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Original Article

A spatial analysis of out-of-pocket payments for healthcare in Malawi

Martin Limbikani Mwale[1,*], Martina Mchenga[2] and Gowokani Chijere Chirwa[3]

[1]Department of Economics, 7 De Beer Rd., Stellenbosch University, 7600 Cape Town, South Africa
[2]Health Financing Unit (HFU), Ministry of Health, Capital Hill, Lilongwe, Malawi
[3]Economics Department, University of Malawi, Chancellor College

*Corresponding author. Department of Economics, 7 De Beer Rd., Stellenbosch University, 7600 Cape Town, South Africa. E-mail: martinresearch4@gmail.com

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Abstract

Out-of-pocket (OOP) expenditures on health remain high in many low- and middle-income countries despite policy efforts aiming to reduce these health costs by targeting their hotspots. Hotspot targeting remains inadequate, particularly where the OOP expenditures are related across geographic regions due to unequal demand, supply and prices of healthcare services. In this paper, we investigate the existence of geographical correlations in OOP health expenditures by employing a spatial Durbin model on data from 778 clusters obtained from the 2016 Malawi's Integrated Household Survey. Results reveal that Malawian communities face geographical spillovers of OOP health expenditures. Furthermore, we find that factors including household size, education and geographical location are important drivers of the OOP health expenditure's spatial dependency. The paper calls for policy in low-income countries to improve the quality and quantity of healthcare services in both OOP hotspots and their neighbouring communities.

Keywords: Healthcare, health financing, spatial analysis, determinants, geography

Key messages

- Malawian communities face geographical spillovers of out-of-pocket (OOP) expenditures.
- Household size, education and geographical location are important factors that drive this spatial dependency in OOP expenditures.
- The quality and quantity of healthcare services should be improved in both densely populated areas and their neighbouring communities, especially in low-income countries that operate overwhelmed public health facilities.

Introduction

Out-of-pocket (OOP) expenditures remain a huge form of financing healthcare in many low- and middle-income countries (LMICs), despite policy efforts aiming to reduce these healthcare costs in their hotspots. Globally, almost 100 million people are impoverished every year due to health expenses, and a majority of them are in Asia and low-income countries (Wagstaff *et al.*, 2018b). The existing empirical evidence from LMICs shows that the increased usage of OOP expenditures in LMICs mainly stems from insufficient financing of public health services and lack of social health insurance (Grigorakis *et al.*, 2016; Wirtz *et al.*, 2017; Myint *et al.*, 2018). Recent evidence from China, however, shows that OOP expenditures on health are geographically related (Zhang *et al.*, 2019). Therefore, the persistent increase in OOP expenditures on health in LMICs could also result from inadequate policy coverage. Policies that are limited to only targeting OOP health expenditures in their hotspots are ineffective, particularly where these health costs are related across geographic regions due to unequal demand, supply and prices of healthcare services (Zhang *et al.*, 2019). These hiccups undermine the efforts towards the attainment of universal health coverage by curtailing the aims of ensuring people's access to healthcare without suffering financial catastrophe (WHO, 2010).

The Sub-Saharan region faces the highest rate of OOP expenditures on health that exceeds 35% of the total health spending (Wagstaff *et al.*, 2018a; Obse and Ataguba, 2020), yet no study has been conducted to understand whether these OOP expenditures are geographically correlated. Besides, evidence from China, cited above, which informed the design of this paper, may not be applicable to the sub-Saharan region due to differences in economic structures, disease burden and healthcare systems. Therefore, specific studies on the possible geographic spillovers of OOP expenditures in sub-Sahara countries remain more necessary but lacking. The dearth of empirical evidence on the topic, in the region, lenders design of OOP reduction strategies poorly informed and ineffective, in cases where there is unknown geographical dependence of OOP expenditures.

The geographical correlation of OOP expenditures could emerge in sub-Saharan countries due to differences in the quality of, and access to, healthcare between neighbouring areas within a country (Moscone *et al.*, 2019). Individuals that reside in areas with poor-quality health facilities or less number of the facilities seek care in the nearest areas that have good-quality and more healthcare structures (Yao and Agadjanian, 2018). The rising demand for healthcare in the host areas increases pressure on healthcare and drives up prices for health services (Sarma, 2009). Furthermore, the prevalent socioeconomic inequalities and demographic differences between neighbouring areas in the region could also alter the price for healthcare (Chuma and Maina, 2012). For instance, people from affluent communities follow affordable services in poor neighbourhoods, driving up the overall prices through increased demand (Pallegedara and Grimm, 2018). Therefore, the spillovers of demand, supply and price of healthcare services could be contributing to the well-established and wide spread catastrophic health spending for the poor (Obse and Ataguba, 2020).

Malawi is one of the countries in the sub-Saharan region, where OOP expenditures are a significant proportion of private health expenditure (Government of Malawi, 2017a). However, existing studies on the subject in the country are limited to estimating the determinants and incidence of the OOP expenditure (Wang *et al.*, 2015; Mchenga *et al.*, 2017; Nakovics *et al.*, 2020; Shin *et al.*, 2020). The closest study examines the exit time from catastrophic health expenditures, with no focus on their spatial spillovers (Mussa, 2016). The narrow focus of these studies could lead to the design of policies that only increase the access and quality of healthcare services in OOP hotspots but fail to adequately reduce the expenditures due to healthcare service demand pressure from the neglected surrounding areas.

Similar to most LMICs, Malawi has not yet publicly funded health insurance (Mchenga *et al.*, 2017). Moreover, in recent years, government contributions to total health expenditure have been consistently low with no significant change, from 9.3% in 2012, to 9.4% in 2019 (Unicef. 2020). This is an indication that many people risk incurring high healthcare costs, despite the fact that the country provides free primary healthcare services in its public facilities (Abiiro *et al.*, 2014). Due to inadequate health financing, Malawi's free healthcare system faces numerous supply-side bottlenecks that make the attainment of the universal health coverage goals challenging. These include shortage of medicines, limited emergency services, lack of health personnel and few health facilities, poor health workers attitudes and poor quality of service provision (Abiiro *et al.*, 2014). Consequently, most people procure prescription medicine from pharmacies OOP, and some Malawians obtain healthcare from private facilities at a user fee (Wang *et al.*, 2015). Therefore, the OOP expenditure remains an area that needs more research in Malawi and many other countries that use similar healthcare financing modalities.

In Malawi, only a few facilities meet good-quality standard healthcare provision. Therefore, findings from the evaluations of spatial spillovers in OOP expenditures on health become important, as people are forced to selectively utilize the facilities (bypassing) in search of good-quality health services (Nakovics *et al.*, 2020). This paper, hence, investigates whether Malawian OOP expenditures on health are geographically related and explore factors that determine the spatial spillover of the OOP expenditures. OOP payments spatial spillovers, also here referred to as spatial dependency, is defined as the relationship between OOP expenditures on health across areas. We use data from a Living Standards Measurement Survey—Malawi's Fourth Integrated Household Survey (IHS4; National Statistical Office, 2017)—and employ a spatial durbin model (SDM) on data from 778 clusters obtained from the survey.

The rest of the paper is outlined as follows: the next section discusses the methods and data used in detail, followed by the results section. After which, the discussion section follows and then the conclusion and policy implication of the results.

Methods

Spatial weight matrix

The spatial relationship between OOP expenditures and their determinants in Malawi can be established by measuring the distance between two areas, with spatial contiguity as a common metric between the two units. One can establish adjacency between the units in three main ways: rook contiguity where two regions share a common border, bishop contiguity that has the regions sharing common vertex without a common edge and queen contiguity whereby two regions share a common border or vertex (Li *et al.*, 2007). The Malawi IHS4 survey that this study uses provided geographical coordinates at the cluster level [enumeration areas (EAs) randomly sampled within each district]. We constructed a spatial weight matrix D_{ij} between cluster i and cluster j using queen contiguity because it closely describes the classical health-seeking behaviour of Malawian households; the health facilities that people visit are not restricted geographically—by boundary or vertex (Iyer *et al.*, 2020). Furthermore, the IHS provides centroids (points) of the survey clusters, not polygons. The points make line boundaries non-applicable, further justifying our usage of queen contiguity in the creation of the weighting matrices using measured distance between the cluster centroids.

Spatial autocorrelation tests

Once the distance between two units is established, the next step is to test the spatial autocorrelation of the outcome using the Moran's I index of the Exploratory Spatial Data Analysis (ESDA). A spatial econometric model is then estimated conditional on the ESDA, indicating the presence of spatial autocorrelation (Fischer and Griffith, 2008). We divided the ESDA into global spatial autocorrelation analysis that used Moran's results and the local spatial associations that used the map of Malawi to show local spatial associations. The Moran's I value lies between −1 and 1. A value greater than zero shows positive spatial autocorrelation amongst the observations, while a value that is less than 0 indicates the presence of a negative spatial correlation between the observations. The value of 0 shows that there is no spatial correlation between the subjects.

The spatial model

The SDM includes spatial lagged regressors and capturing spatial spillovers of OOP expenditures while exploring the determinants of the spatial dependence. The models divide the influence of the determinants into direct and indirect effects. The direct effects are the relationship between the regressors and the local OOP expenditure, while the indirect effects are the impacts on neighbouring changes of the regressors on the local OOP expenditure (Zhang *et al.*, 2019). The functional form of our problem can be presented as follows:

$$lnOOP_i = c + \delta D_{ij} lnOOP_j + \beta X_i + \gamma D_{ij} X_i + \varepsilon_i \quad (1)$$

In equation (1), the OOP expenditure for households in cluster i is a function of a constant c, OOP expenditure in households of a different cluster j weighted by a matrix D_{ij}, a list of determinants X_i . δ is the spatial autoregressive term measuring the existence of OOP dependence across communities and ε_i is the error term, assumed independent and identically distributed.

Following Elhorst (2012), equation (1) can be rewritten into the following form:

$$lnOOP_i = (I - \delta D)^{-1} (\beta X_i + \gamma D_i X_i + \varepsilon_i) \quad (2)$$

In equation (2), I is a unit matrix of $N \times 1$, where N is the number of cross-sections. One can then present the spatial Leontief inverse matrix as follows:

$$(I - \delta D)^{-1} = I(\beta X_i + \gamma D_i X_i + \varepsilon_i) \quad (3)$$

Equation (2) shows the direct effects, while the remaining part shows indirect effects. The first-order condition with respect to the regressors becomes:

$$\frac{\partial lnOOP_i}{\partial X_{ir}} = M_r(D)_{ii} \quad \text{for all } i \text{ and } r \quad (4)$$

$$\frac{\partial lnOOP_i}{\partial X_{ir}} = M_r(D)_{ij} \quad \text{for all } i \neq j \text{ and for all } r \quad (5)$$

$$M_r(D) = (I_N - \delta D)^{-1} (I_N \beta_r) \quad (6)$$

In equation (6), β_r captures the effects of the independent variables. is the diagonal line element capturing the effects of a regressor in region i on the OOP expenditure of region i. This is the direct effect.$M_r(D)_{ij}$ is the off-diagonal element and captures the effects of a regressor in region j on the OOP expenditure of region i. This is the indirect effect, also known as the spatial spillover effect. The summation of the diagonal and off-diagonal effects is the total effect. We employ these models on the Malawi's LSMS-ISA dataset.

Data and variables

Malawi's Fourth Integrated Household Survey

The study used cross-sectional data from the Malawi's Fourth Integrated Household Survey (IHS-IV) collected in 2016 by the country's National Statistical Office (NSO). The IHS is nationally representative and captures multiple topics that measure living standards in Malawi. Among other things, the survey provides comprehensive information on households' consumption, income, employment, health, education and household characteristics. The survey uses a two-stage sampling procedure. In the first stage, it identifies EAs using the 2008 Population and Housing Census as a sampling distribution frame. The second stage of the sampling involves the random identification of households from the chosen EAs.[1] The IHS-IV interviewed 12 447 households in 778 EAs (clusters). The survey also provides geographical coordinates of the households that are offset at a 5-km radius to ensure the de-identification of the respondents for security. Therefore, this study models all households' characteristics averaged at a cluster unit. All communities sampled in the survey (778) were included in the analysis; there were no missing community-level variables.

Social demographic characteristics

Table 1 presents the cluster summary statistics.[2] We converted health spending into per capita terms to eliminate the differences or similarities in the cluster spending that may occur due to variations in average household size. Thus, we divide the total OOP expenditure by household size before averaging the result by cluster. The cluster summaries show that MK 3581.64 was spent on health by a representative household. Each household had a total of four members. In terms of education, 24% of the sampled households had heads who attended primary school. Those with: a junior certificate of education was about 19.8%, Malawi School Certificate of Education were about 13% and post-secondary were about 5%. Almost 11.9% of the households experienced a welfare shock. On average, 30.6% of household heads suffer from some chronic illness. Most households were male-headed (71.4%), and the average age of the household head was 43.

Table 1. Cluster average values for the variables used in the estimations

Variable	Mean	%
Per capita out of pocket expenditure (Malawi Kwacha)	3582	
Household size (count)	4.330	
Primary Education (proportion)		24.4
Junior Certificate of Education (proportion)		19.8
Malawi School Certificate of Education (proportion)		13.0
Post-Secondary Education (proportion)		5.10
Heads suffers chronic illness (proportion)		30.6
Household experienced a shock (proportion)		11.9
Male headed household (proportion)		71.4
Number of under 5 children (count)	7.700	
Number of people above 60 (count)	2.200	
Age of the household head (continuous)	43.311	
Distance to the nearest road (kilometres)	9.462	
Distance to the trading centre (kilometres)	35.712	
Distance to BOMA (kilometres)	23.540	
Distance to the border post (kilometres)	57.440	
Northern region (proportion)	0.199	
Central region (proportion)	0.339	
Southern region (proportion)	0.461	
Observations (number of clusters)		778

Source: Authors estimated from the IHS4.

Results

Geographical distribution of OOP expenditures in Malawi

Figure 1 presents the geographical distribution of per capita OOP expenditures in Malawi in 2016, with the darker colour showing higher per capita OOP expenditures. The figure shows that, except for the top first district (Chitipa), the northern and Central regions are in the fourth and third quartile groups with the highest level of per capita OOP expenditures, while the eastern and southern regions are, mainly, in the second and first quartile groups with the lowest OOP expenditures. Overall, the figure shows that most neighbouring districts have similar OOP distributions, while in other districts, OOP expenditures are not related. However, our formal analysis is at cluster levels as the IHS survey provided geo-coordinates as clusters. In Malawi the IHS clusters are aggregated within a district. The figure could, therefore, indicate within district and, between clusters correlation. This prompts us to formally test the existence of spatial dependency at the cluster level to uncover evidence using spatial econometric models.

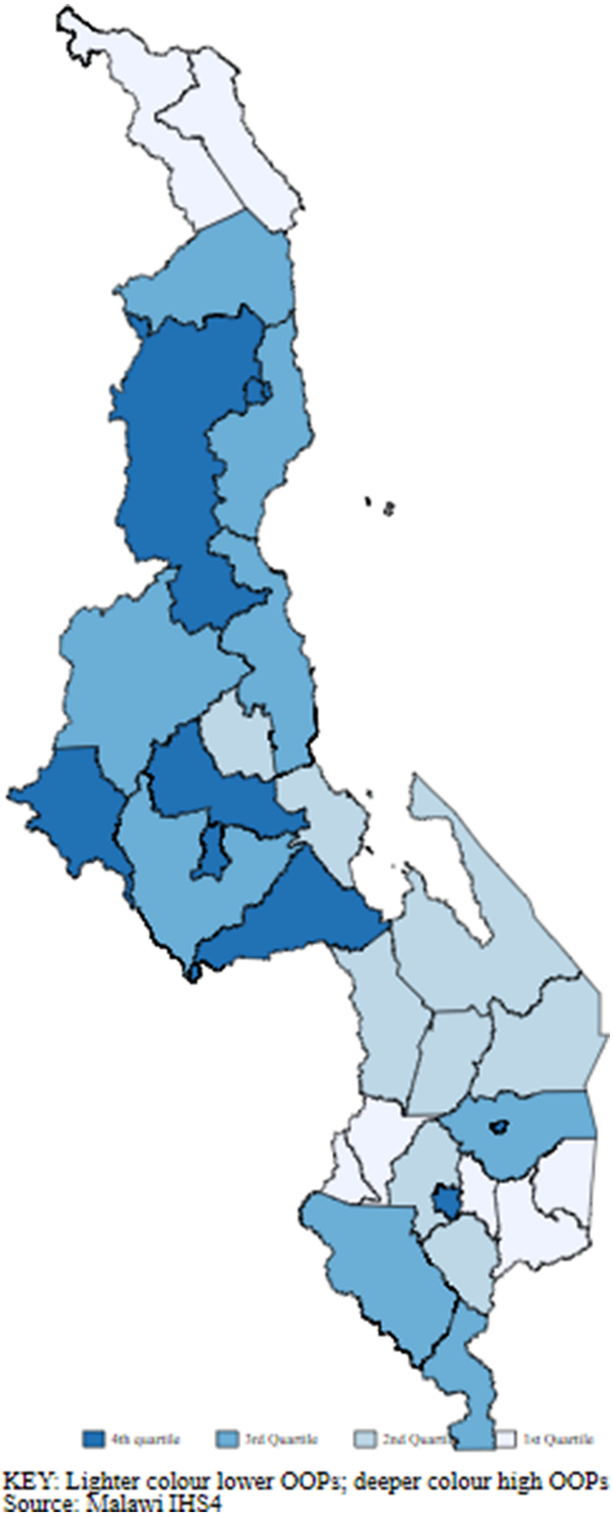

Figure 1. The geographical distribution of OOP in Malawi.

Table 2. Moran test for spatial dependence

Test	Chi-square (1)	P value
Statistic	16.72	0.000

Source: Authors estimated from the IHS4.

Spatial autocorrelation test results

Table 2 provides a result from a formal test of global spatial correlation of OOP expenditures in Malawi, the Moran's I test. The results confirm the presence of a positive spatial correlation at 1% significant level. We then proceed to estimate factors that drive the OOP expenditures and their spatial spillover effects, with results presented in the following section.

Factors that drive OOP expenditure in Malawi

In this section, we present empirical findings of the spatial determinants of OOP expenditures in Malawi. The first set of results shows factors that determine the OOP expenditures using a composite model that also provides results of the spatial dependence of OOP expenditures across communities in our sample. We then derive marginal effects of the determinants of the OOP expenditures that are split by whether the regressors affect the OOP expenditure of the community in which a set of households exist (direct effects) or whether the determinants affect the OOP expenditure of the neighbouring community (indirect effects). We also present the sum of these two effects, the total effects.

Table 3 presents the results of a composite model of factors that affect OOP expenditure in Malawi. The results confirm that there is spatial dependence in OOP expenditures across communities in the country; the spatial lag term is positive and significant. Concerning the spatial regressors that are important for the observed dependence, we observe that household size increases OOP expenditures. Increased education above junior secondary levels is associated with high OOP expenditures. Households with heads suffering from chronic illnesses and those that experienced any welfare shock also spend much on OOP expenditures. Households that live far away from a road have low OOP expenditures, while those far from the BOMA (rural growth centres) have high OOP

Table 3. The composite model of spatial determinants of OOP expenditures in Malawi

	(1) OOP expenditures (log)	(2) SE	(3) *P* value
Household size	0.157**	0.079	0.047
Junior Certificate Education	0.237	0.311	0.446
Senior Secondary Education	0.742*	0.400	0.064
Post-Secondary Education	1.772***	0.405	0.000
Suffering chronic illness	0.973***	0.202	0.000
Household experienced a shock	1.295***	0.336	0.000
Male headed household	0.057	0.299	0.849
Number of under 5 children	−0.044	0.207	0.833
Number of people above 60	0.207	0.370	0.576
Age of the household head	−0.005	0.013	0.710
Distance to the nearest road	−0.006*	0.004	0.075
Distance to the trading centre	−0.006***	0.002	0.004
Distance to BOMA	0.014***	0.002	0.000
Distance to the border post	−0.001	0.001	0.616
Central region	0.461***	0.108	0.000
Southern region	−0.109	0.120	0.361
OOP expenditures (log): spatial lag term	0.104***	0.027	0.000
Constant	5.815***	0.610	
Pseudo R-squared	0.283		
Observations	778	778	

Notes: ***$P<0.01$. **$P<0.05$. *$P<0.1$.
Source: Authors estimated from the IHS4.

expenditures relative to those living closer to these areas. Concerning regions, households in the central of Malawi incur more OOP expenditures relative to those from the northern region. These findings provide evidence of variables that are important spatial determinants of OOP expenditures. However, the results are composite; hence, their magnitude cannot be interpreted at face value because they only show net effects. We, therefore, split the results into direct, indirect and total effects in Table 4

Table 4 presents results for the disaggregated factors that affect OOP expenditures. Household size has both direct and indirect positive relationships with OOP expenditures. The result is larger for direct effects than indirect effects, entailing that communities with larger households spend more on OOP expenditures due to the increased number of people in their own area relative to the influence of the population for the neighbouring communities. Nevertheless, the significance of the indirect effects means neighbouring populations increase the pressure on OOP expenditures in adjacent areas.

Increased education attainment positively relates to OOP expenditures in both direct and indirect ways. The direct relationship between education and OOP is larger than the indirect association between the two. Therefore, the average household per capita OOP expenditure rises with increased

Table 4. Factors that affect OOP expenditures (marginal effects for total, direct and indirect determinants)

Dep. Var. OOP expenditures	Total	Direct	Indirect
Household size	0.166**	0.157**	0.009*
Junior certificate of Education	0.251	0.237	0.014
Malawi School Certificate of Education	0.785*	0.742*	0.043**
Post-Secondary Education	1.876***	1.772***	0.104***
Suffering chronic illness	1.030***	0.973***	0.057***
Household experienced a shock	1.371***	1.296***	0.076***
Male headed household	0.060	0.057	0.003
Number of under 5 children	−0.046	−0.044	−0.003
Number of people above 60	0.219	0.207	0.012
Age of the household head	−0.005	−0.005	0.000
Distance to the nearest road	−0.007*	−0.006*	0.000
Distance to the trading centre	−0.006***	−0.006***	0.000***
Distance to BOMA	0.015***	0.014***	0.001***
Distance to the border post	−0.001***	−0.001	0.000
Central region	0.489***	0.461***	0.027****
Southern region	−0.116	−0.109	−0.006***

Notes: ***$P<0.01$. **$P<0.05$. *$P<0.1$.
Source: Authors estimated from the IHS4.

education attainment of its own community members more than due to increased education attainment of adjacent communities. However, the significance of the indirect relationship between education and OOP expenditures means that education levels of the neighbouring community matter.

There is a positive relationship between distance to the nearest road and OOP expenditures. The relationship is significant only for the direct effects but not the indirect effects. Distance to a trading centre is negatively associated with OOP expenditures within the same community. However, distance to the trading centre in the neighbouring community positively associates with OOP expenditures in the mother community. Thus, communities that are far from a trading centre have low OOP expenditures, while those whose neighbouring communities are far from the trading have high OOP expenditures. Living away from the border post is negatively associated with per capita OOP expenditures. The relationship is, however, weak because it is close to zero. Moreover, this relationship is statistically insignificant when disaggregated into direct and indirect effects.

Besides, geographic locations show important heterogeneities. Living in the central region is positively associated with OOP expenditures relative to the northern region through both direct and indirect means. The direct relationship between the central region and OOP expenditure is larger than the indirect one. On the other hand, living in the southern region associates with reduced OOP expenditures, through only indirect channels. The result reveals that only neighbourhood community effects of OOP expenditures are significant in the southern region, and the relationship is overall negative.

Discussion

The aim of this paper was to establish the existence of spatial spillovers of per capita OOP health payments and identify factors that affect OOP variability using data from Malawi. Results from this paper are essential in guiding the formulation of effective welfare policies that promote access and equity across Malawi's healthcare system. The global spatial autocorrelation tests reveal that Malawi's per capita OOP expenditure is related across communities. Our results concur with evidence from China that shows the existence of spatial dependence in OOP expenditures on health (Zhang *et al.*, 2019). No similar paper has been written in sub-Saharan African. Nevertheless, Jeetoo (2020) shows that aggregate expenditures on health are spatially dependent in the region. This is evidence that sub-Saharan countries make geographically heterogeneous investment in healthcare service that could attract spatial dependence for OOP expenditures in health.

Regarding the influence of direct and indirect determinants of the per capita OOP expenditures, an SDM reveal that communities with more educated individuals or neighbouring areas with highly educated individuals incur high OOP expenditures. The result could emerge from increased health seeking of high-quality services by educated individuals, who often have better knowledge of good healthy living and can pay for health services due to high levels of income (Dismuke and Kunz, 2004). Arguably, this increases demand for healthcare beyond the supply that available public facilities are able to provide. In turn, the prices and hence the cost of private healthcare increase in both the resident communities and the adjacent areas.

OOP expenditure on health is positively related to average household size. The relationship is both direct and indirect. The result could reflect increased demand and hence healthcare prices due to high population density. Larger households demand far more healthcare, which oftentimes results in catastrophic health spending (Barasa *et al.*, 2017). In cases where the local supply of healthcare does not cater to the entire demand, residents move to facilities in neighbouring communities. Thus, pressure on the local health system affects not only the densely populated communities but also their adjacent areas.

Geographic location reveals heterogeneous findings. Communities that are far away from the road have low OOP expenditure, and the relationship is only direct. At the outset, one would marvel at the outcome with the anticipation that more remote areas are safe from health expenses. However, the result could also indicate that the areas are very isolated from neighbours and have limited access to health services that the people can spend on (Zere *et al.*, 2007). Furthermore, the people living in such remote areas are generally poor such that the result may imply inability to pay for good healthcare services (Mussa and Masanjala, 2015).

Another important geographic location factor that we identify is regional variations in OOP spillovers. Relative to the base category northern region, our results reveal that the central region has high both direct and indirect spatial OOP relationships. This has been shown by the high dependence in the SDM model output. This result could also be due to high levels of income in the region leading to increase in demand and prices for healthcare (Nakovics *et al.*, 2020). On the contrary, the southern region communities have only an indirect relationship that is negative. With the low socioeconomic status of the southern region (Benson *et al.*, 2005), it is possible that there is less demand for paid health services leading to downward pressure on prices. Alternatively, the supply for healthcare services in the southern region could be high, exerting downward pressure on prices.

The findings from this paper highlight concerns to the current healthcare financing policy space in Malawi. For instance, government intends to sequentially introduce optional paying wards in the government health facilities of selected district and all central hospitals (Chansa *et al.*, 2018). Despite the possibility of generating revenue, such a policy could maintain inequalities in healthcare access if the pricing mechanism follows the demand and supply of health services in selected districts ignoring spatial dependence of the health expenses. This is because, as this study has revealed, the existence of geographical dependence on health spending would entail that affluent people living in high-cost areas would bypass their health facilities to access cheap services in less-affluent areas. This, in essence, defeats the whole purpose of raising revenue in the high-cost areas.

In addition, these findings highlight healthcare service provision bottlenecks in Malawi. For example, the *de jure* government requirement is that health facilities be located within 5 to 8 km distance apart to ensure adequate coverage of healthcare services (Government of Malawi, 2017c). *De facto*, most areas do not meet this requirement, which leads to increased costs of seeking healthcare due to other admnistratrion costs, such as transportation. Moreover, previous evidence (Nakovics *et al.*, 2020) supports this by showing that, on average, a Malawian spends 2.07$ on transportation to health facilities. This is a serious limitation since 50.7% Malawians live below the poverty line of 1.25$ per day (International Monetary Fund, 2017). In addition, public health facilities are underequipped such that essential medication is only prescribed, and the patients purchase from private providers and pharmacies (Khuluza and Haefele-Abah, 2019). As we show that OOP expenditures are spatially dependent, these private purchases of treatment could be expensive not only due to increased demand within the vicinity of the private providers but also due to demand from the surrounding areas.

Even though we provide compelling evidence on the existence of spatial dependency of OOP expenditures in Malawi, our paper has some limitations. The scope of our paper was limited to investigating the existence of spatial dependency of OOP expenditures and identifying factors that matter only in the case of Malawi. Furthermore, the study did not examine the impact of socioeconomic status, urban-rural location and supply-side factors on geographical dependence in OOP expenditures on health. In addition, our data, the IHS4, like most of the living standard measurements surveys, are not specifically designed to generate health financing, utilization and expenditure data. Surveys that are specific to healthcare service utilization and expenditure provide such information. Future research, with available data, aim to circumnvent these limitations. Furthermore, as we only provide a generic evidence of spatial dependence in OOP expenditures on health, future studies should consider analysing a selected determinant of OOP expenditures from those we have shown to be significant in our analysis. In addition, the investigation should expound the transmission mechanisms through which the selected determinant spatially affects OOP expenditures. Nevertheless, this paper provides useful pioneering information, in both Malawi and sub-Saharan Africa, that health and welfare policy can leverage-OOP expenditures are spatially dependent. Therefore, policy interventions aimed at reducing health expenditure need to account for the spillovers.

Conclusion

The paper was motivated by the growing health OOP expenditures in low-income countries, to investigate their geographic dependence and factors that drive such spillovers. Employing the SDM on 778 clusters of the Malawi IHS4 data, we established that Malawian communities experience geographical spillovers of OOP expenditures. Household size, education attainment and region of residence drive this spatial dependency in OOP expenditures. Therefore, to effectively reduce OOP expenditures and their adverse effects on welfare, policy should not only aim to counter these expenditures in their hotspots but also in the neighbouring areas. This is particularly important for countries with overwhelmed and underfunded public healthcare systems that provide free services, such as Malawi, where OOP expenditures are much important to attain good-quality healthcare. In addition, improving both the quality and quantity of free healthcare is important, considering that the observed low OOP expenditures associated with poor regions could mean the inability to demand good-quality healthcare services due to destitution. The paper calls for future research to re-examine these OOP distributions in other low-income countries.

Data availability statement

The data used in the study is readily available and freely down loadable at https://microdata.worldbank.org/index.php/catalog/2936.

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Ethical approval

The paper did not require ethical approval as it used publicly accessible data that has no human identities.

Conflict of interest statement

The authors declare that they have no conflict of interest.

Notes

1. The IHS data are freely downloaded at https://microdata.worldbank.org/index.php/catalog/2939.
2. An IHS cluster has 25 surveyed households.

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