.48	0.67	0.78	0.87	0.88
Catastrophic health expenditures measures	**Threshold levels z (%)**				
Out-of-pocket health payments as share of total expenditures	**10%**	**20%**	**25%**	**30%**	**40%**
Headcount (H)	4.14	1.31	0.84	0.48	0.11
Standard error for H	0.31	0.17	0.13	0.09	0.04
C_E	0.01	0.01	0.004	0.002	0.001
H^W_{cata}	4.09	1.30	0.84	0.48	0.11
Overshoot (O)	0.35	0.12	0.07	0.04	0.01
Standard error for O	0.04	0.02	0.01	0.01	0.01
C_O	0.002	0.001	0.0004	0.0002	0.0001
O^W_{cata}	0.35	0.12	0.07	0.04	0.01
Mean positive Overshoot (MPO)	8.54	8.99	8.02	7.29	8.23
Standard error	0.51	0.76	0.91	1.19	1.96

*C_E denotes concentration index of catastrophic head count, C_O denotes concentration index of catastrophic overshoot.

The incidence of catastrophic health expenditures varied by socio-economic status, location of the household, type of health facility and type of health service utilized as shown in Table 9.

Incidence of catastrophic health expenditures were high for households in rural areas (1.57%) compared to urban (0.38%), households in middle income groups and for households in the central region (2.09%) compared to southern and northern regions. Incidence of CHEs were also higher among households utilizing religious facilities (2.32%) and outpatient services (11.34%).

Table 9:Incidence and intensity of catastrophic health expenditures by SES, location, region, type of facility and type of health services

Variable	Incidence of CHE: z=40% nonfood expenditures	Intensity of CHE: z=40% nonfood expenditures	Incidence of CHE: z=10% total health expenditures	Intensity of CHE =10% total health expenditures
Socio-economic status				
Quintile 1(Poorest)	0.74(0.36-1.52)	0.09 (0.03-0.14)	3.59(2.70-4.76)	0.25(0.15-0.35)
Quintile 2	1.54(1.03-2.29)	0.15 (0.07-0.22)	4.54(3.59-5.73)	0.34(0.23-0.45)
Quintile 3	1.65(1.09-2.48)	0.24 (0.12-0.37)	3.70(2.84-4.81)	0.39(0.24-0.54)
Quintile 4	1.53(0.98-2.39)	0.19 (0.09-0.28)	4.09(3.15-5.29)	0.36(0.23-0.48)
Quintile 5(Richest)	1.23(0.78-1.92)	0.19 (0.08-0.03)	4.77(3.66-6.18)	0.43(0.27-0.58)
Location of household				
Urban	0.38(0.16-0.86)	0.03 (0.01-0.05)	2.57(1.64-4.01)	0.19(0.09-0.29)
Rural	1.57(1.18-2.06)	0.20 (0.14-0.27)	4.51(3.86-5.26)	0.39(0.30-0.48)
Region				
Northern	0.73(0.42-1.27)	0.08 (0.03-0.14)	3.09(2.17-4.39)	0.22(0.12-0.31)
Central	2.09(1.47-2.96)	0.27 (0.16-0.38)	5.67(4.67-6.89)	0.52(0.38-0.67)
Southern	0.74(0.49-1.11)	0.09 (0.05-0.14)	2.88(2.25-3.68)	0.22(0.15-0.29)
Health facility				
Government	1.28(0.94-1.75)	0.15(0.09-0.21)	3.96(3.35-4.67)	0.34(0.25-0.42)
Religious/Mission	2.32(1.42-3.78)	0.35(0.15-0.55)	6.13(4.38-8.51)	0.54(0.29-0.78)
Private	0.09(0.12-0.72)	0.03(0.02-0.09)	2.71(0.71-9.74)	0.19(0.05-0.45)
Type of service utilization				
Out patient	11.34(8.48-15.02)	1.57(1.01-2.13)	33.16(28.54-38.13)	3.31(2.58-4.04)
Inpatient	7.03(4.63-10.54)	0.88(0.41-1.36)	16.85(12.89-21.71)	1.79(1.06-2.52)

Note: 95% CI in parenthesis, z is the threshold level

5.6 Factors associated with catastrophic health expenditures

Table 10 presents results of the multilevel logistic regression models to assess the factors associated with the incidence of catastrophic health expenditures. Model 1 presents results with catastrophic health expenditures defined at 40% threshold of non-food expenditures and model 2 gives results with catastrophic health expenditures defined at 10% of total expenditures. Results for Both models are presented for comparison, but the discussion is based on results from model 1.

The estimated district level random effects from the model with catastrophic health expenditures defined based on 40% of non-food expenditures were significant indicating variations in CHEs between districts. The district level random effects explained 19% of the variation in CHEs. Figure 3 shows the caterpillar plot of the estimated district residuals for all the districts. The 95% CI of the estimated residuals for three of the districts were significantly higher than zero and one estimated residual was significantly lower than zero indicating significant district effects in incurring CHEs. For example, Ntchisi district had significant highest negative value of the estimated residual indicating lower probability of incurring CHEs while Nsanje, Dedza and Dowa districts had significant highest positive residuals indicating higher probability of incurring CHEs in these districts.

Several factors were associated with the risk of CHEs. We present results with CHEs defined based on 40% of nonfood expenditures. Households with more members had an increased odds of incurring catastrophic health expenditures (OR=1.20, CI=1.08-1.34). Having at least one household member hospitalized increased the odds of CHEs (OR=6.03, CI=4.08-8.90). Households headed by young household heads had a reduced odd of incurring CHEs. For example, households with households' heads who were in the 46 to 55 age group had a 43% less odds of incurring CHEs than households headed by household heads who were over 56 years old (OR=0.43, CI=0.19-0.99). Higher socioeconomic status increased the odds of incurring catastrophic health expenditures. For example, households in the richest income quintile had 2.94 times greater odds of incurring catastrophic health expenditures (OR=2.94, CI=1.39-6.19) compared to households in the poorest income quintile. Location of the household increased the odds of incurring catastrophic health expenditures. For instance, Households in rural areas had 5.13 times more odds of incurring catastrophic expenditures

(OR=5.13, CI=2.14-12.29) compared to urban households and households in central region had 3.54 times more odds of incurring catastrophic health expenditures (OR=3.54, CI=1.79-6.97). Having the nearest medical doctor based at a religious health facility increased the odds of incurring catastrophic health expenditures compared to having nearest medical doctor based at a government health facility (OR=2.27, CI=1.24-4.15).

The findings that household socio-economic status, residency in rural areas and inpatient health services utilization (number of hospitalized household members) is significantly associated with catastrophic health expenditures are in support of the research hypothesis in section 1.6. This implies that income which is an enabling factor for health service use will lead to out-of-pocket health expenditures consequently catastrophic health expenditures. Similarly, inpatient health services utilization and residency in rural location which are need factors for health services use will lead to out-of-pocket health expenditures consequently catastrophic health expenditures.

Table 10:Estimation results from a multilevel logistic model with catastrophic health expenditures as a binary outcome variable

Independent variables	**Model 1**	**Model 2**
	Odds Ratio (95% CI)	**Odds Ratio (95% CI)**
Age of household head (ref= Over 56 years)		
Less than 26 years	0.44(0.17-1.15)	0.68(0.41-1.13)
26-35 years	0.59(0.27-1.32)	0.90(0.58-1.39)
36-45 years	0.52(0.23-1.10)	0.57(0.37-0.89)*
46-55 years	0.43(0.19-0.99)*	0.62(0.39-0.99)*
Sex of household head (ref=Male)	1.16(0.75-1.77)	1.04(0.82-1.32)
Household size	1.20(1.08-1.34)*	1.09(1.02-1.15)*
Socio-economic status (ref=Quintile 1(Poorest))		
Quintile 2	2.08(1.09-3.95)*	1.17(0.85-1.61)
Quintile 3	2.61(1.37-4.97)*	1.07(0.77-1.49)
Quintile 4	2.69(1.37-5.29)*	1.32(0.94-1.85)
Quintile 5(Richest)	2.94(1.39-6.19)*	1.89(1.33-2.70)*
Presence of at least one child (ref=No)	1.16(0.72-1.87	1.22(0.94-1.85)
Presence of at least one elderly member (ref=No)	0.73(0.34-1.53)	1.01(0.67-1.53)
Presence of at least one chronically ill member (ref=No)	1.40(0.94-2.11)	1.37(1.09-1.70)*
Presence of a hospitalized member(ref=No)	6.03(4.08-8.90)*	4.82(3.91-5.95)*
Household location (ref=Urban)	5.13(2.14-12.29)*	2.09(1.30-2.32)*
Distance to the nearest health facility	0.99(0.97-1.00)	1.00(0.99-1.01)
Health facility (ref=government facility)		
Religious	2.27(1.24-4.15)*	1.74(1.30-2.32)*
Private	0.51(0.05-5.34)	1.65(0.83-3.29)
Region (ref=Northern)		
Central	3.54(1.79-6.97)*	2.59(1.46-4.59)*
Southern	1.09(0.54-2.22)	1.10(0.63-1.91)

Independent variables	Model 1	Model 2
	Odds Ratio (95% CI)	**Odds Ratio (95% CI)**
District level random effects		
σ_u^2	0.61(0.24-1.54)*	0.24(0.11-0.49)*

Note: * indicates significant at 95% confidence interval and σ_u^2 is the districts random effects

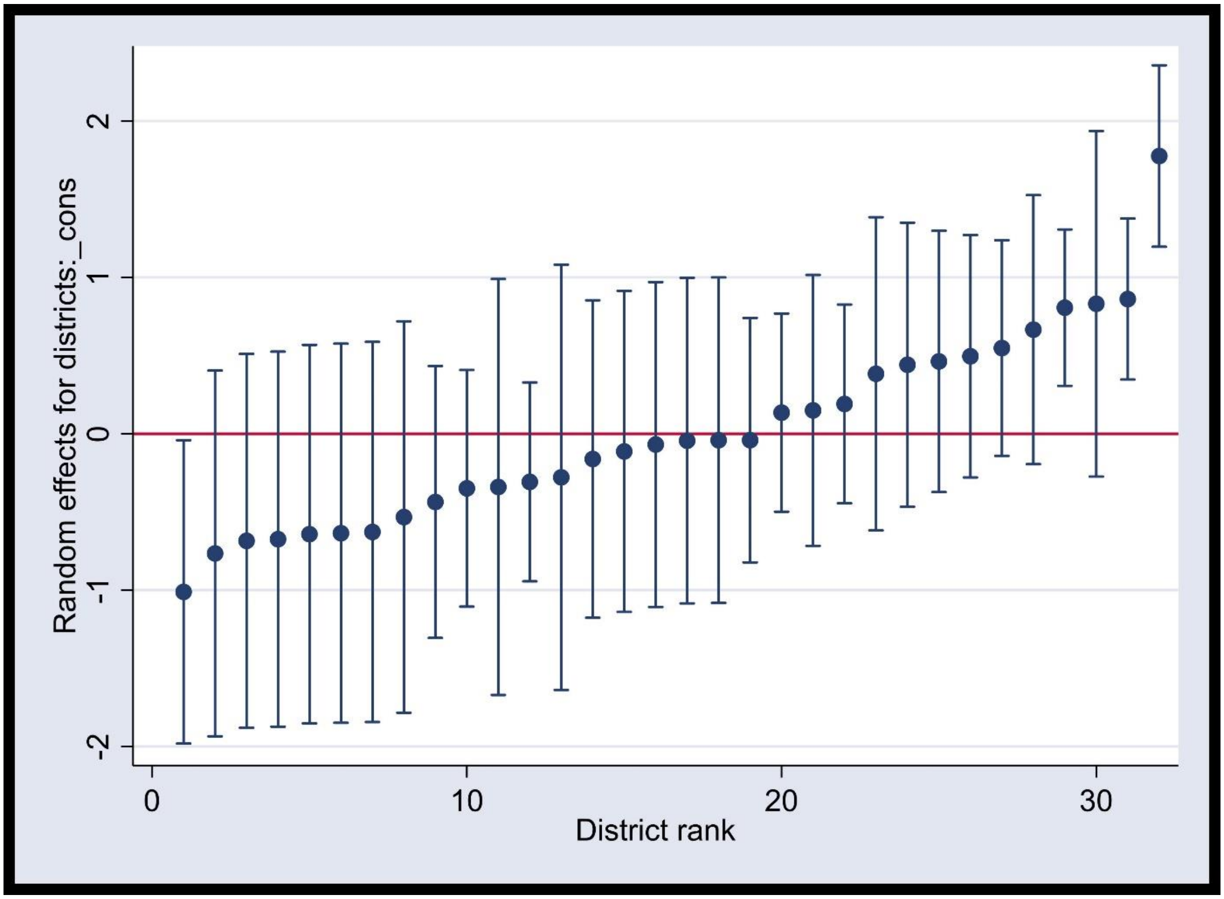

Figure 3:A 95% confidence interval caterpillar plot of ranked district residuals

Note: The circle on the plot indicates the estimated district residuals

5.7 Discussion

This chapter assessed the incidence, intensity of catastrophic health expenditures and its determinants using the most recent Malawi fourth integrated household survey. The results show that out-of-pocket health expenditures are regressive as poorer households bear more financial burden relative to their income than richer households in Malawi. The results also show that catastrophic health expenditures (CHEs) appear to have increased by 37% since the last integrated household survey in 2010/11 (Mchenga et al., 2017). This increase suggests that more people continue to experience disruptions in living standards due to out-of-pocket payments despite government efforts for free access to public health services policy to improve financial protection. There is need for the Malawi government to protect households from the financial burden through other equitable means of financing health such as mandatory health insurance. The level of CHEs at 40% of non-food expenditures in Malawi is similar to what was reported in Lesotho (Akinkugbe et al., 2013), both of which are within the Sothern Africa Development Community, but lower than what was observed in most Sub Saharan African countries (Akazili et al., 2017; Ataguba, 2012; Barasa et al., 2017; Masiye et al., 2016; Ngcamphalala & Ataguba, 2018) . At 10% of total expenditures the level of catastrophic health expenditures in Malawi is very low compared to what was observed in other Sub Saharan African countries (Akazili et al., 2017; Ataguba, 2012; Chuma & Maina, 2012c; Kwesiga et al., 2015; Salari et al, 2019). For example, the proportion who incurred catastrophic health expenditures at 10% of total expenditures were 16%,5%,25% and 23% in Kenya, Ghana, Nigeria, and Uganda respectively.

The low levels of overall incidence of catastrophic health expenditures may not necessarily mean high levels of financial protection considering that the Malawian health care financing system is not as well developed as other sub-Saharan African countries such as Kenya, Rwanda, Tanzania and Ghana (McIntyre et al., 2018) with higher incidence of catastrophic health expenditures. Despite the free access to public health services policy households still contributes to out-of-pocket health expenditures as shown by the analysis in Table 3 that households that accessed care at government facilities contributed more on drugs through out-of-pocket expenditures and spent more on hospitalizations than those that accessed care from religious facilities but less that those that accessed care at private facilities. This may reflect the challenges faced by free access to health services delivery such as constant drug stock outs, poor quality of services. These challenges may force households to buy drugs at private pharmacies, seek high quality health care services in private or mission facilities which charge user fees. Thus the low levels of CHEs may reflect households in ability to afford care due to high costs ; this forces such households to forgo treatment consequently do not incur out-of-pocket health payments and are not counted as incurring CHEs (Ahmed et al., 2018; Myint et al., 2019; Xu et al., 2003). Estimates from the data used in this study show that 4.98% of those who reported illnesses did not seek care due to financial reasons. Moreover, our findings on CHEs by income show that households in poorest income quintile incur lower incidence of CHEs and are at a decreased risk of facing CHEs compared to middle- and richer-income households. Though this finding is contrary from findings by previous studies (Barasa et al., 2017; Ekman, 2007; Ghimire et al., 2018; Khan et al., 2017a; Masiye et al., 2016; Qosaj et al., 2018) a possible explanation could be poor quality of public health services, constant drugs stock outs and poor attitude of medical personnel which forces households in the middle and richer income groups to seek better health care in private facilities and incur greater out-of-pocket health expenditures. On the other hand, inability of poor households to afford better health care at private facilities due to high costs may force them to forgo health care. Government plans to establish a mandatory national health insurance scheme and a health fund financed through tax revenues (Government of the republic of Malawi, 2017a) should also be pursued. This coupled with improved services in public health facilities will ensure that all households, irrespective of their socioeconomic status have access to high quality affordable or free care and do not have to forgo care due to financial hardships.

We found that rural households incur high incidence of CHEs and are at an increased risk of CHEs as reported by other authors (Akinkugbe et al., 2013; Barasa et al., 2017; Masiye et al., 2016; McIntyre et al., 2018; Séne & Cissé, 2015). Rural households in Malawi are burdened with out-of-pocket expenditures due to poverty and high transportation costs in seeking care as health facilities in rural areas are far apart. As such even the little out-of-pocket expenses on transportation by poor households can led to catastrophic health expenditure incidences as observed in other studies (Barasa et al., 2017; Masiye et al., 2016). Though our study did not assess the impact of other direct costs related to seeking health care such as transportation costs; estimates of the mean distance to the nearest health facility with a medical doctor using the data show that on average rural households travel about 17 KMs to seek health care compared to 4 KMs by urban households. In addition, most health facilities in rural areas are privately owned by religious institutions that charge user fees at point of use; higher health care costs puts households at a risk of CHEs and creates a barrier in financial protection among rural households (Abiiro et al., 2014). This implies that policies that aim at increasing financial protection among rural households should also aim at reducing rural poverty and improving accessibility of health services in rural areas.

Our finding that hospitalizations increased the incidence of catastrophic health expenditures is consistent with findings from other studies (Amaya-lara, 2016; Atake & Amendah, 2018; Gotsadze et al., 2009; Li et al., 2013; Oudmane et al., 2019). A study on coping with out-of-pocket payments in 15 African countries including Malawi; found that households with inpatient expenditures are more likely to sell assets and borrow as a means of coping with bills due to hospitalizations (Leive & Xu, 2008). These coping strategies puts pressure on the household limited resources and leads to risk of CHEs.

The result that having the nearest medical doctor based at a religious health facility increased the odds of incurring CHEs than government facility is intuitive in the Malawian context. Religious health facilities charge user fees at point of use this implies households that access care at religious facilities are burdened with higher out-of-pocket payments. This finding corroborates with findings from Kenya (Buigut et al., 2015). For example, visiting a mission hospital increased the odds of incurring catastrophic health expenditures by 2.37 times in Kenya (Buigut et al., 2015). The government of Malawi signed contracts called Service Level Agreements(SLAs) with mission health facilities in 2006 to ensure that households have access to services at these mission facilities without facing financial hardship (Manthalu et al., 2016). Despite other studies showing that service level agreements improved utilization of health services (Manthalu et al., 2016) our finding may suggest that it has not achieved one of its intended purpose of protecting households from the financial burden of health expenditures. This is because many of the mission facilities and needed services are not part of the agreements and the poor who access services at these facilities still incur high out-of-pocket payments (Chansa & Pattnaik, 2018). There is need for government to expand these Service Level Agreements to include more facilities and services needed by households. This innovative financing mechanism has the potential to ensure many households have access to the needed health care without facing financial hardship (Chirwa et al., 2013).

5.8 Chapter summary

Our results are important for monitoring the incidence of catastrophic expenditures in Malawi consequently progress towards achieving Universal Health Coverage. Despite a free public health care policy, our findings suggest that the incidence of catastrophic health expenditures has increased compared to a previous study using similar data. Our finding that rural households face high incidence of catastrophic payments reflects challenges faced by free public health facilities in providing much needed care to households considering that majority of rural population access free public health services. This finding calls for government to improve the challenges faced by free public health services to protect majority rural poor from the financial risk of out-of-pocket payments. This study also shows that access to medical doctors from religious/mission health facilities, living in rural areas and hospitalizations increased the odds of incurring catastrophic payments. There is a need for government to establish more equitable health financing mechanisms such as a mandatory national health insurance scheme or a health fund and expand the innovative financing mechanism of service level agreements to include more mission health facilities and services. This will ensure that the identified vulnerable groups of the population are protected from financial hardship due to out-of-pocket payments.

CHAPTER 6: DECOMPOSING SOCIO-ECONOMIC INEQUALITY IN CATASTROPHIC HEALTH EXPENDITURES

6.1 Introduction

This chapter presents and discusses findings on decomposing socio-economic inequality in catastrophic health expenditures into its determinants. It complements chapter five by providing evidence on the factors which contributes to socio-economic inequality in catastrophic health expenditures. Chapter five briefly examined socio-economic inequality in catastrophic expenditures with the aim of determining the weighted incidence of catastrophic health expenditure to examine how catastrophic health expenditures vary with income distribution of the households. The findings in chapter five indicated that the magnitude of inequality in catastrophic health expenditures as measured by the concentration index is small and that inequality in catastrophic health expenditures is more concentrated among the better-off in Malawi. In this chapter the study provides further evidence on the factors which significantly contribute to inequality in catastrophic expenditure by using the methods for decomposing inequality described in chapter four section 4.5.7. These findings are useful for designing programs and policies to address the causes of socio-economic inequality in catastrophic health expenditures.

6.2 Socio-economic inequality in the incidence and intensity of catastrophic health expenditures

Table 11 gives results of the inequality in the incidence and intensity of catastrophic health expenditures as measured by the concentration index. When catastrophic health expenditure is defined based on non-food expenditures the concentration indices for the incidence of catastrophic expenditure are small in magnitude, positive and statistically significant at all threshold levels. This indicates that catastrophic health expenditure is more concentrated among the better-off. Similarly, the results of the catastrophic overshoot show that the concentration indices at all threshold levels are small in magnitude and positive which indicates that the better off are more likely to overshoot the catastrophic health expenditure threshold levels. Table 11, also provide results on the inequality in the incidence and intensity of catastrophic health expenditures based on total expenditures. The concentration indices are positive at all the threshold levels suggesting that the incidence of catastrophic health expenditure is more concentrated among the better-off, a similar pattern is observed for the intensity of catastrophic expenditures. The concentration indices for the catastrophic overshoot are positive at all threshold levels suggesting that the better off are more likely to overshoot the threshold levels than the worse-off.

Table 11:Concetration indices for the incidence and intensity of catastrophic health expenditures

Catastrophic health expenditures measures			**Threshold levels z (%)**		
Out-of-pocket health payments as share of non-food expenditures	**10%**	**20%**	**25%**	**30%**	**40%**
Headcount (H)					
C_E	0.02	0.003	0.01	0.01	0.004
Overshoot (O)					
C_O	0.003	0.002	0.002	0.002	0.001
Catastrophic health expenditures measures		**Threshold levels z (%)**			
Out-of-pocket health payments as share of total expenditures	**10%**	**20%**	**25%**	**30%**	**40%**
Headcount (H)					
C_E	0.01	0.01	0.004	0.002	0.001
Overshoot (O)					
C_O	0.002	0.001	0.0004	0.0002	0.0001

*C_E denotes concentration index of catastrophic head count, C_O denotes concentration index of catastrophic overshoot.

6.3 Socioeconomic inequality in the determinants of catastrophic health expenditures and decomposition analysis

Table 12 reports the concentration indices of each of the determinants of the incidence of catastrophic health expenditures. Having female headed household $(CI = -0.086, p < 0.01)$, presence of at least one child under five years in the household $(CI = -0.282, p < 0.01)$, larger household size with six to eleven members $(CI = -0.251, p < 0.01)$, residency in rural areas $(CI = -0.363, p < 0.01)$,longer distance to the nearest health facility $(CI = -0.064, p < 0.01)$ and access to religious health facility with medical doctor $(CI =$

$-0.032, p < 0.01$) is concentrated among poor households. On the other hand, having at least one household member hospitalized ($CI = 0.018, p < 0.01$) and access to private health facility with medical doctor ($CI = 0.014, p < 0.01$) is concentrated among rich households.

Table 12:Errygers corrected concentration indices for catastrophic health expenditures and its determinants

Variable	Concentration index (Std. Error)	P-value
Age of household head (ref= $\geq$ 56 years)		
Less than 26 years	0.029(0.007)	0.001***
26-35 years	0.029(0.009)	0.0013**
36-45 years	-0.054(0.009)	0.001***
46-55 years	-0.010(0.007)	0.177
Female household head	-0.086(0.009)	0.000***
Household size (ref $\leq \mathbf{5}$ members)		
6-11 members	-0.2514(0.009)	0.001***
$\geq$ 12 members	-0.0036(0.001)	0.001***
Socio-economic status (ref=Quintile1)		
Quintile 2	-0.311(0.008)	0.001***
Quintile 3	0.001(0.008)	0.991
Quintile 4	0.320(0.008)	0.001***
Quintile 5(Richest)	0.639(0.006)	0.001***
Presence of at least one child	-0.282(0.010)	0.001***
Presence of at least one elderly member	-0.005(0.008)	0.535
Presence of at least one chronically ill member	-0.009(0.009)	0.267
Presence of at least one hospitalized member	0.018(0.007)	0.009**
Rural household location	-0.363(0.012)	0.001***
Distance to the nearest health facility (ref =$\leq$ 34 Km)		
35-69 Km	-0.064(0.006)	0.001***
$\geq \mathbf{70}$ Km	-0.013(0.003)	0.001***
Health facility (ref=government)		
Religious	-0.032(0.006)	0.001***
Private	0.014(0.003)	0.001***
Region (ref=Northern)		
Central	0.081(0.010)	0.001***
Southern	-0.094(0.010)	0.001***

$* \, p < 0.10, ** \, p < 0.05, *** \, p < 0.01$)

Table 13 gives results on decomposing socio-economic inequality in catastrophic health expenditure into its determinants. The analysis was conducted to assess the contribution of inequality in each of the determinants of catastrophic health expenditures to the overall socio-economic inequality in catastrophic health expenditures. The marginal effect in column two indicate the relationship between each determinant and catastrophic health expenditure after controlling for all other determinants. For example, the predicted probability of catastrophic health expenditures was 0.028 greater for households with hospitalized members. The probability of facing catastrophic expenditure was 0.01 greater for rural household and 0.013 greater for households located in central regions. For households with a larger family from 6 to 11 members the probability of facing catastrophic health expenditures was 0.01 greater and it was also 0.01greater for households accessing health services at religious health facilities than government facilities. Compared with households in lower income quintile the probability of facing catastrophic health expenditures was 0.01greater in the richest income quintile.

The contribution of each determinant to the overall inequality is estimated in column five. This column of the absolute contribution is estimated by multiplying four to the product of marginal effects, weighted mean and the Erreygers corrected concentration index of each of the determinants as described in chapter 4 section 4.5.7 of the research methodology. For example, the absolute contribution of residency in rural areas is estimated by 4[0.0097*0.809*(-0.3630)] and the relative contribution was obtained by dividing the absolute contribution by the total contribution of all the determinants. As shown by relative contributions in the last column of table 11; most of the socioeconomic inequality in catastrophic expenditure was mainly due to inequality in residency in rural areas (127%), household socio-economic status (-40%), household size (14%), region in which a household is located (-10%) and having children under five years (10%). Other determinants of catastrophic health expenditure such as female headed household, presence of at least one elder member in the household, presence of at least one hospitalized member, presence of one chronically ill member, access to nearest health facility with medical doctor and distance to the nearest health facility contributed marginally to inequality in catastrophic health expenditure. In total, inequalities in these determinants of catastrophic health expenditures accounted for only 2% of the total inequality in catastrophic health expenditures.

Table 13:Decomposition analysis of concentration index of catastrophic health expenditures

Independent variables	Marginal effects	Weighted Mean	C_k	Contribution to C_y	Contribution to C_y (%)
Age of household head (ref= ≥ 56 years)					-1
≤26 years	-0.0091	0.123	0.0294	-0.0001	
26-35 years	-0.0053	0.267	0.0295	-0.0001	
36-45 years	-0.0067	0.238	-0.0541	0.0003	
46-55 years	-0.0078	0.152	-0.0100	0.00005	
Female household head(ref=male)	0.0009	0.289	-0.0857	-0.0001	1
Household size (ref ≤ 5 members)					14
6-11 members	0.0066*	0.256	-0.2514	-0.002	
≥ 12 members	0.0152	0.0196	-0.0036	-0.0000003	
Socio-economic status(ref=Quintile1)					-40
Quintile 2	0.0071*	0.2	-0.3199	-0.0019	
Quintile 3	0.0093*	0.199	0.0009	0.0000007	
Quintile 4	0.0093*	0.2	0.32032	0.00247	
Quintile 5(Richest)	0.0097*	0.199	0.6397	0.005235	
Presence of at least one child	0.0025	0.535	-0.2825	-0.00141	10
Presence of at least one elderly member	-0.0034	0.198	-0.0051	0.00001	-0.1
Presence of at least one chronically ill member	0.0035	0.223	-0.0096	-0.00003	0.21
Presence of at least one hospitalized member	0.0178*	0.132	0.0182	0.00018	-1.24
Rural household	0.0147*	0.809	-0.3630	-0.018538	127
Distance to health facility (ref =≤ 34 Km)					0.14
35-69 Km	-0.0012	0.098	-0.0644	-0.000028	
≥70 Km	-0.0067	0.0196	-0.0133	0.0000077	
Health facility (ref=government)					0.80
Religious	0.0082*	0.107	-0.0316	-0.00011	
Private	-0.0063	0.021	0.0143	-0.0000069	
Region (ref=Northern)					-10
Central	0.0122*	0.443	0.0798	0.00179142	
Southern	0.0008	0.465	-0.0944	-0.00028	

∗significant at 5% level, C_k is the concentration index a covariate and C_y is the overall concentration index of catastrophic health expenditures.

6.4 Discussion

This chapter aimed at measuring and decomposing socioeconomic inequality in catastrophic health expenditures. The decomposition analysis allowed the study to assess the contribution of inequality in each determinant of catastrophic health expenditures to the overall socio-economic inequality in catastrophic health expenditures. The findings show that socioeconomic inequality is marginally significant and concentrated among the better-off households. Majority of the socioeconomic inequality in catastrophic health expenditures is due to inequalities in residency in rural area, socioeconomic status, household size, having at least a child under five years old and region in which household is located. We discuss these findings in the paragraphs that follows.

Firstly, contrary to findings from previous studies (Akazili et al., 2017; Akinkugbe et al., 2013; Barasa et al., 2017; Gu et al., 2017; Islam et al., 2017; Kavosi et al., 2012; Masiye et al., 2016; Xu et al., 2015) the results demonstrate that catastrophic health expenditure is concentrated among better-off households in Malawi. In Malawi free public health services delivery face many challenges for example constant stock out of drugs, poor quality of services, shortage of human resources which forces the better-off to seek high quality care in private facilities putting households at risk of incurring catastrophic expenditure (Abiiro et al., 2014; Mussa & Masanjala, 2015; The World Bank, 2015) . This is also supported by our finding in table 2 which indicates that access to private health facility is more concentrated among the better-off. Furthermore, other studies have shown that the use of health services and out-of-pocket health expenditures are more concentrated among the better-off households in Malawi (Mwandira, 2011; Nyasulu et al., 2019) which increase the likelihood of incurring catastrophic health expenditures among the better-off.

Another plausible explanation is that due to their ability to pay the better-off households use private health care more than the worse-off as such they incur high out-of-pocket health expenditures putting them at risk of catastrophic health expenditures. This is because the health system in Malawi faces challenges such as shortage of medicines, poor quality of services and shortage of trained medical personnel which forces households to seek care in private facilities. The worse-off may forgo seeking care from private health facilities due to their inability to pay. For example, the worse may forgo purchasing medicine from private pharmacies or accessing private diagnostic tests which may be required if they are not available at public facilities. A health system that gives access to high quality care to the rich due to their ability to pay leaving lower quality care to the poor is inequitable and against the core values of universal health coverage goal (Oxfam, 2016). Malawi has a long history of providing free public health services to reduce inequality and inequity in health services utilization and financial protection however it has been observed that inequities in access and health services utilization still persists (Zere, Moeti, Kirigia, & Mwase, 2007) this exacerbates inequalities in health expenditures (Mwandira, 2011) consequently inequalities in catastrophic health expenditures between the worse-off and better-off. This finding reinforces the need to improve the health systems challenges such as poor quality of services, shortages of medicines and human resources to reduce inequalities in use and access consequently inequalities in health expenditures.

Secondly, our findings that socioeconomic status, residency in rural areas and household size are the major contributors to socioeconomic inequality in catastrophic expenditure are consistent with findings from previous studies (Kavosi et al., 2012; Xu et al., 2015). However, we find that socioeconomic status contributes negatively to inequality in catastrophic health expenditure which indicates that socioeconomic status decreases inequality in catastrophic health expenditure such that catastrophic expenditures is greater among rich households. There are huge income inequalities in Malawi such that these income inequalities and other health inequalities are interrelated (Mussa & Masanjala, 2015). For example, a study in Malawi found that inequality in out-of-pocket expenditures is more concentrated among the rich and the majority of the inequality in out-of-pocket health expenditures are influenced by income inequality (Mwandira, 2011). Thus, in the case of Malawi increasing household socioeconomic status has an effect of reducing inequality in catastrophic health expenditure favoring the poor. Policies that aim to address inequality in catastrophic out-of-pocket health expenditures should simultaneously address income and other related inequalities. This could be through social cash transfer interventions to poor households which could help to reduce income inequalities.

Thirdly, we find that residency in rural areas contributes to most of the socioeconomic inequality in catastrophic health expenditures. The positive contribution to socioeconomic inequality indicates that residency in rural areas increases inequality in catastrophic expenditure such that catastrophic health expenditure is greater among poor rural households. Huge rural –urban income inequalities coupled with poor geographic accessibility of public health facilities in rural areas creates inequality in access to and use of health services disfavoring poor rural households in Malawi (Mussa & Masanjala, 2015). Due to poor geographical accessibility of public facilities poor rural households may incur other direct costs associated with seeking care such as transportation costs which puts them at risk of catastrophic health expenditures as observed by other studies in Kenya and Zambia (Barasa et al., 2017; Masiye et al., 2016) . In Malawi, about 40% of health services in rural areas are provided by Christian Health Association of Malawi(CHAM) health facilities which charge user fee (Chansa & Pattnaik, 2018; Mussa & Masanjala, 2015) as such even smallest expenditures by poor households seeking care at religious health facilities can drive them into catastrophic health expenditures. Moreover, our analysis shows that access to such religious health facilities is concentrated among poor households ($CI = -0.032, p < 0.01$) which means rural poor households disproportionately use religious health facilities more creating inequality in health expenditures disfavoring poor households. The Malawi government introduced service level agreements (SLAs) with CHAM service providers in 2005 to ensure that poor rural households have access to services in these mission facilities without facing financial hardship. However, our finding that inequality in catastrophic health expenditure is greater among rural poor households imply that the SLAs may not have achieved its intended purpose of protecting households and reducing health expenditure disparities in rural areas. It is possible that many of rural CHAM facilities are not part of the SLAs and the poor who access services in these facilities incur catastrophic health expenditure increasing inequality disfavoring the poor. The plans by government to expand these service level agreements to include more facilities should be pursued. This coupled with improving quality of services and geographic accessibility of public health facilities in rural areas could help to reduce the inequality in access and consequently reduce inequality in catastrophic expenditures.

6.5 Chapter summary

The findings of the study have shown that there is weak and marginally significant socioeconomic inequality in catastrophic health expenditures in Malawi. Socioeconomic inequality in catastrophic expenditures is more concentrated among better-off households. Majority of the inequality in catastrophic health expenditures is due to inequality in residency in rural areas, socioeconomic status, region in which the household is located, household size and having children under five years. This suggests that government policies that aim to reduce inequality in catastrophic out-of-pocket payments should simultaneously tackle income, rural-urban and regional related inequalities. For example, policies implemented by the government of Malawi such as Service Level Agreements between mission or religious affiliated health facilities and government that allow households to access free health care at these facilities should be pursued together with policies that aim to reduce income, rural-urban related inequality such as cash transfer policies.

CHAPTER 7: EXTENT OF IMPOVERISHING EFFECTS OF HEALTH EXPENDITURES AND ITS ASSOCIATED RISK FACTORS

7.1 Introduction

This chapter examines the extent of poverty effects of out-of-pocket health expenditures, examines the factors associated with impoverishment to determine population groups vulnerable to impoverishment and quantifies the role of spatial effects on impoverishing effects of out-of-pocket expenditures. Chapter five examined the extent of catastrophic out-of-pocket health expenditures and its determinants using the methods described in chapter four section 4.5.1 and 4.5.3. The results indicated that households in Malawi face catastrophic health expenditures, there were significant district variations in catastrophic health expenditures and several factors were associated with the risk of catastrophic expenditures. However, the analysis of catastrophic out-of-pocket health expenditures in chapter five does not indicate the poverty impacts of out-of-pocket health expenditures on households (Wagstaff & Doorslaer, 2003). This chapter complements chapter five by examining the poverty impact of out-of-pocket health expenditures using the common poverty measures, poverty headcount ratio and poverty gap. The standard poverty measures do not account for out-of-pocket health expenditures as such households that borrow or use savings to finance illnesses are not counted as poor as their total consumption expenditures is raised above the poverty line (O'Donnell & Doorslaer, 2007; Wagstaff & Doorslaer, 2003). This underestimates the poverty levels since such standard poverty measures neglect the impacts of out-of-pocket health expenditures on the welfare of the households.

In this chapter the poverty impact of out-of-pocket expenditures is examined using the measures described in chapter four section 4.5.2. The chapter also examine the factors associated with impoverishing effects of out-of-pocket health expenditures and quantify the role of spatial effects on impoverishing effects of health expenditures using Bayesian spatial multilevel model. Previous studies reported disparities in impoverishing effects of out-of-pocket expenditures across geographical locations (Akazili et al., 2017; Mchenga et al., 2017; Obse & Ataguba, 2020). However, there are no studies that have quantified the role of spatial effects on impoverishing effects of out-of-pocket expenditures. This analysis will help to understand the spatial variations in impoverishing effects of health expenditures, identify areas at greatest risk of impoverishment. Thus, provide evidence to policy makers to design area specific programs and policies to protect vulnerable population groups from financial risk due to illnesses.

7.2 Diagnostics for the binary spatial multilevel logistic model

Results of the models with no predictors fitted to data on impoverishing effects of health expenditures are shown in Table 14. The results show the estimates of district random effects, model fit and complexity measures which are used for comparison in the subsequent models with predictors. The single level binary logistic regression model has no random effects to account for districts variations, the binary multilevel logistic regression model includes unstructured random effects, and the spatial multilevel model includes spatially structured district random effects that accounts for spatial variations. The single level binary logistic model is the least complex ($P_D = 1.00$) among the three models but provided a poor fit to the data ($DIC = 1643.36$). The binary multilevel logistic model is more complex ($P_D = 13.04$) but provided a better fit to the data as indicated by the decrease in DIC from 1643.36 to 1638.49. The spatial multilevel model provided a more improved fit to the data ($DIC = 1635.76$), but the model had an increased complexity ($P_D = 15.88$). This comparison in models with no predictors suggests that the spatial multilevel logistic model provided a more improved fit to the data among the three models. Thus, accounting for spatial variations by including spatially structured random effects provided a significantly improved model. Moreover, the spatially structured district random effects for the spatial multilevel model are significant at 95% credible interval indicating significant spatial variations in impoverishment at district level. The estimate indicating spatial correlation is also significant.

Table 14:Measures of model fit and estimates of district random effects for the null model fitted to data on impoverishment

Variable	Single level model	Multilevel model	Spatial multilevel model
	β	β	β
Intercept	-4.393(-4.557,-4.236)*	-4.448(-4.739,-4.247)*	-4.472(-4.774,-4.254)*
District random effects			
$\boldsymbol{\sigma_u^2}$	___	0.109(0.010,0.503)	0.0002(0.00001,0.001)
$\boldsymbol{\lambda}$	___	___	0.498(0.002,0.998)
Model fit diagnostics			
$\boldsymbol{\bar{D}}$	1642.36	1625.45	1619.88
$\boldsymbol{P_D}$	1.00	13.04	15.88
$\boldsymbol{DIC}$	1643.36	1638.49	1635.76

Note: *Significant at 95% credible interval , σ_u^2 is the districts random effects ,DIC is the Deviance Information Criterion, P_D is the effective number of parameters indicates model complexity,$\bar{D}$ is the deviance evaluated at posterior mean of parameters and goodness of fit of model is the effective number of parameters. 95% credible interval in parenthesis. β represent the regression posterior mean.λ represents a spatial correlation parameter.

Table 15 shows the results of the single level binary logistic, multilevel logistic and spatial multilevel models fitted with all predictors of impoverishment. The single level logistic model is less complex($P_D = 17.52$) but fits the data poorly. The multilevel logistic model is more complex but provided a better fit to the data as indicated by the slight decrease in the DIC from 1536.89 to 1536.23. Accounting for the district variations by including a spatially structured random effect in the spatial multilevel model with all predictors provides a slightly improved the model fit. Nevertheless, the estimated spatially structured district random effect for the model with all predictors is significant indicating significant spatial variations in impoverishment at district level. Thus, the spatial multilevel logistic model provided a better fit to the data compared to the single level logistic and multilevel model.

Table 15:Measures of model fit, estimates of district random effects and coefficients for full models to data on impoverishment

Variable	Single level logistic model	Multilevel logistic model	Spatial multilevel model
	β	β	β
Intercept	-4.749*(-4.740,-3.72)	-4.750*(5.841,-3.710)	-4.737*(-5.885,-3.616)
Age of household head (ref= Over 56 years)			
Less than 26 years	-1.272*(-2.202,-0.391)	-1.275*(-2.206,-0.394)	-1.275*(-2.206,-0.394)
26-35 years	-0.641 (-1.287,0.030)	-0.642 (-1.288,0.030)	-0.641 (-1.287,0.031)
36-45 years	-0.796*(-1.426,-0.141)	-0.796*(-1.426,-0.141)	-0.795*(-1.425,-0.139)
46-55 years	-1.244*(-2.003,-0.502)	-1.247*(-2.006,-0.504)	-1.246*(-2.006,-0.504)
Sex of household head (ref=Male)	-0.024 (-0.396,0.336)	-0.023 (-0.395,0.337)	-0.023 (-0.395,0.337)
Household size	0.050 (-0.049,0.147)	0.05 (-0.05,0.147)	0.05 (-0.05,0.147)
Higher Socio-economic status	-1.063*(-1.488,-0.657)	-1.069*(-1.497,-0.662)	-1.072*(-1.501,-0.664)
Presence of at least one child (ref=No)	0.077 (-0.346,0.506)	0.077 (-0.346,0.507)	0.077 (-0.347,0.507)
Presence of at least one elderly member (ref=No)	-0.299 (-0.893,0.315)	-0.301 (-0.896,0.313)	-0.302 (-0.896,0.313)
Presence of at least one chronically ill member (ref=No)	0.452*(0.099,0.798)	0.451*(0.098,0.798)	0.451*(0.097,0.797)
Presence of a hospitalized member (ref=No)	1.290*(0.933,1.641)	1.289*(0.932,1.640)	1.288*(0.930,1.639)
location (ref=Urban)	0.691*(0.067,1.390)	0.685*(0.045,1.395)	0.710*(0.064,1.450)
Distance to the nearest health facility	-0.006 (-0.017,0.004)	-0.006 (-0.016,0.004)	-0.006 (-0.017,0.004)
Health facility (ref=government)			
Religious	0.312 (-0.151,0.742)	0.305 (-0.164,0.739)	0.304 (-0.166,0.739)
Private	-0.682 (-2.933,1.008)	-0.685 (-2.938,1.007)	-0.697 (-2.952,0.997)
Region (ref=Northern)			
Central	0.361 (-0.086,0.828)	0.353(-0.135,0.845)	0.286(-0.627,0.830)
Southern	-0.086 (-0.531,0.379)	-0.087(-0.560,0.404)	-0.123(-0.838,0.427)
District random effects			
$\boldsymbol{\sigma_u^2}$	___	0.003*(0.0002,0.038)	0.0002*(0.00001,0.001)
$\boldsymbol{\lambda}$	___	___	0.50*(0.002,0.998)
Model fit diagnostics			
$\boldsymbol{\bar{D}}$	1519.37	1515.82	1514.44
$\boldsymbol{P_D}$	17.52	20.41	21.61
$\boldsymbol{DIC}$	1536.89	1536.23	1536.05

Note: *Statistically significant at 95% credible interval, σ_u^2 is the districts random effects, DIC is the Deviance Information Criterion, P_D is the effective number of parameters indicates model complexity, $\bar{D}$ is the deviance evaluated at posterior mean of parameters and goodness of fit of model 95% credible interval in parenthesis. β represent the regression posterior mean. λ represents a spatial correlation parameter.

7.3 Model assumptions for the spatial multilevel logistic model

To further validate the choice of spatial multilevel model for examining factors associated with impoverishing effects of out-of-pocket health expenditures. We assessed the spatially structured district level random effects from the multilevel model. Figure 4 gives the normal probability plot for the spatially structured district random effects. The plot shows some deviation from normality at the end of the tails of the distribution but overall, the plot indicates reasonable normality in the distribution of district random effects as the points are close to the normality line. Moreover, the Shapiro test of normality did not indicate evidence of non-normality in the district random effects ($W = 0.935, pvalue = 0.054$). Thus, the assumption of normality of the district random effects is sufficient. The Moran I test of spatial autocorrelation for the spatially structured district random effects of impoverishment ($Moran\ I\ statistic = 0.204, pvalue = 0.021$) and the observed impoverishment rates ($Moran\ I\ statistic = 0.179, pvalue = 0.034$) are significant indicating spatial clustering in impoverishment. Furthermore, the estimate of the spatial correlation parameter is significant indicating spatial clustering. These results validate the use of binary spatial multilevel logistic model, and the study adopted the spatial multilevel model for the analysis of the factors associated with impoverishing effects of health expenditures.

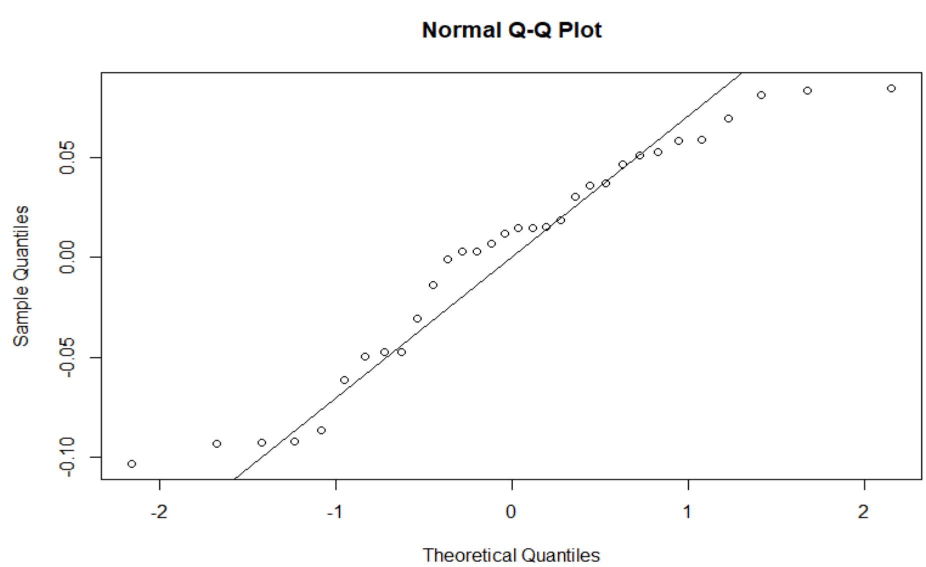

Figure 4:Normal probability plot for random effects from the spatial multilevel model

7.4 Impoverishing effects of out-of-pocket expenditures

This section begins the analysis by providing results on the extent of impoverishing effects of out-of-pocket health expenditures. Table 16 presents results on the impoverishing effects of out-of-pocket health expenditures on households based on the national and international poverty lines. The poverty head count ratio based on total consumption expenditure was 51.53% and subtracting health expenditures from the total consumption expenditure the poverty headcount increased to 53.13%. This implies that over half (51.53%) of the population is considered living below the national poverty line of MWK137425 based on household total consumption expenditures however when out-of-pocket health expenditures are accounted for, about 53.13% of the population is considered poor. Thus about 2% of the population is not considered as poor but could be considered poor if out-of-pocket health expenditures is subtracted from total expenditures. This represented a 3.10% relative increase in the incidence of poverty. The poverty gap increased from MWK23101.75 to MWK 24167.55 after subtracting health expenditures. This represented a 4.61% relative increase in the poverty gap. The normalized poverty gap which is the poverty gap expressed as the percentage of the poverty line increased from 16.81 to 17.59 representing a 4.64% relative increase in the normalized poverty gap. The mean positive gap also increased from 32.62% to 33.10% representing a 1.47% relative increase in the intensity of poverty after accounting for out-of-pocket health expenditures. The increase in the mean positive gap implies that the rise in the poverty gap is because of households that were already poor being pushed deeper into poverty due out-of-pocket health expenditures and those that were not counted as poor based on total expenditures being considered poor when out-of-pocket health expenditure considered.

At the international poverty line, the poverty head count ratio based on total consumption expenditure was 70.31% which was higher than the head count ratio estimated using the national poverty line. When out-of-pocket health expenditure is considered the poverty head count ratio increased to 71.48%. This implies that 1 % of the population is not counted as poor based on total health expenditures but are considered poor when health expenditure is subtracted from total expenditures. This represented a 1.7% relative increase in the poverty head count ratio. As with the national poverty line the normalized mean positive gap increased from 40.99% to

41.60% represent a 1.49% increase. Thus, when using an international poverty line, a lower proportion of population is considered poor when health expenditure is considered.

Table 16:Impoverishing effects of out-of-pocket health expenditures in Malawi using the national and international poverty lines

Poverty measures	Pre-health payments	Post-health payments	Difference	
			Absolute	Relative
	(1)	(2)	3=[(2)-(1)]	[(3)/(1)]*100
National poverty line (MWK137,425 per person per year)				
Poverty head count (%)	51.53	53.13	1.60	3.10
Poverty gap (MWK)	23101.75	24167.55	1065.80	4.61
Normalized poverty gap (%)	16.81	17.59	0.78	4.64
Normalized mean positive gap (%)	32.62	33.10	0.48	1.47
International poverty line (US $1.90 per person per day)				
Poverty head count (%)	70.31	71.48	1.17	1.66
Poverty gap (MWK)	54114	55831.64	1717.64	3.17
Normalized poverty gap (%)	28.82	29.73	0.91	3.16
Normalized mean positive gap (%)	40.99	41.60	0.61	1.49
International poverty line (US $3.20 per person per day)				
Poverty head count (%)	89.43	89.93	0.50	0.56
Poverty gap (MWK)	151570.8	154241.6	2670.8	1.76
Normalized poverty gap (%)	49.45	50.32	0.87	1.76
Normalized mean positive gap (%)	55.29	55.96	0.67	1.21

*Note: MWK is Malawi Kwacha. Poverty head count ratio, normalized poverty gap and normalized mean positive gap are given in percentages.

7.4.1 Impoverishing effects of out-of-pocket health expenditures by household location, region and type of facility utilized

Table 17 shows results of impoverishing effects of out-of-pocket expenditures by location, region and type of facility utilized using the national poverty line. The analysis explores the disparities in impoverishing effects of out-of-pocket expenditures by location, region and type of health facility utilized. Looking at the results on household location the poverty head count ratio increased by 1.83% in rural location while in urban location the headcount ratio increased by 0.57%. The normalized poverty gap increased by 0.90% in rural location while in urban location the increase was 0.18%. This implies that the impoverishing effects of out-of-pocket expenditures was greater in rural than urban location. Further to that the mean positive gap increased by 0.51% in rural locations while in urban locations the mean positive gap increased by 0.21% poverty gap. This increase in the mean positive gap implies that in both rural and urban locations the increase in poverty gap was due to those that were already poor being pushed deeper into poverty when out-of-pocket health expenditures are subtracted from total expenditures and those that were not considered as poor based on total expenditures falling into poverty when out-of-pocket expenditure is considered. However, this deepening of poverty due to out-of-pocket expenditures was greater in rural (0.51%) than urban (0.21%).

Looking at the regional results, the headcount ratio increased by 1.58%, 2.07% and 1.11% in the northern, central, and southern region respectively. The normalized poverty gap increased more in the central region (0.95%) than the northern (0.54%) and southern region (0.65%). This suggests that impoverishing effects of out-of-pocket expenditures was greater in the central region compared to the northern and southern regions. The mean positive gap increased by 0.64% in the central region while in the northern region and southern region the mean positive gap increased by 0.10% and 0.46% respectively. In all the three regions the increase in poverty gap was due to those already poor being pushed deeper into poverty because of out-of-pocket health payments however the results clearly indicate that deepening of poverty was greater in central region than northern and southern region.

The analysis by type of facility utilized is also shown in table 13. The results show that the headcount ratio increased by 1.83 %,1.62%,0.11% when religious/mission, government and private facilities were utilized respectively. The normalized poverty gap increased by 1.07%

among those utilizing religious facilities and it increased by 0.75% and 0.48 among those utilizing government and private facilities respectively. This implies that the poverty effects of out-of-pocket expenditures was greater among the population utilizing religious facilities. The increase in the mean positive gap was 0.42% ,0.73% and 0.97 among those utilizing government, religious and private facilities respectively. Clearly the results show that the increase in poverty gap was due to those that were already poor being pushed deeper into poverty due to out-of-pocket health expenditures. However, it is interesting to note that even though the poverty effects of out-of-pocket expenditures was greater among those utilizing religious facilities; the deepening in poverty due to health expenditures was greater among those utilizing private facilities and lowest among those utilizing government facilities. The results imply that utilizing private facilities push those already poor into poverty indicating that health services are unaffordable among the poor utilizing private health facilities.

Table 17:Impoverishing effects of out-of-pocket health expenditures by location, region, type of facility

Variable	Location		Region			Type of facility		
	Urban	Rural	Northern	Central	Southern	Government	Mission	Private
Poverty head counts (%)								
Pre- payments	17.71	59.45	49.51	47.50	56.03	51.24	58.67	39.40
Post- payments	18.28	61.28	51.09	49.57	57.14	52.86	60.50	39.50
Difference	0.57	1.83	1.58	2.07	1.11	1.62	1.83	0.11
Poverty gaps (MWK)								
Pre- payments	6206.53	27055.79	20756.26	19769.81	26955.92	22793.98	27813.14	16987.32
Post- payments	6458.40	28312.07	21491.83	21072.41	27853.41	23820.25	29287.46	17557.22
Difference	251.84	1256.28	735.57	1302.60	897.50	1026.28	1474.32	569.90
Normalized poverty gaps (%)								
Pre- payments	4.52	19.69	15.10	14.39	19.62	16.59	20.24	12.36
Post- payments	4.70	20.60	15.64	15.33	20.27	17.33	21.31	12.78
Difference	0.18	0.90	0.54	0.95	0.65	0.75	1.07	0.48
Mean positive gap(%)								
Pre- payments	25.50	33.12	30.51	30.29	35.0	32.37	34.49	31.37
Post- payments	25.70	33.61	30.61	30.93	35.46	32.79	35.22	32.34
Difference	0.20	0.51	0.10	0.64	0.46	0.42	0.73	0.97

7.4.2 Impoverishing effects of out-of-pocket health expenditures by district

Figure 5 gives results of the poverty impact of out-of-pocket health expenditures by districts using the national poverty line. This analysis explores the disparities in impoverishing effects of out-of-pocket health expenditures by districts. In nine of the districts, the poverty head count increased by a substantial amount compared to the increase of 1.6% in the head count ratio at national level and the increase in other districts. The head count ratio increased by 3.64%, 3.38% ,2.89% and 2.89% in Dowa, Lilongwe, Mchinji, Dedza districts respectively; all these districts are in the central region. The headcount ratio increased by 3.06 % and 2.06% in Zomba and Chikhwawa districts in the southern region while for districts in the northern region the headcount ratio increased by 2.71%,2.81% and 2.65% in Nkhatabay, Mzimba and Mzuzu city respectively.

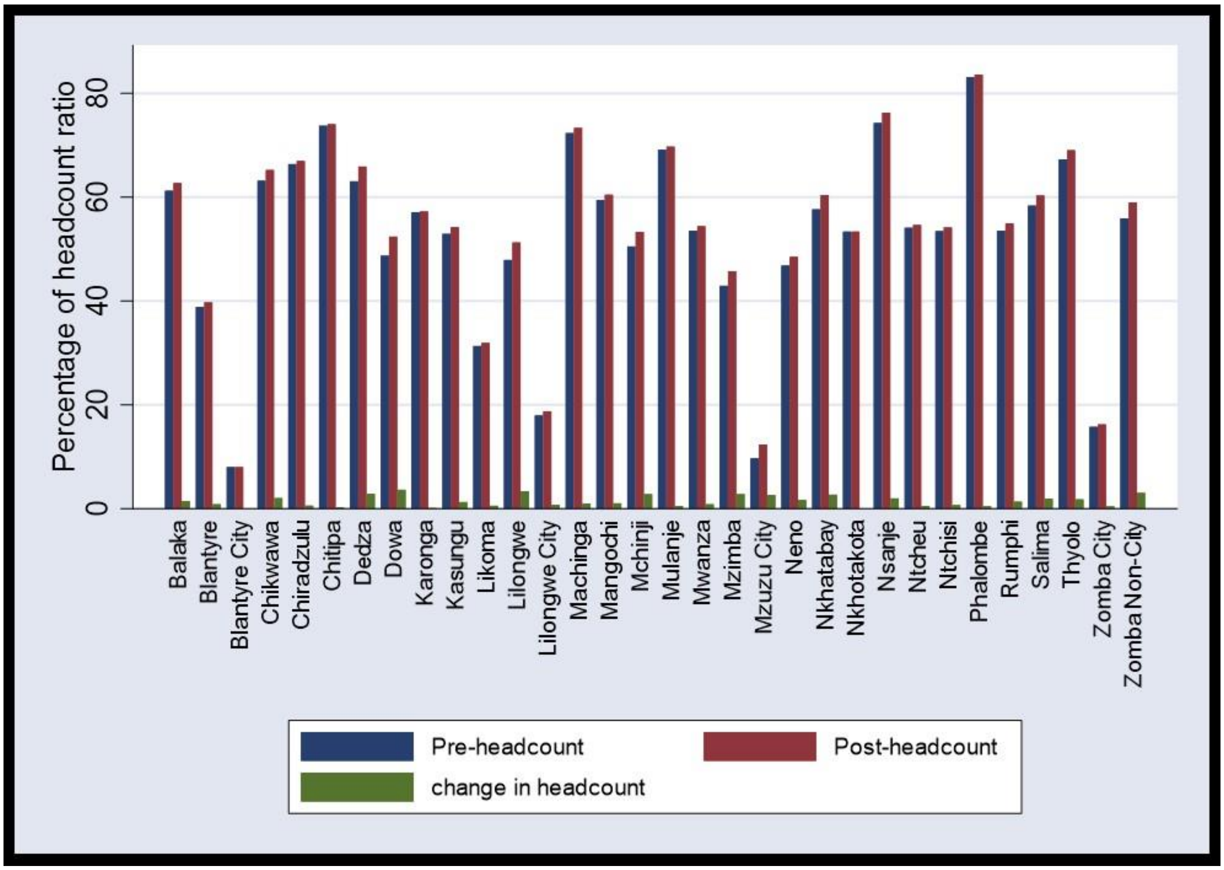

Figure 5:Change in poverty headcount due to out-of-pocket health expenditures

The increase in the normalized poverty gap for two of the districts was substantially higher than the national overall increase of 1.5% and increase in the other districts as shown in Figure 6.

The normalized gap for Dowa and Dedza districts increased by 1.82% and 1.59% respectively. Although in all the districts the increase in the poverty gap was because of the poor population getting poorer due to out-of-pocket health expenditures. The increase in the normalized poverty head count ratio show that the poverty impact of out-of-pocket health expenditures was greater in Dowa and Dedza districts both of which are in central region; this agrees with our finding in table 13 that deepening in poverty due to health expenditures was greater in the central region. From this analysis it is clear that there are variations in the impoverishing effects of out-of-pocket expenditures across districts. In the next section 7.3 the disparities in impoverishing effects of out-of-pocket health expenditures are quantified to understand the role of spatial effects on impoverishing effects on health expenditures.

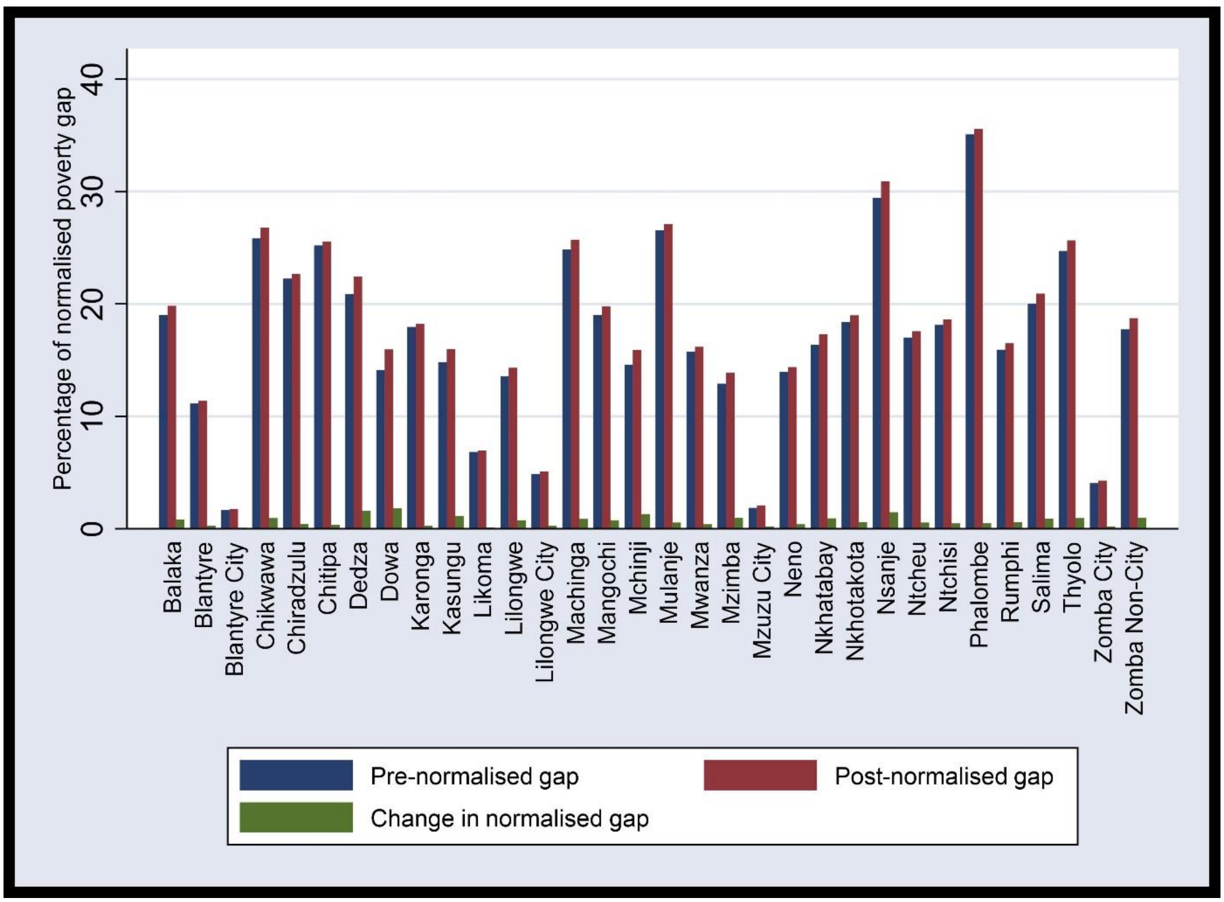

Figure 6. Change in normalized poverty gap due to out-of-pocket expenditures

7.5 Spatial disparities and factors associated with impoverishing effects of out-of-pocket expenditures

This section begins the analysis by assessing the spatial distribution of impoverishing effects of out-of-pocket health expenditures. Figure 7 shows the pattern of the distribution of impoverishing effects of out-of-pocket health expenditures across all the districts in Malawi. It can be observed that impoverishment was higher among the population in central region districts. The clustering pattern in the distribution of impoverishment indicates spatial dependence in impoverishing effects of out-of-pocket health expenditures. The Moran I test of spatial autocorrelation show significant spatial dependence in impoverishing effects of out-of-pocket health expenditures across the districts (Moran I= 0.179, p-value <0.05). This finding reinforces the need to quantify spatial variations in impoverishment across the districts and account for spatial dependence in examining the association between impoverishment and its risk factors. Consequently, a further analysis was conducted to quantify the role of spatial effects on impoverishing effects of out-of-pocket health expenditures by specifically modeling the factors associated with impoverishment using Bayesian spatial multilevel regression modeling techniques described in chapter four section 4.5.5.

To emphasize on the importance of quantifying the role of spatial effects and accounting for spatial effects when assessing factors associated with impoverishing effects of out-of-pocket health expenditures, I first fitted a single level binary logistic regression model that does not account for spatial and neighborhood effects in impoverishing effects of out-of-pocket expenditures, followed by estimation of a multilevel binary logistic model. The multilevel logistic regression models account for clustering effects by assuming within neighborhood effects in this case within districts correlations. Finally, a spatial multilevel logistic model that accounts for clustering effects by accounting for both within districts correlations and between districts spatial correlations was estimated. The deviance information criterion (DIC) was estimated to compare model fit and complexity for the three estimated models.

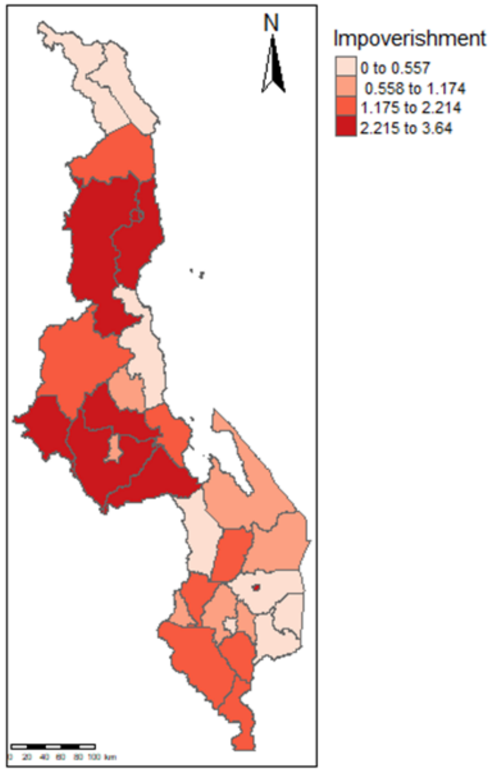

Figure 7: Spatial distribution of impoverishing effects of health expenditures at district level

Table 18 gives the results of the model fit comparisons using the deviance information criterion. The deviance criterion information values were 1536.05,1536.23 and 1536.89 for the spatial multilevel, multilevel, single level logistic models respectively. The differences in DIC values for the three models were small which indicates that all the three models were similar in terms of overall model fit. This may be due to the weakly informative hyper priors used on the random effects when fitting the model as the results of using informative priors indicated a significant difference in the Deviance Information Criterion of the models. Nevertheless, this chapter presents results of the analysis of the association between impoverishment and its risk factors using spatial multilevel model because the thesis aimed to quantify the role of spatial effects on impoverishing effects of health payments. Preliminary analysis indicated spatial clustering in the observed impoverishment rates and the spatial model provided a way to account for spatial clustering in the data.

Table 18:Model fit comparisons for the three models

Model	DIC	P_D	$\bar{D}$
Single level logistic model	1536.89	17.52	1519.37
Multilevel logistic model	1536.23	20.41	1515.82
Spatial multilevel logistic model	1536.05	21.61	1514.44

Note: DIC is the deviance information criterion for the model, P_D is the effective number of parameters. $\overline{D}$ the deviance evaluated at posterior mean of parameters and represents goodness of fit of the model.

Table 19 gives the results of the spatial multilevel model for estimating the probability of impoverishing effects of out-of-pocket health expenditures and quantifying the role of spatial effects. I used the spatial multilevel model to assess the factors associated with impoverishing effects of out-of-pocket health expenditures accounting for both spatial dependence and neighborhood dependence. The estimate of the spatial correlation parameter indicates a moderate significant spatial dependence effect on impoverishment due to out-of-pocket health expenditures (λ=0.50, 95% CI=0.002-0.998).

The results from table 19 show that households in higher socio-economic status had 66% lower odds of experiencing impoverishing effects of out-of-pocket health expenditures compared to those in lower socio-economic status (AOR=0.34, 95% CI=0.22-0.52). Households headed by younger household's heads had 72% lower odds of impoverishing effects of out-of-pocket health expenditures than those with household's heads over 56 years' old (AOR=0.28, 95% CI=0.11-0.67). Households with at least one chronically ill member (AOR=1.56, 95% CI=1.10-2.22) and at least one member hospitalized over the past year (AOR=3.63, 95% CI=2.54-5.15) had an increased odds of experiencing impoverishing effects of out-of-pocket health expenditures. Households in rural areas had 2.03 times greater odds of experiencing impoverishment compared to those in urban areas (AOR=2.03, 95% CI=1.07-4.26).

The findings that household socio-economic status, residency in rural areas and inpatient health services utilization (number of hospitalized household members) is significantly associated with impoverishing effects of health expenditures are in support of the research hypothesis in section 1.6. This implies that income which an enabling factor for health service may lead to out-of-pocket health expenditures consequently household impoverishment. Similarly, inpatient health services utilization and residency in rural location which are need factors for health services use may lead to out-of-pocket health expenditures consequently household impoverishment.

Figure 8 shows the map of the estimated posterior mean of the district level random effects from the spatial multilevel model for quantifying the role of spatial effects. The bright red colors indicate strong positive effect which translate to an increase in the odds of impoverishing effects of health expenditures in those districts. The figure shows a unique spatial pattern in impoverishing effects of out-of-pocket health expenditures across districts in Malawi with low and high values of random effects clustering across the districts. Several districts in the central region have positive posterior mean of the random effects which indicates an increase in the odds of impoverishing effects of out-of-pocket health expenditures among population in the central region districts and several districts in the southern region have negative posterior mean random effects indicating a decrease in the odds of impoverishment. These results in figure 8 confirms those in Table 19 which show households in the central region had an increased odds of experiencing impoverishing effects of out-of-pocket health expenditures.

Table 19:Estimation results from a spatial multilevel model with impoverishing effects of out-of-pocket health expenditures as a binary outcome variable

Independent variables	**Odds Ratio (95% CI)**
Intercept	0.01(0.003-0.03)
Age of household head (ref= Over 56 years)	
Less than 26 years	0.28*(0.11-0.67)
26-35 years	0.53 (0.28-1.03)
36-45 years	0.45*(0.24-0.87)
46-55 years	0.29*(0.12-0.60)
Sex of household head (ref=Male)	0.98 (0.67-1.40)
Household size	1.05 (0.95-1.16)
Higher Socio-economic status (ref=lower)	0.34*(0.22-0.52)
Have at least one child (ref=No)	1.08 (0.71-1.66)
Have at least one elderly member (ref=No)	0.74 (0.41-1.37)
Have at least one chronically ill member (ref=No)	1.56*(1.10-2.22)
Have at least one hospitalized member(ref=No)	3.63*(2.54-5.15)
Rural location (ref=Urban)	2.03*(1.07-4.26)
Distance to the nearest health facility	0.99 (0.98-1.00)
Health facility (ref=government)	
Religious/Mission	1.36 (0.85-2.09)
Private	0.49 (0.05-2.71)
Region (ref=Northern)	
Central	1.33 (0.53-2.29)
Southern	0.88 (0.43-1.53)
λ	0.50* (0.002-0.998)
$\boldsymbol{\sigma^2}$(district)	0.0002(0.00001-0.001)

Note: *Statistically significant at 95% credible interval. The figures in parenthesis represents the lower and upper value of the credible interval. σ^2 represent the district random effects parameter and λ is the spatial correlation parameter.

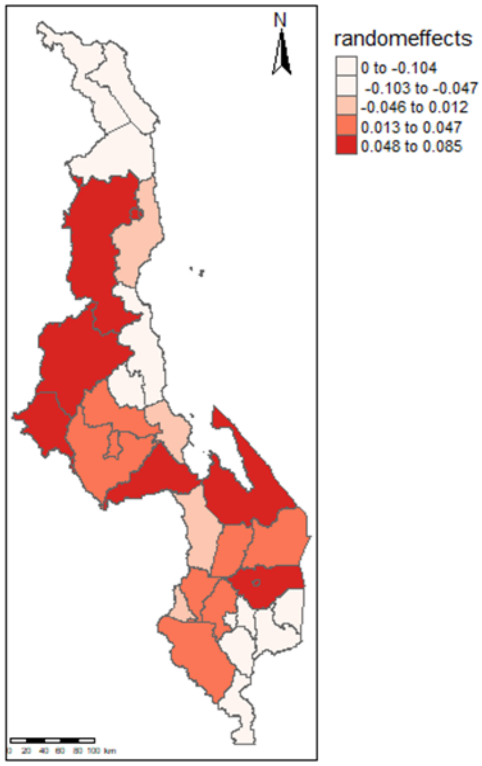

Figure 8:Spatial distribution of district random effects from the Leroux CAR spatial multilevel model

7.6 Sensitivity analysis of model hyper prior distributions

As a robustness check for the spatial multilevel logistic regression model; we conducted a sensitivity analysis using different hyper prior distributions to assess the impact of hyper prior distributions on the estimated parameters. Table 20 presents the posterior mean and standard deviation of the model parameters for different hyper prior distributions. Table 20 includes results of posterior mean and standard deviation for selected important covariates that were significantly associated with impoverishing effects of out-of-pocket health expenditures. The parameter estimates for the fixed effects are generally stable for the different hyper prior distributions used in the sensitivity analysis. However, when a larger hyper prior is assumed on the spatial correlation parameter i.e., $l\mathrm{ogit}(\lambda) \sim \mathrm{N}(0,10)$ and the district level random effects precision i.e., $\tau^2 \sim logGamma(1,0.01)$; the results show substantial differences in the estimate of the spatial and precision parameters. Generally, the results indicate no substantial differences in the fixed effects estimates for the different hyper prior distributions and the choice of the prior distribution does not affect the parameter estimates in our analysis.

Table 20:Posterior mean and standard deviation of model parameters for different hyper prior distributions

Parameter	Prior	Mean (SD)	Age (years)				Higher SES	Chronically ill member	Hospitalized member	Rural location
			< 26	26-35	36-45	46-55				
$\boldsymbol{\lambda}$	N(0,10)	0.564	-1.287	-0.640	-0.789	-1.256	-1.110	0.447	1.280	0.777
		0.324	0.462	0.336	0.329	0.384	0.214	0.179	0.181	0.399
	N(0,100)*	0.498	-1.277	-0.641	-0.794	-1.248	-1.078	0.451	1.287	0.720
		0.374	0.461	0.336	0.328	0.383	0.214	0.178	0.181	0.361
	N(0,200)	0.496	-1.283	-0.640	-0.791	-1.253	-1.098	0.448	1.282	0.759
		0.374	0.462	0.336	0.328	0.383	0.215	0.179	0.181	0.388
	N(0,1000)	0.500	-1.275	-0.641	-0.795	-1.246	-1.072	0.451	1.288	0.710
		0.374	0.461	0.336	0.328	0.382	0.213	0.178	0.180	0.353
$\boldsymbol{\sigma_u^2}$	logGamma(1,0.01)	0.4964	-1.287	-0.640	-0.789	-1.256	-1.110	0.447	1.280	0.777
		0.3411	0.462	0.336	0.329	0.384	0.214	0.179	0.181	0.399
	logGamma(1,0.0001)	0.0003	-1.277	-0.641	-0.794	-1.248	-1.078	0.451	1.287	0.720
		0.0006	0.461	0.336	0.328	0.383	0.214	0.178	0.181	0.361
	logGamma(1,0.001)	0.0044	-1.283	-0.640	-0.791	-1.253	-1.098	0.448	1.282	0.759
		0.0111	0.462	0.336	0.328	0.383	0.215	0.179	0.181	0.388
	logGamma(1,0.00005)*	0.0002	-1.275	-0.641	-0.795	-1.246	-1.072	0.451	1.288	0.710
		0.0003	0.462	0.336	0.328	0.383	0.215	0.179	0.181	0.388

Note: * Denotes the hyper prior distributions used in the analysis

7.7 Discussion

This Chapter examined the extent of impoverishing effects of out-of-pocket health expenditures, the role of spatial effects on impoverishment and the factors associated with impoverishment. Our findings show that a low proportion of the population faced impoverishment due to out-of-pocket expenditures in Malawi. The findings from the spatial multilevel model revealed spatial variations in impoverishing effects of out-of-pocket health expenditures across districts and several factors were associated with impoverishment. We discuss the findings from this chapter in the subsequent paragraphs.

Our finding on the proportion of the population impoverished due to out-of-pocket health expenditures represented a 60% increase since the last Malawi integrated household survey in 2010/11 (Mchenga et al., 2017). The level of impoverishment is similar to what was observed in other African countries (Akazili et al., 2017; Ngcamphalala & Ataguba, 2018; Obse & Ataguba, 2020). This finding implies that a small proportion of Malawians were pushed below the poverty line due to out-of-pocket health payments despite government efforts to increase financial protection through the free access to public health services policy.

The study also finds significant spatial variations in impoverishment across districts with districts in the central region at higher risk of impoverishment as evidenced by clustering of spatial random effects on the map in figure 6. For example, in districts such as Mzimba, Mzuzu, Nkhatabay, Dedza, Dowa, Lilongwe, Mchinji, Salima, Chikwawa, Neno, Thyolo, Zomba impoverishment was higher than the average across all districts. These significant spatial variations in impoverishment across districts may reflects differences in out-of-pocket health expenditures, district economic status, disease pattern, accessibility and availability of health services at district (Borghi et al., 2017; Chirombo et al., 2014; Government of Malawi Ministry of Health and Population, 2019; Kazembe et al., 2007; Kazembe & Kamndaya, 2016; Kazembe & Namangale, 2007; Malawi IFPRI, 2019; Ngwira & Kazembe, 2015; Nutor et al., 2020). For example, previous studies found spatial variations in childhood comorbidities, childhood anemia, Pneumonia, Malaria and HIV in Malawi (Chirombo et al., 2014; Kazembe et al., 2007; Kazembe & Kamndaya, 2016; Kazembe & Namangale, 2007; Ngwira & Kazembe, 2015; Nutor et al., 2020). These studies found clustering of higher risk of childhood comorbidities, Pneumonia and Malaria in districts in the central region. It is possible that the higher burden of diseases in these districts may lead to high out-of-pocket health expenditures among households which pushes households into poverty inducing spatial clustering in impoverishment. This analysis showed spatial clustering with high risk in impoverishing effects of out-of-pocket health expenditures among districts in the central region. Considering the spatial variations in impoverishing effects of out-of-pocket expenditures across districts, programs and policies that aim to protect households from financial risk due to illnesses should be designed according to district specific needs and may target those districts at greatest risk.

This study provide evidence that several factors are associated with impoverishing effects of out-of-pocket health expenditures. Consistent with previous studies (Minh & Xuan, 2012; Shi et al., 2011), the study showed that households with chronically ill members are at a greater odds of facing impoverishing effects of out-of-pocket health expenditures. In Malawi, out-of-pocket health expenditures on chronic diseases as a percentage of total health expenditures are higher than expenditures on other conditions such as infectious diseases and reproductive health. (Government of the republic of Malawi, 2018). This means that households bear a large burden of out-of-pocket health expenditures on chronic diseases. Available evidence also show that chronic illness is significantly associated with higher out-of-pocket expenditures (Nakovics, Brenner, Bongololo, Chinkhumba, & Kalmus, 2020). A different study found that chronic non communicable diseases places a higher burden on the population and increases poverty (Wang et al., 2016). Moreover, data used in our analysis indicate that households with chronically ill members have significantly higher out-of-pocket health expenditures. This suggests that chronic illnesses have a significant financial burden on the population in Malawi. A plausible explanation may be poor availability of medications for chronic illnesses in public facilities and high prices at private facilities (Mendis et al., 2007). This exacerbates out-of-pocket expenditures on medicines for chronic illnesses and places a financial burden on households. This finding also highlights the need to incorporate the burden of chronic illnesses when designing financial protection interventions. Most chronic non communicable diseases are not part of the essential health package which was designed to address the major causes of mortality and morbidity as such households still bear a huge financial burden in accessing care for chronic non communicable diseases (Government of the republic of Malawi, 2017b).

The finding on the relationship between socioeconomic status and impoverishment due to health payments is consistent with findings from previous studies(Minh et al., 2013; Shi et al., 2011).The finding showed that households in higher socioeconomic quintile are less likely to face impoverishment due to health payments. This protective effect of income suggests higher capacity to pay for households in higher expenditure quintiles when seeking care in private health facilities. Low capacity to pay by households in lower expenditure quintiles may imply that out-of-pocket health expenditures as little as expenditures of medicines may easily push such households into poverty as they are already closer to the poverty line (Shi et al., 2011).

In line with other studies (Minh et al., 2013; Obse & Ataguba, 2020; Shi et al., 2011) , the analysis showed that households in rural areas are more likely to face impoverishing effects of health expenditures. This finding suggests lack of financial protection among rural households. This is expected as poverty levels are higher in rural areas in Malawi (Malawi IFPRI, 2019) and coupled with poor geographic accessibility of public health facilities this may entail increased transportation costs for seeking care putting more financial burden on already poor households (Abiiro et al., 2014). Evidence show that the poor bear greater financial burden due to out-of-pocket health expenditures in Malawi (Mwandira, 2011). Considering that many of the rural households are already poor, it is possible that even the little expenditures on illnesses and transportation to seek care may push them into poverty. Moreover, our analysis of the mean positive gap has shown that deepening of poverty due to out-of-pocket health expenditures is greater among rural population. This highlights the need to combine interventions that aim at increasing financial protection and reducing rural poverty.

In 2006 the government of Malawi started contracting out health services to mission health facilities which charge user fees and are mostly concentrated in rural areas. These agreements termed Service Level Agreement (SLAs) were signed with the aim of providing households with access to services at these facilities free of charge and protecting households from the financial risk of illnesses. Although previous studies have shown that Service Level Agreements increased utilization of health services at these facilities (Manthalu et al., 2016) our finding that households in rural areas are more likely to face impoverishment indicate that these agreements may have failed to provide financial protection to rural households due to implementation challenges (Abiiro et al., 2014). In addition, not all of the mission facilities and essential health services are part of these Service Level Agreements as such it is possible that households still face higher health expenditures when accessing other services at these facilities which pushes them into poverty (Chansa & Pattnaik, 2018). The plans by government to expand the Services

Level Agreements to include more mission health facilities and services (Government of the republic of Malawi, 2017a) will help to ensure financial protection among the rural population.

Our finding that hospitalizations increase the risk of impoverishment due to health expenditures is in line with another study (Shi et al., 2011) . Illnesses that require hospitalizations are usually severe and may result in higher out-of-pocket expenditures, this coupled with other expenditures related to seeking care such as costs of food, accommodation and transportation by care givers increase the total out-of-pocket health expenditures (Nakovics et al., 2020). In Malawi, households with malaria episode that required hospitalization faced a higher financial burden than those that required outpatient treatment (Hennessee et al., 2017) . Another study in Malawi found that expenditures on hospitalization for TB were higher than outpatient expenditures (Shin et al., 2020). Considering that access to public health services is free at point of use and is intended to provide financial protection for households including those that face hospitalizations it is possible that the higher expenditures on hospitalizations are worsened by other costs related to seeking care. This challenge highlights the need for interventions that could help the most vulnerable households faced with hospitalizations to cope with other costs related to seeking care. Such interventions could be in a form of cash transfer schemes and other safety net programs to cushion poor households. Evidence from 15 African countries including Malawi suggests that households with higher out-of-pocket expenditures on hospitalizations are more likely to borrow money and sell assets to cope with such expenditures (Leive & Xu, 2008). This put pressure on households limited resources and push them into poverty.

7.8 Chapter summary

The analysis in this chapter shows that out-of-pocket health expenditures in Malawi are not only catastrophic as observed in chapter five but also causes hardship by pushing the non-poor into poverty and those already poor deeper into poverty. This is despite government’s financial protection policies such as free access to public health services and contracting out of services to mission facilities. These findings suggest the need for government to improve services at public health facilities which face many challenges and expand the service level agreements (SLAs) with private facilities to include more facilities and services.

In addition, we showed that having chronically ill members, hospitalizations, rural residency, and lower socioeconomic status increased the odds of impoverishment. Particularly our finding that chronic illnesses is an important determinant of impoverishment reflects the rising burden of chronic diseases in Malawi and suggest the need to incorporate the burden of chronic illnesses in designing financial protection strategies. The analysis in this chapter also showed significant spatial variations in impoverishing effects of out-of-pocket health expenditures across districts with several districts in central region at higher risk. The spatial variations in impoverishing effects of out-of-pocket expenditures may reflect disparities in diseases pattern, health financing pattern, access and utilization of health services. This finding suggests the need to plan financial protection strategies; design interventions according to the district specific needs and target those districts at greatest risk. Further research should explore the specific chronic illnesses which drive households into impoverishment due to out-of-pocket health expenditures. Further research should also understand the unmeasured districts specific factors contributing to clustering of impoverishing effects of out-of-pocket expenditures.

CHAPTER 8: COMPARISON OF SPATIAL MULTILEVEL MODEL TO MULTILEVEL AND SINGLE LEVEL LOGISTIC MODELS

8.1 Introduction

This chapter describes the simulation analysis that was conducted to compare a spatial multilevel logistic regression model with multilevel logistic and single level logistic models when assessing factors associated with impoverishing effects of out-of-pocket health expenditures. The chapter presents and discusses the results from the simulation analysis comparing the three models in terms of performance of the parameter estimates and goodness of fit of the models. It also presents and discusses results from the actual dataset relating impoverishing effects of out-of-pocket health payments to its associated risk factors by comparing the parameter estimates and goodness of fit of the models. These models were fitted to the simulated and actual dataset using the methods described in chapter four section 4.5.5. Lastly the chapter summarizes the findings from the simulation analysis and actual dataset.

8.2 Simulation analysis

A simulation study to compare parameter estimates from a spatial multilevel logistic regression model with multilevel logistic and single level logistic models was conducted. Parameter estimates for the models were compared in terms of performance using percentage bias calculated as the difference between the average estimated parameter value and the true value as a percentage of the true value. The Mean Squared Error (MSE) which is used as a measure of efficiency and precision of the parameter estimates was also computed.

Data was simulated based on the spatial multilevel model relating impoverishing effect of out-of-pocket health expenditures to five covariates. The spatial weight matrix used in the analysis is based on the geography of the fourth integrated household survey (IHS4) dataset described in chapter four section 4.2. The analysis used a row standardized spatial weight matrix based on contiguity of all the districts in Malawi. Only five covariates were included in the models to speed up the simulation. The initial true parameter values were set to the values obtained from fitting a spatial multilevel logistic model to the actual data set. The initial true values for the fixed effect parameters were set to $\beta_0 = -4.1$, $\beta_1 = -1$, $\beta_2 = 1, \beta_3 = 0.4, \beta_4 = 0.6, \beta_5 = 0.01$ and for the random effect part the precision parameter was set to $\tau = 3$ and the spatial correlation parameter was set to three different scenarios $\lambda = 0, \lambda = 0.5, \lambda = 0.9$. The spatial correlation parameter was set to the three scenarios to examine the effect of spatial dependence structure on the parameter estimates obtained using the three models.

Data was simulated under the three different scenarios of the spatial correlation parameter; for $\lambda = 0$ the spatial multilevel logistic regression model reduced to the multilevel model with independently identically distributed random effects with no spatial dependence in the data. A scenario where $\lambda = 0.5$ indicated moderate spatial dependence in the data and $\lambda = 0.9$ indicated strong spatial dependence in the data. The neighborhood structure of Malawi districts was used to obtain the binary adjacent weight matrix W which represented spatial interaction between the neighborhoods and was in turn used in simulating data for the random effects. The random effects u_j which are spatially structured were simulated from a multivariate normal distribution with mean equal to zero and prior precision matrix equal to $\tau^2[diag(1 - \lambda + \lambda w_{j+}) - \lambda W]$ as described in chapter four section 4.5.5.

The response variable impoverishing effects of out-of-pocket health payments which is binary was generated from a binomial simulation with $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + u_j$. The covariates X_1, X_2, X_3, X_4 are also binary and generated from a binomial simulation. X_5 is a continuous variable which represented age of the household head and was simulated based on the actual age of the household head with a mean of 43 and variance of 256. For each of the three scenarios of the spatial correlation parameter 100 data sets were simulated using R statistical software package and the three different models to be compared were fitted to the simulated dataset. Under each scenario, only 100 data sets were simulated to reduce the computation burden resulting from longer processing time during the simulations.

Bayesian model estimation was implemented in R-INLA to estimate the parameters using the simulated datasets. The Normal prior was assigned to the fixed effect parameters i.e., $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5 \sim N(0,1000)$. The precision parameter τ was assigned a weakly informative gamma prior i.e., $\tau \sim logGamma(1,0.001)$ and the spatial correlation parameter λ was assigned a normal prior i.e., $logit(\lambda) \sim N(0,200)$. The posterior means of parameter estimates from the three fitted models were compared using bias and mean squared error to evaluate the performance of the three models in estimating the parameters. Deviance information criterion

(DIC) was used to compare goodness of fit of the models. The same priors were also used in the Bayesian model estimation of the parameters using the actual data on impoverishing effects of out-of-pocket health expenditures.

8.3 Results of model comparisons from the simulation analysis

Table 21 gives the results of the simulation for comparing the three models in terms of performance using the Mean squared Error (MSE) and percentage bias. The table also gives the Deviance Information Criterion (DIC) statistic for assessing model fit. When data was simulated under the scenario with $\lambda = 0$ the parameter estimates obtained using the logistic regression model were slightly lower with a difference observed on the third decimal place while the estimates obtained using spatial multilevel logistic and multilevel logistic model were similar. All the three models performed in a similar manner in terms of precision and efficiency of estimation of the parameters as measured by MSE however a comparison in terms of accuracy show that the parameter estimates from the logistic regression model were less accurate as percentage bias for the estimates were slightly higher compared with the spatial multilevel and multilevel models. A comparison between the spatial multilevel model and multilevel models under this scenario in terms of accuracy also shows that the multilevel model provided more accurate estimates as the percentage bias was smaller although the difference was negligible. The results of the Deviance Information Criterion under this scenario indicates that the multilevel model (5080.83) and the spatial multilevel model (5081.08) provided almost similar fit to the data since the difference in the DICs between the two models was small. However, comparison of the DIC for the logistic regression model (5432.62) to the multilevel model (5080.83) and spatial multilevel model (5081.08) show that the difference in DICs was large which indicates that the logistic regression model provided a poor fit to the data under this scenario.

When data was simulated under the case with $\lambda = 0.5$ the parameter estimates obtained using the multilevel model and the spatial multilevel model were similar. The parameter estimates of the logistic regression model were lower than the spatial multilevel and multilevel model although the difference was very small to be noticeable. Precision and efficiency of the parameter estimates was similar for all the three models however in terms of accuracy the estimates from the spatial multilevel and multilevel models had a lower percentage bias compared with estimates from the logistic model especially on the estimate of the intercept. There was a negligible difference in the Deviance information criterion for the spatial multilevel model (4855.09) and the multilevel model (4855.22) which indicates that the models provided almost similar fit to the data. Nevertheless, the difference in DIC between the multilevel (4855.22), spatial multilevel (4855.09) and the logistic regression model (5164.12) was large indicating that the logistic regression model provided a very poor fit to the data.

For the data simulated under the scenario with $\lambda = 0.9$ the results were similar to those obtained under the scenario with $\lambda = 0.5$. The parameter estimates from the spatial multilevel model and multilevel model were similar while the estimates from logistic regression model were slightly lower. The efficiency and precision as measured by MSE were similar for spatial multilevel model and multilevel model but low for logistic model particularly on the intercept as the measured MSE was slightly higher. Overall, the DIC for the spatial multilevel model was slightly smaller than the multilevel logistic model indicating that there was a slight difference in terms of model fit between the multilevel model and the spatial multilevel model. However, the Deviance information criterion (DIC) for the logistic regression model (5044.4) was larger compared to the spatial multilevel model (4793.56) and multilevel model (4793.63) indicating the logistic regression model provided a poor fit to the data.

Regarding estimation of the random effects variance, the random effects variance was smaller for the multilevel model compared with the spatial multilevel model. Under the two scenarios ($\lambda = 0.9$ and $\lambda = 0.5$) where there was spatial correlation in the data the random effects variances for the multilevel models were slightly lower than that of the spatial multilevel models. This implied that the multilevel models underestimated the random effects variances compared to the spatial multilevel models.

Table 21:Comparison of parameter estimates and model fit statistics under three scenarios of the spatial parameter

		Spatial Multilevel model			Multilevel logistic model			Logistic model		
$\boldsymbol{\lambda = 0}$	TV	AEV	PB	MSE	AEV	PB	MSE	AEV	PB	MSE
$\boldsymbol{\beta_0}$	-4.1	-3.934	**-4.036**	0.060	-3.933	**-4.064**	0.060	-3.929	**-4.158**	0.063
$\boldsymbol{\beta_1}$	-1	-0.979	**-2.056**	0.008	-0.979	**-2.070**	0.008	0.986	**-1.447**	0.007
$\boldsymbol{\beta_2}$	1	0.980	**-1.999**	0.006	0.980	**-2.017**	0.006	0.977	**-2.334**	0.007
$\boldsymbol{\beta_3}$	0.4	0.394	**-1.457**	0.006	0.394	**-1.468**	0.006	0.393	**-1.829**	0.005
$\boldsymbol{\beta_4}$	0.6	0.584	**-2.616**	0.007	0.584	**-2.634**	0.007	0.576	**-3.998**	0.007
$\boldsymbol{\beta_5}$	0.01	0.009	**-3.663**	0.000	0.009	**-3.683**	0.000	0.009	**-0.800**	0.000
$\boldsymbol{\lambda}$			**0.265**			-			-	
$\boldsymbol{\sigma^2}$			**0.002**			**0.003**			-	
DIC			**5081.08**			**5080.83**			**5432.62**	
$\boldsymbol{\lambda = 0.5}$	TV	AEV	PB	MSE	AEV	PB	MSE	AEV	PB	MSE
$\boldsymbol{\beta_0}$	-4.1	-4.009	**-2.227**	0.035	-4.008	**-2.237**	0.035	-4.013	**-2.129**	0.037
$\boldsymbol{\beta_1}$	-1	-0.996	**-0.428**	0.008	-0.996	**-0.434**	0.008	-0.989	**-1.024**	0.007
$\boldsymbol{\beta_2}$	1	0.989	**-1.085**	0.006	0.989	**-1.090**	0.006	0.987	**-1.327**	0.007
$\boldsymbol{\beta_3}$	0.4	0.400	**0.016**	0.005	0.400	**0.013**	0.005	0.398	**-0.408**	0.005
$\boldsymbol{\beta_4}$	0.6	0.589	**-1.811**	0.007	0.589	**-1.817**	0.007	0.581	**-3.125**	0.006
$\boldsymbol{\beta_5}$	0.01	0.009	**-3.537**	0.000	0.009	**-3.547**	0.000	0.009	**-0.420**	0.000
$\boldsymbol{\lambda}$			**0.452**			-			-	
$\boldsymbol{\sigma^2}$			**0.005**			**0.004**			-	
DIC			**4855.09**			**4855.22**			**5164.12**	
$\boldsymbol{\lambda = 0.9}$	TV	AEV	PB	MSE	AEV	PB	MSE	AEV	PB	MSE
$\boldsymbol{\beta_0}$	-4.1	-4.024	**-1.816**	0.032	-4.025	**-1.822**	0.032	-4.034	**-1.598**	0.034
$\boldsymbol{\beta_1}$	-1	-1.003	**0.297**	0.008	-1.003	**0.292**	0.008	-0.989	**-1.038**	0.008
$\boldsymbol{\beta_2}$	1	0.993	**-0.735**	0.006	0.993	**-0.739**	0.006	0.989	**-1.091**	0.007
$\boldsymbol{\beta_3}$	0.4	0.404	**0.972**	0.005	0.404	**0.971**	0.005	0.401	**0.342**	0.005
$\boldsymbol{\beta_4}$	0.6	0.588	**-1.923**	0.007	0.588	**-1.927**	0.007	0.586	**-2.383**	0.007
$\boldsymbol{\beta_5}$	0.01	0.009	**-3.385**	0.000	0.009	**-3.398**	0.000	0.009	**-0.773**	0.000
$\boldsymbol{\lambda}$			**0.452**			-			-	
$\boldsymbol{\sigma^2}$			**0.006**			**0.004**			-	
DIC			**4793.56**			**4793.63**			**5044.4**	

Note: TV is the true value, AEV is the average estimated value, PB is the percentage bias, MSE is the mean squared error, DIC is the Deviance information criterion.

8.4 Results of model comparisons from the actual dataset

Table 22, presents the model estimation results comparing the parameter estimates and model fit of the three models fitted to actual data on impoverishing effects of out-of-pocket health expenditures. The results indicate that the fixed effects estimates were nearly the same for all the three models with a difference only observed at the third decimal place in some cases. Households with at least one chronically ill member, at least one hospitalized member and located in rural areas were significantly more likely to face impoverishing effects of out-of-pocket health expenditures. Households in higher socio-economic status and headed by younger household head were significantly less likely to face impoverishing effects of out-of-pocket health expenditures. The findings on the significance of the predictors in explaining impoverishing effects of out-of-pocket health expenditures were the same across all the three model and there was negligible difference on the size of the posterior means across all the three models.

In terms of the random effects part of the models, the estimated district random effects $\boldsymbol{\sigma^2}$(district) for the multilevel model was significant indicating that the impoverishing effects of out-of-pocket expenditures rates were clustered within districts and that the multilevel model specification was necessary. Comparison of model fit for the three models using the deviance information criterion indicated that there is a slight difference in the DICs between the multilevel logistic model (1524.77) and the spatial multilevel logistic model (1524.56). However, there is a significant difference in DIC between the spatial multilevel model and the standard logistic model (1534.46). The results indicate that the spatial multilevel model provided a better fit to the data compared to the standard logistic regression model. The estimated district random effects $\boldsymbol{\sigma^2}$ (district) for the spatial multilevel model was significant which indicated that the spatial multilevel was the required specification for the data. Moreover, the estimated spatial correlation parameter $(\lambda = 0.394, 95\%\ CI: 0.006, 0.954)$ for the model was significant indicating spatial clustering in the data. Further comparison of the district random effects for the multilevel model and spatial multilevel model shows that the random effects variance for the multilevel model was smaller than the spatial multilevel model. This difference in the district random effects variance implies that the multilevel model may have underestimated the variance due to its failure to account for spatial dependence in the data. On the other hand, the random effects variance increased in the spatial multilevel model as the model accounts for both within districts and spatial dependence in the data.

Table 22:Comparison of parameter estimates and model fit statistics using actual data

Variable	Spatial multilevel model	Multilevel logistic model	Logistic model
	Posterior mean	Posterior mean	Posterior mean
Intercept	-5.702*(-6.708,-4.816)	-5.626*(-5.841,-3.710)	-5.599*(-6.421,-4.836)
Age of household head	0.013*(0.003,0.022)	0.013*(0.003,0.022)	0.013*(0.003,0.023)
Higher Socio-economic status	-1.148*(-1.562,-0.756)	-1.147*(-1.561,-0.755)	-1.105*(-1.513,-0.720)
Presence of at least one chronically ill member (ref=No)	0.432*(0.081,0.776)	0.432*(0.080,0.775)	0.436*(0.086,0.779)
Presence of at least one hospitalized member(ref=No)	1.327*(0.976,1.671)	1.326*(0.975,1.669)	1.332*(0.983,1.672)
Rural household location (ref=Urban)	0.681*(-0.002,1.461)	0.603*(-0.068,1.344)	0.623*(0.016,1.307)
$\boldsymbol{\lambda}$	0.394*(0.006,0.954)	-	-
$\boldsymbol{\sigma^2}$**(district)**	0.374*(0.072,1.026)	0.142*(0.03,0.486)	-
DIC	1524.56	1524.77	1534.46
$\boldsymbol{P_D}$	17.61	17.85	5.94
$\boldsymbol{\bar{D}}$	1506.95	1506.92	1528.52

Note: DIC is the deviance information criterion for the model, P_D is the effective number of parameters and indicates model complexity, $\bar{D}$ is the deviance evaluated at posterior mean of parameters and represents goodness of fit of the model. 95% credible interval in parenthesis. *Statistically significant at 95% credible interval.

Figure 9 shows the distribution of the posterior mean of the district random effects from the spatial multilevel model on the right panel and the multilevel model on the left panel. The maps provide the distribution of risk of impoverishment from the two models. There was a clear smoothed spatial pattern in the risk of impoverishing effects of out-of-pocket from the spatial multilevel model with clustering of high-risk districts in the central region and low risk districts in the southern region. On the other hand, the distribution of the risk of impoverishing effects of out-of-pocket health expenditures from the multilevel model show no clear spatial pattern across the country as spatial dependence is not accounted for in the multilevel model.

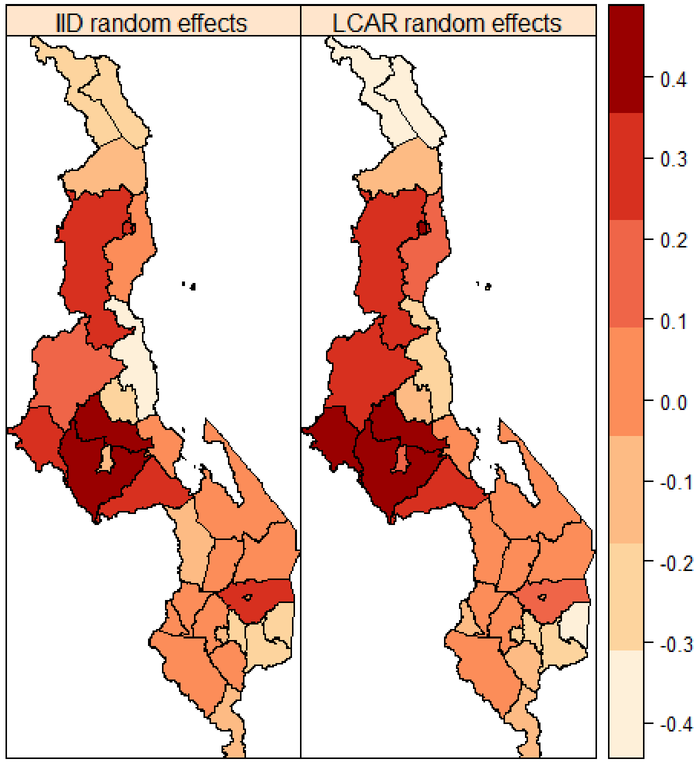

Figure 9. Spatial distribution of the district random effects from the spatial multilevel model on the right panel and multilevel model on the left panel fitted to actual data

8.5 Discussion

This chapter compared a spatial multilevel logistic model with a multilevel and logistic models used for assessing factors associated with impoverishing effects of out-of-pocket health expenditures. The models were compared in terms of performance of the parameter estimates using bias and Mean Squared Error (MSE) based on a simulation analysis and analysis of actual data on impoverishing effects of health expenditures. Model fit was compared using the Deviance Information Criterion (DIC). The paragraphs which follow discuss the findings from the simulation analysis.

First, findings from the simulation analysis show that under a scenario where there was no spatial correlation in the data, the spatial multilevel logistic model and multilevel model performed in a similar manner in terms of estimating the fixed effects parameters while the fixed effects parameters from the logistic regression model were less accurate. This finding is consistent with results from previous simulation analysis which showed that the performance of multilevel and spatial multilevel models in terms of estimating fixed effects parameters were similar (Leroux et al., 1999; Xu, 2014a). Nevertheless, the results of overall fit of the models using the Deviance information criterion indicated that the multilevel model provided the best fit for the data followed by the spatial multilevel model then the logistic model. This result is expected since there was neighborhood correlation but no spatial correlation in the simulated data. These findings imply that in cases where within neighborhood correlation exist in the data and there is no spatial correlation ignoring within neighborhood correlation using a single level logistic regression model may lead to less accurate estimates especially in estimating the intercept as observed in a previous study by Leroux et al.(1999).

Second, under the scenario where both within neighborhood correlation and spatial correlation exist in the data the spatial multilevel model provided the best fit for the data. This finding is consistent with previous studies which reported that models that accounted for both within neighborhood correlation and spatial correlation provided the best fit for the data in a case where the data is spatially correlated (Arcaya et al., 2012; Chaix et al., 2005; Chaix et al., 2005; Ma et al., 2018, 2017; Park & Kim, 2014). Moreover, our finding show that under this scenario the fixed effects parameter estimates for a spatial multilevel model and the multilevel model were nearly similar as reported in other studies(Dasgupta et al., 2014; Leroux et al., 1999; Park & Kim, 2014; Xu, 2014a). On the other hand, comparison of the spatial multilevel and multilevel models to the single level logistic model showed that the single level logistic produced biased estimates as also observed in another study (Leroux et al., 1999). These findings imply that accounting for only within neighborhood correlation or both within neighborhood and spatial correlation could still provide us with similar parameter estimates in our case. It is possible that in our case spatial correlation could be reduced to within neighborhood correlation (Chaix et al., 2005) as such fitting these two models would still provide similar parameter estimates. Nevertheless, neglecting within neighborhood correlation or both within neighborhood and spatial correlation by using single level logistic model leads to biased estimates.

Lastly, the results on the estimates of the random effects variance indicates that in a case where both within neighborhood and spatial correlation exist in the data the multilevel model underestimated the random effects variance as reported in a previous study (Leroux et al., 1999). The findings showed that the random effects variance for the multilevel model was lower than the variance of the spatial multilevel model. This finding implies that when spatial correlation in the data is neglected the estimate of random effects variance is underestimated. This has an implication on the interpretation on the neighborhood effects as it can lead to wrong conclusions on the impact of neighborhood effects on outcome variable of interest (Xu, 2014a).

8.6 Chapter summary

This chapter shows that accounting for both within neighborhood and spatial correlation in the model for assessing factors associated with impoverishment provides a better understanding of the variations in impoverishment. Models that account for both neighborhood and spatial correlation in the data provides a better understanding of variability in the outcome variable of interest as they properly account for the impact of neighborhood and spatial effects on outcome variable of interest. The findings show that in a scenario where both neighborhood and spatial correlation is present in data the spatial multilevel model and multilevel model produced similar parameter estimates while the single level logistic model produced less accurate parameter estimates. This may be due to failure of the single level logistic model to account for the effects of neighborhood and spatial correlation in the data. In addition, the spatial multilevel and the standard multilevel models provided the best fit to the data than the single level logistic model. In the case of our data, the spatial multilevel and standard multilevel models produce similar parameter estimates and lead to the same conclusion in terms of statistical significance of estimates when both neighborhood and spatial dependence exist. Nevertheless, when the main interest is to assess evidence of spatial effects and quantify the role of spatial effects the spatial multilevel model provides the best approach to tackling such a research problem. Researchers using complex survey data should be cautious when analyzing such data as both neighborhood and spatial dependence may exist in the data, and this should be accounted for in the analysis as failure to account for such dependence in data may lead to biased estimates.

CHAPTER 9: CONCLUSION AND RECOMMENDATIONS

9.1 Introduction

This chapter concludes by summarizing the findings of the study in relation to the study aims and objectives which were set in chapter one. Thus, sections two, three, four and five of the chapter summarizes the findings in relation to the objectives which were set in chapter one and serves to indicate that the aims and objectives of the study have been achieved. Section six gives the key contributions of the study and the limitations of the study. Section seven of the chapter gives recommendations to policy makers and researchers arising from the study findings and the last section suggests areas for further research.

The main purpose of the study was to examine the use of single level logistic regression model, multilevel and spatial multilevel models in assessing factors associated with catastrophic health expenditures and impoverishing effects of health expenditures. Specifically the study aimed to describe the extent of catastrophic health expenditures and ascertain the factors associated with catastrophic health expenditures accounting for contextual effects, to assess and decompose socio-economic inequality in catastrophic health expenditures, to describe the extent of impoverishing effects of out-of-pocket health expenditures and ascertain its associated factors accounting for contextual effects ,to compare the spatial multilevel model with multilevel and single level logistic models when assessing the factors associated with impoverishing effects of out-of-pocket health expenditures.

9.2 Extent of catastrophic health expenditures and its associated risk factors

Findings from the study revealed that a moderate proportion of households in Malawi faced catastrophic health expenditures in the year 2016/17. Furthermore, the finding indicates a substantial increase in the extent of catastrophic health expenditures compared to findings from a previous study which used similar data for the year 2010/11 (Mchenga et al., 2017) . This finding implies that the population in Malawi is at risk of catastrophic out-of-pocket health expenditures despite that access to health care services are free at point of use. These findings may indicate the shortfalls of the free access to health services policy which may require governments attention if the Universal Health Coverage is to be achieved.

Our findings also show that residency in rural areas, accessing health care from religious or mission facilities, hospitalizations, being in higher income quintiles increased the likelihood of facing catastrophic health expenditures. The finding that rural residency and access to mission facilities increases the likelihood of facing catastrophic health expenditures may imply that policies such as the SLAs may have failed to achieve some of its intended purposes. In 2005, the Government of Malawi started implementing SLAs with mission facilities which mostly serves the rural population to ensure that the population served by these facilities access care without facing financial hardship. Although a previous study reported an increase in utilization of maternal and child health services as a result of SLAs (Manthalu et al., 2016) ;the findings from this study may suggest that SLAs have failed to provide financial protection from illnesses due to implementation challenges as observed by another qualitative study (Chirwa et al., 2013). Despite these implementation challenges SLAs has a potential to protect households for financial hardship due to illnesses (Chirwa et al., 2013). It is also possible that other costs related to seeking care such as transportation, accommodation places a financial burden on households which increase the likelihood of catastrophic health expenditure among rural households.

Another interesting finding from the study which may indicate challenges with free access to public health services policy is the finding that households from higher income quintiles faced an increased risk of catastrophic health expenditures. Contrary to previous findings this finding is intuitive for Malawi where the public health system faces challenges and this forces households in higher income quintile to access care at private facilities where they incur higher out-of-pocket health payments consequently catastrophic health payments. It is also possible that households in low-income quintiles forgo seeking care in private facilities to avoid high costs as a result they face lower risk of catastrophic health expenditures.

The multilevel logistic model provided evidence that there are district contextual clustering effects on catastrophic health expenditures. With significant variations in catastrophic health expenditures across districts in Malawi. This finding is important for monitoring financial protection at district level and provides evidence to policy makers and development partners to design targeted programs to ensure financial protection in districts with high levels of catastrophic health expenditures.

9.3 Decomposing socio-economic inequality in catastrophic health expenditures

Health inequalities are systematic differences, variations and disparities in health outcomes among population groups (Kawachi & Subramanian, 2002). One of the goals of health systems in both developed and developing countries is to reduce health inequalities in a way that improves the condition of the worse-off (WHO, 2000). Socioeconomic inequalities in health are a great concern among policy makers as most of these inequalities are unjust and unfair and reflect inequality in the social determinants of health (Ataguba et al.,2015; Kawachi & Subramanian, 2002; Wagstaff et al., 2003). Socio-economic inequality in out-of-pocket health expenditures may entail inequality in the burden of catastrophic health expenditures and worsen inequalities in access to and utilization of health services.

Chapter seven provided findings on socioeconomic inequality in catastrophic health expenditures and how inequality in the determinants of catastrophic health expenditures contributes to the overall socioeconomic inequality in catastrophic expenditures. These findings are important for designing programs and policies to address the causes of socio-economic inequality in catastrophic health expenditures consequently reducing unjust and unfair disparities in health expenditures. The findings revealed that the magnitude of socioeconomic inequality is small and that it is concentrated more among the better-off households. These findings are contrary to evidence from previous studies but intuitive in the context of Malawi where free public health system face many challenges as such constant stock out of drugs, poor quality of services. The findings suggest the ability of better-off households to access care from private facilities where they incur higher out-of-pocket health expenditures. On the other hand, it is possible that the worse-off choose forgo health care due high costs of seeking better quality care from private facilities as such they do not incur catastrophic health expenditures. Such a health system that allows the better-off to access higher quality care due to their ability to pay is inequitable and prevents the worse-off to access health care thus creating inequalities and inequities health. Further analysis revealed that most of the socioeconomic inequality in catastrophic health expenditures is as a result of inequality in rural residency, socio-economic status and region. This finding suggests that socioeconomic inequality in catastrophic health expenditures is interrelated with inequality in its determinants which means that addressing inequality in catastrophic expenditures may also require addressing income, rural-urban and regional inequalities.

9.4 Extent of impoverishing effects of health expenditures and its associated risk factors

While assessment of the extent of catastrophic health expenditures indicates how out-of-pocket health expenditures disrupts households living standards and prevents expenditures on other basic needs it fails to capture the poverty effects out-of-pocket health expenditures on the household. The assessment of the impoverishing effects of health payments indicates how health expenditures impacts on poverty head count ratio and poverty gap. Thus provides another important indicator for monitoring financial protection. In addition, assessing factors associated impoverishing effects of health expenditures provides evidence on the characteristics of population groups vulnerable to the likelihood of impoverishment which is important for designing programs and policies for financial protection. As shown in chapter seven the study revealed that a moderate proportion of the population were pushed into poverty due to health expenditures in 2016/17. There was a substantial increase in the extent of impoverishing effects of health expenditures compared to findings from a previous study which used similar data for year 2010/11 (Mchenga et al., 2017). This imply that out-of-pocket health expenditures places a financial burden on the population which can leave the population in a vicious circle of poverty and ill-health. Furthermore, the study revealed that households that were already poor were pushed further into poverty due to health expenditures. This deepening in poverty may indicate vulnerability of the poor to health payments which may require attention. In addition, the findings from the study also revealed that impoverishment and deepening in poverty due to health expenditures varied by region, rural-urban location, and type of health facility where care was accessed. Impoverishing effects of health expenditures and deepening of poverty due to health payments was higher among population groups from rural areas, central region and those accessing care at private health facility

The study revealed that there is evidence of spatial dependence in impoverishing effects of health expenditures. This finding reinforced the need to quantify the role of spatial effects on impoverishing effects of health expenditures using the spatial multilevel model which indicated significant spatial clustering effects. The finding from the modelling showed clustering in the likelihood of impoverishing effects of health expenditures with districts in central region at a higher risk of facing impoverishing effects compared to southern and northern region. This imply that impoverishment vary from district to district due to district contextual factors and this may call for a need to design targeted programs to ensure financial protection among high-risk districts and consequently reduce disparities in the effects of health expenditures.

The findings from the spatial multilevel model revealed that households from lower income quintiles, rural areas, with chronically illness, with hospitalizations are at a higher risk of impoverishing effects of health expenditures. The finding that households in lower income quintile and rural areas are at higher risk may suggest the poor are burdened with out-of-pocket health expenditures in Malawi. The finding that chronic illnesses which included non-communicable diseases (NCDs) increases the risk of impoverishing effects of health expenditures indicates the poverty impacts of chronic illnesses on households which requires attention from policy makers when designing financial protection program and policies.

9.5 Comparison of spatial multilevel model to multilevel and single level logistic models

Previous studies on the characteristics of population groups vulnerable to the risk of impoverishing effects of health expenditures have concentrated on household characteristics and neglected neighborhood and spatial effects. This is despite that the data used in the analysis is geographically referenced with multiple dependence in the observations such as within and between neighborhood dependence which can lead to incorrect inferences and wrong conclusions if neglected. These studies have mainly used single level logistic regression models to examine the characteristics of population groups vulnerable to impoverishing effects of out-of-pocket health expenditures which does not account for neighborhood and spatial effects. By comparing the performance of the spatial multilevel model with multilevel and single level logistic models in terms of model parameter estimates and model fit this thesis demonstrates the importance of accounting for both neighborhood and spatial effects when modelling the characteristics of population groups vulnerable to the risk of impoverishing effects of health expenditures.

Chapter eight compared the spatial multilevel model to multilevel and single level logistic models when assessing factors associated with impoverishing effects of health expenditures. The models were compared in terms of performance of parameter estimates and model fit through a simulation analysis. As evidenced in chapter eight when neighborhood effects are present in the data and there are no spatial effects the multilevel logistic model provided a better fit to the data and unbiased parameter estimates compared to the spatial multilevel model and the single level model. Furthermore, the single level logistic model provided a poorer fit and more biased estimates amongst the three models. This finding implies when neighborhood effects exist in the data and there are no spatial effects neglecting these neighborhood effects by using a single level logistic model may lead to less accurate parameter estimates.

When both spatial and neighborhood effects are present in the data the results in chapter eight revealed that the spatial multilevel model provided the best fit to the data and better parameter estimates than the multilevel and single level model. The results show that there were negligible differences in the parameter estimates from the spatial multilevel and multilevel model. On the other hand, comparison of the spatial multilevel and multilevel models to the single level models indicated that the singles level model provided biased estimates. This finding may imply that in the case of the data used in the study accounting for only neighborhood effects or both spatial and neighborhood effects could still give similar parameter estimates. It is possible that in case of the data used in the analysis spatial effects can be reduced to neighborhood effects such that both models are appropriate for modeling the risk of impoverishing effects of health expenditures. Nevertheless, the results revealed that neglecting both neighborhood and spatial effects or neighborhood effect by using a single level model results into biased estimates and poor model fit.

9.6 Study contributions and limitations

9.6.1 Study key contributions

The study has the following key new contributions to the literature on health systems financing as it relates to financial protection from risk of illnesses in Malawi:

i) As discussed and observed in the literature review chapter only one study in Malawi analyzed the extent of catastrophic health expenditures. This study adds to the existing knowledge by updating the extent of catastrophic health expenditures using the most recent available data at the time of writing the thesis and providing evidence on the characteristics of households vulnerable to the risk of catastrophic health expenditures. This is important for monitoring financial protection and designing policies targeting the most vulnerable groups. More importantly the use of multilevel logistic regression model has highlighted the impact of neighborhood effects indicating significant districts variations in catastrophic health expenditures which needs attention when designing financial protection program and policies.

ii) Another key contribution of the study is the use of spatial multilevel regression model which revealed evidence of spatial clustering in impoverishing effects of health expenditures resulting in significant spatial variations in impoverishment across districts in Malawi. More importantly, using spatial multilevel model, the study has developed risk maps quantifying the risk of impoverishment due to health expenditures across Malawi which are necessary to development partners and policy makers for designing financial protection programs targeting districts at high risk of impoverishing effects of health expenditures.

iii) There is no study in Malawi which has assessed and decomposed socio-economic inequality in catastrophic expenditures. While previous literature in Sub Saharan Africa has assessed socio-economic inequality in catastrophic health expenditures, they failed to decompose inequality into its determinants to understand how socio-economic inequality in the determinants of catastrophic health expenditures contribute to the overall socio-economic inequality in catastrophic health expenditures. The key contribution of the study is the finding that in Malawi, socioeconomic inequality in catastrophic health expenditures is mainly as a result of income, urban-rural and regional inequalities. This finding is important for simultaneously tackling socio-economic inequality in catastrophic health expenditures and inequality in the determinants of catastrophic health expenditures and is not only relevant to Malawi but to other sub-Saharan African countries with similar context.

iv) The study also contributes to the literature in terms of statistical methodological approach for assessing factors associated with impoverishing effects of health expenditures when using data from complex survey design. The study has provided evidence that in the presence of neighborhood effects or both neighborhood and spatial effects; the spatial multilevel model and multilevel model are the appropriate models. This is important to researchers choosing between competing statistical models.

9.6.2 Limitations of the study

The study has limitations. First, the study used self-reported data on consumption expenditures and illnesses from the Malawi integrated household survey which is prone to recall bias and can lead to underreporting as also observed by other authors. This limitation would result in underestimation or overestimation of the incidence of catastrophic health expenditures and impoverishing effects of out-of-pocket expenditures on households.

Second, the measurement of impoverishing effects of out-of-pocket expenditures and catastrophic health expenditures does not count those that forgo seeking care due to inability to pay and this may underestimate the proportion impoverished due to out-of-pocket expenditures and incurring catastrophic health expenditures.

Third, the use of cross-sectional data prevents causal interpretation of the relationship between catastrophic health payments, impoverishing effects of health payments and other factors. Fourth, data on total health expenditures were annualized this could lead to overestimating of total health spending as we assume the same rate of monthly health expenditures over time.

Lastly, for the Malawi integrated household survey data used in the analysis the sampling strategy was conducted in such a way that sampled households are nested within sub districts which are the enumeration areas, and the sub districts are nested within districts. Due to unavailability of the actual sub districts boundary data for estimating the spatial weight matrix to provide information on how the sub district are connected to each other; in the multilevel and spatial analysis we assumed two level nesting where households were nested in districts. This may overestimate or underestimate the results of the impact of spatial and neighborhood effects. In addition, due to the nature of the data and unavailability of district level factors that could explain impoverishing effects of health expenditures and catastrophic health expenditures the study did not include district level variables and assumed that these are captured by the district random error term. This assumption prevented us from understanding the role of neighborhood and spatial effects in more detail.

Despite these limitations the strengths of the study include the use of a multilevel logistic regression model to assess factors associated with the incidence of catastrophic health expenditures which highlighted significant variations by districts, and this is important for monitoring financial protection at district level. The use of Bayesian spatial multilevel model which quantified spatial effects in impoverishment at districts level. The maps from the Bayesian spatial multilevel model also highlighted areas with excess risk requiring further attention. This is important for monitoring financial protection at district level and designing interventions according to district specific needs.

9.7 Recommendations to policy makers and researchers

It is clear from the findings of the thesis that despite government efforts such as free access to public health services policy and the Service Level Agreements with mission facilities to ensure financial protection among all the population groups; Malawians still face the negative consequences of out-of-pocket health expenditures. From the findings of the thesis several recommendations are provided for health policy makers and development partners working in health financing to help ensure financial protection for all population groups.

i) The findings that Malawian population face catastrophic health expenditures and impoverishing effects of out-of-pocket health expenditures indicates the need for government to improve the challenges faced by free public health services policy particularly constant shortage of medicines and poor quality of services in public facilities which forces households to seek care in private health facilities and incur out-of-pocket expenditures.

ii) The finding that living in rural areas and access to religious health facilities increased the odds of incurring catastrophic health expenditures raises the need for government to implement more equitable financing mechanisms such as a mandatory national health insurance, health fund and to expand the existing innovative financing mechanism of Service Level Agreements with mission facilities to include more services and facilities. This will ensure more people have access to the needed health services and financial protection for the vulnerable population groups.

iii) The finding that majority of socio-economic inequality in catastrophic health expenditures is because of inequality in income, urban-rural and regional inequalities imply the need for government to implement programs and policies that tackle inequality in health expenditures together with policies tackling income, urban-rural ad regional inequalities. This will ensure that there is equity and no disparities in health expenditures.

iv) Government of Malawi needs to plan programs and policies on financial protection according to districts specific needs as the findings clearly show significant districts variations in catastrophic health expenditures and impoverishing effects of health expenditures. This will require programs targeting the most vulnerable groups such as the worse-off, households with chronic illnesses and rural households in these high-risk districts.

v) Researchers using complex survey data should be cautious when analyzing such data as both neighborhood and spatial dependence may exist in the data, and this should be accounted for in the analysis as failure to account for such dependence in data may lead to biased estimates.

9.8 Recommendations for further research

The following are recommendations for further research arising from the findings of this study:

The thesis has highlighted the impact of spatial effects in impoverishing effects of health expenditures with other districts experiencing higher risk than others indicating disparities in risk. Considering this finding there is need for further research to understand the unmeasured districts specific factors contributing to clustering of impoverishing effects of out-of-pocket expenditures.

Considering that the findings indicated chronic illnesses in the household as an important factor related to impoverishing effects of health expenditures. Further research should explore the specific chronic illnesses including non-communicable diseases which drive households into impoverishment due to out-of-pocket health expenditures.

One of the limitations of this study is that measures of catastrophic health expenditures and impoverishing effects of health expenditures does not capture those that forgo seeking care to avoid the negative consequences of out-of-pocket health expenditures. There is need for further research to assess the implications of forgoing care on household’s welfare.

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APPENDICES

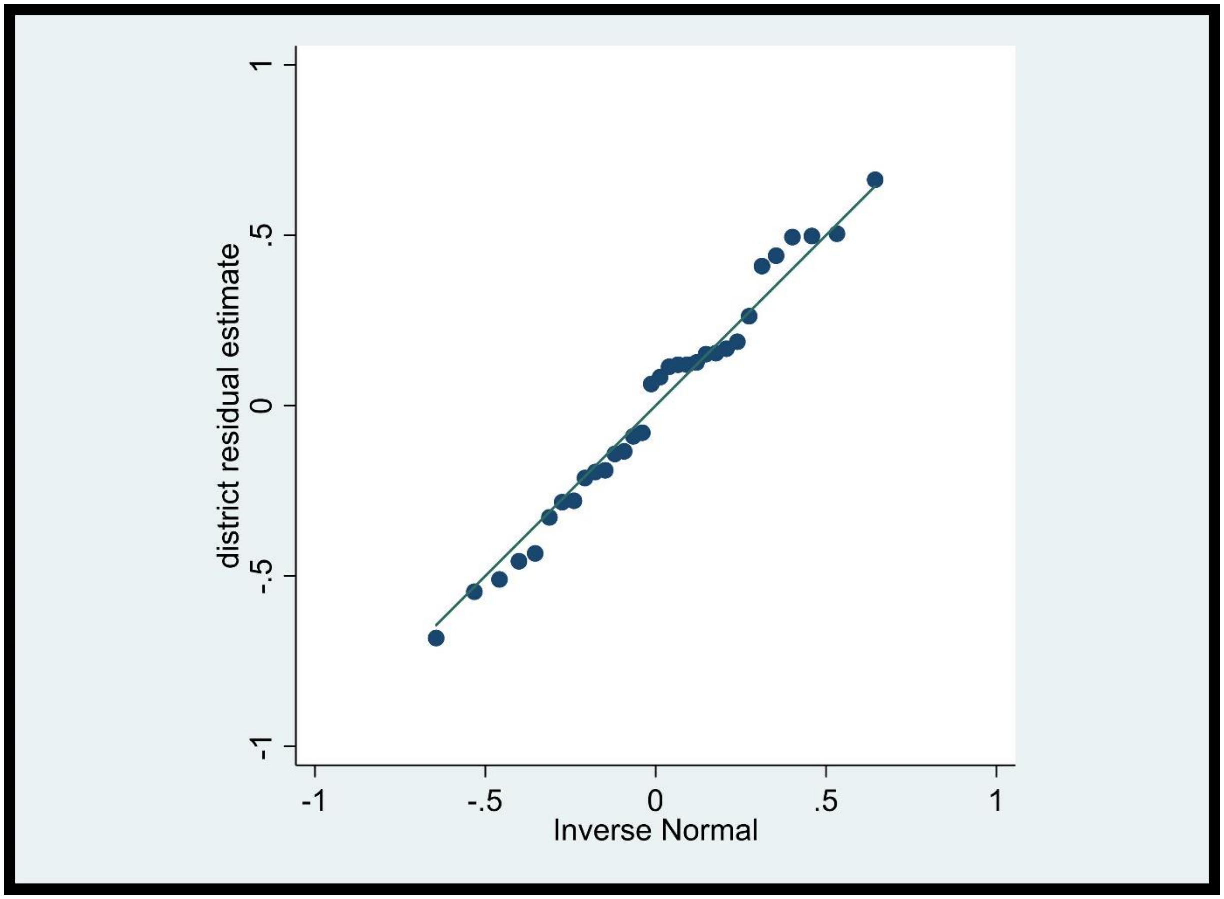
Appendix 1: Impoverishment effects by districts data related to figure 4 and 5

Impoverishing effects of health payments by district based on the national poverty line

Variable	Poverty head count		Difference	Normalized poverty gap		Difference
District	Pre (%)	Post (%)	Absolute (%)	Pre(%)	Post (%)	Absolute (%)
Chitipa	73.82	74.08	0.26	25.19	25.54	0.35
Karonga	57.14	57.27	0.14	17.95	18.21	0.25
Nkhatabay	57.71	60.42	2.71	16.38	17.31	0.93
Rumphi	53.59	54.96	1.37	15.92	16.50	0.58
Mzimba	42.95	45.76	2.81	12.91	13.89	0.98
Likoma	31.38	31.95	0.57	6.83	6.97	0.13
Mzuzu City	9.72	12.37	2.65	1.86	2.08	0.22
Kasungu	52.98	54.30	1.31	14.82	15.97	1.16
Nkhotakota	53.41	53.41	0.00	18.39	18.98	0.58
Ntchisi	53.49	54.22	0.73	18.13	18.61	0.48
Dowa	48.78	52.42	3.64	14.13	15.95	1.82
Salima	58.43	60.37	1.94	20.01	20.91	0.90
Lilongwe	47.93	51.31	3.38	13.55	14.31	0.76
Mchinji	50.54	53.35	2.81	14.59	15.90	1.31
Dedza	63.07	65.95	2.89	20.85	22.43	1.59
Ntcheu	54.13	54.67	0.54	17.01	17.57	0.56
Lilongwe City	18.00	18.76	0.75	4.87	5.12	0.25
Mangochi	59.46	60.51	1.04	19.01	19.77	0.76
Machinga	72.39	73.40	1.01	24.85	25.72	0.88
Zomba Non-City	55.92	58.98	3.06	17.74	18.74	1.00
Chiradzulu	66.42	67.02	0.60	22.25	22.66	0.41
Blantyre	38.87	39.76	0.89	11.13	11.38	0.25
Mwanza	53.57	54.46	0.88	15.77	16.18	0.40
Thyolo	67.27	69.09	1.82	24.71	25.66	0.95
Mulanje	69.22	69.77	0.55	26.55	27.11	0.56
Phalombe	83.16	83.65	0.49	35.07	35.56	0.49
Chikwawa	63.19	65.26	2.07	25.83	26.78	0.95
Nsanje	74.33	76.32	1.99	29.43	30.90	1.47
Balaka	61.28	62.77	1.49	19.00	19.83	0.83
Neno	46.87	48.55	1.68	13.96	14.37	0.40
Zomba City	15.79	16.26	0.47	4.06	4.28	0.22
Blantyre City	8.03	8.03	0.00	1.67	1.76	0.09

Appendix 2:Multilevel logistic model assumptions assessment with impoverishment as the outcome variable

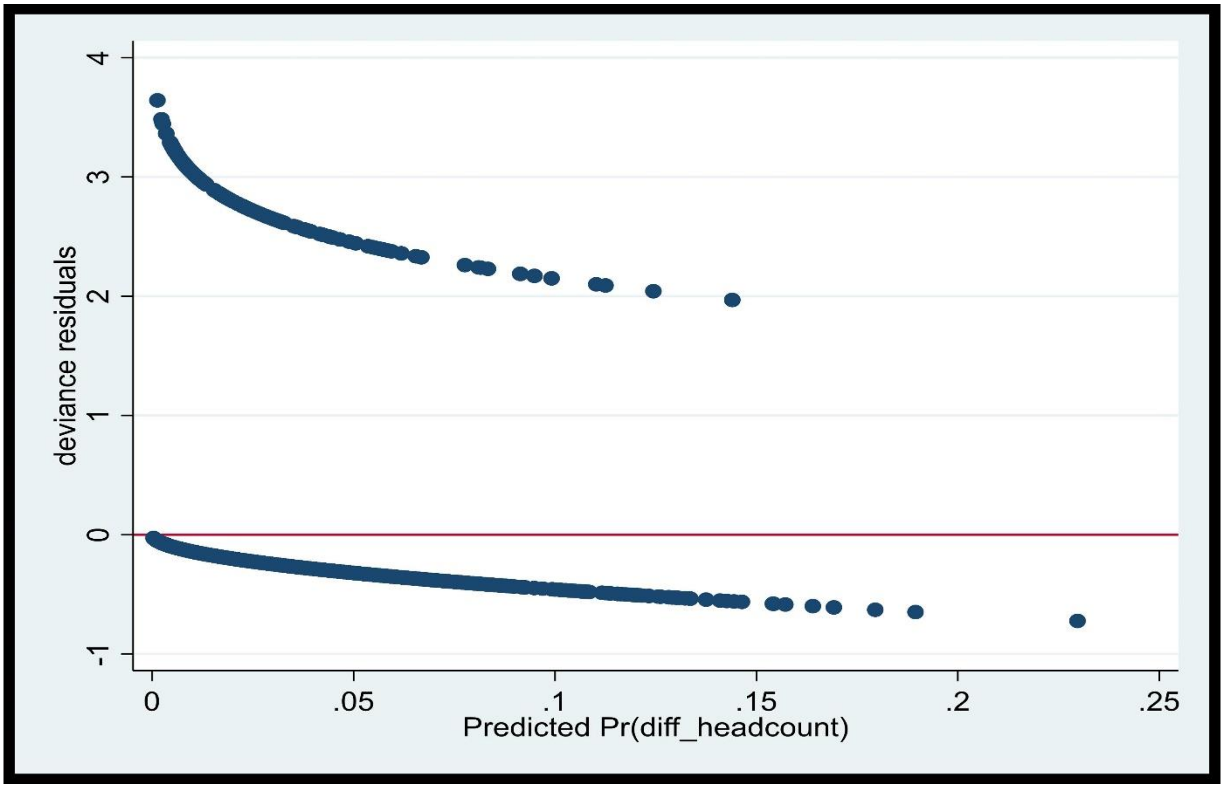
Normality of districts level random effects

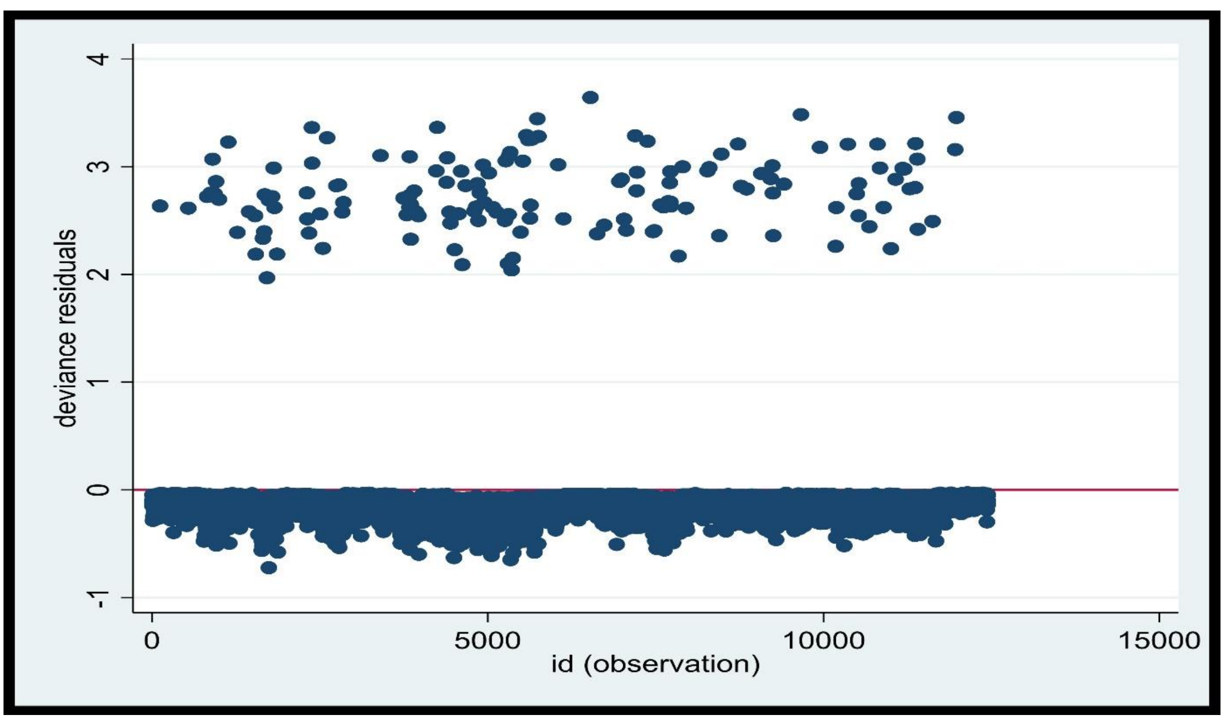


Model specification (omitted variables bias test) to detect non-linearity between the outcome and covariates

```
Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(2)      =     110.25
Log likelihood = -720.59855                     Prob > chi2       =     0.0000
------------------------------------------------------------------------------
diff_HEADCOUNT |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
      fitted_m |   .2444691   .6237563     0.39   0.695    -.9780707    1.467009
   sq_fitted_m |  -.0922611   .0755977    -1.22   0.222    -.2404299    .0559076
         _cons |  -1.468484    1.26577    -1.16   0.246    -3.949348     1.01238
---------------+----------------------------------------------------------------
district2      |
     var(_cons)|   .2395358   .1426375                      .0745592    .7695544
--------------------------------------------------------------------------------
LR test vs. logistic model: chibar2(01) = 8.45        Prob >= chibar2 = 0.0018

. test sq_fitted_m=0

 ( 1)  [diff_HEADCOUNT]sq_fitted_m = 0

           chi2(  1) =     1.49
         Prob > chi2 =     0.2223
```

Influential observations



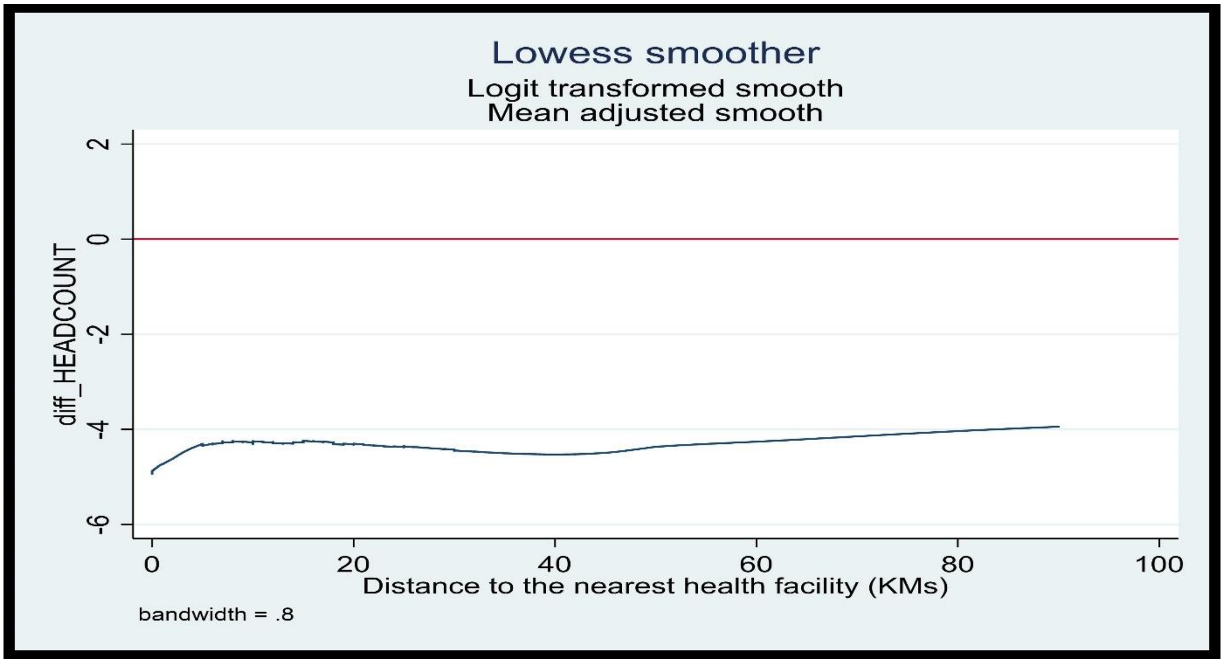


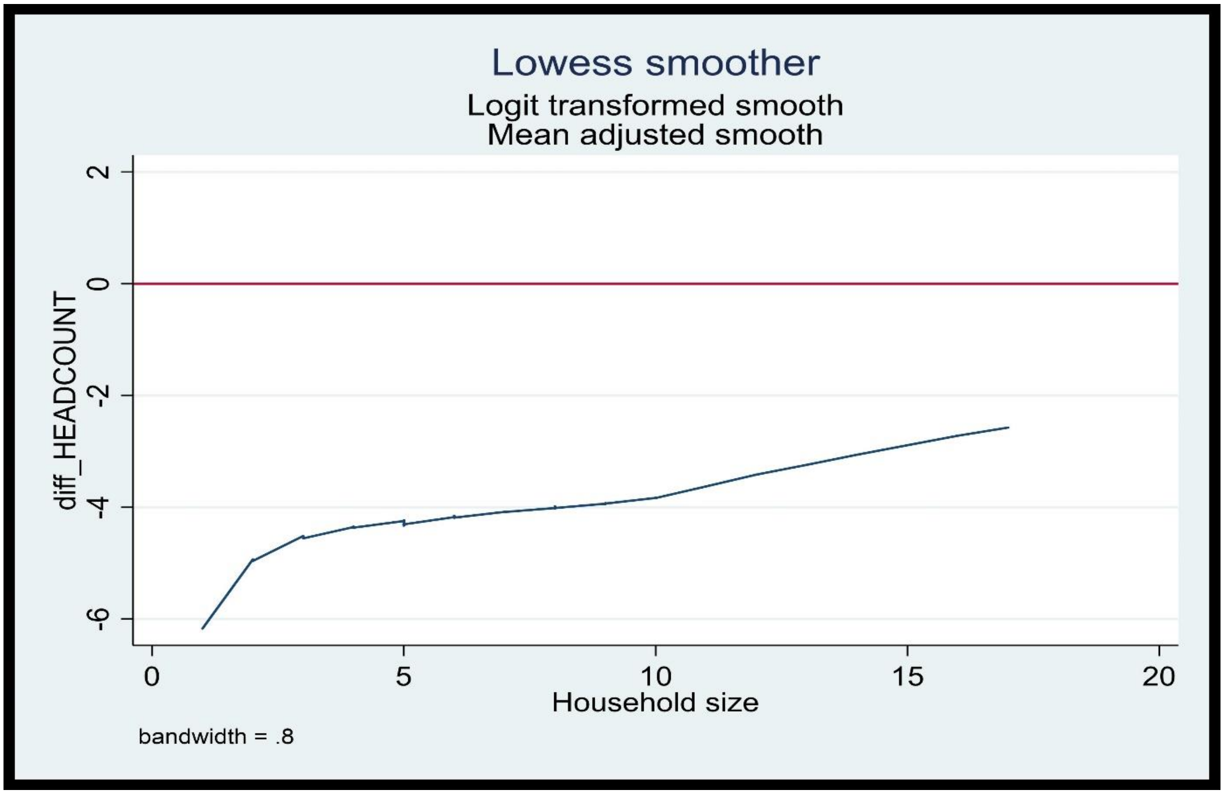
Multicollinearity

Testing for quasi-extreme multicollinearity

```
.   estat vce,corr

Correlation matrix of coefficients of meglm model

              | diff_H~T
              |
              |              1.         2.         3.         4.         2.         2.         1.         1.         1.         1.
         e(V) |   hhsize  hh_hea~p  hh_hea~p  hh_hea~p  hh_hea~p  Expend~2    hh_b03  haseld~r  atlea~ld  atlea~ed  atleas~l
--------------+--------------------------------------------------------------------------------------------------------------------
diff_HEADC~T  |
       hhsize |   1.0000
1.hh_heada~p  |   0.2459    1.0000
2.hh_heada~p  |   0.1599    0.5878    1.0000
3.hh_heada~p  |  -0.0567    0.5164    0.7376    1.0000
4.hh_heada~p  |  -0.0806    0.4111    0.5938    0.6102    1.0000
2.Expendit~2  |   0.2336    0.0080    0.0087   -0.0056   -0.0001    1.0000
    2.hh_b03  |   0.1799    0.0474    0.0551    0.0240    0.0219    0.0928    1.0000
1.haselder~r  |   0.0466    0.4954    0.6907    0.6860    0.5959    0.0116   -0.0209    1.0000
1.atleast~ld  |  -0.3922   -0.2799   -0.3171   -0.1608   -0.0147    0.0448   -0.0040    0.0340    1.0000
1.atleast~ed  |  -0.1035   -0.0735   -0.0655   -0.0388   -0.0365   -0.0753   -0.0277   -0.0324   -0.1015    1.0000
1.atleasto~l  |  -0.0575    0.0471    0.0232    0.0073   -0.0065    0.0061   -0.0973   -0.0635    0.0601   -0.1722    1.0000
     2.urban  |   0.0340   -0.0117    0.0113    0.0175   -0.0069    0.2164   -0.0027   -0.0208   -0.0028    0.0230    0.0224
    2.region  |   0.0364   -0.0224   -0.0236   -0.0246   -0.0161    0.0129    0.0095   -0.0111   -0.0102    0.0430   -0.0132
    3.region  |   0.0558   -0.0226   -0.0211   -0.0230   -0.0102    0.0251   -0.0140   -0.0129   -0.0208    0.0320   -0.0123
  2.com_cd61  |  -0.0037   -0.0083    0.0027    0.0072    0.0127   -0.0046    0.0128    0.0064    0.0303    0.0033   -0.0244
  3.com_cd61  |   0.0026   -0.0058   -0.0040   -0.0089   -0.0120    0.0022    0.0133    0.0001    0.0022    0.0216   -0.0117
    com_cd60a |  -0.0105   -0.0101   -0.0036   -0.0084   -0.0082    0.0061   -0.0173   -0.0064   -0.0143    0.0416    0.0120
        _cons |  -0.4234   -0.3259   -0.4147   -0.3473   -0.2893   -0.3303   -0.1759   -0.3991    0.0346   -0.0238   -0.0735
--------------+--------------------------------------------------------------------------------------------------------------------
/             |
         var( |
_cons[dis~2]) |   0.0006   -0.0124    0.0016    0.0054   -0.0161   -0.0795    0.0197   -0.0108   -0.0036   -0.0134   -0.0131

              | diff_H~T                                                                  | /
              |                                                                           |      var(
              |       2.         2.         3.         2.         3.                      |    _cons[
         e(V) |    urban     region     region  com_cd61  com_cd61  com_~60a      _cons   | distr~2])
--------------+---------------------------------------------------------------------------+----------
diff_HEADC~T  |                                                                           |
     2.urban  |   1.0000                                                                  |
    2.region  |  -0.0782    1.0000                                                        |
    3.region  |  -0.0878    0.6708    1.0000                                              |
  2.com_cd61  |  -0.0987    0.1213    0.0776    1.0000                                    |
  3.com_cd61  |   0.0395    0.0161    0.0006    0.0409    1.0000                          |
    com_cd60a |  -0.1540    0.0218    0.0809    0.0602    0.0211    1.0000                |
        _cons |  -0.5781   -0.3420   -0.3646   -0.0580   -0.0446   -0.0708    1.0000      |
--------------+---------------------------------------------------------------------------+----------
/             |                                                                           |
         var( |                                                                           |
_cons[dis~2]) |   0.0460   -0.0344    0.0391   -0.0721   -0.0341    0.1163   -0.1106      |   1.0000

.
```

Linearity in the logit of the outcome for continuous variables





MORAN I TEST OF THE RESIDUALS FOR TESTING THE NULL HYPOTHESIS OF NO SPATIAL AUTOCORRELATION

Moran I test for spatial autocorrelation of the district residual from the multilevel logistic model

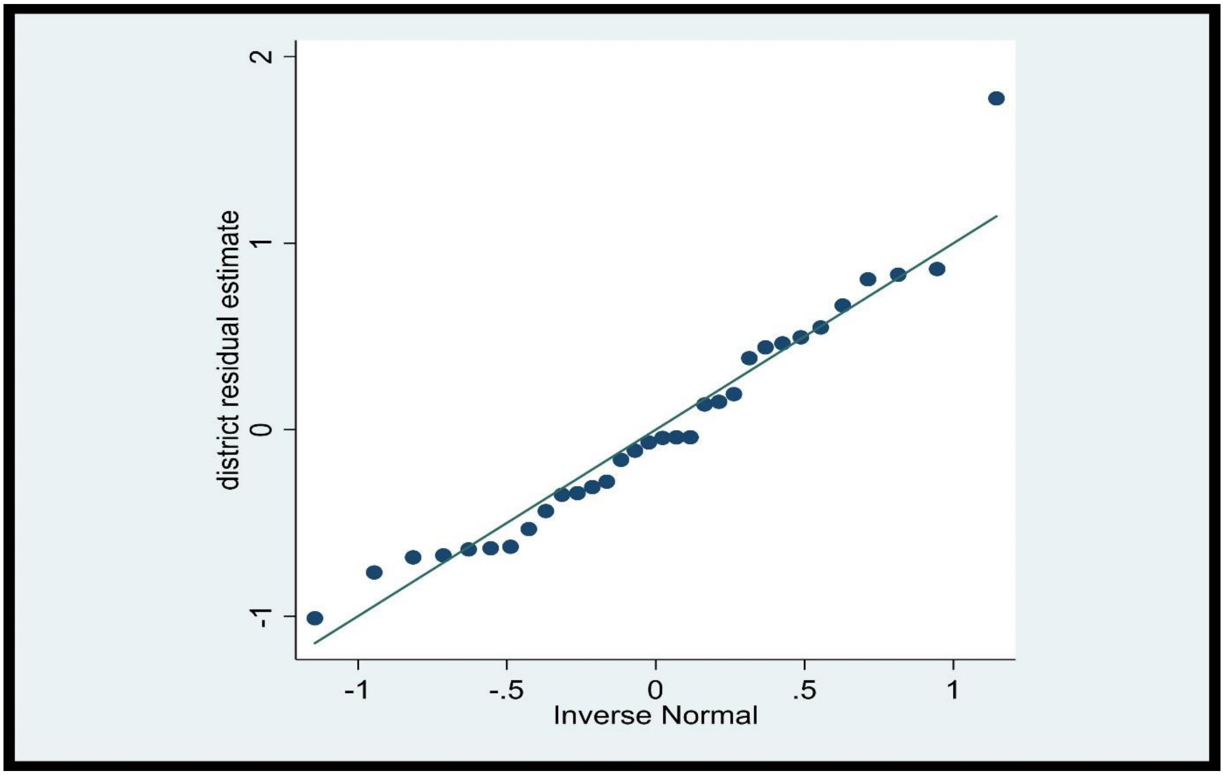
```
Moran I test under randomisation

data:  re1
weights: nbweight.lw  n reduced by no-neighbour observations


Moran I statistic standard deviate = 1.0826, p-value = 0.1395
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
       0.09344169       -0.03333333        0.01371231
```

Moran I test for spatial autocorrelation of the district residual from the spatial multilevel logistic model

```
Moran I test under randomisation

data:  re2
weights: nbweight.lw  n reduced by no-neighbour observations


Moran I statistic standard deviate = 2.0295, p-value = 0.02121
alternative hypothesis: greater
sample estimates:
Moran I statistic       Expectation          Variance
       0.20357823       -0.03333333        0.01362729
```

Appendix 3:Multilevel logistic model assumptions assessment with catastrophic health expenditures as the outcome variable

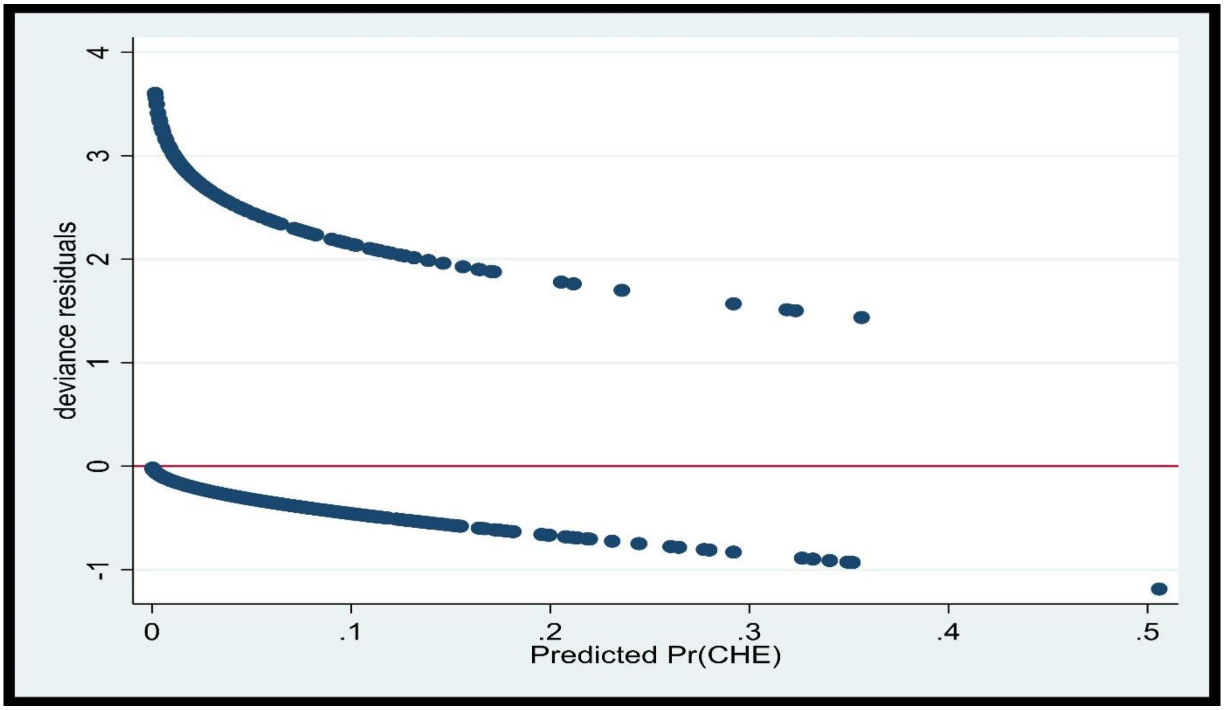
Normality of districts level random effects

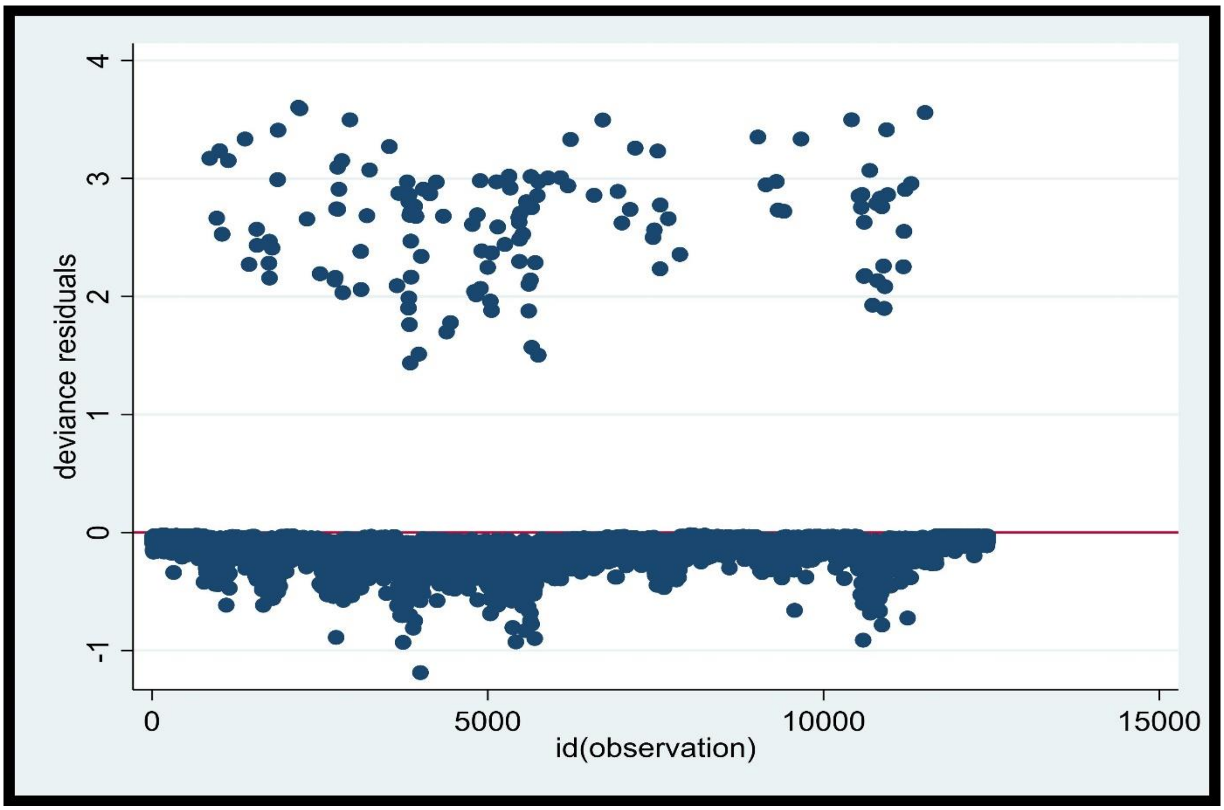


Model specification (omitted variables bias test) to detect non-linearity between the outcome and covariates

```
Integration method: mvaghermite                 Integration pts.  =          7

                                                Wald chi2(2)      =     172.56
Log likelihood = -628.50701                     Prob > chi2       =     0.0000

------------------------------------------------------------------------------
       CHE40 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    fitted_m |    1.34268    .376798     3.56   0.000     .6041698    2.081191
 sq_fitted_m |   .0418754   .0448921     0.93   0.351    -.0461115    .1298622
       _cons |   .6292927   .7764532     0.81   0.418    -.8925276    2.151113
-------------+----------------------------------------------------------------
district2    |
   var(_cons)|   .6053944   .2788944                      .2454172    1.493385
------------------------------------------------------------------------------
LR test vs. logistic model: chibar2(01) = 30.57        Prob >= chibar2 = 0.0000

.
. test sq_fitted_m=0

 ( 1)  [CHE40]sq_fitted_m = 0

           chi2(  1) =    0.87
         Prob > chi2 =    0.3509
```

Influential observations



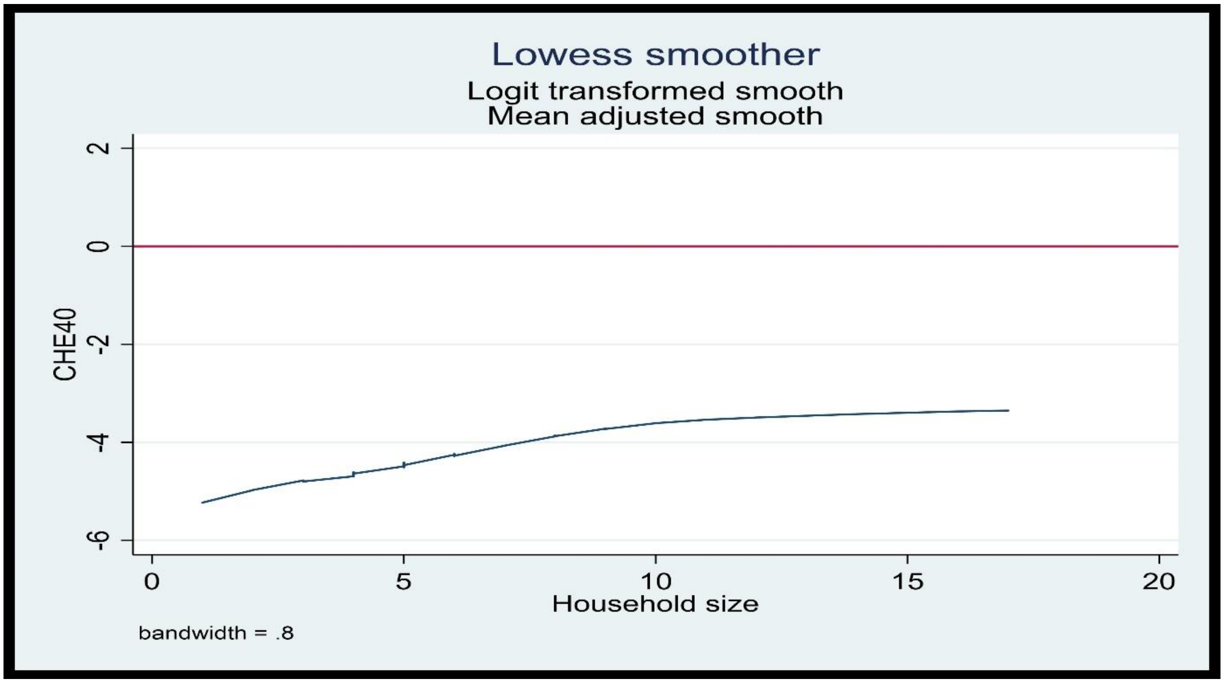


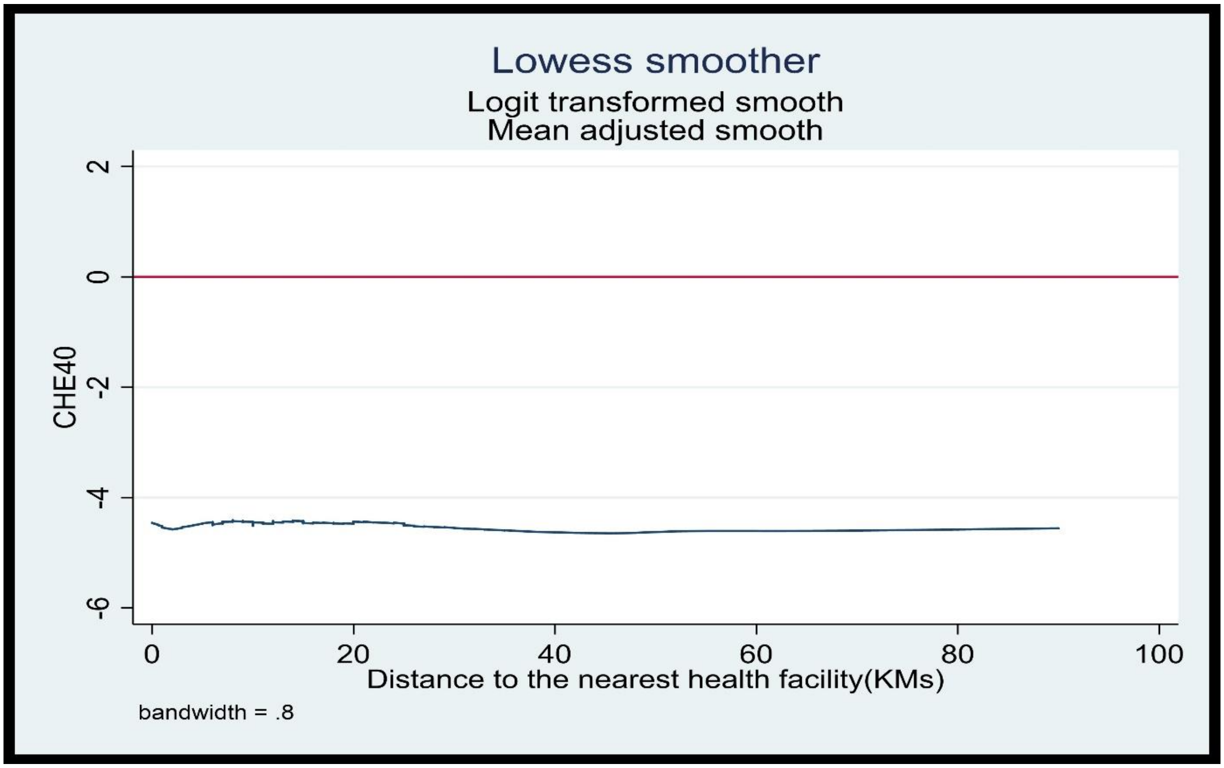
Multicollinearity

Testing for quasi-extreme multicollinearity

```
Covariance matrix of coefficients of meglm model

             | CHE40
             |                   1.          2.          3.          4.          2.          3.          4.          5.
        e(V) |     hhsize  hh_heada~p  hh_heada~p  hh_heada~p  hh_heada~p  Expendit~e  Expendit~e  Expendit~e  Expendit~e
-------------+------------------------------------------------------------------------------------------------------------
CHE40        |
      hhsize |  .00274974
1.hh_heada~p |   .0055261   .21725522
2.hh_heada~p |  .00252683   .12258265   .14846531
3.hh_heada~p | -.00166172   .10869588   .11159207   .14394945
4.hh_heada~p | -.00307201   .09958529   .10350654   .10592137   .16487042
2.Expendit~e |    .001233  -.00185142  -.00110498  -.00167479  -.00317234   .09665419
3.Expendit~e |   .0021193  -.00216559  -.00104723  -.00119581  -.00257116   .06377857   .09765966
4.Expendit~e |  .00325512  -.00587781  -.00176426  -.00326902  -.00435755   .06497682   .06822316   .10829052
5.Expendit~e |   .0046775  -.00169361  -.00145017  -.00306858   -.0062688   .06617541    .0702997   .07500683   .12849339
    2.hh_b03 |   .0018091   .00436633   .00419765   .00169087   .00120337   .00204016   .00483168   .00726616   .00765969
1.haselder~r | -.00031731   .09474272   .09558576   .09444204   .09422293   -.002052   -.00232536  -.00326972  -.00155722
1.atleast~ld | -.00453846  -.03048046  -.02622449  -.01283432  -.00016378   .00150277   .00422142   .00402313   .00633202
1.atleast~ed | -.00080621  -.00725691  -.00433451  -.00397142  -.00334934  -.00285273  -.00240421  -.00315271  -.00576304
1.atleasto~l | -.00085401   .00312219   .00232315   .00122163  -.00084522   .00069495   .00036415   .00208471   .00126242
     2.urban |  .00127611  -.00434593    .0001379  -.00001969  -.00373472   .00284011   .00452106   .01354588   .02710267
    2.region |  .00087117  -.00626013  -.00438552  -.00588548  -.00525343   .00062719   .00306806   .00232784   .00164039
    3.region |   .0012806  -.00547239  -.00420932  -.00519683  -.00312565   .00299151    .0049764   .00588947   .00683645
  2.com_cd61 | -.00014779  -.00328189  -.00115306  -.00084982  -.00066944  -.00154385   .00073622   .00080947    .0008946
  3.com_cd61 |  .00099428   .00592472   .00417631   .00008772  -.00132297  -.00103055    .0006519   .00075254  -.00686883
   com_cd60a | -8.609e-06  -.00004785  -.00002623  -.00001724  -.00003208    .0000485   .00007315   .00005573   .00009059
       _cons | -.01547861  -.10876348   -.1054647  -.08581193  -.07707396  -.07271208  -.08736673   -.1027178  -.12593757
-------------+------------------------------------------------------------------------------------------------------------
/            |
        var( |
_cons[dis~2])|  .00007075   .00066169   .00153838    .0009185  -.00088487  -.00022882   .00192859   .00220935    .0006036

             | CHE40
             |         2.          1.          1.          1.          1.          2.          2.          3.          2.
        e(V) |     hh_b03  haselder~r  atleast~ld  atleast~ed  atleasto~l       urban      region      region    com_cd61
-------------+------------------------------------------------------------------------------------------------------------
CHE40        |
    2.hh_b03 |  .04361562
1.haselder~r | -.00215998   .12830494
1.atleast~ld |  .00107624   .00400666   .05507898
1.atleast~ed | -.00207904    -.002206  -.00581862   .03581862
1.atleasto~l | -.00439642  -.00410731   .00300696  -.00676852   .03900886
     2.urban |    .000324  -.00377297   .00122342   .00081861   .00351093    .2776926
    2.region |  .00113394  -.00333957  -.00084245   .00402517  -.00075016   -.0129959    .2559754
    3.region | -.00069362  -.00313829  -.00122836   .00210101  -.00095261  -.02499727    .1721093   .25448419
  2.com_cd61 |  .00214142  -.00130258    .0024135    .0003474   .00017351  -.01138919   .01177447   .00798885   .05867295
  3.com_cd61 |   .0055237   .00299394  -.00279993   .00444758  -.00003932   .01439804   .00797108   .00467291   .01393651
   com_cd60a | -.00001826  -2.256e-06  -.00002027   .00006137  -1.889e-06  -.00040596    .0000762   .00019446   .00019318
       _cons | -.02660295  -.08787315  -.00181162   -.0040059  -.00991597  -.24858931  -.17280195  -.15928165  -.01220539
-------------+------------------------------------------------------------------------------------------------------------
/            |
        var( |
_cons[dis~2])|  .00026587  -.00028826  -.00092406   .00043414  -.00099118   .01493635   .01611763  -.00752838  -.00316898

             | CHE40                               | /
             |                                     |       var(
             |         3.                          |     _cons[
        e(V) |   com_cd61   com_cd60a       _cons  | district2])
-------------+-------------------------------------+-----------
CHE40        |                                     |
  3.com_cd61 |  1.0652738                          |
   com_cd60a |    .000318   .00003726              |
       _cons |  -.0458743  -.00030397   .67375856  |
-------------+-------------------------------------+-----------
/            |                                     |
        var( |                                     |
_cons[dis~2])|  .00368454   .00006053  -.04082535  |   .0833764

.
```

Linearity in the logit of the outcome for continuous variables





Appendix 4:Ethical approval

NATIONAL COMMISSION FOR SCIENCE & TECHNOLOGY

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Lilongwe

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+265 1 774 189
+265 1 774 869
Fax: +265 1772 431
Email:directorgeneral@ncst.mw
Website:http://www.ncst.mw

NATIONAL COMMITTEE ON RESEARCH IN THE SOCIAL SCIENCES AND HUMANITIES

Ref No: NCST/RTT/2/6 **26th November 2019**

Ms Atupele Ngina Mulaga,
Principal Investigator,
University of Malawi,
The Polytechnic Department of Mathematics & Applied Statistics,
Private Bag 303,
Chichiri,
Blantyre 3.
Email: amulaga@poly.ac.mw

Dear Ms Mulaga,

RESEARCH ETHICS AND REGULATORY APPROVAL AND PERMIT FOR PROTOCOL NO. P.10/19/437: MODELLING CATASTROPHIC OUT-OF-POCKET HEALTH EXPENDITURES AND ITS IMPLICATION FOR HOUSEHOLD WELFARE IN MALAWI: A MULTILEVEL SPATIAL APPROACH

Having satisfied all the relevant ethical and regulatory requirements, I am pleased to inform you that the above referred research protocol has officially been approved. You are now permitted to proceed with its implementation. Should there be any amendments to the approved protocol in the course of implementing it, you shall be required to seek approval of such amendments before implementation of the same.

Committee Address:
Secretariat, National Committee on Research in the Social Sciences and Humanities, National Commission for Science and Technology, Lingadzi House, City Centre, P/Bag B303, Capital City, Lilongwe3, Malawi. Telephone Nos: +265 771 550/774 869; E-mail address: ncrsh@ncst.mw

This approval is valid for one year from the date of issuance of this approval. If the study goes beyond one year, an annual approval for continuation shall be required to be sought from the National Committee on Research in the Social Sciences and Humanities (NCRSH) in a format that is available at the Secretariat. Once the study is finalised, you are required to furnish the Committee and the Commission with a final report of the study. The committee reserves the right to carry out compliance inspection of this approved protocol at any time as may be deemed by it. As such, you are expected to properly maintain all study documents including consent forms.

Wishing you a successful implementation of your study.

Yours Sincerely,

Yalonda .I. Mwanza
NCRSH ADMINISTRATOR
HEALTH, SOCIAL SCIENCES AND HUMANITIES DIVISION

For: CHAIRMAN OF NCRSH

Appendix 5:Published articles in peer-reviewed Journal

RESEARCH ARTICLE

Examining the incidence of catastrophic health expenditures and its determinants using multilevel logistic regression in Malawi

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Editor: Kannan Navaneetham, University of Botswana, BOTSWANA

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Data Availability Statement: The data used in this study are available upon request from the National Statistics office of Malawi through enquiries@statistics.gov.mw. The reasons for data restriction is the data may potentially contain location information of the survey participants and the data restrictions ensures that data users: Do not publish results that could allow survey participants to be identified, use the data for the purpose it was requested for, do not sale the data and do not pass the data to third parties.

Abstract

Background

Despite a free access to public health services policy in most sub-Saharan African countries, households still contribute to total health expenditures through out-of-pocket expenditures. This reliance on out-of-pocket expenditures places households at a risk of catastrophic health expenditures and impoverishment. This study examined the incidence of catastrophic health expenditures, impoverishing effects of out-of-pocket expenditures on households and factors associated with catastrophic expenditures in Malawi.

Methods

We conducted a secondary analysis of the most recent nationally representative integrated household survey conducted by the National Statistical Office between April 2016 to 2017 in Malawi with a sample size of 12447 households. Catastrophic health expenditures were estimated based on household annual nonfood expenditures and total household annual expenditures. We estimated incidence of catastrophic health expenditures as the proportion of households whose out-of-pocket expenditures exceed 40% threshold level of non-food expenditures and 10% of total annual expenditures. Impoverishing effect of out-of-pocket health expenditures on households was estimated as the difference between poverty head count before and after accounting for household health payments. We used a multilevel binary logistic regression model to assess factors associated with catastrophic health expenditures.

Results

A total of 167 households (1.37%) incurred catastrophic health expenditures. These households on average spend over 52% of household nonfood expenditures on health care. 1.6% of Malawians are impoverished due to out-of-pocket health expenditures. Visiting a religious health facility (AOR = 2.27,95% CI:1.24–4.15), hospitalization (AOR = 6.03,95% CI:4.08–8.90), larger household size (AOR = 1.20,95% CI:1.24–1.34), higher socioeconomic status

Funding: ANM was supported by the Consortium for Advanced Research Training in Africa (CARTA). CARTA is jointly led by the African Population and Health Research Center and the University of the Witwatersrand and funded by the Carnegie Corporation of New York (Grant No–B 8606.R02), Sida (Grant No:54100113), the DELTAS Africa Initiative (Grant No: 107768/Z/15/Z) and Deutscher Akademischer Austauschdienst (DAAD). The DELTAS Africa Initiative is an independent funding scheme of the African Academy of Sciences (AAS)'s Alliance for Accelerating Excellence in Science in Africa (AESA) and supported by the New Partnership for Africa's Development Planning and Coordinating Agency (NEPAD Agency) with funding from the Wellcome Trust (UK) and the UK government. The statements made and views expressed are solely the responsibility of the Fellow.The funders had no role in study design, data collection and analysis, decision to publish,or preparation of the manuscript.

Competing interests: The authors have declared that they have no competing interests.

(AOR = 2.94,95% CI:1.39–6.19), living in central region (AOR = 3.54,95% CI:1.79–6.97) and rural areas (AOR = 5.13,95% CI:2.14–12.29) increased the odds of incurring catastrophic expenditures.

Conclusion

The risk of catastrophic health expenditures and impoverishment persists in Malawi. This calls for government to improve the challenges faced by the free public health services and design better prepayment mechanisms to protect more vulnerable groups of the population from the burden of out-of-pocket payments.

Introduction

The goal of health care financing system is to protect households from the financial risk due illnesses. This goal is well articulated in the world health organization 2010 report as the Universal Health Coverage (UHC) goal [1]. The UHC goal ensures that all people have access to health services and do not face financial hardship due to out-of-pocket health payments [1]. One way in which health systems can protect households from financial burden due to out-of-pocket payments is through prepayment mechanisms [2]. In most low and middle income countries (LMICs) health prepayment mechanisms are not well developed and most households rely on out-of-pocket payments for health services [3]. Such reliance places financial burden on households which leads to catastrophic expenditure, impoverishment, prevents households from accessing health care and makes the attainment of the Universal Health Coverage difficult [1].

Catastrophic health expenditures (CHEs) occur when out-of-pocket health payment as a share of household's income or capacity to pay exceeds a predetermined threshold level [4]. CHE pushes households into poverty and leaves members of the households in a vicious circle of poverty and ill health [5,6]. These effects are common in LMICs where many households rely on out-of-pocket for payment of health care services [4]. Multi-country studies showed that an estimated 118.7 and 531.1 million people from Africa and Asia respectively incurred CHEs and 14.9 and 79 million people respectively were impoverished due to health payments by 2010 [7,8]. African and Asian countries accounted for 3.3% of the population impoverished by out-of-pocket health payments [8]. These findings from multi-country studies advance the need to understand the extent of CHEs and its associated risk factors in LMICs to design strategies for financial protection at national level.

Malawian health system is mainly publicly financed through tax revenues and receives substantial funding from external donors [9]. A minimum package of health services is provided for free in all public health facilities through the essential health package (EHP). This acts as a priority setting tool and includes key public health priority areas and cost effective intervention to address the major causes of mortality and morbidity [10]. Total health expenditure in Malawi increased by 14.7% from MWK429.1 billion to MWK502.8 billion over the period 2015–2018 and the average total per capita expenditure over the period was US $39.8 slightly higher than US$ 39.2 reported over the 2012–2015 period. The total per capita expenditure US $39.8 reported is similar to the average total per capita expenditure of US$41 in other low income countries but 2 times lower than the recommended total per capita expenditures of US $ 80 per year by WHO to strengthen health systems and implement a minimum set of essential health interventions [11,12]. Further to that the percapita expenditures is 5 times lower than the Southern Africa Development cooperation average of USD$ 209 in 2018 [13]. Such low total per capita expenditures may hinder the country to provide a minimum essential health services and consequently hinder its progress toward universal health coverage. Over the 2015–2018 period external donors contributed 58.6% of total health expenditures while Government and private health expenditures represented 23.9% and 17.5% of total health expenditures respectively. Out of 17.5% of private health expenditures 12.6% were from household's out-of-pocket expenditures [12]. This shows there was an increased in private health expenditures from 13.4% in 2012–2015 period to 17.5% of total expenditures mainly due to the rise in out-of-pocket expenditures from 8.6% of total health expenditures to 12.6% in the 2015–2018 period.

While access to health services in public facilities is free at point of use, households still contribute to total health expenditure through out-of-pocket payments in Malawi. Two main factors could explain this phenomenon. Firstly, the health system face many bottlenecks such as shortage of drugs, skilled medical personnel, poor quality of services and inaccessibility of facilities [14]. These bottlenecks force households to seek care in private health facilities with better quality services and skilled medical personnel where they incur higher out-of-pocket health payments. Shortage of drugs may also force households to purchase drugs at private pharmacies where they incur higher out-of-pocket payments. Secondly, in Malawi prepayment and risk pooling mechanisms for health financing are underdeveloped. Malawi has no social health insurance or health fund and for the private health insurance coverage is low and only accessible to those in the formal employment sector [15]. For instance, 1% of women and 2% of men aged 15–49 in the formal employment sector have health insurance coverage [15]. These low percentages suggest that higher costs of private health insurance leave many in the formal employment sector and those in the informal sector at a risk of catastrophic health expenditure, impoverishment and constrained when accessing health care.

According to previous studies, out-of-pocket health payments expose households to the risk of CHEs and impoverishment [5,16–21]. These studies also show that households in rural areas, in lower socioeconomic status, with chronically ill members, with children, with elderly members and larger households are at an increased risk of incurring CHEs. A study by Mchenga et al [22] showed that 0.73% to 9.73% of households faced CHEs in Malawi. The same study found that out-of-pocket expenditures increases the incidence of CHE and pushes households into poverty [22]. However, existing research in Malawi has paid limited attention to examining factors associated with CHEs. This paper compliments existing research by determining factors associated with CHEs using the most recent available fourth integrated household survey data (IHS4) in Malawi. We also examine the incidence, intensity of CHEs and the impoverishing effects of out-of-pocket expenditures on households. Our study provides evidence on the extent of CHEs and impoverishing effects of out-of-pocket health payments on households in a context of a country with a free public health services policy. It also provides evidence to policy makers on the characteristics of households that are vulnerable to CHEs. Such evidence is relevant in the designing of financial protection interventions in LMICs.

Methods

Data source

This study is a secondary analysis of data from a nationally representative integrated household survey (IHS4) conducted between April 2016 to April 2017 by the National Statistics office of Malawi [23]. The IHS4 used a stratified two stage sampling design. In the first stage,780 enumeration areas stratified by urban and rural strata were selected with probability proportional to size. The second stage used a random systematic sampling to select 16 primary households and 5 replacement households from the household listing in each sample enumeration area. A total of 12480 households were interviewed and data for 33 households were lost. Data for a total sample of 12,447 households covering 53,885 individuals were collected and this represented a 99.7% response rate. Our analysis used data for all the 12,447 households. The survey collected data on households' economic activities, demographics, welfare and other household characteristics. Particularly, data on the health module collected information on health spending on illnesses and injury over one-month recall period, expenditures on hospitalizations at a health facility and at a traditional healer over twelve months' recall period, chronic illnesses and diagnosis source of illnesses. The consumption expenditure module collected information on food expenditures and nonfood expenditures. The food consumption expenditures information collected over a one-week recall period included expenditures on items such as cereals, roots, tubers, nuts, pulses, vegetables, meat, fish, meat products, milk, milk products, fruits, sugar, fats, oils beverages and other miscellaneous items. For the non-food consumption expenditure different recall periods were used for different items. Expenditures for items such public transport, charcoal, kerosene, cigarettes, newspapers and magazines were collected over one-week recall period. Expenditures for items including groceries, wages paid to servants, motor vehicle service, mortgage, repairs to household item were collected over one-month recall period and clothing over three-month period. Expenditures for items such as carpets, rugs, linen, sleeping mats, construction materials, council rates, funeral and marriage ceremony costs were collected over twelve months' period. The aggregated data for all consumption expenditures were annualized and for consistency we report the findings for annual consumptions expenditures. All data including the food consumption expenditures data were collected using interviewer administered questionnaire.

Ethical considerations

Ethical clearance for this secondary reanalysis was obtained from National Committee on Research in the Social Sciences and Humanities (NCRSH) reference No. P.10/19/434. The National Statistical Office of Malawi enumerators obtained verbal informed consent from the participants and this was recorded on the questionnaire and upon agreement to participate the enumerator proceeded with the interview.

Data analysis

Measuring incidence and intensity of catastrophic health expenditures. To assess catastrophic health expenditures we used measures proposed by Wagstaff and Doorslaer [24]. Wagstaff and Doorslaer [24] proposed two indicators for assessing catastrophic health payments; these are catastrophic payment head count which measures the incidence and catastrophic payment overshoot which measures the intensity of catastrophic health payments.

Catastrophic health expenditure E is defined as [24,25]:

$$E = \begin{cases} 1, \ if \dfrac{T}{x - f(x)} > Z \\ 0, \ otherwise \end{cases} \qquad (1)$$

Where x is the total annual household's consumption expenditure, Z is the threshold level, T is the total annual household's out-of-pocket health payments and $f(x)$ is the total annual household's food expenditures.

Catastrophic payment head count denoted by H_{cata} was estimated as [25]:

$$H_{cata} = \frac{1}{N}\sum_{i=1}^{N} E_i = \mu_E \tag{2}$$

where N is the sample size.

The catastrophic payment overshoot is defined as $O_i = E_i\left[\left(\frac{T}{x-f(x)}\right) - Z\right]$ [24,25].

Therefore, average catastrophic payment overshoot was estimated as [24,25]:

$$O_{cata} = \frac{1}{N}\sum_{i}^{N} O_i = \mu_O \tag{3}$$

where N is the sample size and the average overshoot in (3) measures the intensity of catastrophic health payments. The catastrophic mean positive gap(overshoot) denoted by MPG was estimated as:

$$MPG_{cata} = \frac{O_{cata}}{H_{cata}} = \frac{\mu_O}{\mu_E} \tag{4}$$

In this study households incurred CHEs if out-of-pocket health expenditures as a share of household's capacity to pay exceed 40%, where household's capacity to pay was defined as annual household consumption expenditures remaining after food expenditures [4] and we also defined CHEs based on 10% threshold level of total consumption expenditures [24]. The choice of threshold levels is arbitrary however in the literature threshold levels of 40% of household capacity to pay and 10% of total consumption expenditures have been used [25]. In addition, CHEs defined based on 10% of total consumption expenditures is the official indicator for monitoring universal health coverage financial protection among the Sustainable Development Goals (SDGs indicator 3.8.2) [7,26]. For comparison of results we also reported findings on the incidence and intensity of CHEs for the threshold levels 20%, 25% and 30%. We defined out-of-pocket health expenditures as expenditures made at a point of use of health services [4]. We estimated out-of-pocket health expenditures as expenditures on consultation fees, diagnostic tests, medicines, outpatient and hospitalization fees.

Assessing impoverishing effects of out-of-pocket health expenditures on households. Impoverishment due to out-of-pocket payments occurs when non poor households become poor after paying for health services [24]. To assess the impoverishing effects of out-of-pocket health payments we examined the effects of health payments on two commonly used poverty measures; these are poverty headcount and poverty gap [24,25]. We estimated impoverishment impact due to health expenditures as the difference between post-payment poverty head count and pre-payment poverty headcount. Poverty head count gives the proportion of population with total consumption expenditures below the poverty line and poverty gap gives the extent by which the average total consumptions expenditures of the poor fall below the poverty line. We used the 2016 Malawi national poverty line of 137425 MWK [27] to examine the impoverishing effects of out-of-pocket payments.

Suppose we define $P_i^{pre} = \begin{cases} 1, if\ x_i < PL \\ 0, \quad otherwise \end{cases}$ where PL denotes the poverty line and x_i is the total annual household consumption expenditure per capita for household i; as the individual household i poverty before out-of-pocket health payments. Then the average pre-payment poverty headcount was estimated as [24,25]:

$$H_{poverty}^{pre} = \frac{1}{N}\sum_{i=1}^{N} P_i^{pre} = \mu_{p^{pre}} \tag{5}$$

where N is the sample size. We defined poverty gap before out-of-pocket health payments for each individual household i as $g_i^{pre} = P_i^{pre}(PL - x_i)$. Hence the average prepayment poverty gap was estimated as [24,25]:

$$G_{poverty}^{pre} = \frac{1}{N}\sum_{i=1}^{N} g_i^{pre} = \mu_{g^{pre}} \tag{6}$$

Where N is the sample size. The normalized poverty gap before health payments was estimated as:

$$NGap^{pre} = \frac{G_{poverty}^{pre}}{PL} \tag{7}$$

We obtained similar measures for the post payment poverty head count and gap after subtracting total annual household's out-of-pocket expenditure per capita from total annual household's consumption expenditure per capita and replacing the superscripts in Eqs 5,6 and 7 with post payment.

The difference between the corresponding post and pre poverty measures gives the impoverishing effects of out-of-pocket health payments on households. For example, we estimated the impoverishing effects of out-of-pocket payments on poverty head count and gap using the differences:

$$PI_{headcount} = H_{poverty}^{post} - H_{poverty}^{pre} \text{ and } PI_{gap} = G_{poverty}^{post} - G_{poverty}^{pre}$$

Assessing factors associated with catastrophic health payments. A multilevel binary logistic regression was used to assess the factors associated with catastrophic health expenditures. This regression was used to account for the nested structure of the survey data where households are nested in districts and to ensure correct estimation of standard errors and statistical inference of the model parameters. This binary regression was also used to account for our main outcome variable which takes the value of 1 if a household incurred catastrophic health expenditure and zero otherwise. We estimated two models; model 1 was estimated with CHEs defined based on 40% of household nonfood consumption expenditures and model 2 with CHEs based on 10% of household total consumption expenditures.

Multilevel binary logistic regression model. Let Y_{ij} be the outcome of catastrophic health expenditures for the i^{th} household in j^{th} district, π_{ij} be the probability of incurring catastrophic health expenditures and x_{ij} be some household level covariates. We assume Y_{ij} follows a binomial distribution, i.e. $Y_{ij}{\sim}Bin(1,\pi_{ij})$. Then, the probability of incurring catastrophic health expenditures π_{ij} is modelled using a logit link function and the random intercept model is specified as:

$$logit(\pi_{ij}) = \beta_0 + \beta x_{ij} + u_j \tag{8}$$

Where β is a vector of fixed effects regression coefficients of the corresponding household level covariates x_{ij} and u_j is the district level random effects term which captures the unobserved district level effects. The district level random effects term is assumed to be normally distributed with mean of zero i.e. $u_j \sim N(0, \sigma_u^2)$.

We included as covariates those factors identified in previous literature as determinants of catastrophic health expenditures [5,16–21]. These included household head characteristics such as age in years, sex, education and other household characteristics such as household size, socioeconomic status, presence of at least one chronically ill member in the household, presence of at least one elderly member, presence of at least one child, presence of at least one hospitalized member over the past 12 months, location of household(rural/urban), region in which the household is located, distance to the nearest health facility with a medical doctor and type of health facility with medical doctor. The measure of socioeconomic status was constructed based on total household consumption expenditure per capita. Total consumption expenditure per capita was categorized into five consumption expenditure quintiles from the poorest to the richest quintile. Data analysis was done using Stata 15. All analyses were adjusted for sampling design using survey sample weights and the survey set command in Stata 15. All results were interpreted at 5% significance level.

Results

Socio-economic and demographic characteristics of the sampled households

Table 1, shows the socio-economic and demographic characteristics of the sampled households. About 27% of the household heads were 26 to 35 years old and a larger majority of the households (71.12%) were male headed. About 63% of the household heads had no formal education, 83.32% were unemployed and only 2.34% received social safety nets from government. A larger proportion (80.95%) of the households was rural. More than half of the

Table 1. Socio-economic and demographic characteristics of the sampled households (n = 12447).

Variable	Mean(SD) or %
Age of household head	
Less than 26 years	12.30
26–35 years	26.66
36–45 years	23.79
46–55 years	15.21
Over 56 years	22.04
Male headed household	71.12
Education level of household head	
None	63.16
Primary	12.60
Secondary	19.80
Tertiary	4.44
Household head Employed	16.68
Household received social safety nets	2.34
Household size	4.29(2.00)
Presence of at least one child under 5 years	53.52
Presence of at least one elderly member greater than 60 years	19.75
Presence of at least one chronically ill member	22.33
Presence of at least one hospitalized member	13.16
Rural household	80.95
Distance to the nearest health facility with medical doctor (KM)	13.33(16.85)
Type of health facility from which medical doctor is based	
Government	87.23
Religious	10.68
Private	2.08
Region	
Northern	9.15
Central	44.32
Southern	46.53

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Table 2. Percentage of households reporting illnesses over 2 weeks' recall period by SES, location of household and region(n = 12440).

Variable	No of households reporting illnesses	Total no. of households	% of households reporting illnesses (95% CI)
Socio-economic status			
Quintile 1(Poorest)	655	2504	26.16 (24.23–28.78)
Quintile 2	724	2473	29.28 (28.23–32.89)
Quintile 3	741	2478	29.90 (28.73–33.28)
Quintile 4	784	2441	32.12 (29.67–34.49)
Quintile 5(Richest)	758	2544	29.44 (28.09–32.79)
Location of household			
Urban	546	2268	24.07 (21.61–27.35)
Rural	3116	10172	30.63(29.99–32.86)
Region			
Northern	582	2488	23.39(20.77–25.08)
Central	1372	4218	32.53(30.66–34.89)
Southern	1708	5734	29.79(27.14–30.81)

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households (53.51%) had children under the age of five years old and about 20% of the households had members older than 60 years old. A smaller proportion (13.16%) of the households had at least one member hospitalized and 22.33% had at least one member with chronic illnesses such as diabetes, tuberculosis, HIV/AIDS and arthritis. The average household size was four. A larger proportion (87.23%) reported having a nearest medical doctor at a government health facility. The average distance to nearest health facility with a medical doctor was 13 kilometers.

More households (32.12%) from the fourth income group and 30.63% of the households from rural reported illnesses in the past two weeks preceding the survey as shown in Table 2.

Table 3, presents household annual out-of-pocket health payments on medicine, out-patient care and hospitalizations by socio-economic status and location. Overall, the average total annual out-of-pocket health payment for all households was MWK15648.78. The mean

Table 3. Households out-of-pocket health payments by SES, location of household and region.

Variable	Mean annual out-of-pocket health payments in Malawi Kwacha (MKW)			
	Drugs	Out-patients	Hospitalizations	Total health payments
Socio-economic status				
Quintile 1(Poorest)	3374.11 (2919.87–3828.34)	2185.45 (1567.33–2803.56)	920.89 (724.09–1117.68)	6480.44 (5506.942–7453.942)
Quintile 2	4548.75 (3984.87–5112.64)	4545.97 (3473.23–5618.71)	1393.13 (1110.89–1675.36)	10487.85 (9010.388–11965.31)
Quintile 3	5085.307 (4356.13–5814.48)	6932.79 (5359.91–8505.69)	1303.59 (1007.08–1600.11)	13321.7 (11348.03–15295.37)
Quintile 4	6692.28 (5808.35–7576.19)	9877.10 (7839.55–11914.66)	1693.99 (1343.35–2044.63)	18263.37 (15574.03–20952.72)
Quintile 5(Richest)	7745.14 (6673.76–8816.53)	18528.38 (15009.45–22047.32)	3427.57 (2348.76–4506.39)	29701.10 (24847.66–34554.53)
Location of household				
Urban	6536.27 (5277.23–7795.32)	13589.04 (10012.57–17165.51)	3166.61 (2055.82–4277.39)	23291.92 (18033.83–28550.01)
Rural	5242.33 (4718.81–5765.85)	7194.05 (6010.52–8377.59)	1413.621 (1240.98–1586.27)	13850 (12213.51–15486.5)
Region				
Northern	5570.08 (4631.88–6508.28)	7935.04 (5029.32–10840.75)	1652.61 (1299.11–2006.10)	15157.72 (11489.09–18826.36)
Central	6657.99 (5753.26–7562.72)	11844.2 (9660.37–14028.03)	1748.88 (1457.74–2040.02)	20251.07 (17291.58–23210.56)
Southern	4359.24 (3836.65–4881.83)	5237.4 (4037.11–6437.69)	1765.03 (1288.13–2241.92)	11361.66 (9404.162–13319.17)
All households	5488.84 (5002.78–5975.31)	8412.35 (7239.78–9584.94)	1747.58 (1491.02–2004.14)	15648.78 (13989.75–17307.81)

95% CI in parenthesis.

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Table 4. Out-of-pocket payments as a share of total household expenditures per capita by expenditure quintiles (%).

Expenditure quintile	Drugs	Outpatients	Hospitalizations	Total health expenditures
Quintile 1(Poorest)	4.70	3.01	1.33	9.04
Quintile 2	4.13	4.04	1.26	9.42
Quintile 3	3.42	4.16	0.87	8.90
Quintile 4	3.23	4.67	0.83	8.73
Quintile 5(Richest)	2.09	4.39	0.78	7.26
Kakwani index	-0.29***	-0.06	-0.19*	-0.16*

Note

*** significant at 1%

* * significant at 5%

* significant at 10%. Kakwani index measures the progressivity in health finance and lies between -2(most regressive financing) and +1(most progressive financing) [25].

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total annual out-of-pocket health payment for drugs was MWK 5488.84, MWK 8412.35 for out-patient services and MWK 1747.58 for hospitalizations. A larger amount of a total annual out-of-pocket health payment was spent on out-patient services, this expenditure on out-patient services represented over half (53.75%) of the total out-of-pocket health payments. Households in the richest income quintile spent more on drugs(7745.14MWK), out-patient services(18528.38MWK) and hospitalizations(3427.57MWK) compared to poorest households. Overall, the mean out-of-pocket health spending for richest households was significantly higher (29701.1 MWK) compared to MWK 6480.44 for poorest households. Total annual out-of-pocket health payment was higher (MWK 23291.92) among households in urban compared to rural (MWK13850) areas and was higher in households in central region compared to northern and southern regions.

Table 4 gives results on out-of-pocket expenditures as a share of total household expenditures per capita by consumption expenditure quintiles and the Kakwani indices to measure progressivity of out-of-pocket payments. Overall the share of total out-of-pocket health expenditures as percentage of total household expenditure decrease with increase in total expenditures, indicating that out-of-pocket health expenditures are regressive. The share of expenditures on drugs and hospitalizations as a percentage of total household expenditures decrease with increase in total household expenditure indicating that expenditures on drugs and hospitalizations are regressive. Results of the Kakwani index provide similar conclusions. All the Kakwani indices are negative which implies that out-of-pocket health expenditures are regressive as poor households contributes a larger share of their income in paying for health services than rich households.

Table 5, reports results of the incidence and intensity of catastrophic health expenditures as measured by catastrophic headcount and overshoot respectively. Incidence(headcount) and intensity(overshoot) of catastrophic health expenditures decrease with increase in the threshold level. Overall,1.37% and 4.14% of the households incurred catastrophic health payments at a threshold level of 40% of nonfood expenditures and 10% of total consumption expenditures respectively. The mean positive overshoot (MPO) was 12.71% at 40% of nonfood expenditures. Households that incurred catastrophic health payments at 40% of nonfood expenditures, on average spent over half (52.71%) of total nonfood expenditure on health care.

The incidence of catastrophic health expenditures varied by socio-economic status, location of the household, type of health facility and type of health service utilized as shown in Table 6. Catastrophic health expenditures were high for households in rural areas (1.57%) compared to urban (0.38%), households in middle income groups and for households in the central region

Table 5. Incidence and intensity of catastrophic health expenditures.

Catastrophic health expenditures measures			Threshold levels z (%)		
Out-of-pocket health payments as share of non-food expenditures	10%	20%	25%	30%	40%
Headcount (H)	14.08	5.83	3.99	2.84	1.34
Standard error for H	0.62	0.40	0.32	0.27	0.18
Overshoot (O)	1.68	0.78	0.54	0.37	0.17
Standard error for O	0.12	0.08	0.06	0.05	0.03
Mean positive Overshoot (MPO)	11.96	13.42	13.58	13.16	12.71
Standard error	0.48	0.67	0.78	0.87	0.88
		Threshold levels z (%)			
Out-of-pocket health payments as share of total expenditures	10%	20%	25%	30%	40%
Headcount (H)	4.14	1.31	0.84	0.48	0.11
Standard error for H	0.31	0.17	0.13	0.09	0.04
Overshoot (O)	0.35	0.12	0.07	0.04	0.01
Standard error for O	0.04	0.02	0.01	0.01	0.01
Mean positive Overshoot (MPO)	8.54	8.99	8.02	7.29	8.23
Standard error	0.51	0.76	0.91	1.19	1.96

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Table 6. Incidence and intensity of catastrophic health expenditures: By SES, location of household (urban/rural), region, type of facility and type of health service utilized.

Variable	Incidence of CHE: threshold level z = 40 nonfood expenditures	Intensity of CHE: threshold level z = 40 nonfood expenditures	Incidence of CHE: threshold level z = 10% total health expenditures	Intensity of CHE threshold level z = 10% total health expenditures
Socio-economic status				
Quintile 1 (Poorest)	0.74(0.36–1.52)	0.09 (0.03–0.14)	3.59(2.70–4.76)	0.25(0.15–0.35)
Quintile 2	1.54(1.03–2.29)	0.15 (0.07–0.22)	4.54(3.59–5.73)	0.34(0.23–0.45)
Quintile 3	1.65(1.09–2.48)	0.24 (0.12–0.37)	3.70(2.84–4.81)	0.39(0.24–0.54)
Quintile 4	1.53(0.98–2.39)	0.19 (0.09–0.28)	4.09(3.15–5.29)	0.36(0.23–0.48)
Quintile 5 (Richest)	1.23(0.78–1.92)	0.19 (0.08–0.03)	4.77(3.66–6.18)	0.43(0.27–0.58)
Location of household				
Urban	0.38(0.16–0.86)	0.03 (0.01–0.05)	2.57(1.64–4.01)	0.19(0.09–0.29)
Rural	1.57(1.18–2.06)	0.20 (0.14–0.27)	4.51(3.86–5.26)	0.39(0.30–0.48)
Region				
Northern	0.73(0.42–1.27)	0.08 (0.03–0.14)	3.09(2.17–4.39)	0.22(0.12–0.31)
Central	2.09(1.47–2.96)	0.27 (0.16–0.38)	5.67(4.67–6.89)	0.52(0.38–0.67)
Southern	0.74(0.49–1.11)	0.09 (0.05–0.14)	2.88(2.25–3.68)	0.22(0.15–0.29)
Type of facility				
Government	1.28(0.94–1.75)	0.15(0.09–0.21)	3.96(3.35–4.67)	0.34(0.25–0.42)
Religious	2.32(1.42–3.78)	0.35(0.15–0.55)	6.13(4.38–8.51)	0.54(0.29–0.78)
Private	0.09(0.12–0.72)	0.03(0.02–0.09)	2.71(0.71–9.74)	0.19(0.05–0.45)
Type of service utilization				
Out patient	11.34(8.48–15.02)	1.57(1.01–2.13)	33.16(28.54–38.13)	3.31(2.58–4.04)
Inpatient	7.03(4.63–10.54)	0.88(0.41–1.36)	16.85(12.89–21.71)	1.79(1.06–2.52)

Note: 95% CI in parenthesis.

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(2.09%) compared to southern and northern regions. CHEs were also higher among households utilizing religious facilities (2.32%) and outpatient services (11.34%).

Impoverishing effects of out-of-pocket health expenditures on households

Table 7, presents results on the impoverishing effects of out-of-pocket health expenditures on households. The poverty head count based on nonfood consumption expenditure was 51.53% and subtracting health expenditures from the nonfood expenditure the poverty headcount increased to 53.13%. This implies that over half (51.53%) of the population is considered living below the national poverty line of 137425MWK based on household nonfood consumption expenditures however when out-of-pocket health expenditures are accounted for, about 53.13% of the population is considered poor. This represented a 3.10% relative increase in the incidence of poverty. The poverty gap increased from MWK 23101.75 to MWK 24167.55 after subtracting health expenditures. The mean positive gap increased from 32.62% to 33.10% representing a 1.47% relative increase in the intensity of poverty after accounting for out-of-pocket health expenditures. The increase in the mean positive gap implies that the rise in the poverty gap is as a result of households that were already poor being pushed deeper into poverty due out-of-pocket health expenditures.

Factors associated with catastrophic health expenditures

Table 8, presents results of the multilevel logistic regression models to assess the factors associated with the incidence of catastrophic health expenditures. The estimated district level random effects were significant indicating variations in CHEs between districts. The district level random effects explained 19% of the variation in CHEs. Several factors were associated with the risk of CHEs. We present results with CHEs defined based on 40% of nonfood expenditures. Households with more members had an increased odds of incurring catastrophic health expenditures (OR = 1.20, CI = 1.08–1.34). Having at least one household member hospitalized increased the odds of CHEs (OR = 6.03, CI = 4.08–8.90). Households headed by young household heads had a reduced odds of incurring CHEs. For example, households with households' heads who were in the 46 to 55 age group had a 43% less odds of incurring CHEs than households headed by household heads who were over 56 years old (OR = 0.43, CI = 0.19–0.99). Higher socioeconomic status increased the odds of incurring catastrophic health expenditures. For example, households in the richest income quintile had 2.94 times greater odds of incurring catastrophic health expenditures (OR = 2.94, CI = 1.39–6.19) compared to households in the poorest income quintile. Location of the household increased the odds of incurring catastrophic health expenditures. For instance, Households in rural areas had 5.13 times more odds of incurring catastrophic expenditures (OR = 5.13, CI = 2.14–12.29) compared to urban households and households in central region had 3.54 times more odds of incurring catastrophic health expenditures (OR = 3.54, CI = 1.79–6.97). Having the nearest medical doctor based at a religious health facility increased the odds of incurring catastrophic health

Table 7. Poverty effects of out-of-pocket health expenditures in Malawi, using the national poverty line (MWK137425).

	Gross of health payments	Net of health payments	Difference	
	(1)	(2)	Absolute (3) = (2)-(1)	Relative [(3)/(1)]*100
Poverty head count (%)	51.53	53.13	1.60	3.10
Poverty gap (MWK)	23101.75	24167.55	1065.80	4.61
Normalized poverty gap (%)	16.81	17.59	0.78	4.64
Normalized mean positive gap (%)	32.62	33.10	0.48	1.47

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Table 8. Multilevel logistic regression model for probability of incurring catastrophic health expenditures.

Independent variables	Model 1(CHE using 40% of non-food expenditures)	Model 2 (CHE using 10%of total health expenditures)
	Odds Ratio (95% CI)	Odds Ratio (95% CI)
Age of household head(ref = Over 56 years)		
Less than 26 years	0.44(0.17–1.15)	0.68(0.41–1.13)
26–35 years	0.59(0.27–1.32)	0.90(0.58–1.39)
36–45 years	0.52(0.23–1.10)	0.57(0.37–0.89)*
46–55 years	0.43(0.19–0.99)*	0.62(0.39–0.99)*
Sex of household head (ref = Male)	1.16(0.75–1.77)	1.04(0.82–1.32)
Household size	1.20(1.08–1.34)*	1.09(1.02–1.15)*
Socio-economic status (ref = Quintile 1(Poorest))		
Quintile 2	2.08(1.09–3.95)*	1.17(0.85–1.61)
Quintile 3	2.61(1.37–4.97)*	1.07(0.77–1.49)
Quintile 4	2.69(1.37–5.29)*	1.32(0.94–1.85)
Quintile 5(Richest)	2.94(1.39–6.19)*	1.89(1.33–2.70)*
Presence of at least one child (ref = No)	1.16(0.72–1.87	1.22(0.94–1.85)
Presence of at least one elderly member (ref = No)	0.73(0.34–1.53)	1.01(0.67–1.53)
Presence of at least one chronically ill member (ref = No)	1.40(0.94–2.11)	1.37(1.09–1.70)*
Presence of a hospitalized member(ref = No)	6.03(4.08–8.90)*	4.82(3.91–5.95)*
Household location (ref = Urban)	5.13(2.14–12.29)*	2.09(1.30–2.32)*
Distance to the nearest health facility with medical doctor	0.99(0.97–1.00)	1.00(0.99–1.01)
Type of facility utilized doctor based at (ref = government facility)		
Religious health facility	2.27(1.24–4.15)*	1.74(1.30–2.32)*
Private health facility	0.51(0.05–5.34)	1.65(0.83–3.29)
Region (ref = Northern)		
Central	3.54(1.79–6.97)*	2.59(1.46–4.59)*
Southern	1.09(0.54–2.22)	1.10(0.63–1.91)
District level random effects		
σ_u^2	0.61(0.24–1.54)*	0.24(0.11–0.49)*

Note

* indicates significant at 95% confidence interval.

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expenditures compared to having nearest medical doctor based at a government health facility (OR = 2.27, CI = 1.24–4.15).

Discussion

This study assessed the incidence of catastrophic health expenditures, its determinants and the impoverishing effects of out-of-pocket health expenditures using the most recent Malawi fourth integrated household survey. Our study shows that out-of-pocket health expenditures are regressive as poorer households bear more financial burden relative to their income than richer households in Malawi. This study also shows that CHEs and impoverishment appear to have increased by 37% and 60% respectively since the last integrated household survey in 2010/11 [22]. This increase suggests that more people continue to be pushed into poverty and experience disruptions in living standards due to out-of-pocket payments despite government efforts for a free public health services policy to increase financial protection. There is need for the Malawi government to protect households from the financial burden through other equitable means of financing health such as mandatory health insurance. The level of CHEs at 40% of non-food expenditures in Malawi is similar to what was reported in Lesotho [28], both of which are within the Sothern Africa Development Community, but lower than what was observed in most Sub Saharan African countries [16,17,29–31].

The low levels of overall incidence of catastrophic health expenditures may not necessarily mean high levels of financial protection considering the fact that the Malawian health care financing system is not as well developed as other sub-Saharan African countries such as Kenya, Rwanda, Tanzania and Ghana [32] with higher incidence of catastrophic health expenditures. The low levels of CHEs may reflect poor households in ability to afford care due to high costs; this forces such households to forgo treatment to avoid the consequences of out-of-pocket health payments and are not counted as incurring CHEs [4,33,34]. Estimates from the data used in this study show that 4.98% of those who reported illnesses did not seek care due to financial reasons. Moreover, our findings on CHEs by income show that households in poorest income quintile incur lower incidence of CHEs and are at a decreased risk of facing CHEs compared to middle and richer income households. Though this finding is contrary from findings by previous studies [16,17,35–38] a possible explanation could be the challenges faced by free public health services in Malawi such as poor quality of services, shortages of drugs and poor attitude of medical personnel which forces households in the middle and richer income groups to seek better health care in private facilities and incur greater out-of-pocket health expenditures. On the other hand, inability of poor households to afford better health care from private facilities due to high costs may force them to forgo seeking health care. Government plans to establish a mandatory national health insurance scheme and a health fund financed through tax revenues [9] should be pursued. This coupled with improved services in public health facilities will ensure that all households have access to care and do not have to forgo care due to financial hardships.

We found that rural households incur high incidence of CHEs and are at an increased risk of CHEs as reported by other authors [16,17,28,32,39]. Rural households in Malawi are burdened with out-of-pocket expenditures due to poverty and high transportation costs in seeking care as health facilities in rural areas are far apart. As such even the little out-of-pocket expenses incurred on health care are catastrophic. Though our study did not assess the impact of other direct costs related to seeking health care such as transportation costs; estimates of the mean distance to the nearest health facility with a medical doctor using the data show that on average rural households travel about 17 KMs to seek health care compared to 4 KMs by urban households. In addition, most health facilities in rural areas are privately owned by religious institutions that charge user fees at point of use; higher health care costs puts households at a risk of CHEs and creates a barrier in financial protection among rural households [40]. This implies that policies that aim at increasing financial protection among rural households should also aim at reducing poverty and improving accessibility of health services in rural areas.

Our finding that hospitalizations increased the incidence of catastrophic health expenditures is consistent with findings from other studies [5,20,21,41,42]. Households with hospitalized members may sell assets, use savings and hire external labor as coping mechanisms. A study on coping with out-of-pocket payments in 15 African countries found that households with inpatient expenditures are more likely to sell assets and borrow as a means of coping with bills due to hospitalizations [43]. These coping strategies puts pressure on the household limited resources and leads to risk of CHEs.

The result that having the nearest medical doctor based at a religious health facility increased the odds of incurring CHEs than government facility is intuitive in the Malawian context. Religious health facilities charge user fees at point of use this implies households that access care at religious facilities are burdened with higher out-of-pocket payments. This finding corroborates with findings from Kenya [44]. For example, visiting a mission hospital increased the odds of incurring catastrophic health payments in Kenya [44]. The government of Malawi signed contracts called Service Level Agreements (SLAs) with mission health facilities in 2005 to ensure that households have access to services at these mission facilities without facing financial hardship [45]. Despite other studies showing that service level agreements improved utilization of health services [45] our finding may suggest that it has not achieved one of its intended purpose of protecting households from the financial burden of health expenditures. This is because many of the mission facilities and needed services are not part of the agreements and the poor who access services at these facilities still incur higher out-of-pocket payments [46]. There is need for government to expand these Service Level Agreements to include more facilities and services needed by households. This innovative financing mechanism has the potential to ensure many households have access to the needed health care without facing financial hardship [47].

The study has some limitations. Firstly, the study used self-reported data on consumption expenditures and illnesses which is prone to recall bias which can lead to underreporting as also observed by other authors. This limitation would underestimate the incidence of catastrophic health expenditures and impoverishing effects of out-of-pocket expenditures on households. Secondly, use of cross-sectional data prevents causal interpretation of the relationship between catastrophic health payments and its associated factors. Thirdly, data on total health expenditures were annualized this could lead to overestimating of total health spending as we assume the same rate of monthly health expenditures over time. Despite these limitations, our study makes use of a multilevel logistic regression model to assess factors associated with incidence of CHEs which highlighted variations by districts. In addition, the study assessed the incidence of CHEs, the impoverishing impact of out-of-pocket health payments on households using the most recent available data which is important for monitoring financial protection.

Conclusion

Our results are important for monitoring the incidence of catastrophic expenditures and impoverishing effects of out-of-pocket health expenditures in Malawi consequently progress towards achieving Universal Health Coverage. Despite a free public health care policy, our findings suggest that the incidence of catastrophic health expenditures and impoverishment effect of out-of-pocket health expenditure has increased compared to a previous study using similar data. Our finding that rural households face high incidence of catastrophic payments reflects challenges faced by free public health facilities in providing much needed care to households considering that majority of rural population access free public health services. This finding calls for government to improve the challenges faced by free public health services to protect majority rural poor from the financial risk of out-of-pocket payments. This study also shows that access to medical doctors from religious health facilities, living in rural areas and hospitalizations increased the odds of incurring catastrophic payments. There is a need for government to establish more equitable health financing mechanisms such as a mandatory national health insurance scheme or a health fund and expand the innovative financing mechanism of Service Level Agreements with mission health facilities. This will ensure that the identified vulnerable groups of the population are protected from financial hardship due to out-of-pocket payments.

Author Contributions

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Formal analysis: Atupele N. Mulaga.

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Supervision: Mphatso S. Kamndaya, Salule J. Masangwi.

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PLOS GLOBAL PUBLIC HEALTH

RESEARCH ARTICLE

Decomposing socio-economic inequality in catastrophic out-of-pocket health expenditures in Malawi

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Data Availability Statement: The data used in this study are available upon request from the National Statistical Office of Malawi through enquires@statistics.gov.mw. The data is restricted as it may potentially contain location information of the survey participants and the restrictions ensures that data users :Do not publish results that could allow survey participants to be identified, use the data for its intended purpose, do not sale the data and do not pass the data to third parties. The authors confirm they had no special access or privileges that others would not have.

Abstract

Reducing health inequalities and inequities is one of the key goals that health systems aspire to achieve as it ensures improvement in health outcomes among all population groups. Addressing the factors contributing to inequality in catastrophic health expenditures is important to reducing inequality in the burden of health expenditures. However, there are limited studies to explain the factors contributing to inequalities in catastrophic health expenditures. The study aimed to measure and decompose socio-economic inequality in catastrophic health into its determinants. Data for the analysis come from the fourth integrated household survey. Data for 12447 households in Malawi were collected from April 2016 to April 2017 by the National Statistical Office. The secondary analysis was conducted from June 2021 to October 2021. Catastrophic health expenditure was estimated as a proportion of households whose out-of-pocket health expenditures as a ratio of non-food consumption expenditures exceeds 40% threshold level. We estimated the magnitude of socio-economic inequality using the Erreygers corrected concentration index and used decomposition analysis to assess the contribution of inequality in each determinant of catastrophic health expenditure to the overall socio-economic inequality. The magnitude of the Erreygers corrected concentration index of catastrophic health expenditure (CI = 0.004) is small and positive which indicates that inequality is concentrated among the better-off. Inequality in catastrophic health expenditure is largely due to inequalities in rural residency (127%), socio-economic status (-40%), household size (14%), presence of a child under five years old (10%) and region of the household (10%). The findings indicate that socio-economic inequality in catastrophic health expenditures is concentrated among the better-off in Malawi. The results imply that policies that aim to reduce inequalities in catastrophic health expenditures should simultaneously address urban-rural and income inequalities.

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Introduction

Health inequalities are systematic differences, variations and disparities in health outcomes among population groups [1]. One of the goals of health systems in both developed and developing countries is to reduce health inequalities in a way that improves the condition of the worse-off [2]. Socioeconomic inequalities in health are a great concern among policy makers as most of these inequalities are unjust and unfair and reflect inequality in the social determinants of health [1, 3, 4]. Studies globally have shown that determinants of health contributes greatly to inequality in health and health outcomes [3–8]. For example, a study in South Africa found that inequalities in social determinants of health such as social protection, employment, education and knowledge contributes greatly to inequalities in good self-assessed health [3]. This implies that policies that aim to reduce health inequalities should also be designed to address inequalities in social determinants of health.

Socio-economic inequality in out-of-pocket health expenditures may entail inequality in the burden of catastrophic health expenditures and worsen inequalities in access to and utilization of health services [2, 9, 10]. Prior studies that have assessed the magnitude of inequality in catastrophic health expenditures consistently reported that catastrophic expenditure is concentrated among the worse-off [11–17]. For instance, studies have reported that catastrophic health expenditure is concentrated among the worse-off households and that socioeconomic status, household size, having elderly household members greatly contribute to inequality in catastrophic expenditures [15, 16]. Similar studies in Sub-Saharan African countries have reported that catastrophic health expenditure is concentrated among the worse-off households [11–13]. However, there is limited evidence on decomposing inequality in catastrophic expenditures to understand how inequality in the determinants contribute to inequality in catastrophic health expenditures in sub-Saharan Africa countries. We extend the studies conducted in Sub-Saharan Africa countries by decomposing socio-economic inequality in catastrophic health expenditures in Malawi.

In Malawi the incidence of catastrophic health expenditures was estimated at 0.73% at 40% threshold level of nonfood expenditures in 2011 and using similar data another study estimated the incidence of catastrophic health expenditures at 1.37% at the same threshold level in 2016 [18, 19]. These results indicated an increase in the incidence of catastrophic health expenditures over the five-year period. Nevertheless, the studies did not report socio-economic inequality in catastrophic health expenditures and how inequality in the determinants of catastrophic expenditures contributes to the overall socio-economic inequality.

Analysis of inequalities in Malawi has shown that health inequalities are interrelated to wealth, education, regional and gender inequalities [20]. These inequalities reinforce one another and may require policies that simultaneously address such inequalities [20]. For example, utilization of maternal health services is low among women with lower education, residing in rural areas and in lower wealth quintile in Malawi [21]. These inequalities contribute to poor maternal health to the disadvantage of the worse-off. This is also the case with out-of-pocket health expenditures which is concentrated among the better-off [22]. This study [22] also reported that income and education inequalities contributed to the majority of inequalities in out-of-pocket health expenditures. Such inequalities in health expenditures may exacerbate inequalities in access and utilization consequently inequality in catastrophic health expenditures. However, to the best of our knowledge there is no study that has assessed and decomposed inequality in catastrophic health expenditure in Malawi. Therefore, the aim of the study was to assess and decompose inequality in catastrophic health expenditures into its determinants. The study adds to the existing literature on health inequalities by providing evidence on the major determinants that contribute to inequality in catastrophic health expenditures in a Sub Saharan Africa country. This will help policy makers to understand the magnitude of inequality, the factors contributing to inequality in catastrophic health expenditures and design policies to simultaneously address inequality in catastrophic expenditures and its determinants.

Methods

Study design

The study uses a cross-sectional design using secondary data from a nationally representative survey conducted from April 2016 to April 2017.

Data source and definition of variables

Data for the study come from the fourth integrated household survey (IHS4). Data were collected from April 2016 to April 2017 by the National Statistical Office of Malawi. This secondary reanalysis of the data was conducted between June 2021 to October 2021. The Malawi fourth integrated household is a cross sectional survey that uses a two stage sampling design to select the households. The first stage involved selecting 780 enumeration areas which were stratified by urban and rural strata and were selected with probability proportional to size and the second stage involved selecting 16 primary households and 5 replacement households from the sampling frame of households in each sampled enumeration area using random systematic sampling. The paper used data for a total sample of 12,447 households which included 53,885 individuals. Data collected include information on household characteristics and demographics on each household member, education, food and nonfood consumption expenditures and health.

Outcome variable and covariates

The outcome variable is dichotomous taking the value 1 if a household faced catastrophic health expenditure and 0 otherwise. A household faced catastrophic health expenditure if out-of-pocket health expenditure as a proportion of household capacity to pay exceed 40% threshold level where capacity to pay was defined as household total annual consumption expenditures minus food expenditures.

The covariates included age of household head, sex of household head, household socioeconomic status based on household consumption expenditure per capita and categorized into five quintile groups from poorest to richest, having at least one child under five year old in household or not, having an elderly member in household or not, having at least one hospitalized member in the past year or not, rural or urban household location, region, type of health facility with medical doctor, household size, distance to the nearest health facility.

Ethical clearance

We obtained ethical clearance for the secondary analysis from the National Committee on Research in the Social Sciences and Humanities (NCRSH) reference No. P.10/19/434.

Statistical analysis

Measuring inequality in catastrophic health expenditures. We estimated inequality in catastrophic health expenditures using the concentration index. The concentration index is a common measure used in the literature to assess income related inequality in health variables. The concentration index measures the degree in socioeconomic inequality of a health variable of interest and is defined as two times the area between the line of inequality and the concentration curve [23]. The concentration curve plots the cumulative proportion of the health variable on the y-axis against the cumulative proportion of the sample ranked by socio-economic status from the poorest to the wealthiest on the x-axis [4]. The index lies between -1 and +1 when the health variable of interest is unbounded. However, for bounded health variables Wagstaff [24] has shown that the concentration index lies between $\mu-1$ and $1-\mu$ for large samples. Positive values of the concentration index indicate that inequality is more concentrated among the better-off and negative values indicate that inequality in more concentrated among the worse-off [25]. The concentration index was estimated using the convenient covariance formula as [25]:

$$C = \frac{2}{\mu} cov(y_i, r_i) \quad (1)$$

Where r_i is the fractional rank of i^{th} household across socioeconomic status as measured by consumption expenditure per capita in this study, y_i is the health variable of interest which is the incidence of catastrophic expenditures and μ is the mean of y_i.

For a dichotomous health variable of interest, Wagstaff [24] proposed a normalized concentration index obtained by dividing the standard concentration index in Eq (1) by either the reciprocal of y_i or the upper bound of the concentration index of y_i. However, Erreygers [26] has shown that rank dependent measures of socioeconomic inequality such as the Wagstaff concentration index should satisfy four properties. These include; (i) the mirror image property which states that for any given health distribution the index of a health variable is equal in absolute value to the index of ill-health variable with opposite sign, (ii)cardinal invariance property which states that a positive linear transformation of the health variable does not change the value of index, (iii) transfer property which states that any mean preserving change in health distribution in favor of the wealthier result in change in index in favor of the wealthier and this is also true for change in health distribution in favor of the worse-off, (iv) level of independence property which states that the value of the index does not change with change in health levels of all persons by an equal absolute amount. Whereas the Wagstaff concentration index satisfy properties (i) to (iii) it fails to satisfy the level of independence property. Thus, for bounded health variables, Erreygers [26] proposed a corrected concentration index which satisfies all the properties of rank dependent measures of inequality. In this paper we computed the Erreygers corrected concentration index since our outcome variable is a bounded dichotomous variable. The Erreygers corrected concentration index was estimated as follows [26]:

$$EI = \frac{4\mu}{y^{max} - y^{min}} CI \quad (2)$$

Where μ is the mean of catastrophic health expenditures, y^{max} *and* y^{min} are the upper bound and lower bound of catastrophic health expenditures respectively and *CI* is the concentration index of catastrophic health expenditures which was obtained using (1). The paper used conindex command in Stata 15 [27] to compute the concentration indices. Stata 15 was also used to decompose the concentration index of catastrophic expenditures into its determinants.

Decomposing socio-economic inequality in catastrophic health expenditures into its determinants. The paper used a decomposition analysis to assess the contribution of inequality in each determinant of catastrophic health expenditures to the overall socioeconomic inequality. The method proposed by Wagstaff et al. [4] is used to decompose socioeconomic inequality in catastrophic health expenditures into its determinants. This method has also been used by other authors to decompose inequality in catastrophic health expenditures

[15, 16, 28, 29]. Decomposing the concentration index allows us to understand how inequality in each determinant of catastrophic health expenditure contributes to overall socioeconomic inequality in catastrophic health expenditures. This is important for policy makers to design interventions to tackle inequality in the determinants and consequently inequality in catastrophic health expenditures. The method of decomposing the concentration index as proposed by Wagstaff et al. [4] is based on the linear regression model that relates a continuous health outcome variable y_i to a set of k determinants x_k, given as follows:

$$y_i = \alpha + \sum\nolimits_k \beta_k x_{ki} + \varepsilon_i \tag{3}$$

Where β_k is the vector of regression coefficients, x_k is a set of k determinants and ε_i is the random error term. Wagstaff et al. [4] has shown that the concentration index of y, denoted by C_y can be decomposed as follows:

$$C_y = \sum\nolimits_k \left(\frac{\beta_k \bar{x}_k}{\mu}\right) C_k + \frac{GC_\varepsilon}{\mu} \tag{4}$$

Where μ is the mean for the outcome variable y, $\bar{x}_k$ is the mean of each determinant, C_k is the concentration index for the determinants, β_k represents the estimated regression coefficients for each determinant factor obtained from Eq (3) and GC_ε is the generalized concentration index for the error term. For the Erreygers corrected concentration index a similar decomposition formula for the index is expressed as follows [26]:

$$EI = 4\left(\sum\nolimits_k \beta_k (\bar{x}_k C_k) + GC_\varepsilon\right) \tag{5}$$

Where $\bar{x}_k$ is the mean of each determinant in the regression analysis, C_k is the concentration index for the determinants and β_k is the estimated regression coefficient or marginal effect.

The concentration index C_y and EI for the outcome variable in (4) and (5) respectively is decomposed into two components. The first component represents the explained inequality due to variation in the explanatory variables across socioeconomic status and the second component represents inequality that cannot be explained by variation in the explanatory variables across socioeconomic status [4, 5, 25].

For the decomposition analysis in this paper we used multilevel logistic regression model since our outcome variable is dichotomous taking the value 1 if a household faced catastrophic health expenditure and zero otherwise. In addition, the survey data used is hierarchically structured where households are nested in sub districts hence the multilevel logistic regression account for the hierarchical structure of the data to give correct inference on the estimated parameters of the regression model.

To decompose the overall socioeconomic inequality in catastrophic health expenditures, we first estimated a multilevel logistic regression to obtain the marginal effects indicating the intensity of the relationship between catastrophic expenditures and its determinants. The marginal effects were used together with the estimated concentration indices of each determinant indicating inequality in each determinant and the estimated mean of each determinant in computing the contribution of each determinant to the overall socio-economic inequality in catastrophic health expenditures using Eq (5). The contribution of each determinant to overall inequality was obtained as four times the product of the marginal effect, the estimated concentration index and estimated mean of each determinant. A positive contribution by a variable indicates that the variable increases inequality in catastrophic health expenditures disfavoring the worse-off and a negative contribution indicates reduction in inequality [4, 16].

The decomposition analysis proposed by Wagstaff et al. [4] requires that the regression model relating the health outcome variable such as catastrophic health expenditures to a set of k determinants x_k to be linear in form. However, the logistic regression model used in this paper is nonlinear in form. To deal with this problem we used the logit linear transformation of the logistic regression model as proposed by other authors [5, 30]. This enables the decomposition of the concentration index to be implemented in the same way as proposed by Wagstaff et al. [4] in Eq (4). We used the logit linear transformation on the logistic regression model and the marginal effects of the regression coefficients in the decomposition analysis. Other authors have also used linear transformation of the nonlinear models in decomposing inequality in catastrophic health expenditures [15, 16, 28, 31].

The multilevel logit linear transformation model used in the decomposition analysis is specified as follows:

$$\ln\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \alpha_{ij} + \sum \beta_i^m x_{ij} + u_j \tag{6}$$

Where π_{ij} is the probability of incurring catastrophic health expenditure, β_i^m represents a vector of the estimated regression marginal effects of the corresponding determinant factors x_{ij} and u_j is the higher level random error term. Analysis was implemented using Stata 15 and we adjusted for sampling design using survey sample weights and the survey set command. Results were interpreted at 5% significance level.

Results

Table 1 shows the summary statistics of catastrophic health expenditure and its determinants. More than 71% of the households were male headed and over 26% of the household heads

Table 1. Summary statistics of sampled households (n = 12447).

Variable	Weighted Mean(SD)/percentage
Catastrophic health expenditure Age of household head	1.34
Less than 26 years	12.30
26–35 years	26.66
36–45 years	23.79
46–55 years	15.21
Over 56 years	22.04
Male headed household	71.12
Size of household	4.29(2.00)
Have at least one child under 5 years	53.52
Have at least one elderly member greater than 60 years	19.75
Have at least one chronically ill member	22.33
Have at least one hospitalized member	13.16
Rural location	80.95
Distance to the nearest health facility (KM)	13.33(16.85)
Type of health facility	
Government	87.23
Religious	10.68
Private	2.08
Region	
Northern	9.15
Central	44.32
Southern	46.53
Total annual consumption expenditure (MWK)	831433(94289)
Total annual health expenditure (MWK)	15649(7449853)

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were aged 26 to 35 years old. More than half (53.5%) of the households had at least one child under five years' old. On average households had four members. Only 20% of the households had an elderly household member, 22% had at least one household member chronically ill and 13% had at least one household member hospitalized in the 30 days preceding the survey. Majority (81%) of the sampled households were rural. On average the distance to nearest health facility was 13 km and about 87% of the households reported government health facility as the nearest facility where medical doctors were based. On average the total annual household consumption expenditure was MWK 831433 and the household total annual out-of-pocket health expenditures was MWK 15649. Only 1.3% of the sampled households faced catastrophic health expenditures at 40% level of non-food expenditures. About 3%, 6% and 14% faced catastrophic health expenditures at 30%,20% and 10% threshold level respectively (results not reported in Table 1).

Socioeconomic inequality in catastrophic health expenditure and decomposition analysis

Table 2 reports the estimated socio-economic inequality in catastrophic health expenditures and each of the covariate associated with catastrophic health expenditures as measured by the concentration index. The concentration Index(CI) of incurring catastrophic health expenditure ($CI = 0.004$, $p<0.10$) indicates that inequality in catastrophic health expenditure is moderate and concentrated among better-off households. Female headed household ($CI = -0.086$, $p<0.01$), presence of at least one child under five years in the household ($CI = -0.282$, $p<0.01$), larger household size with six to eleven members ($CI = -0.251$, $p<0.01$), residency in rural areas ($CI = -0.363$, $p<0.01$), longer distance to the nearest health facility ($CI = -0.064$, $p<0.01$) and access to religious health facility with medical doctor ($CI = -0.032$, $p<0.01$) is concentrated amongst poor households. On the other hand, having at least one household member hospitalized ($CI = 0.018$, $p<0.01$) and access to private health facility with medical doctor ($CI = 0.014$, $p<0.01$) is concentrated amongst rich households.

Table 3, gives results on decomposing socio-economic inequality in catastrophic health expenditure into its determinants. The analysis was conducted to assess the contribution of inequality in each determinant of catastrophic health expenditures to the overall socio-economic inequality in catastrophic health expenditures. Column two gives the marginal effect estimated from the fitted regression model. The column indicates the magnitude of the relationship between each determinant and catastrophic health expenditure after controlling for all other determinants. For example, the predicted probability of catastrophic health expenditures was 0.028 greater for households with hospitalized members. The probability of facing catastrophic expenditure was 0.01 greater for rural household and 0.013 greater for households located in central regions. For households with a larger family from 6 to 11 members the probability of facing catastrophic health expenditures was 0.01 greater and it was also 0.01greater for households accessing health services at religious health facilities than government facilities. Compared with households in lower income quintile the probability of facing catastrophic health expenditures was 0.01greater in the richest income quintile.

Column three gives the weighted mean for each of the determinants associated with catastrophic health expenditures and column four gives the estimated concentration index for each of the determinants.

The contribution of socio-economic inequality in each determinant to the overall socio-economic inequality is estimated in column five. This column of the absolute contribution is estimated by multiplying four to the product of marginal effects, weighted mean and the Erreygers corrected concentration index of the determinant as described in Eq (5). For example, the

Table 2. Erreygers corrected concentration indices for catastrophic health expenditures and its determinants.

Variable	Concentration index (Std.Error)	P-value
Catastrophic health expenditure (CHE)	0.004(0.0024)	0.099*
Age of household head(ref = ≥ 56 years)		
Less than 26 years	0.029(0.007)	0.001***
26–35 years	0.029(0.009)	0.0013**
36–45 years	-0.054(0.009)	0.001***
46–55 years	-0.010(0.007)	0.177
Female household head	-0.086(0.009)	0.000***
Size of household (ref ≤ **5** members)		
6–11 members	-0.2514(0.009)	0.001***
≥ 12 members	-0.0036(0.001)	0.001***
Socio-economic status		
Quintile 2	-0.311(0.008)	0.001***
Quintile 3	0.001(0.008)	0.991
Quintile 4	0.320(0.008)	0.001***
Quintile 5(Richest)	0.639(0.006)	0.001***
Have at least one child	-0.282(0.010)	0.001***
Have at least one elderly member	-0.005(0.008)	0.535
Have at least one chronically ill member	-0.009(0.009)	0.267
Have at least one hospitalized member	0.018(0.007)	0.009**
Rural location	-0.363(0.012)	0.001***
Distance to the nearest health facility (ref = ≤ **34** Km)		
35–69 Km	-0.064(0.006)	0.001***
≥ **70** Km	-0.013(0.003)	0.001***
Type of health facility (ref = government)		
Religious	-0.032(0.006)	0.001***
Private	0.014(0.003)	0.001***
Region (ref = Northern)		
Central	0.081(0.010)	0.001***
Southern	-0.094(0.010)	0.001***

*$p<0.10$

**$p<0.05$

***$p<0.01$

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absolute contribution of residency in rural areas is estimated by 4[0.0097*0.809*(-0.3630)] and the relative contribution was obtained by dividing the absolute contribution by the total contribution of all the determinants. As shown by the relative contributions in the last column of Table 3; the majority of socioeconomic inequality in catastrophic expenditure was mainly due to inequality in residency in rural areas (127%), household socio-economic status (-40%), household size (14%), region in which a household is located (-10%) and having children under five years (10%). Other determinants of catastrophic health expenditure such as female headed household, having at least one elder member in the household, having at least one hospitalized member, having of one chronically ill member, access to nearest health facility with medical doctor and distance to the nearest health facility contributed marginally to inequality in catastrophic health expenditure. In total, inequalities in these determinants accounted for only 2% of the total inequality in catastrophic health expenditures.

Table 3. Decomposition analysis of concentration index for catastrophic health expenditures.

Independent variables	Marginal effects	Weighted Mean	C_k	Contribution to C_y	Contribution to C_y (%)
Age of household head (ref = ≥ 56 years)					-1
≤26 years	-0.0091	0.123	0.0294	-0.0001	
26–35 years	-0.0053	0.267	0.0295	-0.0001	
36–45 years	-0.0067	0.238	-0.0541	0.0003	
46–55 years	-0.0078	0.152	-0.0100	0.00005	
Female household head	0.0009	0.289	-0.0857	-0.0001	1
Household size (ref ≤ **5** members)					14
6–11 members	0.0066*	0.256	-0.2514	-0.002	
≥ 12 members	0.0152	0.0196	-0.0036	-0.0000003	
Socio-economic status (ref = Quintile1)					-40
Quintile 2	0.0071*	0.2	-0.3199	-0.0019	
Quintile 3	0.0093*	0.199	0.0009	0.0000007	
Quintile 4	0.0093*	0.2	0.32032	0.00247	
Quintile 5(Richest)	0.0097*	0.199	0.6397	0.005235	
Have at least one child	0.0025	0.535	-0.2825	-0.00141	10
Have at least one elderly member	-0.0034	0.198	-0.0051	0.00001	-0.1
Have at least one chronically ill member	0.0035	0.223	-0.0096	-0.00003	0.21
Have at least one hospitalized member	0.0178*	0.132	0.0182	0.00018	-1.24
Rural location	0.0147*	0.809	-0.3630	-0.018538	127
Distance to health facility (ref = ≤ **34** Km)					0.14
35–69 Km	-0.0012	0.098	-0.0644	-0.000028	
≥70 Km	-0.0067	0.0196	-0.0133	0.0000077	
Type of health facility (ref = government)					0.80
Religious	0.0082*	0.107	-0.0316	-0.00011	
Private	-0.0063	0.021	0.0143	-0.0000069	
Region (ref = Northern)					-10
Central	0.0122*	0.443	0.0798	0.00179142	
Southern	0.0008	0.465	-0.0944	-0.00028	

*significant at 5% level.

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Discussion

This study aimed at measuring and decomposing socioeconomic inequality in catastrophic health expenditures to assess the contribution of inequality in each determinant of catastrophic health expenditures to the overall inequality. The findings show that socioeconomic inequality is marginally significant and concentrated among the better-off households. Majority of the socioeconomic inequality in catastrophic health expenditures is due to inequalities in residency in rural area, socioeconomic status, household size, having at least a child under five years old and region in which household is located. We discuss these findings in the paragraphs that follows.

Firstly, contrary to findings from previous studies [11, 13–16, 32–34] the results demonstrate that catastrophic health expenditure is concentrated among better-off households in Malawi. This could be attributed to the challenges faced by free public health services delivery in Malawi such as constant stock out of drugs, poor quality of services, shortage of human resources which forces the better-off to seek high quality care in private facilities putting households at risk of incurring catastrophic expenditure [20, 35, 36]. This is also supported by our finding in Table 2 which indicates that access to private health facility is more concentrated among the better-off. Furthermore, other studies have shown that the use of health care services and out-of-pocket health expenditures are more concentrated among the better-off households in Malawi [22, 37]. This high out-of-pocket health expenditures among the better-off increase the likelihood of incurring catastrophic health expenditures.

Another plausible explanation is that due to their ability to pay the better-off households use private health care more than the worse-off as such they incur high out-of-pocket health expenditures putting them at risk of catastrophic health expenditures. A health system that gives access to high quality care to the rich due to their ability to pay leaving lower quality care to the poor is inequitable and against the core values of universal health coverage goal [38]. Malawi has a long history of providing free public health services to reduce inequality and inequity in health services utilization and financial protection however it has been observed that inequities in access and health services utilization still persists [39] this exacerbates inequalities in health expenditures [22] consequently inequalities in catastrophic health expenditures between the worse-off and better-off. This finding reinforces the need to improve the health systems challenges such as poor quality of care, shortages of drugs and human resources to reduce inequalities in use and access consequently inequalities in health expenditures.

Secondly, our findings that socioeconomic status, residency in rural areas and household size are the major contributors to socioeconomic inequality in catastrophic expenditure are consistent with findings from previous studies [15, 16]. However, we find that socioeconomic status contributes negatively to inequality in catastrophic health expenditure which indicates that socioeconomic status decreases inequality in catastrophic health expenditure. This shows that the combined effect of the marginal effect of socio-economic status on catastrophic health expenditures and its inequality is to reduce inequality in catastrophic health expenditures such that catastrophic health expenditures is greater among the better-off. There are huge income inequalities in Malawi such that these income inequalities and other health inequalities are interrelated [20]. For example, a study in Malawi found that inequality in out-of-pocket expenditures is more concentrated among the rich and the majority of these inequalities are influenced by income inequality [22]. Thus, in the case of Malawi increasing household socioeconomic status has an effect of decreasing inequality in catastrophic health expenditure. Policies that aim to address inequality in catastrophic out-of-pocket health expenditures should also address income and other related inequalities. This could be through social cash transfer interventions to poor households which could help to reduce income inequalities.

Thirdly, we find that residency in rural areas contributes to the majority of socioeconomic inequality in catastrophic health expenditures. The relative positive contribution to socioeconomic inequality indicates that residency in rural areas increases inequality in catastrophic expenditure disfavoring the poor. Huge rural–urban income inequalities coupled with poor geographic accessibility of public health facilities in rural areas creates inequality in access to and use of health services disfavoring poor rural households in Malawi [20]. Due to poor geographical accessibility of public facilities poor rural households may incur other costs associated with seeking care such as transportation which puts them at risk of catastrophic health expenditures as observed by other studies in Kenya and Zambia [32, 34]. In Malawi, about 40% of health services in rural areas are provided by Christian Health Association of Malawi (CHAM) health facilities which charge user fee [20, 40] as such even smallest expenditures by poor households seeking care at religious health facilities can drive them into catastrophic health expenditures. Moreover, our analysis show that access to such mission/religious health facilities is concentrated among poor households which means rural poor households disproportionately use religious health facilities more creating inequality in health expenditures disfavoring poor households. The government of Malawi introduced service level agreements

(SLAs) with Christian Health Association of Malawi (CHAM) service providers in 2005 which allow poor rural households to access free health care in these mission facilities without facing financial hardship [41]. However, our finding that residency in rural areas contributes to inequality in catastrophic health expenditure disfavoring poor households imply that the SLAs may not have achieved its intended purpose of protecting households and reducing health expenditure disparities in rural areas. Nevertheless these SLAs have a potential to improve financial protection from the risk of illnesses among vulnerable population groups as observed by a previous study [42]. It is possible that many of the rural CHAM facilities and essential services are not included in the SLAs and poor households who access care in these health facilities face catastrophic health expenditure increasing inequality disfavoring the poor in rural households. The plans by government to improve the SLAs to include more health facilities and essential services should be pursued. This coupled with improving quality of services and geographic accessibility of public health facilities in rural areas could help to reduce the inequality in access and consequently reduce inequality in catastrophic expenditures.

The study has limitations. The study uses cross sectional data which prevents causal interpretation of the relationship between catastrophic health expenditures and its determinants used in the decomposition analysis. The use of self-reported data on household consumption expenditures may introduce recall bias which can lead to underestimation or overestimation of catastrophic health expenditures. The analytical method for estimating catastrophic health expenditures does not count households that forgo care due to inability to pay. In addition, households that borrow to finance health care may increase their consumption expenditures and may be classified into higher expenditure quintiles. These limitations may underestimate or overestimate the incidence of catastrophic health expenditures.

Conclusion

The findings of the study have shown that socioeconomic inequality in catastrophic expenditures is more concentrated among better-off households. Majority of the inequality in catastrophic health expenditures is due to inequality in residency in rural areas, socioeconomic status, region in which the household is located, household size and having children under five years. The findings suggest that government policies and programs that aim to reduce inequality in catastrophic health expenditure should simultaneously reduce income, rural-urban and regional related inequalities. A future study should explore whether low catastrophic health expenditures among the worse off in Malawi is a result of households experiencing financial protection or is simply as a result of forgoing health care to avoid catastrophic health expenditures.

Author Contributions

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Spatial disparities in impoverishing effects of out-of-pocket health payments in Malawi

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ABSTRACT

Background: Out-of-pocket health payments as a means of financing health services are a cause of concern among households in low and middle-income countries. They prevent households from accessing health care services, can disrupt households' living standards by reducing consumption of other basic needs and push households into poverty. Previous studies have reported geographical variations in impoverishing effects of out-of-pocket health payments. Yet, we know relatively little about spatial effects on impoverishing effects of health payments.
Objective: This paper assesses the factors associated with impoverishing effects of health payments and quantifies the role of districts spatial effects on impoverishment in Malawi.
Methods: The paper uses a cross sectional integrated household survey data collected from April 2016 to April 2017 among 12447 households in Malawi. Impoverishing effect of out-of-pocket health payments was calculated as the difference between poverty head count ratio before and after subtracting health payments from total household consumption expenditures. We assessed the factors associated with impoverishment and quantified the role of spatial effects using a spatial multilevel model.
Results: About 1.6% and 1.2% of the Malawian population were pushed below the national and international poverty line of US$1.90 respectively due health payments. We found significant spatial variations in impoverishment across districts with higher spatial residual effects clustering in central region districts. Higher socio-economic status (AOR=0.34, 95% CI=0.22-0.52) decreased the risk of impoverishment whereas hospitalizations (AOR=3.63, 95% CI 2.54-5.15), chronic illness (AOR=1.56, 95% CI=1.10-1.22), residency in rural area (AOR=2.03, 95% CI=1.07-4.26) increased the risk of impoverishment.
Conclusions: Our study suggests the need to plan financial protection programs according to district specific needs and target the poor, residents of rural areas and those with chronic illnesses. Policy makers need to pay attention to the importance of spatial and neighborhood effects when designing financial protection programs and policies.

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Background

The impact of out-of-pocket health payments as a means of financing health services is a cause of concern among households in low and middle-income countries (LMICs) [1]. Out-of-pocket health payments prevent households from accessing health care services, can disrupt households living standards by reducing consumption of other basic needs and push households into poverty [1–3]. These effects may hinder progress toward Goal 3.8 on Universal Health Coverage (UHC) within the Sustainable Development Goals (SDGs). The target of this goal is to ensure that people have timely access to the needed health care services and do not face financial hardship due to health payments [1]. One way of monitoring progress towards attaining the financial protection dimension of the UHC goal is assessing the extent of catastrophic health payments and impoverishment due to out-of-pocket payments [4,5]. Catastrophic health payments occur when out-of-pocket health payments as a proportion of total expenditures exceed a predetermined threshold level and impoverishment due to health payments occur when non-poor households are pushed below the poverty line and those already poor are pushed further below the poverty line after paying for health services [2,3].

Global estimates show that out-of-pocket health payments impoverished 89.7 million people in 2015 [4]. Further evidence shows that impoverishing effects of out-of-pocket health payments occur in all countries at different development stages but is more common in LMICs [2,5,6]. For example, of the 89.7 million people impoverished in 2015, 88.1 million were from Asian and sub-Saharan African (SSA) countries [4]. This scenario is mainly

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due to heavy reliance on out-of-pocket payments for financing health services in these countries [1,6]. In several SSA countries, out-of-pocket payments account for over 40% of total health expenditures [7] which is higher compared with less than 20% to ensure financial protection as suggested by previous research [8].

The health system in Malawi follows a four tier system; the community, primary, secondary and tertiary levels which are linked to each other through an organized referral system [9]. The community-level system includes health posts, village clinics, dispensaries and maternity clinics. The services at community level are mainly preventive health care. The primary-level system includes health centres and community hospitals. At primary level, the services include outpatient, inpatient services and minor procedures. The secondary-level system consists of district hospitals. These hospitals provide referral services to facilities at primary level in addition to providing inpatient and outpatient services to the communities in their districts. The primary and secondary health care systems are managed by district health management teams under district councils. The district health management team in consultation with communities and service providers develop the implementation plan, the annual plan for delivery of health services and the annual budget. Annual allocation of public resources across districts is based on a formula which takes into account disease burden, population size, costs of treatment and variation of costs across districts [10]. However, this method of allocating resources for health across districts is not strictly followed. Instead, resources are allocated based on previous year's allocations [10]. This method of resource allocation results in substantial variations in total per capita health expenditures and levels of expenditures from different sources of health financing across districts [10,11]. The tertiary level health system consists of central hospitals. These hospitals provide specialized health services and referral services to districts hospitals within the region in which the tertiary hospitals are located. Tertiary level health system is managed by hospital directors under the Ministry of health [9].

The Malawi health system is mostly financed by government through taxes and external donors. The government provides free health services through the essential health package which contains cost effective interventions designed to address the major causes of mortality and morbidity [9]. In the period of 2017/18, external donors contributed 58.6% of total health expenditure. During the same period, public and private contributions to total health expenditure was at 23.9% and 17.5% respectively. Private health expenditure as a percentage of total health expenditure rose from 13.4% in 2014/15 to 17.5% in 2017/18 [12]. This rise was mainly attributed to the rise in households' out-of-pocket payments from 8.6% in 2014/15 to 12.6% in 2017/18. Such an increase in out-of-pocket health payments is of concern as it puts households at risk of poverty and may disrupt households' living standards by reducing consumptions on other basic needs. Thus, despite free access to public health services policy in Malawi, households still contribute to total health financing through out-of-pocket payments. This phenomenon is because the free public health services delivery faces many challenges such as constant shortages of medicines, poor quality of services, poor attitude of personnel and shortage of human resources [13]. These challenges force households to seek care from private facilities and buy medicines from private pharmacies exposing households to high out-of-pocket payments [14].

Over the years the Government of Malawi has undertaken health sector reforms to ensure its commitment of financial protection from the risk of illnesses among its population. These reforms which started in the mid 2000's led to the signing of Service Level Agreements (SLAs) with Christian Health Association of Malawi (CHAM) health facilities in 2006 [15]. These agreements were to ensure free access of health services in CHAM facilities by the population in areas where government facilities are out of reach [15]. Evidence show that SLAs increased utilization of maternal health services [16] and have a potential to improve health and financial protection from out-of-pocket health payments [17].

Prior study in Malawi has shown that health payments impoverish households and there are urban/rural and regional variations in impoverishment [18]. These disparities may reflect geographical variations in disease burden across districts [19–23], district economic status [24], district health funding levels [11], type of health provider utilized [25] and availability of health services [26]. For example, in terms of economic status, poverty levels vary across districts with districts in the southern region experiencing higher incidence of poverty than districts in the northern and central regions [24]. The Malawi harmonized health facility assessment survey also observed substantial variations across districts in terms of availability and quality of health services [27]. Moreover another study in Malawi observed significant variations in total per capita health expenditures and levels of expenditures by sources across districts [11]. Consequently, impoverishment due to health payments may vary from district to district. Similar studies in SSA countries have shown urban/rural and regional variations in impoverishment due to health payments [29–32] which may reflect variations in characteristics from place to place.

There are limited studies assessing the factors associated with impoverishment [29–32] and quantifying spatial and neighborhood effects on impoverishment due to health payments. For example, a study using multilevel logistic model to quantify the effect of village characteristics showed significant effect of village deprivation index on impoverishment due to health payments [30]. However, a multilevel model provides incomplete information on spatial effects on health outcomes as it assumes within area correlation and neglects spatial correlation [33]. Moreover, evidence shows that accounting for both within area correlation and spatial correlation may provide more valuable information on spatial variations in health outcome variables [34]. We address these gaps in the literature by assessing the factors associated with impoverishing effects of health payments and quantifying district spatial effects on impoverishment using a spatial multilevel model. We also add to the literature by quantifying districts variations on impoverishment due to health payments to understand the role of districts spatial effects on impoverishing effects of health payments using data from Malawi. Further, we identify areas at higher risk of impoverishing effects of health payments which could be targeted for financial protection programs according to district specific needs. Furthermore, our study provides evidence on the population groups vulnerable to impoverishing effects of health payments necessary for designing financial protection program and policies in Malawi.

Methods

Study design

The study uses a cross-sectional design using secondary data from a nationally representative survey conducted in Malawi from April 2016 to April 2017.

Data source

Data for this paper come from the Malawi integrated household survey (IHS4). The survey was conducted by the National Statistical Office from April 2016 to April 2017. The secondary analysis of the data for this paper was conducted from January 2021 to March 2021. The aim of the survey was to collect information on the levels of poverty, vulnerability and socioeconomic indicators that are relevant for evidence-based policy formulation. The survey used a stratified two stage sampling design. In the first stage of sampling, 780 enumeration areas stratified by urban and rural strata were selected with probability proportional to size. In the second stage a total of 16 primary households were selected from the household listing in each sample enumeration area using random systematic sampling. Five households were also selected to allow replacement of the households if the sampled households were not available. The enumeration areas are nested in districts which are the geographical domains of estimation for the survey. The survey covered all the 32 districts in Malawi. This sampling resulted into a sample size of 12,480 households. Data were collected using a questionnaire implemented on Android tablets using a survey software. Data were collected from all the sampled households however data for 33 households were lost during data collection due to difficulties with the data collection platform. The paper uses data for 12,447 households covering 53,885 individuals. Detailed information on the data collection methods and information collected is provided in the Malawi Integrated Household Survey report 2016–2017 [35]. Data on district boundaries were obtained from the Malawi National Statistical Office to compute the spatial weight matrix, which provided information on how the districts are connected to each other in the spatial analysis.

Outcome variable and covariates

The outcome variable for the study is household's impoverishment due to out-of-pocket health payments where out-of-pocket health payment was estimated as payment on consultation fees, medicines, diagnostic tests, inpatient, out-patient and hospitalization fees. The outcome variable is binary taking the value of 1 if a household was impoverished due to health payments and zero otherwise.

We included as covariates the variables identified in the literature as predictors of impoverishing effects of out-of-pocket health payments [29–32]. These included household characteristics such as age of household head, sex of household head, household socioeconomic status categorized into lower and higher socio-economic status based on household consumption expenditure per capita, having at least one child under five year old in the household or not, having an elderly member in household or not, having at least one hospitalized member in the past year or not, household location, region, type of nearest health facility with medical doctor defined as categorical, household size and distance to the nearest health facility defined as continuous variables.

Measurement of the outcome variable

To assess impoverishing effects of health payments we used the poverty head count ratio and poverty gap given by Wagstaff & Doorslaer and O'Donnell & Doorslaer [3,36]. Poverty head count ratio was defined as proportion of the population with total expenditures falling below the poverty line and poverty gap was defined as the amount by which total consumption expenditures of the poor fall short to reach the poverty line. Impoverishing effects of health payments was estimated as the difference between poverty head count ratio before and after deducting out-of-pocket health payments. Impoverishment was estimated using the Malawi national poverty line of 137,425 MWK per person per year as provided in the methodology for poverty measurements in Malawi (2016/17) [37] and the international poverty lines of US$1.90 and US$ 3.20 per person per day at Purchasing Power Parity(PPP) in 2011 prices. These international poverty lines converted to MWK 526.2 and MWK 886.2 per person per day using 2016 prices respectively as provided in the poverty and equity brief document [38]. A detailed description of the measurement of impoverishing effects of health payments is given by Wagstaff & Doorslaer and O'Donnell & Doorslaer [3,36] and has also been summarized in our previous paper [39].

Bayesian spatial multilevel modelling

We estimated the probability of facing impoverishing effects of health payments and quantified the role of districts spatial effects using Bayesian spatial multilevel model. We used impoverishing effects of health payments estimated at the national poverty line in fitting the Bayesian spatial multilevel model.

Let y_{ij} be a binary response for household i (level 1) in area j (level 2) and assume that y_{ij} is distributed as binomial random variable i.e. $y_{ij}\tilde{B}in(1,\pi_{ij})$. We define $y_{ij}=1$ if household i nested in district j was impoverished due to health payments and $y_{ij}=0$ otherwise. Then, following Goldstein [40] and Congdon [41] a Bayesian standard multilevel logistic regression model with logit link function is specified as:

$$logit(\pi_{ij}) = \alpha + \beta X_{ij} + \gamma Z_j + u_j \qquad (1)$$

where X_{ij} is a vector of household level covariates with β as a vector of corresponding regression coefficients to be estimated, Z_j is a vector of district level covariates and γ is a vector of corresponding regression coefficients to be estimated. The term u_j is independently identically normally distributed random term with mean of zero and variance equal to σ_u^2. It captures the unobserved district level random effects.

The Bayesian standard multilevel logistic model (1) accounts for the dependence in observations within the same geographic area such as districts defined by administrative boundaries and fails to capture dependence in observations due to close proximity in geographic space as it assumes no spatial dependence among geographic areas [33]. We assumed that the relationship between impoverishment due to out-of-pocket health expenditures and associated factors is affected by district level random effects and that the random effects are spatially dependent. We therefore used a spatial multilevel model to account for the spatially dependent random effects using Leroux, Lei and Breslow Conditional autoregressive (CAR) prior [42]. Following Ma et al [43] the CAR prior is denoted by LCAR and specified as [44,45]:

$$u_j|u_{-j}, W, \lambda, \tau^2\tilde{N}\left(\frac{\lambda\sum_{j\tilde{i}}u_i}{1-\lambda+\lambda w_{j+}}, \frac{1}{\tau^2(1-\lambda+\lambda w_{j+})}\right) \qquad (2)$$

where u_{-j} represents random effects different from the j^{th} random effects, W is the neighborhood spatial proximity matrix defined as $w_{ij}=1$ if districts j and i share borders (denoted by $j\tilde{i}$) and zero otherwise, w_{j+} represents the number of districts sharing borders with j^{th} district, λ is the spatial correlation parameter that lies between zero and one, and τ^2 is a precision parameter equal to the inverse of the variance σ_u^2.

Equation (2) indicates that the conditional expectation of the random effects u_j, $E(u_j|u_{-j})$ is the weighted mean of the random effects of its neighbors. The full conditionals of all the J random effects gives a distinctive Gaussian Markov Random Field, $u_j\tilde{M}VN(0,\Omega_{LCAR})$, where Ω_{LCAR} is a $J\times J$ precision matrix equal to $\tau^2[diag(1-\lambda+\lambda w_{j+})-\lambda W]$ [44,46]. Our spatial multilevel model for the probability that a household faced impoverishing health payments is specified as:

$$logit(\pi_{ij}) = \alpha + \beta X_{ij} + u_j \qquad (3)$$

This multilevel spatial model (3) reduces to a standard multilevel logistic model (1) when there is no spatial correlation (i.e. when $\lambda=0$) [46].

Estimation of the parameters in models (1) and (3) follows an approximate Bayesian approach. The fixed effects regression coefficients were assigned a Gaussian prior (i.e. $\alpha,\beta,\gamma\tilde{N}(0,100)$). The variance components in the regression models (3) and (1) were assigned the default minimally informative prior (i.e. $\tau^2\tilde{l}ogGamma(1,5e^{-5})$). The spatial correlation parameter λ expressed on a logit scale; logit (λ) was assigned a diffuse normal prior $i.elogit(\lambda)\tilde{N}(0,100)$.

Models (1), (3) and the standard single level logistic regression were implemented using the integrated nested Laplace approximation (INLA) approach through R-INLA package [47,48]. Comparisons for the three models were done using the deviance information criterion (DIC), which is defined as the sum of twice the effective number of model parameters and the estimated posterior mean deviance [49]. The model with the smallest DIC value was considered as the model with a better fit. Descriptive analysis was done in Stata 15. All analyses were adjusted for

Table 1. Descriptive statistics of sampled households (n = 12,447).

Variable	Weighted Mean/ percentage
Age of household head	
Less than 26 years	12.30 (1531)
26–35 years	26.66 (3318)
36–45 years	23.79 (2961)
46–55 years	15.21 (1893)
Over 56 years	22.04 (2743)
Male headed household	71.12 (8852)
Have at least one child under 5 years	53.52 (6662)
Have at least one elderly member greater than 60 years	19.75 (2458)
Have at least one chronically ill member	22.33 (2779)
Have at least one hospitalized member	13.16 (1638)
Rural location	80.95 (10076)
Type of health facility	
Government	87.23 (10858)
Religious/Mission	10.68 (1330)
Private	2.08 (259)
Region	
Northern	9.15 (1139)
Central	44.32 (5516)
Southern	46.53 (5791)
Distance to the nearest health facility (KM)	13.33
Size of household (number of household members)	4.29
Total annual consumption expenditure (MWK)	831,433
Total annual out-of-pocket health expenditure (MWK)	15,649

MWK is Malawi Kwacha and KM is Kilometers. Number of households n for each category in parenthesis.

survey sampling design using survey sample weights and the survey set command in Stata 15. Results were interpreted at 95% credible level.

Results

Table 1 gives the descriptive characteristics of the sampled households. Over 80% of the households are rural and the average number of household members is 4. A large proportion of households are male headed (71%). Over half of the households have children under five years of age. A large proportion of households accessed health care at a government health facility and the average distance to the nearest health facility is 13 Kilometers. The average annual out-of-pocket health expenditure and household consumption expenditures were 15,649 and 831,433 respectively.

Table 2 gives results of the impoverishing effects of health payments in Malawi based on the national and international poverty lines. Using the international poverty line of US $1.90, the poverty head count ratio based on total consumption expenditure was 70.31% and subtracting health payments from the total consumption expenditure the poverty headcount increased to 71.48%. This implies that about 1.2% of the population were pushed into poverty due to health payments and this represented a 1.66% relative increase in the poverty head count ratio due to health payments. The poverty gap increased from MWK 54,114 to MWK 55832 after subtracting health payments. This represented a 3.17% relative increase in the poverty gap. The normalized poverty gap which is the poverty gap expressed as the percentage of the poverty line increased from 28.82 to 29.73 representing a 3.16% relative increase in the normalized poverty gap. The mean positive gap increased from 40.99% to 41.60% representing a 1.49% relative increase in the intensity of poverty after accounting for health payments. The increase in the mean positive gap implies that the rise in the poverty gap is as a result of the poor being pushed further below the poverty line and those counted as non-poor based on total expenditures being pushed below the poverty line due health payments.

Table 3, presents results of impoverishing effects of health payments by expenditure quintile group, household location, region, sex of household head, health facility utilized and health service utilization. Proportion of the population that was pushed into poverty due to health payments was higher in lower expenditure quintile (2.13%), rural areas (1.83%),

Table 2. Impoverishing effects of out-of-pocket health payments in Malawi.

	Pre-health payments (1)	Post-health payments (2)	Difference: Absolute 3 = [(2)-(1)]	Difference: Relative [(3)/ (1)] * 100
National poverty line (MWK137,425 per person per year)				
Poverty head count (%)	51.53	53.13	1.60	3.10
Poverty gap (MWK)	23101.75	24167.55	1065.80	4.61
Normalized poverty gap (%)	16.81	17.59	0.78	4.64
Normalized mean positive gap (%)	32.62	33.10	0.48	1.47
International poverty line (US $1.90 per person per day)				
Poverty head count (%)	70.31	71.48	1.17	1.66
Poverty gap (MWK)	54114	55831.64	1717.64	3.17
Normalized poverty gap (%)	28.82	29.73	0.91	3.16
Normalized mean positive gap (%)	40.99	41.60	0.61	1.49
International poverty line (US $3.20 per person per day)				
Poverty head count (%)	89.43	89.93	0.50	0.56
Poverty gap (MWK)	151570.8	154241.6	2670.8	1.76
Normalized poverty gap (%)	49.45	50.32	0.87	1.76
Normalized mean positive gap (%)	55.29	55.96	0.67	1.21

*MWK is Malawi Kwacha. Poverty head count ratio, normalized poverty gap and normalized mean positive gap are given in percentages. The international poverty lines $1.90 and $3.20 per person per day converts to MWK526.2 and MWK886.2 per person per day in 2016 prices.

Table 3. Impoverishing effects of health payments by expenditure quintile, household location (urban/rural), region, health facility and health service utilized based on the national poverty line.

Variable	Poverty head count (%) Pre	Poverty head count (%) Post	Difference Absolute	Normalized poverty gap (%) Pre	Normalized poverty gap (%) Post	Difference Absolute
Expenditure quintile						
Lower	90.65	92.78	2.13	29.57	30.86	1.29
Higher	0.00	0.89	0.89	0.00	0.09	0.09
Household location						
Urban	17.71	18.28	0.57	4.52	4.70	0.18
Rural	59.45	61.28	1.83	19.69	20.60	0.91
Region						
Northern	49.51	51.09	1.58	15.10	15.64	0.54
Central	47.50	49.57	2.07	14.38	15.33	0.95
Southern	56.03	57.14	1.11	19.62	20.27	0.65
Health facility						
Government	51.24	52.86	1.62	16.59	17.33	0.75
Religious	58.67	60.50	1.83	20.24	21.31	1.07
Private	39.40	39.50	0.10	12.36	12.78	0.41
Service utilized						
Out patient	26.43	33.94	7.51	6.55	9.48	2.92
Inpatient	48.89	52.68	3.79	14.89	16.81	1.92
Sex of household head						
Male	49.32	50.84	1.52	15.76	16.53	0.77
Female	58.24	60.06	1.82	19.99	20.79	0.80

MWK is Malawi Kwacha. National poverty line (2016/17) was MWK137, 425 per person per year. Poverty head count ratio and normalized poverty gap are given in percentages

Table 4. Impoverishing effects of health payments by district based on the national poverty line.

Variable District	Poverty head count (%) Pre	Poverty head count (%) Post	Difference Absolute	Normalized poverty gap (%) Pre	Normalized poverty gap (%) Post	Difference Absolute
Chitipa	73.82	74.08	0.26	25.19	25.54	0.35
Karonga	57.14	57.27	0.14	17.95	18.21	0.25
Nkhatabay	57.71	60.42	2.71	16.38	17.31	0.93
Rumphi	53.59	54.96	1.37	15.92	16.50	0.58
Mzimba	42.95	45.76	2.81	12.91	13.89	0.98
Likoma	31.38	31.95	0.57	6.83	6.97	0.13
Mzuzu City	9.72	12.37	2.65	1.86	2.08	0.22
Kasungu	52.98	54.30	1.31	14.82	15.97	1.16
Nkhotakota	53.41	53.41	0.00	18.39	18.98	0.58
Ntchisi	53.49	54.22	0.73	18.13	18.61	0.48
Dowa	48.78	52.42	3.64	14.13	15.95	1.82
Salima	58.43	60.37	1.94	20.01	20.91	0.90
Lilongwe	47.93	51.31	3.38	13.55	14.31	0.76
Mchinji	50.54	53.35	2.81	14.59	15.90	1.31
Dedza	63.07	65.95	2.89	20.85	22.43	1.59
Ntcheu	54.13	54.67	0.54	17.01	17.57	0.56
Lilongwe City	18.00	18.76	0.75	4.87	5.12	0.25
Mangochi	59.46	60.51	1.04	19.01	19.77	0.76
Machinga	72.39	73.40	1.01	24.85	25.72	0.88
Zomba Non-City	55.92	58.98	3.06	17.74	18.74	1.00
Chiradzulu	66.42	67.02	0.60	22.25	22.66	0.41
Blantyre	38.87	39.76	0.89	11.13	11.38	0.25
Mwanza	53.57	54.46	0.88	15.77	16.18	0.40
Thyolo	67.27	69.09	1.82	24.71	25.66	0.95
Mulanje	69.22	69.77	0.55	26.55	27.11	0.56
Phalombe	83.16	83.65	0.49	35.07	35.56	0.49
Chikwawa	63.19	65.26	2.07	25.83	26.78	0.95
Nsanje	74.33	76.32	1.99	29.43	30.90	1.47
Balaka	61.28	62.77	1.49	19.00	19.83	0.83
Neno	46.87	48.55	1.68	13.96	14.37	0.40
Zomba City	15.79	16.26	0.47	4.06	4.28	0.22
Blantyre City	8.03	8.03	0.00	1.67	1.76	0.09

MWK is Malawi Kwacha. National poverty line (2016/17) was MWK137, 425 per person per year. Poverty head count ratio and normalized poverty gap are given in percentages [34].

central areas (2.07%) and female headed households (1.82%). Impoverishing health payments was higher in population groups utilizing religious health facilities (1.83%) and outpatient health services (7.51%).

Table 4 presents results on impoverishment by districts. Impoverishing effects of health payments by district show variations in proportion of population that fell into poverty due to health payment. The proportion of the population that fell into poverty due to health payments was highest in Dowa (3.64%) and lowest in Blantyre city and Nkhotakota districts compared to the national average across all districts. For all the districts the normalized poverty gap also increased which indicates deepening in poverty due to health payments across the districts. The deepening in poverty was greater in Dowa, Dedza, Nsanje, Mchinji and Kasungu districts.

Spatial distribution of impoverishing effects of health payments

Figure 1 shows pattern of the spatial distribution of impoverishing effects of health payments across the districts in Malawi. The clustering pattern in the distribution of impoverishment indicates spatial dependence in impoverishment due to health payments. The Moran I test of spatial autocorrelation show significant spatial dependence in impoverishment due to out-of-pocket health payments across the districts (Moran I = 0.179, p-value <0.05). This finding reinforces the need to account for spatial dependence in examining the association between impoverishment and its risk factors.

Assessing factors associated with impoverishing effects of health payments

We estimated a single level logistic regression, multilevel logistic model and spatial multilevel logistic model to assess the relationship between impoverishing effects of health payments and its associated risk factors. The deviance information criterion (DIC) values to compare model fit were 1536.05, 1536.23 and 1536.89 for the spatial multilevel, multilevel, single level logistic models respectively. The DIC values were the same for the three models which indicates that all the three models were similar in terms of model fit. However, we preferred the spatial multilevel model estimation in reporting the association between impoverishment and its risk factors because our study aimed to quantify spatial effects in impoverishing effects of health payments. Table 5, shows the results of the spatial multilevel model for estimating

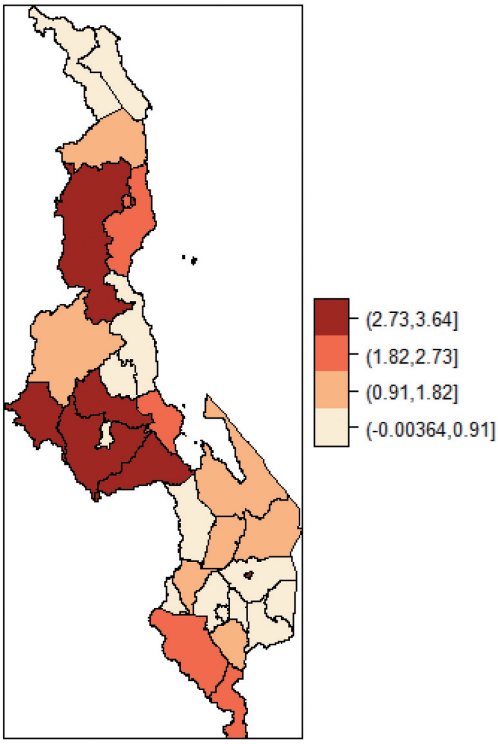

Figure 1. Spatial distribution of impoverishing health payments at district level in Malawi.

Table 5. Estimation results from a multilevel spatial model with impoverishing effects of health payments as a binary outcome variable.

Independent variables	OR (95% CI)
Intercept	0.01 (0.003–0.03)
Age of household head (ref = Over 56 years)	
Less than 26 years	0.28* (0.11–0.67)
26–35 years	0.53 (0.28–1.03)
36–45 years	0.45* (0.24–0.87)
46–55 years	0.29* (0.12–0.60)
Sex of household head (ref = Male)	0.98 (0.67–1.40)
sizeHousehold size	1.05 (0.95–1.16)
Higher Socio-economic status (ref = lower)	0.34*(0.22–0.52)
Have at least one child (ref = No)	1.08 (0.71–1.66)
Have at least one elderly member (ref = No)	0.74 (0.41–1.37)
Have at least one chronically ill member (ref = No)	1.56*(1.10–2.22)
Have at least one hospitalized member (ref = No)	3.63*(2.54–5.15)
Rural location (ref = Urban)	2.03*(1.07–4.26)
Distance to the nearest health facility	0.99 (0.98–1.00)
Health facility (ref = government)	
Religious/Mission	1.36 (0.85–2.09)
Private	0.49 (0.05–2.71)
Region (ref = Northern)	
Central	1.33 (0.53–2.29)
Southern	0.88 (0.43–1.53)
λ	0.50* (0.002–0.998)
σ^2 (district)	0.0002(0.00001–0.001)

*Statistically significant at 95% confidence interval. The figures in parenthesis represents the lower and upper values of the 95% interval. σ^2 represent the district random effects parameter and λ is the spatial correlation parameter.

the probability of impoverishing effects of out-of-pocket health payments. The estimate of the spatial correlation parameter indicates a moderate significant spatial dependence effect on impoverishment due to out-of-pocket health expenditures (λ = 0.50, 95% CI = 0.002–0.998).

Households in higher socio-economic status had 66% lower odds of facing impoverishing effects of health payments compared to those in lower socio-economic status (AOR = 0.34, 95% CI = 0.22–0.52). Households headed by a younger household head had 72% lower odds of facing impoverishing effects of health payments than those with household head over 56 years' old (AOR = 0.28, 95% CI = 0.11–0.67). Households with at least one chronically ill member (AOR = 1.56, 95% CI = 1.10–2.22) and at least one member hospitalized over the past year (AOR = 3.63, 95% CI = 2.54–5.15) were at increased odds of facing impoverishing effects of health payments. Households in rural areas had 2.03 times greater odds of facing impoverishment compared to those in urban areas (AOR = 2.03, 95% CI = 1.07–4.26).

Figure 2 shows the map of the estimated posterior mean of the district level random effects from the spatial multilevel model. The figure shows a unique spatial pattern in impoverishment due to out-of-pocket health payments across districts in Malawi with low and high values of random effects clustering across the districts. A number of districts in the central region have positive posterior mean of the random effects which indicates an increase in the odds of impoverishment due to out-of-pocket health payments among population in the central region districts and several districts in the southern region have negative posterior mean random effects

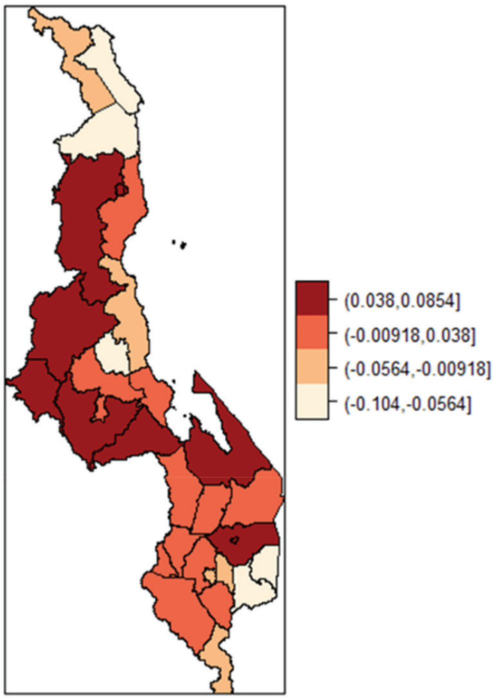

Figure 2. The spatial distribution of district random effects from the Leroux CAR spatial multilevel model.

indicating a decrease in the odds of impoverishment. These results in Figure 2 confirm those in Table 5 which show households in the central region had an increased odds of experiencing impoverishment due to out-of-pocket health payments.

Discussion

We assessed the factors associated with impoverishing effects of health payments and quantified districts spatial variations in impoverishing effects of health payments in Malawi. Our findings show that a low proportion of the Malawian population faced impoverishment due to out-of-pocket health payments in 2016/2017. The findings from the spatial multilevel model revealed significant spatial variations in impoverishment across districts and several factors were associated with impoverishment.

The proportion of the population impoverished due to out-of-pocket health payments based on the national poverty line represented a 60% increase since the last Malawi integrated household survey in 2010/11 [18] as reported in our previous study [39]. The level of impoverishing health payments is low and similar to what was reported in other African countries using the international poverty line of US$1.90 [28,29,50]. This finding implies that a small proportion of Malawians were pushed below the poverty line due to out-of-pocket health payments despite government efforts to increase financial protection through the free access to health care services policy.

We also find significant spatial variations in impoverishment across districts with districts in the central region at higher risk of impoverishment as evidenced by clustering of spatial random effects on the map. For example, in districts such as Mzimba, Mzuzu, Nkhatabay, Dedza, Dowa, Lilongwe, Mchinji, Salima, Chikwawa, Neno, Thyolo, Zomba impoverishment was significantly higher than the average across all districts. These variations in impoverishment across districts may reflects differences in out-of-pocket expenditures, district economic status, disease pattern, accessibility and availability of health services at district level [11,19–25]. For example, previous studies found spatial variations in childhood comorbidities, childhood anemia, Pneumonia, Malaria and HIV in Malawi [19–23].These studies found clustering of higher risk of childhood comorbidities, Pneumonia and Malaria in districts in the central region. It is possible that the higher burden of diseases in these districts may lead to high out-of-pocket health payments which push households into poverty inducing spatial clustering in impoverishment. This analysis showed significant spatial clustering with high risk in impoverishment due to out-of-pocket health payments among districts in the central region. Considering the spatial variations in impoverishment due to health payments across districts, interventions that aim to protect households from financial consequences of illnesses should be designed according to district specific needs and may target those districts at greatest risk.

Consistent with previous studies [30,31], the study show that households with chronically ill members are at a greater odds of facing impoverishment due to out-of-pocket health payments. In Malawi, out-of-pocket health payments on chronic diseases as a percentage of total health expenditures are higher than expenditures on infectious diseases [51]. This means that households bear a large burden of health expenditures on chronic diseases. Available evidence also show that chronic illness is significantly associated with higher out-of-pocket payments [52]. A different study found that chronic non communicable diseases place a higher burden on the population and increases poverty [53]. Moreover, data used in our analysis indicate that households with chronically ill members have significantly higher out-of-pocket health payments. This result suggests that chronic illnesses have a significant financial burden on the population in Malawi. A plausible explanation for this finding may be poor availability of medications for chronic illnesses in public facilities and high prices at private facilities [54]. This exacerbates out-of-pocket payments on medicines for chronic illnesses and places a financial burden on households. This finding also highlights the need to incorporate the burden of chronic illnesses when designing financial protection interventions. Most chronic non communicable diseases are not part of the free essential health package which was designed to address the major causes of mortality and morbidity as such households still bear the financial burden in accessing care for chronic non communicable diseases [9].

In line with other studies [29,30,32], our analysis showed that households in rural areas are more likely to face impoverishment. This finding suggests lack of financial protection among rural households. This is expected as poverty levels are higher in rural areas in Malawi [24] and coupled with poor geographic accessibility of public health facilities this may entail increased transportation costs for seeking care putting more financial burden on already poor households [14]. Evidence show that the poor bear greater financial burden as a result of health payments in Malawi [55]. Considering that many of the rural households are already poor, it is possible that even the little expenditures on illnesses and transportation to seek care may push them into poverty. Our analysis of the mean positive gap shows a deepening in poverty due to health payments. This highlights the need to combine interventions that aim at increasing financial protection and reducing rural poverty. Our finding that households in rural areas are more likely to face impoverishing effects of health payments indicate that Malawi governments' free access policies such as Service Level Agreements with mission health facilities may have failed to provide financial protection to rural households due to implementation challenges [14]. In addition, not all of the mission facilities and essential services are part of these Service Level Agreements [15] as such it is possible that households still face higher out-of-pocket health payments when accessing other services at mission facilities which pushes them into poverty. The plans by government to improve the Services Level Agreements to include more mission health facilities and services [9] will help to ensure financial protection among the rural population.

Our finding that hospitalizations increase the probability of facing impoverishing effects of health payments is consistent with another study [30]. Illnesses that require hospitalizations are usually severe and may result in more health payments, this coupled with other expenditures incurred when seeking care such as costs of food, accommodation and transportation by care givers increase the total health payments [52]. In Malawi, households with malaria episode that required hospitalization faced a higher financial burden than those that required outpatient treatment [56]. Another study in Malawi found that expenditures on hospitalization for TB were higher than outpatient expenditures [57]. Considering that access to public health services is free at point of use and is intended to provide financial protection for households including those that face hospitalizations it is possible that the higher expenditures on hospitalizations are worsened by other costs related to seeking care. This challenge highlights the need for interventions that could help the most vulnerable households faced with hospitalizations to cope with other costs incurred when seeking care. Such interventions could be in a form of cash transfer schemes and other safety net programs to cushion poor households. Evidence from 15 African countries including Malawi suggests that households with large out-of-pocket payments on hospitalizations are more likely to borrow money and sell assets to cope with health payments [58]. This situation may put pressure on households limited resources and push them into poverty.

The study has limitations. Firstly, we used self-reported data collected using a four weeks' recall period which is subject to recall bias and may result in underestimation or overestimation of household expenditures. Secondly, the measurement of impoverishing effects of health payments does not include those that forgo seeking care due to inability to pay and this may underestimate the proportion impoverished due to out-of-pocket payments. Thirdly, the association between impoverishing effects of health payments and its determinants cannot be interpreted as causal due to the cross-sectional design of the survey data used in the analysis. Despite these limitations our study contributes to the literature by identifying characteristics of population groups vulnerable to impoverishment. This is important for designing effective financial protection policies and programs at national level. Importantly, the use of spatial multilevel logistic regression model is novel in providing evidence on spatial variations in impoverishment at districts level and highlighting areas with higher risk which require targeted attention. This is important for monitoring financial protection at district level and designing interventions according to district specific needs.

Conclusion

Our study showed significant spatial variations in impoverishing effects of health payments across districts in Malawi. Several districts in the central region were at a higher risk of impoverishing effects of health payments. This finding suggest the need to plan financial protection strategies according to the district specific needs and target those districts at greatest risk. We also showed that out-of-pocket health payments pushed non poor individuals and those already poor into poverty. This is despite the Malawi government's financial protection policies such as free access to public health services and contracting out of services to mission facilities. In addition, we showed that having chronically ill members, hospitalizations, rural residency and being in lower socioeconomic status increased the odds of impoverishing effects of health payments. Particularly, our finding that chronic illness is an important determinant of impoverishing effects of health payments reflects the rising burden of chronic diseases and suggests the need to incorporate the burden of chronic illnesses in designing financial protection strategies. Further research should explore the specific chronic illnesses which drive households into impoverishing effects of health payments. Further research should also understand the unmeasured local factors contributing to clustering of impoverishing effects of health payments.

Author contributions

ANM: Study conceptualization and design; data acquisition, analysis and interpretation; writing, revising and approving the final draft. MSK and

SJM: Data interpretation, revising and approving the final draft.

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Ethics and consent

Although the paper is based on publicly available secondary data, ethical approval was obtained from the National Committee on Research in the Social Sciences and Humanities (NCRSH) reference No. P.10/19/434.

Paper context

One way of monitoring financial protection is by assessing the extent of impoverishing effects of out-of-pocket health payments and factors associated with impoverishment. However, there is a dearth of studies to understand the factors associated with impoverishment and the role of spatial effects on impoverishment. The paper shows that several factors are associated with impoverishment and there are significant spatial effects on impoverishment. The findings are important for designing targeted programs to ensure financial protection.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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