SPATIAL AGGLOMERATION EFFECT OF MULTIDIMENSIONAL POVERTY IN MALAWI

MASTER OF ARTS (ECONOMICS) THESIS

By

EDSON NTODWA
Bachelor of Social Science (Economics) –University of Malawi

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DECLARATION

I, the undersigned, hereby declare that this thesis is my own original work, and it has never been submitted for similar purposes to this or any other university or institution of higher learning. Where other people's work has been used acknowledgements have been made. All errors contained herein are the author's sole responsibility.

EDSON NTODWA

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CERTIFICATE OF APPROVAL

The undersigned certify that this thesis represents the student's own work and effort, and it makes acknowledgements where other sources of information are used. The thesis is submitted with our approval.

Signature: ________________________________Date: _______________________

Gowokani Chijere Chirwa, PhD (Associate Professor)

Supervisor

DEDICATION

To myself for being myself and for the courageous decisions I made

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ABSTRACT

High and persistent levels of multidimensional poverty pose the most significant challenge in Malawi. As a result, finding effective methods to eradicate poverty in all its forms remains a significant policy concern. Spatial theories of poverty suggest that the persistence of high levels of moneymetric poverty stems from spatial dependence and its spillover effects. In other words, the level of moneymetric poverty in a specific area is influenced by the level of poverty in neighbouring areas. Moreover, other socio-economic factors in a particular area also affect the level poverty in neighbouring areas. However, the previous studies never evaluated the situation in the case of multidimensional poverty aka nonmentary poverty The study aims to determine whether the level of multidimensional poverty in a specific area is affected by the level of multidimensional poverty in its neighbouring areas in Malawi. Additionally, the study seeks to analyse the effect of education levels in a particular area on the level of multidimensional poverty in neighbouring areas. By utilizing data from Malawi's fifth Integrated Household Survey (IHS V) in 2019, the study employs the Spatial Lag (SAR) model to examine the spatial spillover effects of multidimensional poverty in the country. The results show that multidimensional poverty in the country exhibits spatial dependence, signifying that multidimensional poverty in one area is influenced by multidimensional poverty in neighbouring areas. Furthermore, the findings also show that an increase in education levels in a particular area reduces multidimensional poverty of neighbouring areas. These findings imply that a multidimensional poverty reduction in Malawi can be achieved by targeting anti-poverty programs in areas that are highly dependent or hotspots. Specifically, by investing more in education.

Keywords: Multidimensional poverty, Spatial Lag Model, Agglomeration, Integrated Household survey, Malawi.

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LIST OF ACRONYMS AND ABBREVIATIONS

AF	Alkire-Foster
EA	Enumeration Area
FGT	Foster-Greer-Thorbecke
GPS	Global Positioning System
GWR	Geographically Weighted Regression
IHS	Integrated Household Survey
IV	Instrumental variable
LM	Lagrange Multiplier
MGDS	Malawi Growth and Development Strategy
MIP	Malawi vision 2063 First 10-year Implementation Plan
M-MPI	Malawi-Multidimensional Poverty Index
MPI	Multidimensional Poverty Index
NPC	National Planning Commission
NSO	National Statistical Office
OLS	Ordinary Least Squares
OPHI	Oxford Poverty and Human Development Initiative
SAR	Spatial Autoregressive Model/Spatial Lag Model
SARAR	Autoregressive Lag model with Autoregressive Errors
SDG	Sustainable Development Goal
SDM	Spatial Durbin Model
SEM	Spatial Error Model
SLX	Spatial lag X
UBN	Unsatisfied Basic Needs
UNDP	United Nations Development Programme

CHAPTER ONE
INTRODUCTION

1.1 Background

Goal No. 1 of the United Nations' Sustainable Development Goals (SDGs), adopted in 2015, aims to end poverty in all its forms by the year 2030. It includes addressing multidimensional poverty, which goes beyond a lack of income to encompass various deprivations such as poor health, lack of education, inadequate living standards, limited access to quality work, and a poor environment (United Nations Development Programme (UNDP) & Oxford Poverty and Human Development Initiative (OPHI), 2023). The concept of multidimensional poverty was a key gap identified during the previous Millennium Development Goals (MDGs) era, between 2000 and 2015, where poverty reduction focused primarily on income, leaving out other critical aspects of poverty (United Nations, 2015). The SDGs aim to fill this gap by addressing a broader spectrum of human deprivation.

As of 2023, more than half of the SDGs' implementation period has elapsed, but a substantial portion of the global population remains multidimensionally poor. According to the 2023 Global Multidimensional Poverty Index (MPI) Report by UNDP and OPHI, 1.1 billion people—approximately 18% of the world's 6.1 billion people—are considered multidimensionally poor. The situation remains particularly dire in many developing regions of Africa, Asia, and Latin America, where people continue to experience various forms of deprivation despite the adoption of social protection schemes aimed at addressing extreme poverty, inequality, risk, and vulnerability (Borga & D'Ambrosio, 2021).

Approximately five out of six poor people live in the sub-Saharan region or South Asia (UNDP & OPHI, 2023). Despite tremendous progress in economic growth, with many developing nations moving from low-income to middle-income, multidimensional poverty remains a major concern, as approximately 65% of the poor live in middle-income countries (UNDP & OPHI, 2023). Considering the enduring prevalence of poverty in low-and middle-income nations, the elimination of multidimensional poverty continues to pose a formidable challenge.

Like many developing nations, Malawi endures high levels of multidimensional poverty. According to the 2022 Malawi multidimensional poverty index report by the National Statistical Office of Malawi, about 59 out of every 100 individuals suffer from various forms of poverty, and on average, poor people lack about 54% of the possible deprivations. The multidimensional poverty index stood at 0.316, signifying that if everyone was poor in Malawi, on average, a poor person would be deprived of approximately 32% of the possible deprivations (National Statistical Office (NSO) of Malawi, 2022).

A pivotal step in the literature's endeavour to eradicate poverty in all its forms has been the shift from solely monetary measurements to a multidimensional approach. Sen (1985) argued that poverty should not only be defined or measured in monetary terms, as it is multidimensional in nature. He contended that poverty is a complex concept that must consider people's diverse characteristics and circumstances. The poor generally lack not only income but also education, health, justice, credit, and other productive resources and opportunities. Thus, poverty should be viewed as a deprivation of capabilities that limits what people can achieve, rather than merely a lack of income. Scholars and policymakers have also praised the multidimensional measurement of poverty for its ability to adequately capture the various deprivations people experience and provide a more comprehensive understanding of deprivation (Alkire & Foster, 2011; Martinez Jr. & Perales, 2014).

Prior to 2021, Malawi has solely relied on the income or monetary measure of poverty. However, to complement the monetary measure and to get a more comprehensive understanding of deprivation, the Malawi Multidimensional Poverty Index (M-MPI) was developed by incorporating various dimensions of poverty beyond income such as health, education, work, and environment. In the effort to eradicate poverty, Malawi has, since its independence in 1964, implemented various growth and poverty medium-term strategies, namely the Malawi Poverty Reduction Strategy Paper (2002–2005), Malawi Growth and Development Strategies I-III (2006, 2011, 2018), and currently, the Malawi 2063 first 10-year implementation plan (NPC 2020). These include aspects such as the Agricultural Input Subsidy Programme and social protection schemes such as the social cash transfer programme and public works programmes.

Despite evidence that these programs reduce monetary poverty in Malawi, multidimensional poverty remains high in the country (NSO, 2022). According to the Malawi Poverty Report for 2020, using an absolute poverty line of MWK 165,879 per person per year, 51.7 percent of the population is considered poor (NSO, 2021). This figure is significantly lower than the multidimensional poverty headcount ratio of 59 percent reported in the same year. This discrepancy suggests that the monetary measure of poverty does not adequately capture the complexity of poverty in Malawi, as it tends to underestimate the extent of deprivation in the country. This implies that the Malawi Multidimensional Poverty Index (M-MPI), by incorporating various dimensions of poverty beyond income—such as health, education, work, and environment—provides a richer and more nuanced picture of poverty in Malawi.

A study by Mtocha et al (2024) highlights that multidimensional poverty changes in Malawi are attributable to unfavourable weather conditions, climate shocks, big household sizes, lack of education and low income. Specifically, households that experienced shocks, had larger sizes, participated in social protection programs, were in rural areas, and were headed by individuals who were married, illiterate, or had lower levels of education tended to have higher MPI scores. In contrast, households with higher incomes, and access to credit (though the results were ambiguous).

The ineffectiveness of social protection schemes in reducing multidimensional poverty but instead being associated with higher levels of it as found by Mtocha et al (2024) is not overall surprising. It may suggest that these interventions have a direct effect on reducing monetary poverty but not the other dimensions of poverty and the indirect effect may not be strong enough to affect the other dimensions of poverty. Additionally, high and persistent levels of multidimensional poverty in Malawi maybe attributed to spatial dependence which may hamper the effectiveness of these programmes in reducing it.

Economic and human geographical theories suggest that poverty persists due to spatial dependence and the resulting neighbourhood or spillover effects. Galvis and Roca (2010) state that poverty is a persistent phenomenon that occurs over time, caused by what is known as neighbourhood effects, or the presence of contagious effects in certain areas that remain stagnant alongside their neighbouring regions. Spatial dependence denotes the tendency of neighbouring locations to influence one another and share similar characteristics (Goodchild, 1992).

Therefore, multidimensional poverty in one geographical area may be influenced by multidimensional poverty in nearby areas. This argument is supported by Tobler's first law, which states that "everything is related to everything else, but near things are more related to each other than distant things" (Tobler, 1970). It is also supported by the membership theory of poverty, which emphasizes the role of residential neighbourhoods in determining an individual's poverty status (Durlauf, 2004). According to this theory, an individual's socio-economic prospects are greatly influenced by the groups they are associated with throughout their life.

The spatial spillover effects of multidimensional poverty can also be explained by economic agglomeration theory, which explains the clustering of similar industrial firms and how their proximity attracts supportive services and markets, thereby attracting more firms. Similarly, areas that share similar multidimensional poverty levels or conditions that contribute to poverty tend to concentrate together, resulting in a higher prevalence of poverty. This can be explained by existence of economic interdependencies among clusters or areas that are near each other. For instance, neighbouring areas rely on each other for trade, infrastructure, and social services such as education and healthcare, which directly affect multidimensional poverty. Consequently, any changes in these factors in one area not only affect the levels of multidimensional poverty in that area but also in the surrounding areas that depend on it.

Spatial dependence can have both positive and negative effects on multidimensional poverty reduction. Positive spillover effects can be beneficial; multidimensional poverty in one area may decrease due to favourable socioeconomic conditions in neighbouring areas, such as improved health, education, and transportation infrastructure. Conversely, socioeconomic factors that contribute to high multidimensional poverty in an area often spill over to nearby areas, creating a cycle that reinforces multidimensional poverty. This is why when multidimensional poverty becomes concentrated in neighbouring areas, it tends to persist and even increase, which can also render anti-poverty interventions ineffective, as they may be counteracted by negative factors from neighbouring regions or geographic units.

However, positive spatial spillovers can have a multiplying effect on poverty reduction when the impacts on neighbouring areas are transmitted back to the original area.

Studies on multidimensional poverty reveal significant spatial spillover effects, where poverty in one area influences neighbouring regions. Turriago-Hoyos et al. (2020) found clusters of poverty linked to unemployment and low urbanization in Colombia. Wang et al. (2022) identified poverty hotspots in Balochistan, Pakistan, influenced by neighbouring districts' income levels. Similarly, Peng et al. (2018) demonstrated that financial development in China reduced rural poverty through direct spillover effects. Urbanization in rural China negatively affects economic poverty but has a limited impact on health and education poverty (Wang et al., 2023). In Ecuador, financial inclusion significantly reduces poverty significantly (Álvarez-Gamboa et al., 2021), while property tax revenues in Colombia have notable spillovers (Ramírez et al., 2017). Studies in Ghana and Morocco have emphasized addressing spatial inequalities through tailored policies (Amaghouss & Ibourk, 2020; Annim et al, 2012 and Oteng-Abayie et al., 2023).

Previous studies on multidimensional poverty in Malawi have mainly focused on the incidence, changes, and direct determinants of multidimensional poverty (Kaluwa & Kunyenje, 2019; Mussa, 2011; McCarthy et al., 2016; NSO, 2022; Mtocha et al., 2024) and have largely ignored the influence of geography and space. Additionally, studies on the determinants of multidimensional poverty have also overlooked the spatial spillover effects of education (see Liu et al., 2021; Hofmarcher, 2021; Niazi, M. I., & Khan, A., 2012; Omar, M. A., & Hasanujzaman, M., 2021; Robson et al., 2022; and Qiu, J., Wang, H., & Aikerbayr, A., 2023). However, public goods theory suggests that education is a congestible public good with positive externalities (Samuelson, 2024). The benefits of education are not limited to those who have attained it; they are also enjoyed by neighbours without compensation. Ignoring the spillover effects of education on multidimensional poverty may lead to an underestimation of its poverty-reducing effect.

Against this background, this paper aims to investigate whether multidimensional poverty in one area is influenced by multidimensional poverty levels in neighbouring areas. Additionally, it aims to explore the spatial spillover effects of education on multidimensional poverty in the country.

The rest of this paper is organized as follows: the remainder of this chapter presents the problem statement, objectives, and hypotheses of the study. Chapter 2 provides a review of both theoretical and empirical literature. Chapter 3 presents the research design, and the empirical strategy employed in the study. Empirical results and discussion are presented in Chapter 4. Chapter 5 concludes and provides policy recommendations.

1.2 Problem statement

High and persistent levels of multidimensional poverty pose the most significant challenge in Malawi. As a result, finding effective methods to eradicate poverty in all its forms remains a significant policy concern. Although monetary poverty levels have been declining in the country, more than half of the country's population continues to suffer from various forms of poverty (NSO, 2022). The 2022 Malawi Multidimensional Poverty Index report indicated that about 59 percent of the population is poor and the MPI has marginally and insignificantly declined from 0.337 to 0.316 between 2016 and 2020 (NSO, 2022).

The sluggish decline and persistence of high levels of multidimensional poverty in Malawi raises concerns over the well-being of Malawians and casts doubt on realizing the 2030 Agenda for Sustainable Development (SDG), especially Goal No. 1, to eradicate poverty in all its forms. In addition, the realisation of the medium-term goal of the Malawi agenda 2063's medium term goal to raise the country's income status to a lower-middle level by 2030 and to meet most of the Sustainable Development Goals (SDGs) appears gloomy. Hence, it sparks interest in the search for other reasons why multidimensional poverty persists, and factors that may hamper the effectiveness of anti-poverty interventions in reducing it.

Economic and human geographical theories suggest that poverty persists due to spatial dependence and the resulting neighbourhood or spillover effects (Galvis & Roca, 2010). Thus, multidimensional poverty in one geographical area may be influenced by multidimensional poverty in nearby areas. This argument is supported by Tobler's first law, which states that "everything is related to everything else, but near things are more related to each other than distant things" (Tobler, 1970). Spatial clustering of multidimensional poverty may also be explained by economic interdependences among neighbourhoods highlighted by the economic agglomeration theory explained earlier.

Studies on multidimensional poverty have also revealed significant spatial spillover effects, where poverty in one area influences neighbouring regions (see Álvarez-Gamboa et al., 2021; Turriago-Hoyos et al., 2020; Wang et al., 2022; Peng et al. 2018; Amaghouss & Ibourk, 2020; Annim et al, 2012 and Oteng-Abayie et al., 2023). However, despite education being a congestible public good with unintended positive effects, as highlighted by Samuelson's theory of public expenditure, studies on the effect of education on multidimensional poverty have overlooked its spatial spillover effects (see Liu et al., 2021; Hofmarcher, 2021; Niazi, M. I., & Khan, A., 2012; Omar, M. A., & Hasanujzaman, M., 2021; Robson et al., 2022; Qiu, J., Wang, H., & Aikerbayr, A., 2023). Ignoring the spillover effects of education on multidimensional poverty may result in an underestimation of its poverty-reducing impact. Therefore, this study intends to fill this gap.

Additionally, previous studies on poverty in Malawi have mainly focused on the monetary or income poverty (see Kaluwa & Kunyenje, 2019; Mussa, 2011, McCarthy et al, 2016; NSO 2022) and the few studies on multidimensional poverty have ignored the influence of geography and space (Mtocha et al., 2024). However, as illustrated by figure 1, a look into the multidimensional poverty indices across neighbouring districts in Malawi shows some form of similarity, suggesting that there may be some spatial dependence of multidimensional poverty within neighbourhoods.

Therefore, this study also adds to the scanty literature on multidimensional poverty in Malawi by considering the influence of geography and space.

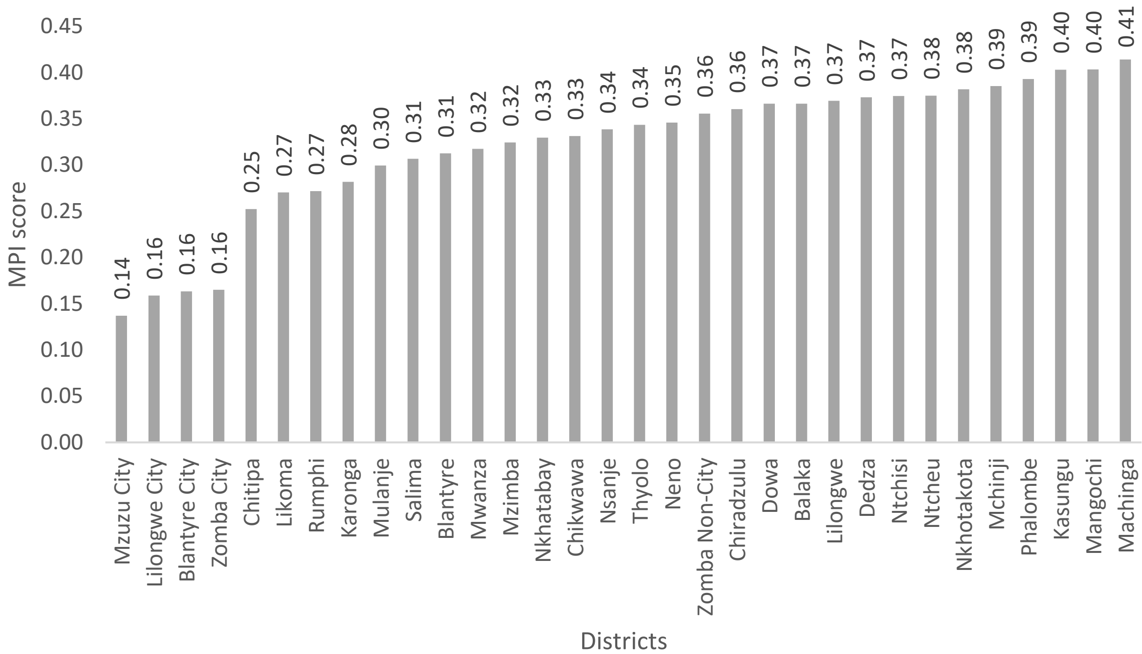


Figure 1: Incidence of M-MPI (Percent) by District, Malawi 2019/2020

1.3 Objectives of the Study

The main objective of the study is to investigate the spatial agglomeration effect of multidimensional poverty in Malawi. Specifically, the study

i. Investigates the effect of multidimensional poverty of neighbouring areas on multidimensional poverty of a particular geographical area.
ii. Investigates the effect of education levels in a particular area on multidimensional poverty in neighbouring areas.

1.4 Hypotheses of the Study

To achieve the study's specific objectives, the following null hypotheses are tested:

i. Multidimensional poverty levels in neighbouring areas do not affect multidimensional poverty of a particular geographical area.
ii. Education levels in a particular area do not affect multidimensional poverty of neighbouring areas.

1.5 Justification

The study is pertinent as Malawi strives to achieve the Sustainable Development Goals (SDGs), particularly Goal No. 1, which aims to eradicate poverty in all its forms and realize the country's medium-term goal of becoming a lower middle-income nation by 2030. As of 2024, we are in the second half of the SDGs' implementation period, and nearly half of the timeframe for the Malawi First 10-Year Implementation Plan (MIP-1) for the country's Agenda 2063 has elapsed; however, multidimensional poverty remains very high. This situation raises doubts about the feasibility of achieving both the 2030 Agenda for Sustainable Development, especially Goal No. 1, and MIP-1. This underscores the need to further understand multidimensional poverty and identify the most effective ways to eradicate it.

In light of this, the study offers a novel approach to understanding why poverty persists by employing a spatial econometric framework to examine the influence of geography and space. Recent literature suggests that poverty in a particular area is influenced by poverty in neighbouring areas, which may contribute to its persistence; however, no study on multidimensional poverty in Malawi has explored this aspect.

Additionally, the pure theory of public expenditure by Samuelson (2024) posits that education has external benefits. The advantages of improved education are not only experienced by the target communities but also by nearby communities. Nevertheless, studies on multidimensional poverty globally have often overlooked its spatial spillover effects. Therefore, this study considers the influence of geography and space in examining multidimensional poverty in Malawi while exploring the spatial spillover effects of education.

CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction

This section reviews existing theoretical and empirical literature to lay the foundation for analysing the spatial spillover effect of multidimensional poverty in Malawi. Section 2.2 reviews theoretical literature on poverty's determinants, distribution, and maintenance, while Section 2.3 synthesises empirical literature on multidimensional poverty and its spatial spillover effects.

2.2 Theoretical literature review

2.2.1 Sen's capability theory

Sen (1985) conceptualized poverty as a "capability failure," meaning the inability of individuals to achieve essential 'beings and doings' fundamental to human life, such as being healthy, educated, and socially included. According to Sen, poverty is a multidimensional concept that goes beyond a lack of income, emphasizing the deprivation of capabilities that restrict individuals' ability to live the lives they value. These capabilities include access to education, healthcare, justice, credit, and other essential resources and opportunities.

Sen argued that poverty results from a lack of essential capabilities rather than merely a lack of income, predicting an inverse relationship between human development and multidimensional poverty. Therefore, addressing poverty requires enhancing people's skills, education, and health to expand their opportunities and choices, enabling them to achieve a desirable quality of life.

However, Sen's Capability Theory has several limitations. Measuring capabilities is difficult because they are subjective and vary by context, complicating comparisons across different populations. This has resulted in countries developing country specific multidimensional poverty indices that meets reflects their understanding deprivation and criticise the use of the global multidimensional poverty index published by UNDP and OPHI. Furthermore, it understates the importance of economic resources (income) that support capability development. For instance, individuals with more income can pay for good education, good health and housing.

2.2.2 Geographical theories of poverty

Geographical theories of poverty provide explanations for the spatial concentration and distribution of poverty. They offer explanations about why some regions or areas remain poor while others flourish, as well as why areas with similar poverty characteristics tend to concentrate together. According to Chimhowu (2009), these theories are classified as deterministic and possibilistic. Deterministic theories focus on the influence of the physical topography in causing poverty; possibilistic theories focus on spatiality, or the interaction between the physical conditions and human processes to give poverty outcomes.

2.2.2.1 *Environmental determinism theory*

Jeffrey Sachs (2011) developed the Geographical Determinism Theory in his influential work *The End of Poverty: How We Can Make It Happen in Our Lifetime*. He argues that a country's geographical environment significantly shapes its economic outcomes, including its poverty levels. According to Sachs, differences in geographical features explain why some nations are trapped in poverty while others achieve prosperity. Countries endowed with natural resources, fertile soils, ample rainfall, navigable rivers, and proximity to the sea tend to experience economic growth, while those that are landlocked or resource-poor face persistent poverty.

Landlocked countries, regions located in high mountain ranges, and areas lacking navigable rivers, long coastlines, or good natural harbors suffer from high transportation costs and limited access to global markets. These geographical disadvantages impose trade barriers that hinder economic development, leaving such countries trapped in poverty. Additionally, nations prone to natural disasters like floods, droughts, and adverse weather conditions often experience reduced agricultural productivity, further perpetuating poverty. Tropical environments exacerbate poverty through fragile and infertile soils, a high prevalence of pests and crop diseases, and ecological conditions favourable to human infectious diseases such as malaria (Sachs, 2011; Landes, 1998).

While the Geographical Determinism Theory highlights important environmental constraints, it has several limitations. Firstly, it cannot explain why countries with similar geographical features experience different development outcomes including poverty. Additionally, it does not explain why some resource rich countries remained poor and conversely, why some resource poor countries flourished. For example, the Democratic Republic of the Congo (DRC) has abundant natural resources, including minerals like cobalt and diamonds but has remained stagnant. On the other hand, a country like Singapore with limited natural resources prospered.

This limitation is highlighted by Acemoglu and Robinson (2012) in *Why Nations Fail* argue that institutions, not geography, are the primary determinants of economic prosperity. They contend that inclusive institutions—those that ensure political stability, enforce property rights, and create opportunities for social mobility—enable countries to overcome geographical disadvantages. In contrast, extractive institutions concentrate power and wealth among elites, trapping nations in cycles of poverty regardless of their natural resource endowment. Therefore, while geography can influence development, institutional quality ultimately determines whether countries thrive or remain poor.

2.2.2.2 Spatial economic agglomeration theory

Agglomeration refers to the clustering of economic activities within a specific geographical area (Malmberg, 2009). In the context of this study, it denotes the spatial concentration of poverty in certain regions. Agglomeration theory is a core concept in new economic geography, providing a micro-founded approach to spatial economics by explaining the uneven distribution of economic activity and income across space. According to Fujita and Thisse (1996), Krugman, P. (1991b) and and Venables (1996), the spatial clustering of firms or households is driven by three main factors: the existence of externalities, increasing returns to scale, and spatial competition.

Applying this framework to poverty reveals that the clustering of poverty in specific areas can be attributed to spatial spillover effects. Some areas remain trapped in poverty because they are surrounded by other high-poverty areas. Geographically close areas often depend on each other for socio-economic activities and infrastructure. For instance, neighbouring areas frequently rely on one another for trade, transportation networks, education, and healthcare services, all of which influence multidimensional poverty levels. As a result, changes in these factors in one area can directly affect poverty levels in adjacent regions.

This theory may explain the clustering of poverty that is observed in many developing countries where rural areas often remain trapped in poverty due to limited access to essential services and infrastructure. For instance, sub-Saharan Africa has several poverty clusters, where poor agricultural productivity, limited infrastructure, and inadequate education systems perpetuate poverty across adjacent regions.

Despite its explanatory power, agglomeration theory has limitations in poverty analysis. First, it primarily emphasizes economic drivers, potentially overlooking social and political dynamics—such as discrimination, conflict, or governance failures—that can also contribute to poverty clustering. Second, the theory treats spatial proximity as the main factor driving interdependence, neglecting the increasing influence of digital connectivity and migration patterns.

2.2.3 The Memberships theory of poverty

According to Durlauf (2001), an individual's socioeconomic prospects are heavily influenced by the groups to which they belong throughout their life. This theory emphasizes the importance of social networks and group affiliations in determining economic outcomes. Durlauf argues that individuals who are part of high socioeconomic status groups are more likely to experience upward mobility, while those in low-status groups are more likely to experience downward mobility. These groups include residential neighbourhoods, schools, workplaces, and even ethnic communities.

The socioeconomic outcomes of these group memberships are shaped through various mechanisms, such as peer group effects, role model influences, social learning, and social complementarities. Peer group effects, for instance, can impact individuals' behaviours, aspirations, and opportunities, while role models within these groups can shape one's expectations and career paths. Furthermore, social learning allows individuals to adopt behaviours and strategies for success based on the social norms and practices of their group.

In a similar vein, geographic location plays a crucial role in determining socioeconomic outcomes. Areas surrounded by neighbourhoods with high poverty levels are more likely to experience persistent poverty, while areas surrounded by wealthier, low-poverty neighbourhoods are more likely to prosper (Durlauf, 2004). The proximity to wealthier areas provides residents with better access to education, employment opportunities, and social networks, facilitating upward mobility and breaking the cycle of poverty.

While the Membership Theory of Poverty offers a valuable lens for understanding the complex dynamics of poverty, it is not without its critics and limitations. One critique is that the theory may overemphasize the role of social networks and underestimate the role of individual agency and resilience in overcoming poverty (Sharkey, 2013).

Critics argue that the theory can lead to a deterministic perspective, suggesting that individuals are simply trapped by their social circumstances, overlooking the possibility for individuals to make choices and exert agency in shaping their economic outcomes. The theory may neglect the effect of personal factors like individual motivation, skills, and willingness to work on economic outcomes (Ioannides & Topa, 2010).

2.3 Empirical literature review

This section provides an overview of existing studies on multidimensional poverty in Malawi and beyond. However, the focus is on literature pertaining to spatial determinants of multidimensional poverty. Additionally, it also examines literature on other determinants of multidimensional poverty in Malawi.

2.3.1 Spatial determinants of Multidimensional poverty

Studies have been conducted elsewhere on the spatial spillover effect of multidimensional poverty, and the findings on the subject matter differ across contexts and depending on the policies in the country. To begin with, Turriago-Hoyos et al. (2020) analysed the spatial effects of multidimensional poverty in Columbia using the Unsatisfied Basic Needs (UBN) Index. The results from an autoregressive lag model with autoregressive errors (SARAR) confirm the existence of spatial effects of poverty; poverty in one municipality is positively influenced by the poverty of neighbouring municipalities. The results from the local Moran's I indicate the presence of spatial clusters and hotspots in the Pacific Chocó region, the Caribbean Coast, and the southern region of the country, and these clusters are characterised by high levels of unemployment, low levels of urbanisation, and are of large sizes.

A spatial analysis of multidimensional poverty in Pakistan revealed that poverty levels in one district are influenced by both local and neighbouring districts' poverty and income levels (Wang et al., 2022). The study employed the Alkire-Foster methodology to construct a multidimensional poverty index. Findings from the Moran scatter plot analysis indicated the existence of significant poverty clusters, identifying hotspots and cold spots across the country. Cold spots, characterized by low-poverty districts surrounded by similar neighbours, were predominantly located in Punjab province. Conversely, Balochistan and parts of Sindh province exhibited hotspots, where high-poverty districts clustered together. Spatial regression models further demonstrated that income levels in neighbouring districts negatively affect poverty in a given district, emphasizing the interconnectedness of poverty dynamics.

Spatial disparities and key determinants of multidimensional child poverty in China were also examined. The study applied spatial autocorrelation analysis and the geo-detector method, highlighting family conditions, economic development, urbanization levels, support capacity, and cultural environment as critical factors shaping these disparities (Wang et al., 2022). These findings underscore the complexity of factors contributing to child poverty in diverse geographic contexts.

Research on the spatial clustering of multidimensional poverty and the effects of financial development on poverty alleviation in China provided further insights. Using provincial panel data from 1999 to 2014, Peng et al. (2018) employed spatial econometric models to analyze rural poverty in income, education, and healthcare dimensions. The results confirmed that poverty in all three forms is spatially correlated, with poor regions tending to cluster together. Additionally, rural financial development was found to have both direct and indirect effects on reducing income and education poverty, with spillover effects surpassing direct impacts. However, healthcare poverty reduction appeared to rely more heavily on government fiscal expenditure and local economic growth.

Wang et al. (2023) explored the spatial spillover effects of urbanization on multidimensional poverty reduction in rural China using panel data from 30 provinces spanning 2009 to 2019. The study examined four dimensions of poverty: economic, education, health, and living standards. Applying the spatial autocorrelation test and the Spatial Durbin model, the analysis confirmed spatial dependence and urbanization's spatial spillover effects. Results indicated negative spillover effects on economic and living poverty, while the effects on education and health poverty were insignificant. Additionally, poverty in one province was found to be positively influenced by poverty in neighbouring provinces.

The relationship between municipal property tax revenues and multidimensional poverty reduction in Colombia was investigated by Ramírez et al. (2017). They measured poverty using a headcount ratio and poverty gap based on the Alkire-Foster methodology. Employing an instrumental variable-spatial autoregressive lag model with spatial autoregressive errors (IV-SARAR), the study addressed the endogeneity of property taxes. Findings revealed a causal negative effect of per capita property tax revenues on both the multidimensional poverty headcount and poverty gap. Significant spillover effects across municipalities highlighted the need for geographically differentiated public policy interventions, which were validated by counterfactual policy tests.

Álvarez-Gamboa et al. (2021) analysed the influence of financial inclusion on multidimensional poverty in Ecuador using panel provincial data from 2015 to 2018. Utilizing a panel SARAR model with random effects, they assessed spatial effects of financial inclusion on poverty. The results demonstrated that financial inclusion significantly reduces multidimensional poverty. Additionally, spatial dependence was evident, with poverty in one province being reinforced by poverty in neighbouring provinces.

In Morocco, Amaghouss and Ibourk (2020) examined trends in multidimensional poverty from 2004 to 2014 and assessed poverty convergence between peripheral and central provinces. The spatial lag convergence model indicated that poverty in Morocco is geographically driven, with a low convergence speed. This suggests that targeted policies addressing spatial inequalities are essential for reducing multidimensional poverty.

Oteng-Abayie et al. (2023) studied the effect of microfinance on spatial inequality and poverty in Ghana using data from the 6th (2012/2013) and 7th (2016/2017) rounds of the national living standards survey. Applying spatial econometric techniques, they explored microfinance's spatial relationships with inequality and poverty. Findings showed that microfinance reduces spatial inequality and poverty both directly within districts and indirectly through spillovers to neighbouring districts. However, the spillover effects diminished with an increasing number of neighbouring districts. Additionally, disparities within districts were influenced by microfinance outreach, while inter-district disparities were shaped by uneven microfinance credit distribution.

2.3.2 Studies on Multidimensional poverty in Malawi

In Malawi, most studies have focused on the unidimensional (monetary) measurement of poverty (Mussa 2011, 2014, 2017; Kalua & Kunyenje, 2019; Mwale et al., 2022; and McCarthy et al., 2016), and only a few have studied multidimensional poverty. Mtocha et al. (2023) analysed changes in multidimensional poverty in Malawi over the period 2010–2019. Using the Malawi Integrated Household survey data, they constructed the Malawi multidimensional poverty index (M-MPI) following the Alkire-Foster methodology. The Blinder-Oaxaca decomposition method and an unconditional quantile regression model were used to explore significant drivers of multidimensional poverty changes in the country. The findings revealed that income and education are crucial for multidimensional poverty reduction. In contrast, household size, shocks, social protection, marriage, and rural residence increase multidimensional poverty in Malawi.

Benson et al. (2005) examined the spatial determinants of poverty in rural Malawi. The study focused on small, local populations in rural Malawi rather than all of Malawi to simplify the analysis. The Foster-Greer-Thorbecke (FGT) headcount ratio was used to measure the prevalence of poverty in rural aggregated enumeration areas (EAs). To guide the selection of the potential determinants, the risk-chain conceptualization of household economic vulnerability was employed. The study used a spatial lag model to control for the spatial correlation in the errors, as revealed by the Moran's I test results, and the findings showed that only eight of the 24 determinants selected for analysis proved significant.

Furthermore, the study employed a geographically weighted regression (GWR) to account for the differences in the spatial processes accounting for poverty in rural Malawi, i.e., spatial non-stationarity. All determinants considered were significant in at least some of the local models developed in geographically weighted regression. More importantly, the findings demonstrated that spatial determinants of poverty in rural Malawi are non-stationary, suggesting poverty reduction efforts should be targeted at district and sub-district levels.

Mussa (2011) analysed the poverty-inequality relationship from a multidimensional perspective in Malawi. He recognised the multidimensional nature of poverty and inequality by not only focusing on monetary measures but also non-monetary measures of well-being, in particular, education and health. Using the second Integrated Household Survey (IHS 2), he estimated the contribution of within-group and between-group inequalities to poverty, and the findings differ across dimensions. The study suggests that reducing vertical inequalities in consumption would have a higher poverty-reducing effect than reducing horizontal inequalities. The study also found that between-region inequalities in health have a larger and positive effect on the health poverty headcount, while within-region inequalities in health have a larger and positive relationship with the health poverty gap and severity. Finally, the study found that an increase in both within and between region education inequalities reduces the education poverty headcount but increases the education poverty gap and severity.

2.4 Contribution to literature

The study contributes to the literature on the spatial effects of multidimensional poverty in two ways. First, it uses a country-specific index, the Malawi multidimensional poverty index, which was recently launched in 2021. This index is different from the global MPI and other country-specific indices because it is customised to suit the specific needs and priorities of Malawi and reflects the national understanding of poverty as well as the country's policy priorities. Moreover, previous studies on multidimensional poverty in Malawi have ignored the influence of geography and space, and hence this study contributes highly to the country's scanty literature on multidimensional poverty by considering the influence of geographical clustering and space.

Secondly, to the author's knowledge, studies on multidimensional poverty across the globe, have overlooked the spatial spillover effects of education. Therefore, this study contributes highly to existing literature across the globe by examining the spatial spillover effects of education on Multidimensional poverty.

CHAPTER THREE
METHODOLOGY

3.1 Introduction

This chapter describes the data, research design, and empirical estimation strategy that was employed to analyse the spatial agglomeration effect of multidimensional poverty in Malawi.

3.2 Data sources and sampling design

This study uses data from Malawi's fifth Integrated Household Survey (IHS V) (2019/2020). The IHS is a multi-topic survey implemented by the government of Malawi through the National Statistical Office (NSO). It collects data on household consumption (both food and non-food), demographic characteristics, health, education, labour force participation, credit and loans, household enterprises, agriculture, housing infrastructure, asset ownership, and food security indicators. The IHS uses a stratified two-stage sampling procedure to select the households. In the first stage, primary sampling units (enumeration areas (EAs)) were identified using the 2018 Population and Housing Census as the sampling distribution frame. The sampling frame was stratified first by district, and then by rural/urban classification. The second stage of sampling involves random identification of households from randomly sampled EAs. IHS V collected data from 11,434 households

3.3 Spatial Modelling

3.3.1 Spatial weight matrix

Before performing any spatial analysis, it is necessary to define and construct a spatial weight matrix. Identifying the presence of spatial dependence and analysing its effect on multidimensional poverty can only be accomplished by incorporating a spatial weight matrix denoted as W. A spatial weight matrix is a square matrix that defines the adjacency of geographical units under study and is specified as follows:

$$W = \begin{bmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nn} \end{bmatrix}$$

Where n is the number of observed enumeration areas or clusters (EAs) and w_{ij} is ij^{th}element of spatial weight matrix indicating the geographical proximity between clusters i and j.

The design of a spatial weight matrix is a crucial and challenging task in spatial econometrics. Various spatial matrices have been used in previous studies, including the queen contiguity matrix, inverse distance matrix (with or without a cut-off point), and economic distance matrix (Ramirez et al., 2017; Wang et al., 2023). In the queen contiguity matrix, geographical units are considered neighbours if they share common borders. On the other hand, the inverse distance matrix utilizes geographic distance to determine neighbours. According to geographic distance, the theory suggests that spatial dependence should be stronger among units that are closer to each other than among those that are more distant. However, both the queen contiguity and inverse distance matrices do not consider the economic and social relations among geographical units. Hence, an economic distance matrix was developed to account for the level of economic interdependence among geographical areas.

Because of the sampling design of the IHS and the use of enumeration areas as the unit of analysis, it is impractical to use the queen contiguity matrix. Systematic sampling of enumeration areas makes it very unlikely to sample contiguous clusters; therefore, many clusters will end up without neighbours because contiguous clusters are not sampled. Additionally, it is challenging to use the economic distance matrix because it relies on the economic outcomes of the cluster, such as per capita income, trade, and cost of living, to compute economic distance. The multidimensionality of economic indicators complicates their definition. Furthermore, the unavailability of data on other economic outcomes in the IHS prevents the construction of an economic indicator that reflects all economic factors, thus making this a more subjective spatial weight matrix.

Nevertheless, the IHS provides GPS coordinates for central points within clusters, enabling the calculation of the geographic distances between clusters. Therefore, an inverse distance matrix is used to consider the effect of space. Furthermore, LeSage and Pace (2009) argued that the choice of spatial matrix does not significantly affect the findings, as its sensitivity to W is not as strong as commonly believed. This justifies the use of an inverse distance matrix.

3.3.2 Spatial Autocorrelation analysis

To examine whether there exists a spatial association between the multidimensional poverty score of a particular geographical unit and poverty scores of neighbouring areas, the global Moran's I and Geary's C test statistics were used. The Global Moran's I is used to test the existence of global spillovers. Global spillovers arise when changes in a characteristic of one region impact all regions' outcomes (LeSage & Pace, 2021). In our case, multidimensional poverty in one area impacts the immediate neighbours, and the neighbours affect their neighbours, and so on. The global spillovers may also have feedback effects since impacts can be passed on to neighbours and back to the area of origin.

Mathematically, the global Moran's I and Geary's C statistics are given by equations 1 and 2 respectively.

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i-\bar{y})^2}, i \neq j \qquad 1$$

$$C = \frac{(n-1)\sum_{j}^{n}\sum_{i}^{n} w_{ij}(y_j-\bar{y})^2}{2W\sum_{i=1}^{n}(y_i-\bar{y})^2}, i \neq j \qquad 2$$

Where n denotes the number of spatial units, which in our case are clusters or enumeration areas (EAs); $y_i$and y_j are the multidimensional poverty scores of $i^{th}$and j^{th} clusters, respectively, $\bar{y}$ represents the mean score of multidimensional poverty of all clusters; w_{ij} is the spatial weight for clusters i and j. Both the global Moran's I and Geary's C statistics ranges between -1 and 1. A positive value ($I > 0$) indicates that multidimensional poverty scores are spatially agglomerated, a negative value ($I < 0$) means that the multidimensional poverty scores of neighbouring areas are inversely associated and a value of zero ($I = 0$) means that the multidimensional poverty is randomly distributed. For the Moran's I statistic, a value closer to one indicate a strong spatial autocorrelation and a value closer to zero indicates a weak spatial autocorrelation. In contrast, for Geary's C, a correlation coefficient close to zero indicates strong spatial autocorrelation, while a coefficient closer to one signifies a weak spatial autocorrelation.

3.3.3 Spatial regression model

Following Anselin and Rey (1997), clusters may be correlated in three different ways: first, the multidimensional poverty score of one area may affect the poverty score of the neighbouring areas. Second, socio-economic characteristics such as health, education, employment and many others, of one area may influence multidimensional poverty in neighbouring areas . Lastly, unobserved characteristics that affect multidimensional poverty in one region may be correlated with unobserved characteristics in neighbouring areas.

Therefore, as proposed by Anselin and Rey (1997) and modified by LeSage and Pace (2009), the general spatial model is expressed as follows:

$$Y = \alpha\iota_N + \rho WY + WX\beta + \mu \qquad 3$$

Where $\mu = \lambda W\mu + \varepsilon$

Where Y represents a $N \times 1$ vector of observations of the dependent variable (multidimensional poverty). X is $N \times k$ matrix of observations of independent variables, W is the $N \times N$ spatial weight matrix, μ is a $N \times 1$ vector of the spatially correlated error terms, θ, λ and ρ are spatial parameters. ε is $N \times 1$ vector of white noise error terms.

According to Burridge et al. (2016), there are no technical difficulties to estimating the general model which includes spillover effects among the dependent variable, the independent variables, and the disturbance terms. However, the parameters cannot be interpreted in a meaningful way since the different types of spillover effects cannot be distinguished from each other because there are many parameters to be estimated. Therefore, from the general model, distinct models can be generated and estimated depending on the type of spatial dependence observed in the data and zero parameter restrictions imposed. When the spatial correlation arises from the spatial correlation in values of the dependent variable only ($\lambda = 0, \rho \neq 0 \ and \ \theta = 0$), then the model can be reduced to a spatial Autoregressive (SAR) model, given as:

$$Y = \alpha\iota_N + \rho WY + X\beta + \varepsilon \qquad 4$$

When spatial correlation is emanating from correlation between the dependent variable (multidimensional poverty) in a particular area and socio-economic factors from neighbouring areas only ($\lambda = 0, \rho = 0$ and $\theta \neq 0$), the model reduces to a Spatially Lagged X (SLX) Model:

$$Y = \alpha\iota_N + WX\beta + \varepsilon \qquad 5$$

When the correlation is between the error terms only ($\lambda \neq 0, \rho = 0$ and $\theta = 0$), the model becomes a Spatial Error model (SEM):

$$Y = \alpha\iota_N + X\beta + \lambda W\mu + \varepsilon \qquad 6$$

When ($\lambda = 0, \rho \neq 0$ and $\theta \neq 0$), the general model reduces to a Spatial Durbin model (SDM):

$$Y = \alpha\iota_N + \rho WY + WX\beta + \mu \qquad 7$$

When ($\lambda \neq 0, \rho \neq 0$ and $\theta = 0$), the model becomes a spatial autoregressive model with spatial autoregressive disturbances (SARAR). The SARAR model, proposed by Anselin and Florax (1995), accounts at the same time for spillover effects in the dependent variable and for spatial autocorrelation of the errors (correlation among unobservable). SARAR model is expressed as:

$$Y = \alpha\iota_N + \rho WY + X\beta + \lambda W\mu + \varepsilon \qquad 8$$

For this study, a Spatial Lag model (SAR) was employed because it incorporates the spatial lag of the dependent variable, permitting examination of the influence of multidimensional poverty in neighbouring areas on the corresponding poverty in the area. Furthermore, it allows disaggregation of the effects of the explanatory variables into direct and indirect (spillover) effects, allowing exploration of spillover effect of education levels in a particular area on multidimensional poverty of neighbouring areas.

3.3.4 Direct and indirect (spillover) effects

Rearranging Eq. 4, the Spatial Lag Model can be expressed as follows:

$$Y = (I - \rho W)^{-1}(\alpha\iota_N + X\beta) + (I - \rho W)^{-1}\varepsilon \qquad 9$$

When $|\rho| < 1$ this expression can be expressed as an infinite series, the Leontief expansion, involving the explanatory variables and the error terms:

$$Y = (I_N + \rho W + \rho^2 W^2 + \cdots)(\alpha\iota_N + X\beta) + (I_N + \rho W + \rho^2 W^2 + \cdots)\varepsilon \qquad 10$$

The Leontief expansion allows for defining two effects: a multiplier effect involving the explanatory variables and a spatial diffusion effect involving the error terms (Le Gallo, 2021). On one hand, in terms of the explanatory variables, this means that, on average, the value of y is influenced not only by the explanatory variables associated with its own location, but also by those associated with all other locations (whether they are neighbours or not) through the inverse spatial transformation $(I_N - \rho W)^{-1}$. This spatial multiplier effect diminishes as the order of the spatial weight matrix increases, indicating a decrease in influence with distance (ibd). On the other hand, in terms of the error process, this means that a random shock in one location not only affects the value of y in that location, but also has an impact on the values of y in all other locations through the same spatial inverse transformation. This is the diffusion effect, which also decreases with distance (Le Gallo, 2021).

LeSage and Pace (2021) caution against directly interpreting the coefficients from the spatial lag model as marginal effects for two reasons. First, the model, in its reduced form (see Equation. 9), is nonlinear. Therefore, the coefficients cannot be interpreted directly, but rather the calculated marginal effects, as is the case with other nonlinear models. Second, multiplier effects arising in spatial lag models causes the marginal effects to be different from coefficients from a standard regression model.

To calculate the marginal effects, we obtain partial and cross-partial derivatives from expression 10 in the following way:

$$\begin{bmatrix} \frac{\partial E(y_1|x_i')}{\partial x_{1k}} & \cdots & \frac{\partial E(y_1|x_i')}{\partial x_{nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(y_n|x_i')}{\partial x_{1k}} & \cdots & \frac{\partial E(y_n|x_i')}{\partial x_{nk}} \end{bmatrix} = (I - \rho W)^{-1} \beta_k$$

The resulting matrix of partial and cross-partial derivatives provides both direct and indirect effects. The direct effects are represented by the diagonal elements of the matrix, while the indirect (spillover) effects are represented by the off-diagonal elements.

3.4 Constructing multidimensional poverty index

3.4.1 Alkire-Foster (AF) methodology

The Alkire-Foster (AF) methodology was developed by Alkire and Foster (2011) to measure multidimensional poverty. AF methodology involves two stages: the identification stage and the aggregation stage.

Identification stage: The Dual cut off approach

This stage involves identifying individuals or households that are considered multidimensionally poor. In the multidimensional measurement setting, where there are multiple variables, identification is a substantially more challenging exercise, and there are various approaches that can be used in this regard. According to Alkire and Foster's (2011) methodology, identification is achieved using the dual cut-off counting approach. This approach first requires determining who is deprived in each dimension or indicator by comparing the person's achievement against the corresponding deprivation cut-off. This ensures that individuals facing significant deprivation in a specific area are not overlooked, even if they meet the minimum requirements in other areas (Mtocha et al, 2024, Mtocha et al, 2023).

Given a set of d dimensions with r indicators, a vector of d deprivation cut-offs are denoted by $z = (z_1, \cdots, z_d)$. Denoting households' achievement in an indicator j by x_j, a household i said to be deprived of an indicator j if $x_{ij} < z_j$. For each indicator a deprivation dummy variable g_{ij}^0 is generated such that:

$$g_{ij}^0 = \begin{cases} 1, & if\ x_{ij} < z_j \\ 0, & otherwise \end{cases}, \text{ for all } j = 1, 2 \cdots, r \text{ and } i = 1, 2 \cdots, n$$

The deprivation in each of the dimensions may not have the same relative importance. Thus, different weights w_j maybe attached to different dimensions depending on their relative importance. To determine household's deprivation level in each dimension, a deprivation score (c_i) is calculated as the summation of the weighted deprivation values:

$$c_i = \sum_{j=1}^{d} w_j \, g_{ij}^0.$$

The score increases as the number of deprivations a household experiences increases and reaches its maximum when the person is deprived in all dimensions. A person who is not deprived in any dimension has a deprivation score equal to 0.

In addition to the deprivation cut-offs z_j, the AF methodology uses a second cut off to identify the multidimensionally poor households and is called the poverty cut off (k). A household is regarded poor when the proportion of the weighted deprivations it experiences exceeds the threshold k. Thus, the poverty identification function is given by

$$\rho_k(x_i; Z) = \begin{cases} 1, & if\ \frac{c_i}{n_d} > k \\ 0, & otherwise \end{cases}$$, where n_d is the number of dimensions

Upon identification, the deprivations of non-poor persons were censored or replaced with zero values in the censored deprivation matrix.

Aggregation stage

The computation of the MPI requires two components: the MP incidence or headcount ratio and MP intensity. The headcount ratio or incidence is the proportion of the population that is multidimensionally poor. This involves counting poor households or individuals identified using the poverty cutoff and dividing the total by the total number of households or individuals. The multidimensional poverty incidence is given by: $H = \frac{q}{n} = \frac{1}{n}\sum_{i=1}^{n} \rho_k(x_i; Z)$, where q is the number of poor households and n is the total number of households (poor or not).

Intensity of multidimensional poverty is average share of weighted indicators in which poor people are deprived. It is calculated as the sum of deprivation scores of the poor and dividing them by the total number of poor people. Mathematically, $A = \sum_{i=1}^{q} \frac{C_i(k)}{q}$, where $c_i(k) = \sum_{j=1}^{d} w_j g_{ij}^0(k)$. The intensity of multidimensional poverty (A) is also sometimes known as the breadth of poverty.

The Multidimensional poverty index also known as the adjusted headcount ratio is derived by the product of the MP incidence (H) and the intensity (A).

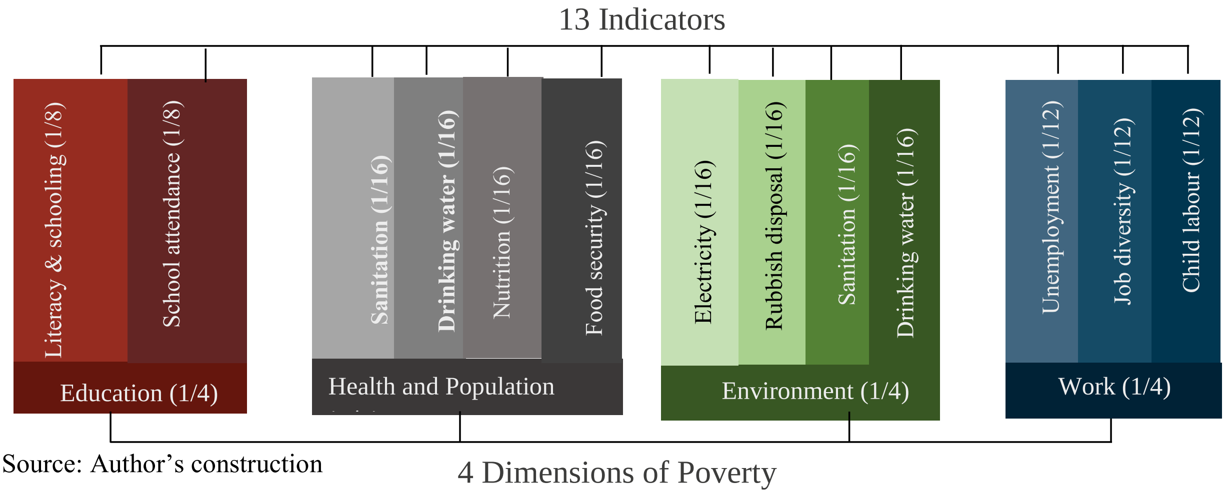
$$M_0 = H \times A = \frac{q}{n} \times \sum_{i=1}^{q} \frac{c_i(k)}{q}$$

$$MPI(M_0) = \frac{1}{n}\sum_{i=1}^{n} c_i(k) = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{d} w_j g_{ij}^{0}(k)$$

An important property of MPI computed using the AF methodology is that the MPI can be decomposed by population subgroup. This means that overall poverty is a population-share weighted sum of subgroup poverty levels. This property is useful in analysing poverty by geographical area, which is the focus of our study.

3.4.2 The Malawi Multidimensional poverty index (M-MPI)

The study uses the 2022 Malawi multidimensional poverty index (M-MPI) as the dependent variable. The M-MPI was created using the multidimensional measurement method of Alkire and Foster (2011). The multidimensional poverty index encompasses the deprivation of individuals or households in various other dimensions of life other than income. M-MPI consists of four dimensions: health and population, education, environment, and work. Within the four dimensions, 13 indicators were identified, and these are given in Figure 2. Each dimension is equally weighted, and each indicator within a dimension is also equally weighted.



Source: Author's construction

Figure 2: Structure of the Malawi MPI

The choice of dimensions and a set of indicators to be considered in the multidimensional poverty measure was preliminarily key. The dimensions and their respective indicators were selected to suit the specific needs and priorities of Malawi and to reflect the national understanding of poverty as well as the country's policy priorities. The choice of the dimensions was guided by the Malawi Growth and

Development Strategy (MGDS) III. The future MPI will be informed by the first 10-year implementation plan (MIP-1) of the Malawi vision 2063.

The poverty cut off for the Malawi multidimensional poverty index (M-MPI) is set at 38 percent. Thus, a household which is deprived in one and a half (38 percent) of the four dimensions is considered multidimensionally poor. Similarly, a household which is deprived of 38 Percent of the 13 indictors is considered poor. Table 1 presents the dimensions, indicators, weights and deprivation cut offs for the Malawi multidimensional poverty index.

Table 1: Dimensions, indicators, weights and deprivation cut-offs for Malawi Multidimensional poverty index

Dimension	**Indicator**	**Deprivation cut-offs**
Education (1/4)	Literacy and schooling(1/8)	A household is deprived if all members aged 15+ have less than 8 years of schooling OR cannot read or write in any language.
	School Attendance (1/8)	A household is deprived if at least one child aged 6-14 is not attending school
Health and population (1⁄4)	Sanitation (1/16)	A household is deprived if the sanitation facility is not flush or a VIP latrine or a latrine with a roof OR if it is shared with other households
	Drinking Water (1/16)	A household is deprived if their main source of water is unimproved OR it takes 30 minutes or more (round trip) to collect it
	Nutrition (1/16)	A household is deprived if there is at least one child under 5 who is either underweight, stunted or wasted
	Food Security (1⁄16)	A household is deprived if, in the past 12 months, they were hungry but did not eat AND went without eating for a whole day because there was not enough money or other resources for food

Dimension	Indicator	Deprivation cut-offs
Environment (1⁄4)	Electricity (1⁄16)	A household is deprived if they do not have access to electricity
	Rubbish Disposal (1⁄16)	A household is deprived if rubbish is disposed of on a public heap, is burnt, disposed of by other means or there is no disposal
	Housing (1⁄16)	A household is deprived if at least two of the following dwelling structural components are of poor quality: -Walls (grass, mud, compacted earth, unfired mud bricks, wood, iron sheets or other materials) -Roof (grass, plastic sheeting or other materials) -Floor (sand, smoothed mud, wood or other materials)
	Asset Ownership (1⁄16)	A household is deprived if they do not own more than two of the following basic livelihood items: radio, television, telephone, computer, animal cart, bicycle, motorbike or refrigerator AND do not own a car or truck
Work (1⁄4)	Unemployment (1⁄12)	A household is deprived if at least one member aged 18-64 has not been working but has been looking for a job during the past four weeks
	Job diversity (1⁄12)	A household is deprived if all working members are only engaged in farm activities, household livestock activities or casual part-time work (ganyu)
	Child Labour (1⁄12)	A household is deprived if any child aged 5-17 is engaged in any economic activities in or outside of the household

Source: Author’s construction from document review

3.5 Independent variables

Education

It is inherently difficult to measure education. In the literature, years of schooling is often used as a proxy (Hofmarcher, 2021). However, the Malawi-integrated household surveys (IHS) do not directly ask for years of schooling. Instead, respondents were asked to report the highest-class level they had ever attended. An attempt was made to estimate the years of schooling from the education categorical variable. For example, if an individual has attended secondary form one, it is considered that they have completed nine years of schooling.

However, this method of calculating years of education would be inaccurate, because it does not account for class repetition. For instance, an individual who repeated Standard 8 despite passing exams but was not selected for a secondary school, and later achieved Form 4 as their highest level of education, would be considered as having completed 12 years of schooling, when in reality it should be more than 12. The same issue applies to individuals who repeated Form 4 despite passing the exams but were not selected for a university. Errors in measuring education could lead to a potential endogeneity problem in the regression model (Cameron & Trivedi, 2010). To mitigate this issue, the presence of a school in a cluster was used as a proxy for education.

Control variables

The control variables used in this study include household size, climate shocks, area of residence, percentage of male-headed households, age of the household head, and other cluster characteristics such as the availability of health care centres and community markets. Table 2 provides the definitions of all independent variables used in the study, including their a priori expectations.

Table 2: Variable definitions and their expected signs

Variable	Definition and measurement	Expected sign
Household size	A continuous variable capturing number of individuals within a household	−/+
Residence	Location of the cluster (rural=1, urban=0)	+
Age	A continuous variable capturing the average age of household heads in a cluster	−/+
Male-headed	Percentage of male-headed households in a cluster	+
Dependency ratio	Dependents, both young (under 18 years old) and elderly (65 years and older) as percentage of working age group (18-64)	+
Climate shock	Number of households that were affected by a climate shock	+
Market access	A dummy variable capturing availability of a market (daily or weekly) in the community	−
Health centre	A dummy variable indicating availability of a clinic or hospital in the community (yes=1)	−
Schools	A dummy variable indicating availability of schools, public or private (yes=1)	−

Source: Author's construction

3.6 Diagnostic tests

Model specification tests

Specification tests for spatial effects

The Moran's I test for spatial dependence helps to detect the existence of the dependence without specifying the source. It does not specify whether the spatial autocorrelation emanates from the dependent variable, the error term, or from the exogenous variables. To explicitly specify the source of spatial dependence, various Lagrange multiplier (LM) tests have been developed. Anselin (2009) developed LM tests for spatially lagged error terms and spatially lagged dependent variables. However, the challenges with these LM tests are that they have power over the other alternatives.

That is, the LM error test rejects the null in the presence of spatial lag, and on the other hand, the LM lag test rejects the null in the presence of spatial error.

To resolve this, robust counterparts of these tests were developed (Elhorst, 2014). Robust LM tests are used only when both LM error and LM lag tests reject the null hypotheses, and in the case where both robust LM tests are significant, the one with a higher value is preferred. Joint LM tests were also developed to test the joint significance of spatial parameters in the SARAR and SDM models (Anselin, 2022). Therefore, in this study, LM tests will be run sequentially, beginning with non-robust tests, followed by robust LM tests.

3.7 Chapter summary

This chapter has presented and explained in detail the estimation methods used to address the research questions or objectives. In summary, the study utilised the fifth Integrated Household Survey data (2019/2020) collected by the National Statistical Office of Malawi. The dataset is available online at the World Bank's Microdata Library, under the Living Standards Measurement Study (LSMS) at https://doi.org/10.48529/mpyk-ds48.

The Malawi multidimensional poverty index, the dependent variable, was constructed using the Alkire and Foster method developed in 2011. Global Moran's I and Geary's C statistics were employed to assess spatial dependency, examining whether multidimensional poverty levels in neighbouring clusters are related. The presence of spatial dependency necessitates the estimation of a spatial regression model; however, it is essential first to identify the correct spatial regression model that adequately captures the nature of spatial dependency. To achieve this, Lagrangian Multiplier tests, including robust versions, were used.

Subsequently, a spatial lag regression (SAR) model was employed to estimate the influence of multidimensional poverty in one cluster on poverty levels in neighbouring clusters. From the spatial regression model, marginal effects were computed to estimate the spatial spillover effects of education on multidimensional poverty.

CHAPTER FOUR
EMPIRICAL RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the findings of the study. It begins by laying out the summary statistics of the variables used in the study. After the summary statistics, the chapter presents the results from the tests for spatial autocorrelation. Lastly, it presents the results obtained from spatial lag model and corresponding marginal effects.

4.2 Descriptive statistics

Table 3 summarises the multidimensional poverty levels in Malawi, categorized by area, and analysed over time. At the national level, the results show that, in 2019/2020, approximately 61% of Malawi individuals lived in multidimensional poverty. Regarding the intensity, on average, a poor person was deprived in 51% of the weighted indicators. A multidimensional poverty index of 0.312 indicates that if all Malawians were poor, they would be deprived of 31% of the weighted indicators.

In relation to multidimensional poverty by area of residence, the findings reveal that rural residents experience greater deprivation than their urban counterparts. Specifically, approximately 66% of individuals in rural areas live in multidimensional poverty, compared to 30% in urban areas. Similarly, regarding the intensity of poverty, the results indicate that, on average, a poor individual in a rural area is deprived in about 52% of the weighted indicators, compared to 48% for a typical urban resident. The urban MPI (0.148) is lower than the MPI for rural individuals (0.342).

At the regional level, the results indicate that the central region has the highest percentage of individuals experiencing multidimensional poverty (62.56%), followed by the southern region (61.24%). Conversely, the region with the lowest percentage of individuals suffering from various forms of poverty was the northern region (53.66%). Additionally, the northern region exhibited the lowest MPI score (0.269) compared with the southern (0.314) and central regions (0.322). Regarding the intensity of multidimensional poverty, the results demonstrate that an average poor individual from the northern region faces the same level of deprivation in terms of weighted indicators as an average individual from either the south or central region, albeit slightly lower in intensity for the former.

Table 3: Multidimensional poverty in Malawi

Area	M0	H	A
National	0.312	60.83%	51.25%
Urban	0.148	30.90%	47.91%
Rural	0.342	66.37%	51.54%
Northern region	0.269	53.66%	50.15%
Central region	0.322	62.56%	51.52%
Southern region	0.314	61.24%	51.26%

Source: Author's construction based on IHS V data, 2019/20

Regarding the changes in Malawi's multidimensional poverty over time, the results presented in Table 4 show that multidimensional poverty declined in the country between 2016 and 2019. However, this decrease was minimal. The MPI score decreased slightly from 0.332 in 2016 to 0.312 in 2019. The incidence of multidimensional poverty decreased from 64% in 2016 to 61% in 2019. The intensity of poverty declined slightly from approximately 52% to 51% in 2019.

Table 4: Changes in Malawi MPI over time

Measure	t_0=2016	t_1=2019	Absolute change $\Delta t = (t_1 - t_0)$
M0	0.332	0.312	-0.02
H	64.00%	60.83%	-3.17%
A	51.88%	51.25%	-0.63%

Source: Author's calculations based on IHS IV and V data

Table 4 presents summary statistics for the clusters. The subsequent analyses utilized the most recent data from Malawi's living standards measurement survey, specifically the fifth Malawi integrated household survey (IHS V). The IHSV collected data from 717 clusters or enumeration areas that provided geographical coordinates for households. These coordinates were offset within a 5-km radius to ensure the security and de-identification of respondents. Consequently, this study examined the characteristics of all households at the cluster level. However, it is important to note that the geographical coordinates for the nine clusters were not recorded, and as a result, these clusters were not included in the spatial analysis of multidimensional poverty.

Table 5: Cluster average values for the variables used in the estimations

Variable	Mean/frequency	Standard deviation	Minimum	Maximum
Household size	4.42	0.63	2.81	6.94
Age of household head	43.20	4.85	30.94	58.13
HH climate shock (%)	61.43	26.91	0.00	100.00
Male headed households (%)	69.52	15.18	12.50	100.00
Dependency ratio (%)	60.19	26.62	2.38	181.82
Rural=1 (%)	81.73			
School=1 (%)	46.86			
Health clinic=1(%)	25.10			
Community market=1(%)	51.05			
Number of clusters	717			

Source: Author's calculations based on IHS V data

The cluster summaries reveal that, on average, 16 households were sampled in each cluster, with about 70% of them being headed by males. The largest cluster encompassed 17 households, while the smallest cluster had 4 households. The largest household had 7 members, whereas the smallest household had 3 members. About 60% of the cluster's population were dependants (aged either below 18 or above 60 years). Approximately 61% of households experienced a climate shock. Reflecting the country's urbanization status, 82% of the clusters were in rural areas. Furthermore, 25% of the clusters had access to a health facility, and 46% of the communities had a school. Around 51% of the clusters had access to a community market, either on a weekly or daily basis.

4.3 Spatial distribution of Multidimensional poverty in Malawi

Figure 3 illustrates the geographical distribution of multidimensional poverty in Malawi. The darker colours represent areas with higher levels of multidimensional poverty. Upon analysing the distribution of multidimensional poverty across districts, it becomes apparent that districts close to one another or those that share borders tend to have similar poverty levels. This observation suggests the presence of positive spatial dependence of multidimensional poverty within the country. Additionally, the figure reveals that districts in the northern region of Malawi experience lower poverty levels than districts in the central and southern regions. Furthermore, it is noteworthy that the four cities of Malawi, namely Mzuzu, Lilongwe, Zomba, and Blantyre, exhibit the lowest levels of multidimensional poverty.

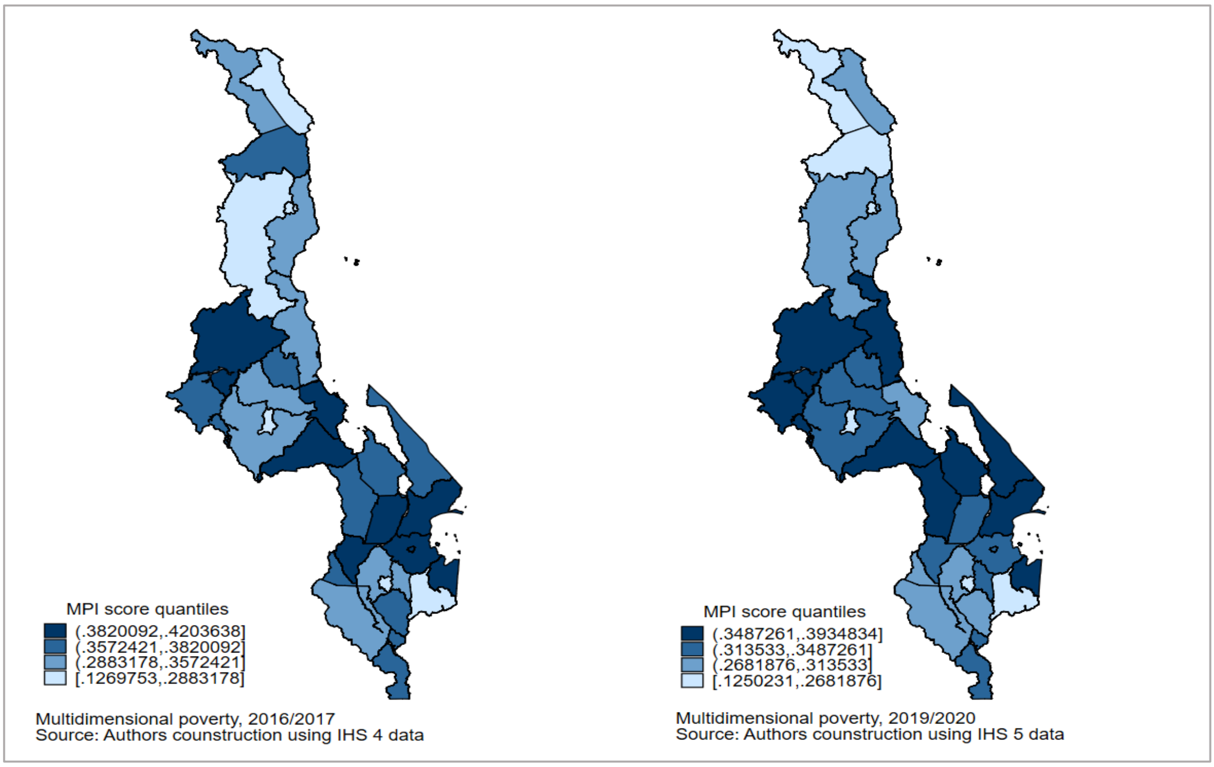


Figure 3: Spatial distribution of Multidimensional poverty by districts

4.4 Measures of Spatial dependence

To examine whether neighbouring clusters depend on each other, the study employed the multivariate Moran's I test for spatial autocorrelation. Moran's I is test that is run after running an OLS regression with spatial data. It performs the spatial autocorrelation test among OLS residuals. The findings of multivariate Moran's I test are presented in

Table 6. The Chi-square statistic of 26.76 is highly statistically significant, indicating that neighbouring clusters depend on each other.

Table 6: Multivariate Moran’s I test for spatial dependence

Test	Chi-square (1)	P-value
Moran’s I	26.76	0.000

Source: Author’s calculations based on IHS V data

However, the multivariate Moran’s I test does not explicitly indicate the source of spatial dependence, whether it emanates from the dependent variable (multidimensional poverty), the explanatory variables or the error terms. Therefore, to examine whether multidimensional poverty levels in one cluster is influenced by multidimensional poverty levels in neighbouring clusters, this study employed the univariate global Moran's I and Geary's C tests for spatial autocorrelation. The findings are presented in Table 7. Both the coefficient estimates for Moran's I and Geary's C statistics are positive and statistically significant. This implies that the levels of multidimensional poverty in one cluster are influenced by the levels of multidimensional poverty in neighbouring clusters. The Moran's scatter plots depicted in Figure 3 further demonstrate the positive spatial correlation in multidimensional poverty. The fitted lines in the Moran's plots for MPI scores and incidence (H) display a positive slope, indicating that a cluster's multidimensional poverty is influenced by the levels of multidimensional poverty in its neighbouring clusters.

Table 7:Univariate spatial dependence tests results

Moran's I					
Variables	I	E(I)	sd(I)	z	p-value*
M0	0.410	-0.001	0.034	11.941	0.000
Geary's c Variables	c	E(c)	sd(c)	z	p-value*
M0	0.628	1.000	0.037	-10.177	0.000

*2-tail test

Source: Author’s calculations based on IHS V data

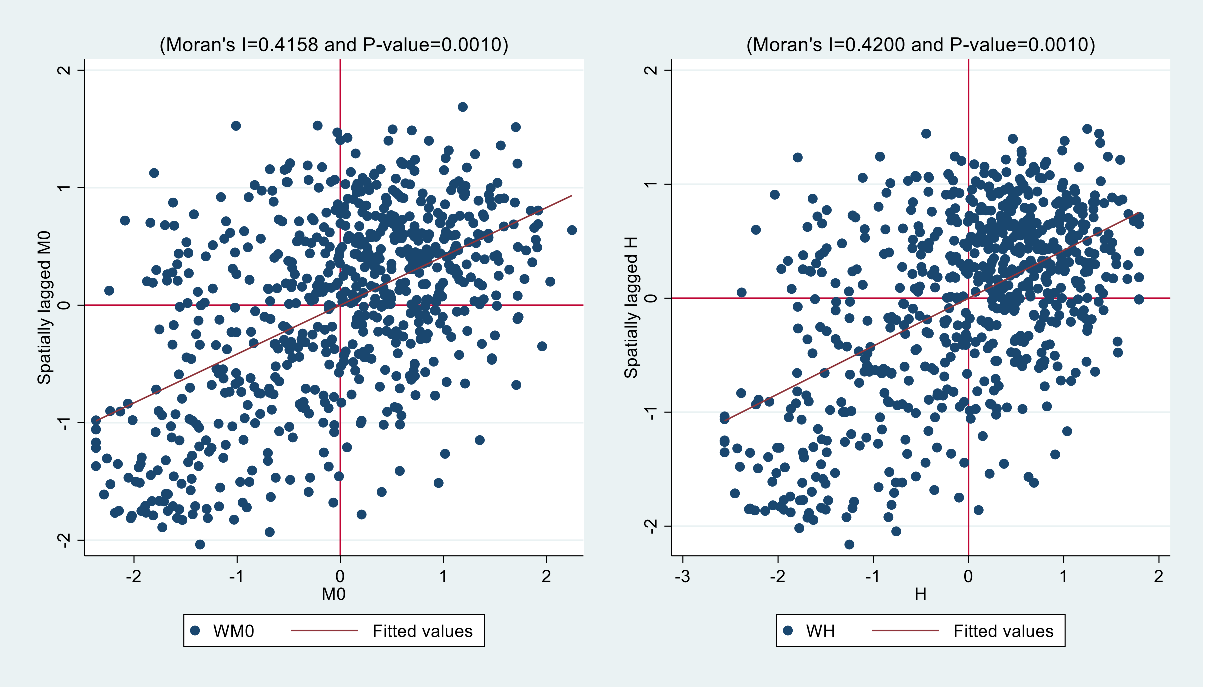


Figure 4: Moran's I scatter plots of multidimensional poverty index and incidence.
Source: Author's construction based on IHS V data

4.5 Spatial regression model specification tests

The presence of spatial correlation necessitates estimating the spatial regression model to accommodate it. Failing to account for the presence of spatial correlation in the model specification, despite its existence in the underlying data generating process, leads to biased, inefficient, and inconsistent estimates (omitted variable bias) (Le Gallo, 2021). However, different spatial regression models can be estimated depending on the form or type of spatial dependence present in the data generating process. Spatial dependence may arise when values of the dependent variable in a particular cluster are correlated with the values of the dependent variable in neighbouring clusters (spatial lag), or when unobserved characteristics in a particular area are correlated with unobserved characteristics in the neighbouring clusters (spatial error), or when observed characteristics in neighbouring clusters are correlated with values of the dependent variable in a particular cluster (spatial X). Therefore, to detect the form of spatial dependence and thus choose a model that best fits the data, Lagrange multiplier (LM) tests were employed.

The results of the LM tests are presented in Table 7. The findings indicate that the Chi-square statistics for both the spatial error and spatial lag specifications are significant. This suggests that both the spatial lag and spatial error models are appropriate. However, both the LM-Error and LM-Lag have power against the other alternative, meaning that either test rejects the null hypothesis in the presence of the other. To correct this, robust LM tests were developed. When both the robust LM error and lag tests are also significant, the model with the most significant statistic is selected (Anselin et al., 1996). The findings indicate that both the robust LM tests were significant. However, the test statistic for the spatial lag model is the most significant. Hence, a spatial lag model was selected.

Table 8: Lagrange multiplier tests for spatial dependence

Test	Chi-square	df	p-value
Spatial error:			
Moran's I	3.213	1	0.001
Lagrange multiplier	9.195	1	0.002
Robust Lagrange multiplier	5.650	1	0.017
Spatial lag:			
Lagrange multiplier	18.032	1	0.000
Robust Lagrange multiplier	14.486	1	0.000

Source: Author's own estimation in Stata

4.6 Spatial lag regression model results

Based on the findings presented in Table 8, a spatial lag model was estimated, and the corresponding results are presented in Table 9. The coefficient (W.M0=0.204) for the spatial lag is both positive and statistically significant, as evidenced by the p-value being less than 1%. This implies that the multidimensional poverty levels in a specific cluster are positively affected by the multidimensional poverty levels in surrounding clusters. Furthermore, the coefficient for the spatially lagged dependent variable serves as an indicator for the extent of spatial autocorrelation while accounting for the influence of other variables. This finding demonstrates the concept of agglomeration effects in multidimensional poverty. It explains that when multidimensional poverty becomes concentrated in neighbouring areas, it tends to persist and even increase. This is because socioeconomic factors that contribute to high multidimensional poverty in one area often spill over to nearby areas, creating a cycle that reinforces multidimensional poverty.

Regarding the other variables, the findings indicate that household size, climate shocks and dependency ratio are associated with higher levels of multidimensional poverty. In contrast, the availability of a school, availability of a community market, age of the household head and male headed households lowers multidimensional poverty.

As previously mentioned, and cautioned by LeSage and Pace (2021), the coefficients derived from the spatial lag model should not be interpreted directly, but rather computed as marginal effects. Consequently, instead of interpreting the results of the spatial lag regression, the focus is on interpreting the marginal effects presented in Table 10.

Table 9: Estimation results from the spatial lag (SAR) model

	Spatial lag model	
M0		
School	-0.030***	(0.007)
Household size	0.011**	(0.006)
Rural	0.109***	(0.012)
Climate shock	0.005***	(0.001)
Health clinic	-0.021**	(0.008)
Community market	-0.017**	(0.007)
Age_head	-0.002***	(0.001)
Male_headed	-0.001**	(0.000)
Dependency ratio	0.001***	(0.000)
_cons	0.188***	(0.043)
W.M0	0.204***	(0.042)
N	708	

Standard errors in parentheses

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

Source: Author's own estimation in Stata

4.7 Marginal effects: Direct and indirect (spillovers) effects

The calculation of marginal effects from a spatial lag model results in a matrix of partial and cross-partial derivatives. The partial derivatives represent direct effects, whereas the cross-partial derivatives represent indirect or spillover effects. The computed marginal effects are displayed in Table 10

The findings demonstrate that having a school within a cluster reduces multidimensional poverty, both within the cluster and in neighbouring clusters. Specifically, clusters that have a school have an average multidimensional score that is 0.03 lower than clusters without a school. Additionally, clusters with neighbouring clusters that have a school are 0.007 less poor than clusters without neighbouring schools. The availability of schools has a spillover effect because government schools are congestible public goods. When a school is available in one area, residents from neighbouring clusters can also attend, if the school is not already full. This means that even if social services, like schools, are not available in one cluster, individuals can still access services in neighbouring clusters. This finding also explains the socio-economic interdependence among geographical areas, especially those that are closer or share borders.

Regarding the control variables, the findings show that climate shocks in Malawi have both direct and spillover effect on multidimensional poverty. They indicate that climate shocks not only affect the communities directly affected, but also have ripple effects on nearby communities. More specifically, for each additional household affected by a climate shock within a cluster, the cluster's multidimensional poverty index increases by 0.005. Additionally, neighbouring clusters experience an increase of 0.001 in their multidimensional poverty index.

Having a healthcare facility in a cluster has a positive effect on reducing multidimensional poverty, not only within the cluster itself but also in neighbouring clusters. Specifically, clusters that have a healthcare facility have an average multidimensional score that is 0.021 lower than clusters without such facilities. Moreover, clusters that are located near clusters with healthcare facilities tend to be 0.005 less impoverished than clusters without neighbouring healthcare facilities. The presence of a healthcare facility allows individuals to access healthcare services easily, leading to improved health outcomes. This aligns with human capital theory, which suggests that improved health enhances worker productivity and ultimately leads to higher income levels. As a result, higher income levels contribute to a reduction in multidimensional poverty.

The presence of a market in one community reduces multidimensional poverty in that community as well as multidimensional poverty in neighbouring communities. Clusters that have a market have an average multidimensional score that is 0.017 lower than clusters without a market. Additionally, clusters with neighbouring clusters that have a market are 0.004 less poor than clusters that together with their neighbours do not have a community. The availability of markets allows households, particularly smallholder farmers, to sell their goods and generate income. This additional income then enables these households to access improved housing, education, healthcare, and nutrition, thus effectively decreasing levels of multidimensional poverty. Like the effect of the availability of a school, having a market in one cluster does not exclude neighbours from using or benefiting from it.

Table 10: Marginal effects: Direct, indirect and total effects

	Direct effect	Indirect effect	Total effect
School	-0.030^{***}	-0.007^{***}	-0.037^{***}
Household size	0.011^{**}	0.003^{*}	0.014^{**}
Rural	0.109^{***}	0.027^{***}	0.136^{***}
Climate shock	0.005^{***}	0.001^{***}	0.007^{***}
Health clinic	-0.021^{**}	-0.005^{**}	-0.026^{**}
Community market	-0.017^{**}	-0.004^{**}	-0.022^{**}
Age_head	-0.002^{***}	-0.001^{**}	-0.003^{***}
Male headed	-0.001^{**}	0.000^{**}	-0.001^{**}
Dependency ratio	0.001^{***}	0.0001^{***}	0.001^{***}

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

Furthermore, the results show that household size directly affects multidimensional poverty positively, but this effect does not extend to neighbouring clusters. This means that clusters containing larger households tend to have higher levels of multidimensional poverty compared to clusters with smaller households. Specifically, having one additional household member increases the multidimensional poverty index by 0.011. This finding reflects the situation in Malawi, where many households live in extended families (McCarthy et al., 2016). As a result, one household head is responsible for providing for a larger number of individuals. For example, they must pay school fees for more children and provide food for more people. Consequently, the available resources are stretched thin and often insufficient to support everyone in the household. As a result, these households face food insecurity, children are more likely to drop out of school, and they may engage in economic activities to help support the household.

This finding is supported by the positive effect that the dependency ratio has on multidimensional poverty. The results indicate that clusters with a higher number of dependents, both young (under 18 years old) and elderly (60 years and older), experience higher levels of multidimensional poverty compared to clusters with fewer dependents. Specifically, a one percentage point increase in the dependency ratio within a cluster leads to a 0.001 increase in multidimensional poverty levels within that same cluster. Like the effect of household size, having more dependents means that the breadwinner must support a greater number of individuals. Consequently, the available resources are thinly shared among a larger number of people, insufficient to meet their needs.

The results also indicate that the age of the household head has a negative effect on multidimensional poverty. On average, clusters with older household heads have lower levels of multidimensional poverty compared to clusters with younger household heads. Specifically, each additional year of age decreases the levels of multidimensional poverty in a particular cluster by 0.002 and in neighbouring clusters by 0.001. The reduction in multidimensional poverty can be attributed to the fact that older household heads have accumulated more assets and wealth over a longer period than younger household heads. Consequently, older household heads are more economically and financially stable, enabling them to better support their households compared to younger households who are still in the early stages of asset accumulation. In addition to that, older household heads might have adult children who support them economically through domestic or international remittances.

Furthermore, the results indicate that clusters with a higher percentage of male-headed households have lower levels of multidimensional poverty, as compared to clusters with a relatively lower percentage of male-headed households. Specifically, a one percentage point increase in male-headed households within a cluster leads to a 0.001 reduction in multidimensional poverty for that cluster. This finding can be attributed to the greater economic engagement of men compared to women, particularly in rural areas.

Regarding the effect of location or residence area, the findings indicate that rural clusters experience higher multidimensional poverty compared to urban clusters. On average, the multidimensional poverty index for a rural cluster is 0.07 higher than that of an urban cluster, and having neighbouring rural clusters further widens the poverty gap by 0.01 between rural and urban clusters. Considering both direct and indirect effects, the overall level of multidimensional poverty in a rural cluster is 0.08 higher than that in an urban cluster. This result emphasizes the significance of urbanization in reducing multidimensional poverty.

4.8 Discussion of the main findings

The findings show that levels of multidimensional poverty in one area are positively affected by levels of multidimensional poverty in neighbouring areas. This finding is consistent with the research conducted by Turriago-Hoyos et al. (2020), Álvarez-Gamboa (2021), Khan (2023), and Ramírez (2017). The results also confirm the economic agglomeration theory discussed earlier. The existence of spatial dependence in the levels of multidimensional poverty across clusters can be explained by the economic interdependencies among clusters or areas that are near each other. For instance, neighbouring areas rely on each other for trade, infrastructure, and social services such as education and healthcare, which directly affect multidimensional poverty. Consequently, any changes in these factors in one area not only affect the levels of multidimensional poverty in that area but also in the surrounding areas that depend on it.

The study results also demonstrate that education (the availability of a school) plays a crucial role in reducing multidimensional poverty levels in Malawi. The findings show that besides the direct effect education has on reducing multidimensional poverty within a cluster, its effect spills over to neighbouring clusters. That is, not only does an increase in the education level in one cluster reduce multidimensional poverty levels in that cluster but it also reduces multidimensional poverty in neighbouring clusters. The evidence that education has negative spillover effect on multidimensional poverty is notable because it is not commonly found in the existing literature. For instance, a similar study conducted in Malawi by Mussa (2017) examined the contextual effects of education on poverty and concluded that education at the community level has a spillover effect on poverty at the household level. Thus, the study confirmed the presence of spillover effects within the community, but did not find evidence of spillover effects across communities.

The negative spillover effect of education on multidimensional poverty can be explained by the pure theory of public expenditure by Samuelson (2024), which posits that education is a congestible public good with positive externalities. The benefits of education are not limited to those who have attained it; they are also enjoyed by others without any compensation (Abramitzky et al., 2021). According to the human capital theory, education enhances worker productivity (Folland et al, 2024), leading to economic growth (Todaro & Smith, 2020). This growth, in turn, creates more jobs and increases income, thereby reducing poverty. Economic interdependencies among neighbours further contribute to these positive effects, as high economic growth brings about job creation and trade. Moreover, educated individuals can share their knowledge with others within their communities, as well as neighbouring communities. This knowledge sharing fosters overall skill development, which in turn promotes economic growth and reduces multidimensional poverty.

Another significant finding is the spillover effect of climate shock on multidimensional poverty. The results show that apart from increasing multidimensional poverty in the areas directly affected, climate shocks have ripple effects on nearby communities. However, this finding is not common in the literature. Climate shocks such as floods, earthquakes, and landslides result in temporary or permanent displacement of households in Malawi (Abid et al, 2020). This displacement leads to an influx of people into the nearby communities. This, in turn, increases the need for housing, jobs, healthcare, and education, which puts strain on local resources and infrastructure, as has been the case in Malawi (Government of Malawi, 2023)

Additionally, and nearby communities often have economic ties to the affected area. For instance, if a climate shock damages a major transportation route or a primary agricultural area, it can result in disruptions to the supply of goods, not only in the affected communities but also in the neighbouring communities that depend on them. Floods and droughts in significant agro-ecological zones, such as the Lower Shire Valley and the lakeshore plains in Malawi, result in food shortages within these zones and in the surrounding regions (Maganga et al., 2021).

4.9 Summary of the main findings

The study aimed to investigate the effect of multidimensional poverty in neighbouring clusters on the level of multidimensional poverty in a specific area. Additionally, it sought to analyse how the education level in a particular area affects multidimensional poverty in neighbouring areas. The findings from the global Moran's I and Geary's C tests for spatial autocorrelation indicate that the level of multidimensional poverty in one cluster is associated with the level of multidimensional poverty in neighbouring clusters. The positive and significant spatial lag coefficient from the spatial regression model results confirms that multidimensional poverty in neighbouring clusters has a positive influence on multidimensional poverty in a specific cluster, while accounting for other factors. The results from the marginal effects suggest that education has both a direct and indirect effect on reducing multidimensional poverty in Malawi. This means that not only does the availability of schools in one cluster or area decrease multidimensional poverty levels in that cluster, but it also reduces multidimensional poverty in neighbouring clusters.

CHAPTER FIVE
CONCLUSION AND POLICY IMPLICATIONS

5.1 Conclusion

The study used the Malawi's fifth Integrated Household Survey (IHS V) data to investigate the spatial agglomeration effect of multidimensional poverty in Malawi. Specifically, the study sought to examine whether multidimensional poverty in one area is influenced by multidimensional poverty in neighbouring areas. Furthermore, the study sought to investigate the spillover effect of education on multidimensional poverty; the effect of education levels in one area on multidimensional poverty in neighbouring areas. The study employed the Malawi multidimensional poverty index, which is constructed using the Alkire-Foster methodology but customised to suit Malawi's specific needs and priorities and reflect the country's national understanding of poverty as well as policy priorities.

To achieve its objectives, the study employed the spatial lag model. Spatial analysis necessitates defining a spatial weight matrix, a square matrix that defines the proximity of geographical areas under study. Various spatial matrices have been used in previous studies, including the queen contiguity matrix, the inverse distance matrix (with or without a cut-off point), and the economic distance matrix (Ramirez et al., 2017; Wang et al., 2023). However, due to the sampling design of the IHS and the use of a survey cluster as a unit of analysis, made the use of contiguity matrix impractical. As a result, the study employed the inverse distance matrix with a distance band of 20 kilometres.

The study used the global Moran's I test for spatial autocorrelation to determine whether neighbouring clusters depend on each other, and the results confirmed the dependence of neighbouring geographical units or clusters. To examine whether multidimensional poverty levels in one cluster is associated with multidimensional poverty levels in neighbouring clusters, this study employed the univariate global Moran's I and Geary's C tests for spatial autocorrelation. The findings revealed that multidimensional poverty is spatially dependent.

To explicitly indicate the source of spatial dependence in the data generating process and thus choose the correct specification of spatial regression model, Lagrange multiplier (LM) tests and their robust versions were employed. The LM test results indicated that the spatial autocorrelation emanated from both the dependent variable (multidimensional poverty) and the error term. Since both LM error and LM lag tests were significant, the robust LM tests are employed. Following Anselin's (1996) advice, when both robust LM error and robust LM lag tests are significant, the model with the most significant test statistic is preferred. The robust LM test results indicated that the spatial autocorrelation is stronger among the observations of the dependent variable (MPI) relative to the observations of the error term. Therefore, the spatial lag model was estimated.

The results of the spatial lag regression model indicate the presence of a positive and statistically significant spatial lag parameter. This implies that the levels of multidimensional poverty in a particular cluster are positively influenced by the levels of multidimensional poverty in neighbouring clusters. This finding is consistent with the research conducted by Turriago-Hoyos et al. (2020), Álvarez-Gamboa (2021), Khan (2023), and Ramírez (2017). The existence of spatial dependence in the levels of multidimensional poverty across clusters can be explained by the economic interdependencies among clusters or areas that are near each other. For instance, neighbouring areas rely on each other for trade, infrastructure, and social services such as education and healthcare, which directly affect multidimensional poverty. Consequently, any changes in these factors in one area not only affect the levels of multidimensional poverty in that area but also in the surrounding areas that depend on it.

However, as advised by LeSage and Pace (2021), the coefficients from the spatial lag cannot be directly interpreted. Instead, the marginal effects should be calculated. By computing the marginal effects, we can determine both the direct and indirect (spillover) effects. The marginal effects indicate that education has both a direct and an indirect negative effect on multidimensional poverty. Specifically, higher levels of education not only reduce multidimensional poverty within a particular cluster, but also decrease multidimensional poverty levels in neighbouring clusters. This finding is notable because it is not commonly found in the existing literature. For instance, a similar study conducted in Malawi by Mussa (2017) examined the contextual effects of education on poverty and concluded that education at the community level has a spillover effect on poverty at the household level. Thus, the study confirmed the presence of spillover effects within the community, but did not find evidence of spillover effects across communities.

Regarding the control variables, the findings indicate that climate shocks have both direct and spillover effects on multidimensional poverty in Malawi. This suggests that climate shocks not only affect the directly affected communities but also have a ripple effect on neighbouring communities. Furthermore, the findings indicate that larger household sizes and higher dependency ratios are associated with higher levels of multidimensional poverty within a cluster. In contrast, the presence of a school, the presence of a community market, and the age of the household head are all factors that reduce multidimensional poverty within a cluster.

5.2 Policy implications

The findings indicate that levels of multidimensional poverty in one area are influenced by levels of multidimensional poverty in neighbouring areas. This discovery holds significant implications for policy, as the government is intensifying its efforts to achieve Sustainable Development Goal No. 1, which is to eradicate poverty in all its forms by 2030. This finding highlights the need for targeted and effective strategies to address multidimensional poverty. It suggests that a comprehensive approach is necessary to reduce or eliminate multidimensional poverty. To achieve this, anti-poverty programs should be focused on poverty hotspots; clusters that are highly dependent. This is because, the poverty reducing effect would be transmitted to neighbouring clusters making the intervention more effective than intended.

The findings also reveal that education plays a crucial role in reducing multidimensional poverty in Malawi. The results suggest that to effectively reduce multidimensional poverty, there should be increased investment and prioritization in education. This can be achieved by constructing more schools and implementing programs that specifically support individuals in pursuing further education. Furthermore, the finding that education has a multiplier effect on reducing multidimensional poverty highlights its significance as a powerful policy tool. This implies that the benefits of an education program targeted in one area extend to neighbouring areas, resulting in a larger impact than initially intended.

Finally, the study has shown that climate shocks result in increased multidimensional poverty. Moreover, the study reveals that these shocks not only affect the directly affected areas but also influence the surrounding regions. This finding emphasizes the critical importance for the country to improve its preparedness and response to climate shocks to effectively reduce their effect on multidimensional poverty. Implementing strategies such as integrating early warning systems that offer information about upcoming climate shocks, investing in risk mitigation measures like weather-indexed insurance, and implementing targeted social cash transfers can help alleviate the effect of climate shocks.

5.3 Limitations of the study

The author acknowledges the limitations of the study. IHS V collected data from 717 clusters or enumeration areas, which provided geographical coordinates for the households. However, the geographical coordinates of these nine clusters were not recorded. Consequently, these clusters were not included in the spatial analysis of multidimensional poverty. The exclusion of these nine survey clusters may have influenced the strength of spatial autocorrelation. This is because the exclusion of these clusters has created islands (clusters without neighbours) or led to some clusters having distant neighbours. According to LeSage and Pace (2021), the strength of spatial correlation decreases with distance. Therefore, these results should be cautiously interpreted.

5.4 Direction for Further Research

As an extension, this study can be extended by conducting a spatial analysis of multidimensional vulnerability to poverty. This analysis allowed us to identify groups of people or areas that are currently poor and in need of poverty alleviation strategies. However, expanding the study to spatially explore multidimensional vulnerability will enable researchers to identify areas or groups of people who are not currently poor but have a high chance of becoming poor in the future, hence needing poverty prevention strategies.

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