Partial mean and inequality effects on catastrophic health payments: methods with application to Malawi

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Partial Mean and Inequality Effects on Catastrophic Health Payments: Methods with Application to Malawi

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Abstract

This paper develops distribution-sensitive partial mean effects of determinants of out-of-pocket (OOP) catastrophic health payments. It also proposes methods that can be used to measure how changes in the distribution of the correlates of catastrophic health payments affect the incidence of catastrophic health payments; an inequality effect. The proposed methods are then applied to Malawian data from the Third Integrated Household Survey. The empirical application shows that a failure to account for these inequalities in the correlates, at least normatively, leads to a mismeasurement of the magnitudes of their partial effects. The results also indicate that the signs of the combined effects of a *ceteris paribus* unit increase in the mean and inequality effects are mixed; for some variables the inequality effect dominates the mean effect while for other variables a reverse pattern is observed.

Keywords: Mean effect; inequality effect; Malawi

1 Introduction

Out-of-pocket (OOP) payments on health care can be catastrophic if they severely disrupt household living standards. Such catastrophic payments can threaten living standards either in the short term through the sacrifice of current consumption, or in the long term, through depletion of assets, dissavings or accumulation of debts (Xu *et al.*, 2003; Russell, 2004; Wagstaff, 2006; Sparrow *et al.*, 2013). Additionally, faced with illness, households may decide to forgo treatment at the expense of depreciating their human capital (Sparrow *et al.*, 2013), and this may in turn also affect future household welfare. The financial protection of households from catastrophic payments is a widely accepted conception of fairness in health finance (WHO, 2000, 2010). Besides, the economic risks associated with catastrophic health care payments have motivated the recommendation for health care finance systems to transition towards some kind of pre-payment mechanism such as taxes or universal medical insurance (WHO, 2005).

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Households face significant binding constraints to reducing financial catastrophe. The identification of factors that influence catastrophic health payments is significant for health finance policy as it provides useful insights into the constraints that should be removed or relaxed to reduce or mitigate against the ill effects of financial catastrophe. The focus of the existing literature on determinants of catastrophic health payments (e.g. Su *et al.*, 2006; Pal, 2012; Li *et al.,* 2012; Narcı *et al.*, 2014) has been on the signs, magnitude, and statistical significance of the correlates of catastrophic health spending. In this case, the signs and magnitude of marginal effects are used to assess how the prevalence of catastrophic health payments responds to changes in the average levels of the correlates. However, in the extant literature, these mean effects are not adjusted for income-related inequalities.

The opportunity cost of health spending may not be the same between poor and rich households (O'Donnell et al., 2008). Consequently, from a social welfare perspective, one might wish to place a normative interpretation on the relationship between the incidence of catastrophic payments and its correlates, such that more weight is given to the effects of changes in factors that are concentrated among poorer households. Although Wagstaff and van Doorslaer (2003) develop distribution-sensitive aggregate measures of the prevalence of catastrophic health spending, the idea is yet to be extended to the study of determinants of catastrophic payments. Allowing for income-related inequalities in the effects of explanatory variables would thus ensure that the partial effects reflect the differentials in opportunity costs. Most importantly, a failure to account for these socioeconomic inequalities in the partial effects may at least normatively lead to a mismeasurement of the partial effects in terms of their magnitude, and hence, inaccurate and misleading policy implications.

In addition to adjusting the partial mean effects of the correlates for distribution sensitivity, it may also be useful to see how changes in income-related inequalities in the correlates themselves affect the prevalence of catastrophic health payments. Does rising income-related inequality in the correlates lead to an increase or a decrease in the prevalence of catastrophic health payments? For instance, a rise in inequality in a factor which in turn implies increasing concentration of the variable among the rich may lead to a reduction or an increase in the incidence of catastrophic health payments depending on how (in terms of sign) the factor affects the likelihood of catastrophic health payments.

This paper addresses these shortcomings by making three contributions to the literature on OOP catastrophic health payments. First, the paper develops methods that can be used to account for distribution-sensitivity in the partial effects of explanatory variables on the incidence of catastrophic health payments, a distribution-sensitive mean effect. Second, the paper proposes methods that can be used to measure how changes in the distribution of the correlates of catastrophic health payments affect the incidence of catastrophic health payments, an inequality effect. Finally, the proposed methods are then applied to Malawian data from the Third Integrated Household Survey.

The rest of the paper is structured as follows. Section 2 develops distribution-sensitive partial mean effects, and partial inequality effects. Section 3 presents the Malawian context, and describes the data and variables used. This is followed by the empirical results in Section 4. Finally, Section 5 concludes.

2 Methods

The two partial effects that I develop in this paper are predicated on a linear regression specification of average marginal effects from a probit model of catastrophic health payments. This regression includes variables that are hypothesized to influence the likelihood of catastrophic health payments. The linearized partial effects are then used to derive methods for measuring how changes in the covariates and their income-related inequalities affect the incidence of OOP catastrophic health payments. I develop the methods next.

2.1 A partial effects specification of a probit model

Consider a household i, and let $s_i \in [0, 1)$ be the share of per capita health spending in total per capita household expenditure net of food. Total per capita household expenditure net of food measures a household's ability to pay for health (Wagstaff and van Doorslaer, 2003). One can alternatively define the fraction of health spending without deducting food expenditure. The share of a household's OOP is considered catastrophic if it exceeds a fractional threshold z i.e. $s_i > z$. Typically, binary probit or logit models are used to model the determinants of catastrophic health payments (e.g. Su *et al.*, 2006; Pal, 2012; Li *et al.,* 2012; Narcı *et al.*, 2014).

Let y_i be a binary indicator of catastrophic spending defined as; $y_i = 1$ if $s_i > z$, and $y_i = 0$ otherwise. The probability, p_{0i} that a household incurs catastrophic OOP is modelled using the following probit

$$p_{0i} = \text{Prob}(y_i = 1|x_i) = \Phi\left(\beta_0 + \sum_k \beta_k x_{ik}\right) \tag{1}$$

where $\text{Prob}(\cdot)$ denotes probability, $\Phi(\cdot)$ is the cumulative density function of the standard normal distribution, β_0 is an intercept, and $\beta_k\,(k = 1, ...K)$ are slope coefficients for covariates x_{ik}.

Effects of covariates on the probability of catastrophic health spending can be measured by using average marginal/partial effects. For a continuous regressor x_{ik}, the average partial effect is given by

$$\frac{\partial p_{0i}}{\partial x_{ik}} = \beta_k \frac{1}{N} \sum_i \phi \left(\beta_0 + \sum_k \beta_k x_{ik} \right) \tag{2}$$

where $\phi(\cdot)$ is the standard normal probability density function. The effects of dummy independent variables are calculated differently from partial effects with respect to continuous variables discussed above. For these variables, the changes resulting from a discrete (0 to 1) change in each dummy independent variable is simulated holding other things constant.

Let the probability of catastrophic health payments for each household be approximated by a linear expression of the partial effects as follows

$$p_{0i} = \alpha + \sum_k \beta_k^m x_{ik} + \varepsilon_i \tag{3}$$

where α is an intercept, $\beta_k^m = \beta_k \frac{1}{N} \sum_i \phi\left(\beta_0 + \sum_k \beta_k x_{ik}\right)$, N is the total number of households in the sample, and ε_i is an approximation error. Since p_{0i} are unobserved, predicted probabilities from the probit, $\hat{p}_{0i}$ are used instead to estimate equation (3).

Interestingly, equation (3) suggests that the average partial effect from the probit model (equation (2)) can be approximated by estimating the slope coefficients in this linear regression. Averaging across equation (3) yields

$$p_0 = \alpha + \sum_k \beta_k^m \bar{x}_k + \bar{\varepsilon}_i \tag{4}$$

where $p_0 = \frac{1}{N}\sum_i p_{0i} = \frac{1}{N}\sum_i \hat{p}_{0i}$ is a catastrophic health spending headcount, it gives the proportion of households that incur catastrophic health payments, $\bar{x}_k = \frac{1}{N}\sum_{ij} x_{ik}$ is the mean of covariate x_{ik}, and $\bar{\varepsilon}_i = \frac{1}{N}\sum_i \varepsilon_i$. The averages ignore sampling weights for expositional purposes, however in the empirical application sampling weights are used. Consequently, a distribution-insensitive change in the catastrophic headcount following a change in the mean of covariate x_{ik} is $\frac{\partial p_0}{\partial \bar{x}_k} = \beta_k^m$. The existing literature has exclusively focused on β_k^m, and in cases where the logit model has alternatively been used, changes in odds ratio have also been utilised when analysing the determinants of catastrophic health payments.

2.2 Distribution-sensitive partial mean effects

I weight the probabilities that a household exceeds the spending threshold p_{0i} by weights defined by Wagstaff and van Doorslaer (2003). Let r_i denote a household's absolute rank in ascending order of income or consumption expenditure. This is equal to 1 for the poorest household, 2 for the second poorest household, and N for the richest household.

The weights by Wagstaff and van Doorslaer (2003) are defined as

$$m_i = 2\frac{N+1-r_i}{N} \tag{5}$$

Thus, $m_i = 2$ for the poorest household i.e. $r_i = 1$, and $m_i = \frac{2}{N}$ for the richest household i.e. $r_i = N$. Taking an average of the weighted probabilities, $m_i p_{0i}$, yields the distribution-sensitive catastrophic payment headcount generated using a probit model as

$$\begin{aligned} p_0^c &= \frac{1}{N}\sum_i m_i p_{0i} \\ &= p_0(1-C) \end{aligned} \tag{6}$$

where C is a concentration index.

Result 1: The partial effect of a change in the mean of a regressor on the distribution-sensitive catastrophic health spending headcount is given as

$$\frac{\partial p_0^c}{\partial \bar{x}_k} = \beta_k^m (1 - C_k) \tag{7}$$

where C_k is the concentration index for x_k. $C_k > 0$ if x_{ik} is concentrated among rich households, and $C_k < 0$ if x_{ik} is concentrated among poor households.

Proof of Result 1: The concentration index for p_{0i} is expressed as (see e.g. van Doorslaer and Koolman (2004)),

$$C = \frac{2}{p_0} cov(p_{0i}, R_i) \tag{8}$$

where, $cov(.)$ is a covariance. Using Wagstaff et al. (2003), and substituting equation (3) into the concentration index in equation (8) yields

$$\begin{aligned} C &= \frac{2}{p_0} cov(p_{0i}, R_i) \\ &= \sum_k \left(\beta_k^m \frac{\bar{x}_k}{p_0}\right) C_k + \frac{GC_\varepsilon}{p_0} \end{aligned} \tag{9}$$

where GC_ε is the generalised concentration index for ε_i. Finally, substituting equation (9) into equation (6), and taking derivatives gives

$$\begin{aligned} \frac{\partial p_0^c}{\partial \bar{x}_k} &= \frac{\partial p_0}{\partial \bar{x}_k} - \left(\frac{\partial p_0}{\partial \bar{x}_k} C + p_0 \frac{\partial C}{\partial \bar{x}_k}\right) \\ &= \beta_k^m - \left[\beta_k^m C + p_0 \left(\frac{\partial C}{\partial \bar{x}_k} + \frac{\partial C}{\partial p_0}\frac{\partial p_0}{\partial \bar{x}_k}\right)\right] \\ &= \beta_k^m - (\beta_k^m C + \beta_k^m C_k - \beta_k^m C) \\ &= \beta_k^m (1 - C_k) \end{aligned} \tag{10}$$

The distribution-sensitive partial effect of a change in $\bar{x}_k$ is therefore given as the distribution-neutral partial effect multiplied by the complement of the concentration index of regressor x_{ik}.The sign of the distribution-sensitive partial mean effect is still determined by β_k^m, but its magnitude is determined by how a regressor is distributed among nonpoor and poor households. If an independent variable is equally distributed ($C_k = 0$), then the distribution-sensitive and distribution-neutral partial effects are equal i.e. $\frac{\partial p_0^c}{\partial \bar{x}_k} = \frac{\partial p_0}{\partial \bar{x}_k} = \beta_k^m$. In this case, a failure to account for the distribution of the correlates would not lead to a mismeasurement (at least in the normative sense) of the true magnitude of the effect of a change in $\bar{x}_k$.

However, the distribution-neutral partial mean effect may overstate or understate the size of the effect when a correlate of catastrophic health spending is unequally distributed among the rich and the poor. If a variable in question increases the likelihood of catastrophic health spending, and the variable is more concentrated among the rich i.e. $C_k > 0$, then $\frac{\partial p_0^c}{\partial \bar{x}_k} < \frac{\partial p_0}{\partial \bar{x}_k}$. Thus, the distribution-insensitive partial mean effect overstates the impact of $\bar{x}_k$ on catastrophic health spending. In contrast, if there is a positive relationship between catastrophic health payments and x_{ik}, but x_{ik} is more concentrated among the poor i.e. $C_k < 0$, then $\frac{\partial p_0^c}{\partial \bar{x}_k} > \frac{\partial p_0}{\partial \bar{x}_k}$. This means that the distribution-insensitive partial mean effect underestimates changes in the prevalence of catastrophic health spending.

2.3 Partial inequality effects

Result 2: The partial effect on the catastrophic health payments headcount of a change in the distribution of a variable x_{ik} is

$$\frac{\partial p_0^c}{\partial C_k} = -\beta_k^m \bar{x}_k \tag{11}$$

Proof of Result 2: Substituting equation (9) into equation (6) gives

$$p_0^c = p_0 \left[1 - \sum_k \left(\beta_k^m \frac{\bar{x}_k}{p_0} \right) C_k + \frac{GC_\varepsilon}{p_0} \right] \tag{12}$$

and differentiating with respect to C_k yields equation (11).

The marginal effect of a change in the socioeconomic inequality of x_k depends on whether x_k increases the probability of catastrophic health spending (i.e. $\beta_k^m > 0$) or dampens it (i.e. $\beta_k^m < 0$). A rise in inequality in x_k, suggesting an increasing concentration of the variable among the rich, leads to a reduction in the catastrophic headcount if $\beta_k^m > 0$, and an increase in the headcount if $\beta_k^m < 0$. In contrast, an increase in concentration of x_k among the poor i.e. a reduction in C_k, is associated with an increase in the headcount if $\beta_k^m > 0$, and a decrease in the headcount if $\beta_k^m < 0$.

The two partial effects, equations (7) and (11, essentially capture the mean effect and the inequality effect respectively, of a regressor on the incidence of catastrophic health payments. The two effects are offsetting in that they have opposite signs, and the combined effect of a *ceteris paribus* unit increase in the mean and inequality effects is then given as $\beta_k^m\left[(1-C_k)-\bar{x}_k\right]$. The sign of the combined effect depends on which of the two dominates the other. For statistical inference in the empirical application, the standard errors and t-statistics for the mean and inequality effects are computed by using a nonparametric bootstrap procedure (Efron and Tibshirani, 1986).

3 Empirical Application to Malawi

3.1 Context

Formal health care services in Malawi are dominated by two players namely; the government and the Christian Health Association of Malawi (CHAM). For instance, over the period 2002-2009, the government was providing an average of about 61% of health care services, CHAM's contribution stood at 37%, and the remainder was covered by other providers such as private practitioners and commercial companies (GOM, 2007, 2012). All government facilities provide free health care services, with the exception of private wings that exist in a small number of district hospitals and all central hospitals and outpatient departments. Unlike government facilities, all CHAM facilities charge user fees, which are heavily subsidized by the government and donors.

The health finance system in Malawi comprises the government, foreign donors, private individuals and players through direct OOP payments, and medical insurance. Donor funding dominates total health expenditure in Malawi. For example, over the period, 2005-2009, donor contributions accounted for an average of 60% of total health expenditure. Donor contributions rose from 46% to 66% of total health expenditure between 2002/03 and 2008/09, while the share public sector domestic financing decreased from 35% to 18%. Household health expenditure shares in total health expenditures, marginally declined from 12.2% in 2002/03 to about 11% in 2008/09 (World Bank, 2013).

Malawi has no social medical insurance, and private medical insurance, plays a marginal role as a source of health care finance; for instance, private health insurance managed an average of 3% of total health spending between 2007 and 2009 (GOM, 2012). The limited availability of private health insurance is unlikely to change in a significant way. Malawi has a small formal sector from which health insurance premiums could be collected with relative ease. Besides, the informal sector is characterised by low wages and salaries. The presence of a predominantly free public health care system distorts the incentive for households to insure against unexpected illness and the consequent medical costs (GOM, 2012).

The heavy reliance on donor funding to finance health expenditure is unsustainable and leaves Malawi in a vulnerable position to external shocks such as aid suspension, and financial crises in donor economies. For instance, the execution of donor pledges was affected by the global financial crisis which started in 2008 such that in 2011/12 only 25% of pledges were released (World Bank, 2013). This risk is further compounded by the fact that pre-payment mechanisms such as taxes or universal medical insurance have limited scope for growth in Malawi. All this then points to a strong possibility that going forward, Malawi's health care financing system will shift towards full cost recovery or cost sharing arrangements. This in turn suggests that in order to mitigate against the financing risks, and although the share of OOP health care spending is relatively low, it is likely to increase rather than decrease in the future.

3.2 Data and variable description

The data used in the paper come from the Third Integrated Household Survey (IHS3) conducted by Malawi's National Statistical Office (NSO). This is a multi-topic survey which is statistically designed to be representative at both national, district, urban and rural levels. It was conducted from March 2010 to March 2011. The survey collected information from a random sample of 12271 households which are located in a random sample of 768 communities. The household level information collected includes socioeconomic and demographic characteristics of households and individual household members. It also collected household level data on OOP health care payments to cover: medicines (including non-prescription medicines), tests, consultation, cost of travel to a medical facility, in-patient fees, preventative health care, pre-natal visits, check-ups, out-patient costs, and hospitalization costs including the cost of stay at a traditional healer's or faith healer's dwelling. Information on a range of community-level variables and conditions such as access to and availability of physical infrastructure and public services was collected through interviewing key informants in each community. I consider the household as the unit of analysis.

In keeping with the previous literature (e.g. Su *et al.*, 2006; Pal, 2012; Li *et al.*, 2012; Narcı *et al.*, 2014), I use, as my dependent variable, the share of health spending in a household's nondiscretionary expenditure or capacity to pay (Xu *et al.*, 2003; Wagstaff and van Doorslaer, 2003), which is defined as per capita total household expenditure net of per capita expenditure on food. Since the data used in the study were collected from different locations and times of the year, the dependent variable is converted into real values by using a temporal and spatial deflator. As argued by O'Donnell et al.(2008), researchers should not impose their own judgment but rather should present results for a range of values of the threshold, and let the reader choose where to give more weight. The paper adopts the following two thresholds; 10% and 20%. It should be pointed out that the existing literature, commonly uses 40% when nondiscretionary expenditure is used as the denominator (e.g. Xu et al., 2003). The choice of the lower thresholds is motivated by the fact that as noted earlier, Malawi's health services are to a large extent free, and therefore lower thresholds would be more appropriate.

Table 1 reports results on the pattern of OOP health care payments. The distribution of the share of OOP is highly right skewed with the mean about ten times the median. The asymmetry in the distribution of the share is further confirmed by the Gini coefficient which is about 0.8; suggesting that few households register high OOP shares. The coefficient of variation for the OOP share is greater than two, and this implies that health care payments are highly unpredictable. The concentration index is negative, indicating that poor households spend a larger fraction of their resources on health care.

I now turn to the independent variables included in the regressions. Household size is a potential determinant of catastrophic health payments. As argued by O'Donnell *et al.* (2005), the sign of the effect of household size on health care payments is ambiguous, because on the one hand, in the case of a contagious disease, the proportion of a household that is sick will be greater for larger households, on the other hand, larger households have a larger supply of informal carers that can substitute for formal medical care and so constrain health costs. In keeping with Pradhan and Prescott (2002), I include the age composition of the household as a proxy for health care needs. Health care needs vary with age in that households with young children and elderly persons are more likely to spend on health care. The age and sex of the household head are also included in the model.

The higher the household income, the higher is the household's capacity to pay for health care. I use the log of per capita household expenditure as a measure of household economic status. The asset index might still suffer from omitted variable bias if a household experienced health shocks which led to the depletion of assets, and an increase in health expenditure. This problem is resolved by including a variable which captures whether or not in the last 12 months, a household was affected by a serious illness or accident of household member(s).

Education is another important variable that might affect OOP health payments. An educated household may make more effective use of modern medicine, and, this efficiency effect of education (Grossman, 1999; Cowell, 2006), implies that households with higher levels of schooling may be less likely to incur large expenditures on self-medication and traditional therapies (O'Donnell *et al.*, 2005). The effect of education on catastrophic payments is captured by education-sex variables which reflect the qualifications of males and females in a household. This gender differentiation reflects the fact that the returns to male and female education may be significantly different. The number of chronically ill members in a household is included to capture the possibility that the presence in a household of members who suffer from chronic illnesses could lead to more health care payments which in turn would increase the likelihood of incurring catastrophic payments (Su *et al.*,. 2006; Li *et al.,* 2012*)*. Household living conditions can affect health care payments to the extent that hygienic home environments lower the likelihood of catching diseases. I use the availability of sanitary toilets, safe drinking water and solid housing with durable roof and walls in a household as measures of household living conditions.

In order to measure availability of and access to basic medical infrastructure and services in a community, I use community level medical infrastructure indices. The presence of medical infrastructure and services in a community would for instance entail better living conditions, which in turn would lead to a lower prevalence of diseases, and hence, lower medical expenses. The two indices are constructed by using multiple correspondence analysis (MCA) (see e.g. Asselin (2002) and Blasius and Greenacre (2006) for more details). The health infrastructure index is constructed from information on the availability in a community of the following: a place to purchase common medicines, a health clinic, a nurse, midwife or medical assistant, and groups or programs providing insecticide-treated mosquito bed nets free or at low cost. I also include rural-urban and regional fixed effects to capture locational differences in OOP health care payments. More detailed descriptions and summary statistics for all the independent variables are reported in Table 2.

4 Results

4.1 Probit and linear regression results

The results for the empirical application are obtained in three steps: first, I estimate a probit model of catastrophic health payments, second, I generate predicted household specific probabilities of catastrophic health payments from the probit, and then finally, these predicted probabilities are used to estimate a linear model using ordinary least squares. Table 3 shows a comparison between predicted headcounts from the linear model and actual headcounts based on the raw data. It also reports correlation coefficients of predicted probabilities from the probit and predicted probabilities from the linear model. The headcounts are qualitatively similar in magnitude. This finding also holds for the distribution-sensitive headcounts. The correlation coefficients of the predicted probabilities are positive and significantly high. All this implies that the partial effects approximation as represented by the linear model is a good one.

The suitability of the linear approximation is further examined by comparing marginal effects from the linear and probit models. In both cases, the marginal effects measure how the probability of a household incurring catastrophic health payments is affected by different regressors. The results of this analysis are reported in Table 4. Again, the marginal effects from the two models are similar in both sign and magnitude. This conclusion is independent of threshold adopted. Furthermore, the signs of the marginal effects conform to *apriori* expectations.

4.2 Mean effect results

Tables 5 and 6 present distribution-sensitive and distribution-insensitive partial mean effects using the 10% and 20% thresholds of catastrophic health payment respectively. The tables also contain concentration indices of the regressors. The results indicate that concentration indices are fairly large in magnitude, and they are also statistically different from zero. The signs of the concentration indices are different; and this implies that the distribution of the regressors is either in favour of rich households (if the sign is positive) or poor households (if the sign is negative).

As expected, the results show that there is a high concentration among rich households of for example: education, good housing conditions, and health infrastructure. In contrast, there is a high concentration among poor households of for example: health shocks, young and eldery household members. The presence of these income-related inequalities in the regressors means that a failure to account for these inequalities by simply using marginal effects from a probit or logit model would at least normatively lead to a mismeasurement of the magnitudes of their partial effects. A comparison of the distribution-sensitive and distribution-insensitive partial effects indicates that the extent of this mismeasurement depends on the size as well as the sign of the concentration index.

The differences in the distribution-sensitive and distribution-insensitive partial mean effects are tested for statistical significance Two things are noteworthy about the statistical significance test results. Firstly, allowing for distribution sensitivity leads to statistically significant differences between the two partial effects for some variables. Secondly, the statistical significance of the differences depends on the threshold used. The differences become insignificant as one moves from the lower threshold of 10% to the higher threshold of 20%. This simply reflects the fact in the Malawian context, with a free health delivery system, relatively fewer households would be expected to incur catastrophic health spending for higher thresholds.

I now take a closer at the results for individual variables. Regardless of threshold used, the results indicate that education plays an important role in reducing the likelihood of catastrophic health payments. Since education is distributed in favour of rich households, a failure to account for this leads to overstated partial effects. For instance, using the 10% threshold, the results show that the extent of the overestimation is sizable, it ranges from 17% to 56%. The overestimation by the distribution-neutral partial effects for education are statistically significant across the two thresholds. The results further reveal that the size of the partial effects are gendered. The number of females in a household relative to males with either junior or senior secondary qualifications have a larger effect on the probability of catastrophic health payments. This finding is consistent with previous studies (e.g. Pal, 2012) which find that female literacy matters more for health outcomes.

The effect of household size on health care payments is positive and statistically significant for both thresholds. This perhaps reflects the possibility that in the case of a contagious disease, the number of household members who are sick might be greater for larger households (O'Donnell *et al.*, 2005). Since large household sizes are concentrated among the poor, the results indicate that a failure to control for this distributional pattern underestimates the size of the partial effect. For instance, using the 10% threshold, the distribution-insensitive partial effect is 0.0069, but this rises to 0.0076 after controlling for income-related inequalities in household size.

There is a significant positive relationship between health care needs as captured by the number of young and elderly household members, and catastrophic health payments. Health care needs are distributed to the disadvantage of poor households, hence, the distribution-sensitive partial effects are larger than the distribution-insensitive partial effects. The differences between the two effects are statistically significant for the two thresholds. Regardless of choice of threshold, the results show that households with a larger number of chronically ill members are more likely than others to incur catastrophic health expenditures. The distribution of chronic illness is biased in favour of better off households, and its magnitude though statistically significant, is quantitatively insubstantial. Consequently, if one was to simply use marginal effects from a probit, the effect of chronic illness would be overestimated by about 2% only; and this overestimation is found to be statistically insignificant.

The distribution of health shocks is biased against poor households. As a result, although the partial effects are positive and statistically significant, they are larger when they are adjusted for the socioeconomic distribution of health shocks. Household living conditions as captured by the availability of a durable roof and walls, and the availability of a toilet have a statistically significant negative influence on the likelihood of catastrophic health care payments. As expected, the distribution of good household living conditions is favourable to better off households. As a result, at least from a social welfare perspective, the distribution-insensitive mean effects of household living conditions are overstated. However, this overstatement is statistically significant for the availability of a durable roof and walls only.

Irrespective of the threshold used, richer households are more likely to incur catastrophic health expenditures. Three possible explanations can be offered for this finding. First, it could be that poor people fail recognize that they are ill, as a result, they do not make use of health care services through payments. Second, it could also be in the presence low insurance coverage or credit constraints, poor people simply forgo treatment when they become ill. Finally, it could be that, better off households, go for expensive medical procedures, which in turn lead to larger medical bills. Although the distribution sensitive and insensitive mean are effects are statistically significant, allowing for inequalities in household consumption reduces the measured effect of household economic status on the incidence of catastrophic health spending. Further to this, the reduction in the effect is statistically for the 20% threshold only. Significantly, all this points to the usefulness of adjusting the partial effects for distribution, as household economic status should normatively have a smaller effect on the incidence of catastrophic health payments.

Holding other things constant, the availability of health infrastructure such as clinics in a community increases the prevalence of catastrophic health payments. Perhaps reflecting the possibility that rich households are more likely to demand better services, the availability of health infrastructure is distributed in favour of the better off. Thus, the distribution-sensitive partial effects across the two thresholds are smaller. However, allowing for distribution sensitivity in the mean effect of health infrastructure leads significantly lower effects only when the 10% threshold is used. Household location matters when it comes to health care payments. Relative to urban households, rural households have a higher incidence of catastrophic health payments. This perhaps reflects price differences in medical care between rural and urban areas.

4.3 Inequality effect results

The above results have shown how the partial mean effects can be underestimated or overestimated if income-related inequalities in regressors are not accounted for. The next issue that I look at is how the income-related inequalities in regressors in and of themselves affect the incidence of catastrophic health spending. The results for this analysis are presented in Table 7. The results also include combined effect of a *ceteris paribus* unit increase in the mean and inequality effects. The signs of the combined effects are mixed; for some variables the inequality effect dominates the mean effect while for other variables a reverse pattern is observed.

The results show that, holding all else fixed, increases in income-related inequalities in education i.e. an increase in the concentration of education among the rich, increases the prevalence of catastrophic health payments. This reflects the fact that education and the likelihood of catastrophic health spending are negatively related. This means the inequality and the mean effects have countervailing impacts on the catastrophic payments. Using the 10% threshold, and looking at the number of females with a junior secondary qualification, the mean effect is -0.0133, and the inequality effect is 0.0015. The combined effect of a *ceteris paribus* unit increase in the two is -.0118; thus, the change in inequality has to be larger (more than 0.0133) for the incidence of catastrophic payments to increase. Similar to the mean effects, these inequality effects have a gender dimension. Across the two thresholds, the sizes of the effects are larger for the number of females in a household relative to males with either junior or senior secondary qualifications.

There is a statistically significant negative relationship between the incidence of catastrophic health payments and income-related inequalities in household health care needs as measured by the number of young and elderly household members. An increase in the concentration of health care needs among the rich, representing an increase in inequality, is associated with a reduction in the headcount because of the positive relationship between health care needs and the probability of catastrophic health payments. The results further indicate that the combined inequality and mean effect is dominated by the mean effect. For instance, employing the 10% threshold, the combined effect of a *ceteris paribus* unit increase in the two for the number of children below 5, is 0.0047. This suggests that improvements in the average levels of health care needs are more effective in reducing catastrophic payments than efforts that focus on improving the distribution of health care needs.

Income inequality and the incidence of catastrophic health payments have a statistically significant positive relationship. Increasing income inequality, *ceteris paribus*, leads to increasing prevalence of catastrophic health payments. The combined mean and inequality effects of household economic status is negative for both thresholds; this means that substantial improvements is income distribution would be required for the incidence of catastrophic spending to decline. The results also show that increasing inequality in household living conditions as measured by the availability of a durable roof and walls, and the availability of a toilet lead to increasing catastrophic health payments. However, the combined inequality and mean effect is negative and statistically significant across the two thresholds, implying that in order to effectively reduce catastrophic payments, attention should be more focused on improving the availability of better living conditions rather than their distribution.

Regardless of the choice of threshold, income-related inequalities in health infrastructure have a negative and statistically significant relationship with the prevalence of catastrophic health payments. The combined inequality and mean effect is negative and significant for the two thresholds. This means that the inequality effect dominates the mean effect, consequently, reductions in the distribution of health infrastructure such as the availability of clinics, are more effective in reducing catastrophic payments.

5 Concluding Comments

The paper has developed distribution-sensitive partial mean effects of determinants of out-of-pocket (OOP) catastrophic health payments. It has also proposed methods that can be used to measure how changes in the distribution of the correlates of catastrophic health payments affect the incidence of catastrophic health payments, an inequality effect. The proposed methods have then applied to Malawian data from the Third Integrated Household Survey.

The empirical application has shown that a failure to account for these inequalities in the correlates, at least normatively, leads to a mismeasurement of the magnitudes of their partial effects. The results also indicate that the signs of the combined effects of a *ceteris paribus* unit increase in the mean and inequality effects are mixed; for some variables the inequality effect dominates the mean effect while for other variables a reverse pattern is observed.

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Table 1: OOP payments for health care as a percentage of non-food expenditure

Statistic	Share of non-food expenditure
Mean	3.690
Median	0.341
Coefficient of variation	2.102
Concentration index	-0.036
Gini coefficient	0.781
Observations	12271

Note: sample weights are applied in the computation of all statistics to give population estimates

Table 2: Summary statistics

Variable	Description	Mean	SD
male	Sex of household head (male=1, female=0)	0.76	0.43
age	Age of household head in years	42.17	16.22
jce_female	Number of females aged 20-59 with JCE	0.07	0.28
jce_male	Number of males aged 20-59 with JCE	0.11	0.33
msce_female	Number of females aged 20-59 with MSCE	0.04	0.22
msce_male	Number of males aged 20-59 with MSCE	0.09	0.32
size	Household size	4.56	2.21
num_5	Number of members under 5 years old	0.91	0.92
num_60	Number of members over 60 years old	0.24	0.53
lcap_exp_total	log of per capita households expenditure	10.72	0.79
chronic	Number suffering from chronic illness	0.24	0.53
shock	Household affected by health shock (1=yes, 0=no)	0.12	0.33
wall_durable	House has durable wall (1=yes, 0=no)	0.79	0.41
roof_durable	House has durable roof (1=yes, 0=no)	0.36	0.48
toilet	House has a toilet (1=yes, 0=no)	0.91	0.29
health_index	Index of health infrastructure	2.38	1.17
north	Regional dummy, north=1	0.19	0.39
centre	Regional dummy, centre=1	0.34	0.47
south	Regional dummy, south=1, base	0.47	0.50
rural	Rural-urban dummy, rural=1 if rural	0.82	0.39
Observations		12271	

Notes: JCE is Junior Certificate of Education, and it is a junior secondary certificate. MSCE is Malawi School Certificate of Education, and it is a senior secondary certificate.

Table 3: Comparison of actual and predicted catastrophic payments

Threshold	Headcount		Concentration		Rank-Adjusted Headcount	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
Threshold=10%	11.33	11.33	-0.045	-0.050	11.84	11.90
Threshold= 20%	4.27	4.27	-0.012	-0.023	4.32	4.37
Threshold=10%	Correlation	0.97				
Threshold= 20%	Correlation	0.93				

Table 4: Marginal effects from the probit and linear models of catastrophic payments

Variable	Threshold=10%				Threshold=20%			
	Probit	SE	Linear	SE	Probit	SE	Linear	SE
male	0.0012	(0.0081)	0.0006*	(0.0004)	0.0009	(0.0050)	0.0008***	(0.0003)
age	-0.0001	(0.0003)	-0.0002***	(0.0000)	-0.0001	(0.0002)	-0.0001***	(0.0000)
jce_female	-0.0238	(0.0152)	-0.0210***	(0.0009)	-0.0212**	(0.0106)	-0.0162***	(0.0007)
jce_male	-0.0137	(0.0112)	-0.0132***	(0.0006)	-0.0077	(0.0087)	-0.0074***	(0.0004)
msce_female	-0.0409**	(0.0202)	-0.0314***	(0.0017)	-0.0282*	(0.0154)	-0.0195***	(0.0011)
msce_male	-0.0069	(0.0148)	-0.0071***	(0.0006)	-0.0090	(0.0097)	-0.0078***	(0.0005)
size	0.0063***	(0.0021)	0.0069***	(0.0001)	0.0039***	(0.0013)	0.0044***	(0.0001)
num_5	0.0173***	(0.0048)	0.0177***	(0.0003)	0.0060**	(0.0029)	0.0060***	(0.0002)
num_60	0.0244***	(0.0092)	0.0266***	(0.0006)	0.0092	(0.0057)	0.0100***	(0.0004)
lcap_exp_total	0.0145**	(0.0058)	0.0160***	(0.0004)	0.0118***	(0.0034)	0.0126***	(0.0003)
chronic	0.0370***	(0.0063)	0.0448***	(0.0008)	0.0193***	(0.0036)	0.0265***	(0.0008)
shock	0.0783***	(0.0088)	0.1000***	(0.0011)	0.0339***	(0.0052)	0.0471***	(0.0009)
wall_durable	-0.0413***	(0.0098)	-0.0497***	(0.0006)	-0.0221***	(0.0055)	-0.0281***	(0.0005)
roof_durable	-0.0197**	(0.0095)	-0.0190***	(0.0004)	-0.0101*	(0.0059)	-0.0096***	(0.0003)
toilet	-0.0051	(0.0117)	-0.0049***	(0.0006)	-0.0029	(0.0079)	-0.0027***	(0.0005)
health_index	0.0115**	(0.0046)	0.0117***	(0.0002)	0.0060**	(0.0024)	0.0059***	(0.0002)
North	-0.0413***	(0.0132)	-0.0348***	(0.0009)	-0.0258***	(0.0093)	-0.0194***	(0.0007)
Centre	0.0258**	(0.0109)	0.0285***	(0.0006)	0.0096	(0.0060)	0.0118***	(0.0004)
Rural	0.0398**	(0.0180)	0.0342***	(0.0013)	0.0159	(0.0106)	0.0140***	(0.0008)
N	12271		12271		12271		12271	

Notes: In parenthesis are standard errors (SE), *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 5: Distribution-sensitive and insensitive partial effects of catastrophic payments, 10 percent threshold

Variable	C_k	SE	DI	SE	DS	SE	Diff.	SE
male	0.0175***	(0.0029)	0.0006*	(0.0004)	0.0006*	(0.0004)	0.0000	(0.0006)
age	-0.0166***	(0.002)	-0.0002***	(0.0000)	-0.0002***	(0.0000)	0.0000	(0.0000)
jce_female	0.3661***	(0.0187)	-0.0210***	(0.0009)	-0.0133***	(0.0007)	0.0077***	(0.0011)
jce_male	0.1768***	(0.0147)	-0.0132***	(0.0006)	-0.0109***	(0.0005)	0.0023***	(0.0008)
msce_female	0.5562***	(0.0255)	-0.0314***	(0.0017)	-0.0139***	(0.0013)	0.0175***	(0.0021)
msce_male	0.4094***	(0.0163)	-0.0071***	(0.0006)	-0.0042***	(0.0004)	0.0029***	(0.0007)
size	-0.1008***	(0.0023)	0.0069***	(0.0001)	0.0076***	(0.0001)	0.0007***	(0.0001)
num_5	-0.1722***	(0.005)	0.0177***	(0.0003)	0.0207***	(0.0003)	0.0030***	(0.0004)
num_60	-0.0592***	(0.0117)	0.0266***	(0.0006)	0.0282***	(0.0007)	0.0016**	(0.0009)
lcap_exp_total	0.0407***	(0.0001)	0.0160***	(0.0004)	0.0154***	(0.0003)	-0.0006	(0.0005)
chronic	0.0175*	(0.0112)	0.0448***	(0.0008)	0.0440***	(0.0010)	-0.0008	(0.0013)
shock	-0.0332***	(0.0135)	0.1000***	(0.0011)	0.1034***	(0.0019)	0.0034*	(0.0022)
wall_durable	0.0467***	(0.0027)	-0.0497***	(0.0006)	-0.0474***	(0.0005)	0.0023***	(0.0008)
roof_durable	0.2996***	(0.0064)	-0.0190***	(0.0004)	-0.0133***	(0.0003)	0.0057***	(0.0005)
toilet	0.027***	(0.0016)	-0.0049***	(0.0006)	-0.0047***	(0.0006)	0.0002	(0.0008)
health_index	0.0503***	(0.0025)	0.0117***	(0.0002)	0.0111***	(0.0001)	-0.0006***	(0.0002)
north	-0.0361***	(0.0092)	-0.0348***	(0.0009)	-0.0361***	(0.0007)	-0.0013	(0.0011)
centre	0.0654***	(0.0074)	0.0285***	(0.0006)	0.0266***	(0.0004)	-0.0019***	(0.0007)
rural	-0.0921***	(0.0022)	0.0342***	(0.0013)	0.0374***	(0.0006)	0.0032**	(0.0014)

Notes: Bootstrapped standard errors (SE) after 1000 replications, for the regressor concentration indices (C_k), the null hypothesis that they are equal to zero is tested against the alternative that they not equal to zero i.e. there is inequality in their distribution either favouring the nonpoor (Ck >0) or disfavouring the poor (Ck <0), DI denotes insensitive partial effects, DS denotes distribution-sensitive partial effects, Diff=DS-DI, *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 6: Distribution-sensitive and insensitive partial effects of catastrophic payments, 20 percent threshold

Variable	C_k	SE	DI	SE	DS	SE	Diff.	SE
male	0.0175***	(0.0029)	0.0008***	(0.0003)	0.0007**	(0.0003)	-0.0001	(0.0004)
age	-0.0166***	(0.002)	-0.0001***	(0.0000)	-0.0001***	(0.0000)	0.0000	(0.0000)
jce_female	0.3661***	(0.0187)	-0.0162***	(0.0007)	-0.0103***	(0.0005)	0.0059***	(0.0009)
jce_male	0.1768***	(0.0147)	-0.0074***	(0.0004)	-0.0061***	(0.0004)	0.0013***	(0.0006)
msce_female	0.5562***	(0.0255)	-0.0195***	(0.0011)	-0.0086***	(0.0008)	0.0109***	(0.0014)
msce_male	0.4094***	(0.0163)	-0.0078***	(0.0005)	-0.0046***	(0.0003)	0.0032***	(0.0006)
size	-0.1008***	(0.0023)	0.0044***	(0.0001)	0.0048***	(0.0001)	0.0004***	(0.0001)
num_5	-0.1722***	(0.005)	0.0060***	(0.0002)	0.0070***	(0.0002)	0.0010***	(0.0003)
num_60	-0.0592***	(0.0117)	0.0100***	(0.0004)	0.0106***	(0.0005)	0.0006	(0.0006)
lcap_exp_total	0.0407***	(0.0001)	0.0126***	(0.0003)	0.0120***	(0.0003)	-0.0006*	(0.0004)
chronic	0.0175*	(0.0112)	0.0265***	(0.0008)	0.0261***	(0.0008)	-0.0004	(0.0011)
shock	-0.0332***	(0.0135)	0.0471***	(0.0009)	0.0486***	(0.0011)	0.0015	(0.0014)
wall_durable	0.0467***	(0.0027)	-0.0281***	(0.0005)	-0.0268***	(0.0004)	0.0013**	(0.0006)
roof_durable	0.2996***	(0.0064)	-0.0096***	(0.0003)	-0.0067***	(0.0002)	0.0029***	(0.0004)
toilet	0.027***	(0.0016)	-0.0027***	(0.0005)	-0.0026***	(0.0005)	0.0001	(0.0007)
health_index	0.0503***	(0.0025)	0.0059***	(0.0002)	0.0056***	(0.0001)	-0.0003	(0.0002)
north	-0.0361***	(0.0092)	-0.0194***	(0.0007)	-0.0201***	(0.0005)	-0.0007	(0.0009)
centre	0.0654***	(0.0074)	0.0118***	(0.0004)	0.0111***	(0.0003)	-0.0007*	(0.0005)
rural	-0.0921***	(0.0022)	0.0140***	(0.0008)	0.0153***	(0.0004)	0.0013*	(0.0009)

Notes: Bootstrapped standard errors (SE) after 1000 replications, for the regressor concentration indices (C_k), the null hypothesis that they are equal to zero is tested against the alternative that they not equal to zero i.e. there is inequality in their distribution either favouring the nonpoor (Ck >0) or disfavouring the poor (Ck <0), DI denotes insensitive partial effects, DS denotes distribution-sensitive partial effects, Diff=DS-DI, *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 7: Changes in inequalities in regressors and catastrophic health payments

Variable	Threshold=10%				Threshold=20%			
	C_k	SE	Combined	SE	C_k	SE	Combined	SE
male	-0.0005*	(0.0003)	0.0001	(0.0005)	-0.0006**	(0.0002)	0.0001	(0.0004)
age	0.0066***	(0.0007)	0.0064	(0.0007)	0.0048***	(0.0006)	0.0047	(0.0006)
jce_female	0.0015***	(0.0001)	-0.0118	(0.0007)	0.0012***	(0.0001)	-0.0091	(0.0005)
jce_male	0.0015***	(0.0001)	-0.0094	(0.0005)	0.0008***	(0.0001)	-0.0053	(0.0004)
msce_female	0.0012***	(0.0001)	-0.0127	(0.0013)	0.0008***	(0.0001)	-0.0078	(0.0008)
msce_male	0.0006***	(0.0001)	-0.0036	(0.0004)	0.0007***	(0.0000)	-0.0039	(0.0003)
size	-0.0315***	(0.0006)	-0.0239	(0.0006)	-0.0199***	(0.0005)	-0.0151	(0.0005)
num_5	-0.0160***	(0.0003)	0.0047	(0.0004)	-0.0055***	(0.0002)	0.0015	(0.0003)
num_60	-0.0063***	(0.0002)	0.0219	(0.0007)	-0.0024***	(0.0001)	0.0082	(0.0005)
lcap_exp_total	-0.1719***	(0.0034)	-0.1565	(0.0034)	-0.1347***	(0.0029)	-0.1227	(0.0029)
chronic	-0.0107***	(0.0003)	0.0333	(0.0010)	-0.0063***	(0.0002)	0.0198	(0.0008)
shock	-0.0123***	(0.0003)	0.0911	(0.0019)	-0.0058***	(0.0002)	0.0428	(0.0011)
wall_durable	0.0392***	(0.0004)	-0.0082	(0.0006)	0.0221***	(0.0004)	-0.0047	(0.0006)
roof_durable	0.0068***	(0.0002)	-0.0065	(0.0004)	0.0034***	(0.0001)	-0.0033	(0.0002)
toilet	0.0044***	(0.0005)	-0.0003	(0.0008)	0.0024***	(0.0004)	-0.0002	(0.0006)
health_index	-0.0278***	(0.0004)	-0.0167	(0.0004)	-0.0141***	(0.0003)	-0.0085	(0.0003)
north	0.0065***	(0.0002)	-0.0296	(0.0007)	0.0036***	(0.0001)	-0.0165	(0.0005)
centre	-0.0098***	(0.0002)	0.0168	(0.0004)	-0.0041***	(0.0001)	0.0070	(0.0003)
rural	-0.0280***	(0.0005)	0.0094	(0.0008)	-0.0115***	(0.0003)	0.0038	(0.0005)

Notes: The combined effect captures a *ceteris paribus* unit increase in the mean and inequality effects, bootstrapped standard errors (SE) after 1000 replications, C_k are concentration indices of regressors, *** indicates significant at 1%; ** at 5%; and, * at 10%.