Catastrophic health payments in Malawi: analysis of determinants using a zero-inflated beta regression

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Abstract

The existing literature on out-of-pocket (OOP) health payments has tended to use binary models to analyse the determinants of catastrophic health spending. In so doing, the literature ignores the fact that shares of out-of-pocket health care payments which are used to define the binary dependent variables are fractional with a mass point at zero. Further to this, the literature makes no distinction between factors which influence the level and the risk of catastrophic health payments. In order to address these shortcomings, this paper departs from this approach, and uses the zero-inflated beta regression instead. The paper also derives elasticity formalae for the zero-inflated beta regression. These elasticities allow one to talk about both the statistical, and economic significance of the different determinants of health nonpayment, catastrophic health spending, and the risk of catastrophe. Data from Malawi's Third Integrated Household survey are used. The empirical results indicate that the same variable can have a different effect on the levels, and risk of catastrophic health spending as well as OOP health nonpayment.

Keywords: Out-of-pocket payments; catastrophic payments; zero-inflated beta; elasticities; 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, in the face of 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

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associated with catastrophic health care payments have motivated the recommendation for health care finance systems transition towards some kind of pre-payment mechanism such as taxes or universal medical insurance (WHO, 2005).

In terms of policy, the identification of factors that influence households to incur catastrophic health payments is important, as it provides useful insights into which population groups are in most need of protection against incurring financial catastrophe. In order to model the determinants of catastrophic health payments, existing studies (e.g. Su *et al.*, 2006; Pal, 2012; Li *et al.,* 2012; Narcı *et al.*, 2014; Savitha and Kiran, 2015), typically estimate binary probit or logit models where the binary dependent variable is defined as whether a household's share of out-of-pocket (OOP) health care payments in the budget is catastrophic or not i.e. it exceeds a pre-determined fractional threshold. However, this approach has four major drawbacks. First, using a threshold to demarcate households into catastrophic spenders and non-catastrophic spenders leads to a loss of information. Those below the threshold are treated as one homogeneous group and those above the threshold as another homogeneous group. Second, the choice of the threshold is inherently arbitrary, and therefore a matter of subjective judgement, and this can lead to an internal logical inconsistency as noted by Pudney (1999) in the income poverty literature. For different thresholds, it is possible to have reversals in the relationships between catastrophic spending and the same set of determinants.

Third, the usual binary estimators are premised on the existence of an unobserved but continuous latent variable which generates an observed binary variable (Wooldridge, 2010). In the case of catastrophic payments, the binary variable is derived from an observed continuous variable, the share of OOP in the budget. Finally, household health expenditure like other forms of household expenditure exhibits a point mass at zero. That is, some households may not spend on health at all. Households may select into making health payments, and therefore treating all households that don't make health payments, and those whose health payments are less than the catastrophic threshold as the same ignores the fact that separate stochastic processes may determine the decision to spend, and how much to spend. It is well documented in the household health expenditure literature (e.g. Deb *et al.*, 2006), that excess zeros may arise from two decision process being at play. Ignoring the presence of excess zeros leads to biased and inconsistent coefficients and standard errors (Wooldridge, 2010).

The contributions of this paper are twofold. First, the paper contributes to the literature on catastrophic health payments through a re-examination of the determinants of catastrophic OOP payments using a modeling approach which addresses the aforementioned problems. Specifically, the paper uses a zero-inflated beta regression to analyse determinants of catastrophic health payments in Malawi. A key feature of the zero-inflated beta regression is that it nests the binary probit or logit, and the beta regression, and this makes interpretation of results increasingly difficult. The second contribution that this paper makes, relates to the interpretation of results from the zero-inflated beta regression. Specifically, the paper derives elasticities for the zero-inflated beta regression. These elasticities allow one to easily talk about the relative magnitude of the effects of different independent variables on catastrophic health care payments.

The results from the zero-inflated beta regression offer more policy relevant insights into catastrophic health payments which can never be gleaned from the binary logit or probit models as used in the existing literature. The model is able to distinguish between the mean effect of regressors, which captures changes in the expected value of the OOP budget share, and the variance effect of regressors, which measures risk. Increasing mean effects of OOP share can be addressed through for example, reducing user charges across a wide range of health services, while reducing the risk of catastrophic payments requires concentrating on payments for expensive but rare medical treatments (O'Donnell *et al.*, 2005).

The studies which are based on binary models effectively lump together households that do not make any health payments i.e. zero shares, with those that have small OOP budget shares, and then treat them as not incurring catastrophic medical expenditures. This ignores the fact that those that cannot meet medical expenses could be foregoing treatment. Arguably, such households, through the subsequent deterioration of health, probably suffer a greater reduction in living standards than those incurring catastrophic payments (Van Doorslaer *et al.*, 2007). By isolating those households with zero OOP shares, the zero-inflated beta regression allows one to also examine policy relevant factors that could be adopted to minimize health care nonpayment.

The rest of the paper proceeds as follows. Section 2 describes the health care finance situation in Malawi. Section 3 presents the empirical strategy, and the variables and data used. This is followed by the empirical results in Section 4. A discussion of the results and their policy implications is done in Section 5. Finally, Section 6 concludes.

2 Health care finance in Malawi

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.

Already catastrophic health spending- defined as the ratio of health care payments to household resources in excess of a fractional threshold (e.g. Wagstaff and van Doorslaer, 2003; Van Doorslaer *et al.*, 2007) - is showing a worsening trend. Figure 1 shows levels and trends of the incidence (in percentage) of catastrophic health care payments. The headcounts cover the period 2005 and 2011, and they are measured using different catastrophic payment thresholds. Two measures of the share of OOP health payments are employed namely; the OOP share in total household expenditure, and the share of OOP in household non-food expenditure.

The incidence of catastrophic payments for all thresholds, and the two OOP shares, is consistently higher in 2011 than in 2005. For instance, looking at OOP share of non-food expenditure and the 10% threshold, the figure indicates that 9.7% of Malawian households in 2005 incurred catastrophic health payment, and the prevalence of catastrophic health payments rose to 11.3% in 2011. Further to this, the deterioration in catastrophic health care payments, is more evident for the OOP share in non-food expenditure than it is for the OOP share in total household expenditure.

3 Empirical Strategy

3.1 The zero-inflated beta regression

Let f_i be per capita expenditure on food of household i, c_i be per capita total household expenditure, then $y_i = c_i - f_i$ is a household's ability to pay for health. One can alternatively define the fraction of health spending without deducting food expenditure. Define the fraction of health spending (h) in a household's ability to pay for health as $v_i = \frac{h_i}{y_i} \in [0, 1)$, then household health payments are catastrophic if $v_i > z$, where $z \in (0, 1)$ is a threshold above which spending on health is considered catastrophic. The existing literature then uses either the binary logit or probit to model the determinants of catastrophic health payments. As pointed out earlier, this approach has its problems, and to address these problems, I model the determinants of catastrophic health spending directly by using the variable v_i as a dependent variable instead. Since the proportion that a household spends on health can have a point mass at zero, I use a sequential model which distinguishes between the extensive margin (whether the proportions of health payments are zero or nonzero), and the intensive margin (nonzero health payments proportions). The presence of zeros means that the proportion that a household spends on health is mixed with discrete and continuous components, and its density is a discrete-continuous density which can be defined as (Cook *et al.*, 2008; Ospina and Ferrari, 2012)

$$g(v; \mu, \phi, \pi) = \begin{cases} 0 & \text{if } v < 0 \\ \pi & \text{if } v = 0 \\ (1-\pi) f(v; \mu, \phi) & \text{if } 0 < v < 1 \end{cases} \tag{1}$$

where

$$f(v; \mu, \phi) = \frac{\Gamma(\phi))}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} v^{\mu\phi-1}(1-v)^{(1-\mu)\phi-1} \tag{2}$$

is a standard two-parameter beta distribution (Ferrari and Cribari-Neto, 2004; Smithson and Verkuilen, 2006) which gives the probability density of v on the interval $(0, 1)$, and $\Gamma(\cdot)$ denotes the gamma function. For the mixture density, $E(v) = (1-\pi)\mu$ and $Var(v) = \sigma^2 = (1-\pi)V(\mu) + \pi(1-\pi)\mu^2$, where $V(\mu) = \frac{\mu(1-\mu)}{1+\phi}$ is a variance function. The parameter μ is a location parameter, and the parameter ϕ is a precision parameter since for fixed μ, the larger the value of ϕ, the smaller the variance of v. Different values of the parameters μ and ϕ generate different shapes of the beta density.

Using the above zero-inflated density, Cook *et al.* (2008) propose a zero-inflated beta regression which was later generalized by Ospina and Ferrari (2012). The generalization allows for the modeling of the variance of v_i as well as the possibility of one-inflation. I use the model by Ospina and Ferrari (2012) as it allows one to handle excess zeros in proportions, and the modeling of the variance of the proportion. The zero- inflated beta regression model can be defined as follows. Assume that each v_i is an independently and identically distributed random variable with probability density function given in equation (1), then the zero-inflated beta regression model is given by

$$f\left(v_i|x\right) = 1 - \Lambda\left(x_i'\alpha\right) \text{ if } v_i = 0 \tag{3}$$

and

$$f\left(v_i|x\right) = \Lambda\left(x_i'\alpha\right)\left[\frac{\Gamma\left(\phi_i\right))}{\Gamma\left(\mu_i\phi_i\right)\Gamma\left(\left(1-\mu_i\right)\phi_i\right)}v_i^{\mu_i\phi_i-1}\left(1-v_i\right)^{\left(1-\mu_i\right)\phi_i-1}\right] \text{ if } 0 < v_i < 1 \tag{4}$$

where $\Lambda\left(\cdot\right)$ a cumulative density function of a logistic distribution which is strictly monotonic and twice differentiable, α is a conformable parameter vector, and x_i is a vector of exogenous regressors. The unconditional mean is modeled as $E(v_i|x) = \Lambda\left(x_i'\alpha\right)\mu_i = \Lambda\left(x_i'\alpha\right)E(v|v \in (0,1), x) = \Lambda\left(x_i'\alpha\right)\Lambda\left(x_i'\beta\right)$, where α and β and are conformable parameter vectors. The unconditional mean comprises the probability that a households makes health payments, and the conditional mean of the proportion of health payments for households that actually make health payments. $\Lambda\left(x_i'\beta\right)$ ensures that predicted values of v_i are bounded between zero and one. If β_j has a positive sign, it means that covariate x_j increases the share of OOP health spending, which in turn indicates that it increases the likelihood of catastrophic health payments.

I use the logit link functions for both equation (3) and the conditional mean, $E(v_i|v_i \in (0,1), x)$, as this is consistent with other studies (e.g. Smithson and Verkuilen (2006) and Cook *et al.* (2008)) that use proportional data. Other possible link functions include; a probit link, a complementary log-log link, and a log-log link (see Smithson and Verkuilen (2006) and Ospina and Ferrari (2012) for details on link functions). To analyze whether a variable contributes to the variance of v_i beyond its effect on the mean, the conditional precision parameter ϕ_i is modeled as follows

$$\phi_i = \exp(x_i'\theta) \tag{5}$$

where θ is a conformable parameter vector. A positively-signed θ_j denotes an increase in precision, which in turn means a reduction in the variance or risk of catastrophic health care payments. Since variances cannot be negative, in keeping with previous studies (e.g. Smithson and Verkuilen (2006) and Cook *et al.* (2008)), I adopt the log link function to ensure that this constraint is not violated. One can alternatively use the square root link function. The zero-inflated beta regression reduces to the beta regression with precision when $\Lambda\left(x_i'\alpha\right) = 1$, and without precision when $\Lambda\left(x_i'\alpha\right) = 1$ and $\exp(x_i'\theta) = 1$.

In a nutshell, the zero-inflated beta regression used in this paper has three submodels. The first (equation(3)) is a selection submodel; it captures how the probability that a household spends on health depends on x. The second, $\mu_i = \Lambda\left(x_i'\beta\right)$, is a location submodel, it looks at how the average share of health spending varies with x conditional on a household deciding to make health payments. Finally, the third model represented by equation (5), is a precision submodel, it allows one to see whether, given the mean, the risk of catastrophic health payments improves or worsens as a result of changes in x. The vector of exogenous variables for the three submodels need not be the same i.e. there can be partial or complete overlap of the exogenous variables. Estimation of the parameters of the zero-inflated beta regression is done through maximum likelihood (Ospina and Ferrari, 2012).

3.2 Elasticities in the zero-inflated beta regression

The zero-inflated beta models developed by Cook *et al.* (2008) and Ospina and Ferrari (2012) only focus on signs and statistical significance of the estimated coefficients. Simply using the estimated coefficients one cannot say anything about the relative magnitude of the effects of different independent variables. In this paper, I derive formulae for elasticities for the zero-inflated beta model. Elasticities allow one to talk about the relative magnitude of the effects of different independent variables. The estimated coefficients from the zero-inflated beta regression can be used to calculate elasticities for the three submodels.

The elasticity of the probability that a household spends on health with respect to a continuous explanatory variable x_j is given by

$$\frac{\partial \mathrm{Prob}\left(v_i > 0|x\right)}{\partial x_j}\frac{x_j}{\mathrm{Prob}\left(v > 0|x\right)} = \frac{\alpha_j x_j}{1+\exp(x_i'\alpha)} \tag{6}$$

where $\mathrm{Prob}(\cdot)$ denotes probability.

If the household spends on health, the conditional elasticity of the average proportion spent on health with respect to a continuous explanatory variable x_j is

$$\frac{\partial E(v_i|v_i \in (0,1)}{\partial x_j}\frac{x_j}{E(v|v \in (0,1)} = \frac{\beta_j x_j}{1+\exp(x_i'\beta)} \tag{7}$$

Using equations (6) and (7), the unconditional elasticity of the average proportion spent on health by all households together, that is those with zero and nonzero health payments, with respect of x_j is expressed as

$$\frac{\partial E(v_i|x)}{\partial x_j}\frac{x_j}{E(v_i|x)} = x_j\left[\frac{\alpha_j}{1+\exp(x_i'\alpha)} + \frac{\beta_j}{1+\exp(x_i'\beta)}\right] \tag{8}$$

Thus, the unconditional elasticity of the average proportion of health spending, the mean effect, is made up of two parts: the first part is an elasticity of probability of spending on health (the first term), and the second part is a conditional elasticity of the average proportion of health spending for those households that make health payments. Similar formulae are derived by Ramalho and da Silva (2009) for the two-part fractional regression model.

I now turn to the derivation of elasticities for the precision submodel. Similar to the elasticities for the mean of the proportion spent on health, there are three possible elasticities for precision namely; the elasticity of probability, and the conditional and unconditional elasticities. If the household makes health payments; the elasticity of precision with respect to a continuous explanatory variable x_j is found by differentiating equation (5) to get

$$\frac{\partial \phi_i}{\partial x_j}\frac{x_j}{\phi_i} = x_j\theta_j \tag{9}$$

Furthermore, the elasticity of unconditional precision with respect to x_j is given by

$$\frac{\partial \phi_i \Lambda\left(x_i'\alpha\right)}{\partial x_j}\frac{x_j}{\phi_i \Lambda\left(x_i'\alpha\right)} = x_j\left[\frac{\alpha_j}{1+\exp(x_i'\alpha)} + \theta_j\right] \tag{10}$$

Thus, the elasticity in the unconditional precision model, the variance effect, can be decomposed into two parts: the first part is an elasticity of probability of spending on health (the first term); this is the same as that for the mean represented by equation (6), and the second part (the second term) is an elasticity of precision for those households with nonzero health payments.

Standard errors for the elasticities are calculated by using the delta method. The elasticities along with their standard errors are calculated at the sample means of all explanatory variables. The effects of dummy independent variables are calculated differently from elasticities 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.

3.3 Data, variables, and descriptives

The data used in the paper come from the Third Integrated Household Survey (IHS3) conducted by Malawi's National Statistical Office (NSO). It 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), 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. Figure 2 and Table 1 show results of the pattern of OOP health care payments. The figure shows that the OOP share has a mass point at zero. Specifically, close to half of the households register zero OOP health care payments. This is to be expected in light of the fact that Malawi has a largely free public health care system. The fact that about half of the households have to make OOP payments on health care could be a reflection of the poor quality of the public health delivery system which is characterised by drug and staff shortages (GOM, 2012).

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. There are about 5841 households, representing 47.6% of the total sample, with zero OOP expenditure on health. In terms of modeling, this clump-at-zero and skewness of the shares suggests that a zero-inflated beta distribution may be a suitable model for the data. 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.

The set of independent variables that are hypothesized to determine the share of health care payments, and hence catastrophic health expenditure, include household and community characteristics, and locational fixed effects. 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. Following 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 a household wealth/asset index instead of total household expenditure as a measure of household economic status, in order to avoid endogeneity problems (O'Donnell *et al.*, 2005; van Doorslaer *et al.*, 2007), associated with total household expenditure. The asset index avoids the endogeneity problem, because fixed assets are unlikely to be affected by health expenditure, and measurement error. Dummy variables generated from quartiles of the household asset index are then used as regressors in the model. The asset index is constructed by using multiple correspondence analysis (MCA) (see e.g. Asselin (2002) and Blasius and Greenacre (2006) for more details). The index is based on a household's ownership of the following assets: radio, television, furniture, washing machine, sewing machine, refrigerator, bicycle, motorcycle, and car. 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. To resolve this problem, I include 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).

Another important variable that might affect OOP health payments is education. 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.

I include community level medical infrastructure and economic infrastructure indices to measure availability of and access to basic medical and economic infrastructure and services in a community. The presence of public 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 MCA. 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. The economic infrastructure index is based on the presence of the following in a community: a perennial and passable main road, a daily market, a weekly market, a post office, a commercial bank, and a microfinance institution. I also include rural-urban and regional fixed effects to capture locational differences in OOP health care payments. Definitions and summary statistics for all the independent variables are given in Table 2.

4 Results

4.1 Model selection

Model selection criteria for the OOP share of total expenditure, and non-food expenditure are summarized in Table 3. For both shares, four models are compared namely; the beta regression with and without precision, the zero-inflated beta with and without precision. The log-likelihood, the Akaike information criterion, and the Schwarz Bayesian criterion are employed to select the best model. These criteria suggest that the zero-inflated beta regression with precision outperforms the other three models. The interpretation of these results is twofold. Firstly, they point to the inadequacy of the beta specification in modeling determinants of catastrophic health payments. This means that there are two separate stochastic processes; one governing the decision to spend (the extensive margin), and the other governing how much to spend (the intensive margin). Secondly, the results give further support to the generalized specification which accounts for risk as captured by the precision model in OOP payments.

4.2 Results of the zero-inflated beta regression

Maximum likelihood estimates of the zero-inflated beta regression are displayed in Table 4. Considering that the data used is cross-sectional, the estimated model has a fairly good fit, with the McFadden pseudo R^2 equal to 0.44. All the variables included in the model are jointly statistically significant, with $\chi^2 = 423.12$ and p-value=0.00. A mixed picture is observed in terms of how the variables affect the level and risk of catastrophic health payments as well as the probability of OOP health nonpayment. The results indicate that the direction and statistical significance of some variables is different for the three submodels. This justifies the use of the zero-inflated beta as it enables one to examine the differential impacts of the same variable on the levels and risk of catastrophic health spending- as measured by the variance of the OOP health payment share- and nonpayment. I now turn to a more detailed look at the results.

Since the zero-inflated beta regression is more generalized, interpretation of results becomes increasingly difficult. To avoid this difficulty, I focus on elasticities developed in this paper rather than parameter estimates. The elasticities offer more insight into the relative magnitudes of the effects of the different variables. With the elasticities in hand, one can also talk about the economic significance of the variables and not just their statistical significance. The elasticities of probability, conditional level and unconditional level for the location and precision submodels, along with their standard errors are presented in Table **5**. These elasticities reflect the likelihood of nonpayment, and the conditional and unconditional mean and variance effects.

The sex of the household head has no statistically significant effect on the probability that a household spends on health, and on the conditional level and unconditional levels of the mean and variance of health payments. The age of the household head positively influences the probability that a household does not spend on health; it however does not influence the likelihood and risk of catastrophic health payments. The effects of household size on the probability, unconditional mean and unconditional precision of the OOP share of health payments are statistically significant. Household size negatively affects the probability of nonpayment as well as the precision of health spending, but positively influences the unconditional mean of health spending. This means that large households are more likely to make OOP health payments, and, when they do, the payments are large, and, the risk of making those payments is high.

The number of young and elderly household members, which captures household health care needs, significantly increases the likelihood that a household will incur OOP health expenses. Conditional on spending on health, there is a statistically significant positive relationship between the number of young and elderly household members, and the OOP share of health payments; implying that an increase in health care needs raises the likelihood of catastrophic payments. Overall, holding all else constant, an increase in health care needs is associated with an increasing risk of catastrophic health payments as measured by the variance. Furthermore, the elasticities of health care needs with respect to the unconditional mean of OOP health payments are 0.111 and 0.042 for children and elderly household members. For the unconditional variance effect, the elasticities are -0.075 and -0.025 for children and elderly household members. The differences in the mean and variance effects are statistically with z-statistics (p-values) of 2.6 (0.00) and -2.5 (0.01) respectively. This suggests that households that have young children are at a higher risk of facing catastrophic health payments than those have elderly members.

The effects of household economic status as measured by quartiles of an asset index show some interesting patterns. The quartiles are largely statistically significant in the three submodels. Households that belong to higher wealth quartiles are less likely to make OOP health payments. But conditional on making health payments, a positive relationship exists between household economic status and share of OOP health spending; this implies that richer households are more likely to incur catastrophic health expenditures. Further to this, the signs of the elasticities for the third and fourth quartiles in the precision submodel are negative and statistically significant; this means that relative to poor households, rich households have significantly more unstable health payments; which in turn suggests that nonpoor households face a higher risk of incurring catastrophic health payments.

Education has a gender-differentiated effect on the probability of nonpayment as well as the mean and the precision of OOP health payments. Only the number of females with either junior or senior secondary qualifications matters. Precisely, the number of females in a household with a senior secondary qualification is statistically significant in the three submodels while the number of females in a household with a junior secondary school qualification is significant in the location and precision submodels only. Although, the findings indicate that the elasticities for females with junior secondary school qualification are larger in absolute value than those for senior secondary school qualification, the differences are statistically and economically insignificant. For instance, the z-statistics (p-values) for the differences in the conditional elasticities between the two levels of qualification for the mean and variance effects are -0.31 (0.38) and 0.28 (0.61) respectively.

Households with a larger number of chronically ill members are more likely than others to make health payments, to incur high levels of health expenditures, and to experience less stable and therefore risky health payments. A similar pattern is observed for households that experienced a health shock in the past twelve months. Since the elasticities can be used to talk about the relative strengths of the effects of the different variables, the results indicate that the impact of the number of chronically ill members in a household has the same order of magnitude as the impact of experiencing a health shock. This pattern holds across the probability, conditional, and unconditional levels of the mean and variance effects.

Living in a house which has a durable roof or durable walls does not influence the probability that a household makes health payments. In contrast, and conditional on making health payments, household living conditions as captured by the availability of a durable roof and walls have a statistically significant negative influence on the mean of health spending which in turn means that they lower the likelihood of catastrophic health care payments. In addition, households that have a durable roof relative to those that do not, have a lower variance of OOP payments; suggesting that they have a lower risk of incurring catastrophic OOP payments. Furthermore, variables reflecting the availability of a toilet and clean drinking are not statistically significant in the three submodels.

Both health and economic infrastructure in the community influence health payments. Specifically, the presence of economic infrastructure increases the likelihood that a household would spend on health, but economic infrastructure does not influence the level and risk of catastrophe. In contrast, community level health infrastructure is only statistically significant in the location submodel, where the effect is negative, and in the precision submodel, where the effect is positive. This suggests that the availability of health infrastructure such as clinics lowers the likelihood spends on health as well as the mean and variance of OOP health payments. A comparison of the magnitudes of the elasticities across the three submodels reveals that they are consistently larger for health infrastructure than for economic infrastructure.

Household location matters when it comes to health care payments. Holding other things constant, and relative to households in the southern region, households in the northern region have lower mean and variances of health spending while households in the central region have higher mean and variances of health payments. Rural households are more likely to spend on health, and conditional on nonzero spending, they are more likely to incur catastrophic health payments. The results further show that there is a statistically significant rural-urban difference in the risk of catastrophe where the unconditional variance effect is 20.2% lower for rural households.

5 Discussion and Policy Implications

Using the zero-inflated beta regression provides some advantages over the standard approach of using binary models to study the determinants of catastrophic health payments. The results are able to distinguish among factors that influence the probability of health payments, the mean share of health spending, and the variance of the share of health payments.

The results indicate that poor households in Malawi are less likely to make health payments. A possible explanation for this finding is that poor households are constrained from diverting their resources to pay for health care. This has long term policy implications in that poor households maybe locked in an intergenerational poverty trap. Forgoing treatment can lead to a deterioration of the human capital of household members (Sparrow *et al.*, 2013), which can in turn affect future household welfare. The results have shown that better-off households are more likely than poor households to incur catastrophic health spending. This finding is consistent with previous studies (e.g. Narcı *et al.*, 2014). It has also been found that they have a higher variance effect which implies that they are also more likely to be at a greater risk of having higher OOP health shares.

The large variance effect can be explained by the fact that public medical services in Malawi are largely free but of low quality (GOM, 2012), which turn means that rich households go for high quality and expensive medical services offered by private clinics. Thus, policies which improve the quality of public health services would instill confidence in the public health delivery system by the rich, which in turn would reduce the risk of OOP health payments. These findings further suggest introducing user fees in public hospitals as a possible way to improve the quality of health care may have the unintended consequence of worsening the problem of catastrophic health payments among poor households.

To the best of my knowledge, there is no study which has conducted a gender disaggregated evaluation of the effect of education of household members on catastrophic health payments. The existing literature (e.g. Pal, 2012; Li *et al.,* 2012; Narcı *et al.*, 2014) simply focuses on the education of the household head. Focusing on the household head, ignores the fact that a household can have better health outcomes on account of having educated members even when the household head is not educated; that is, they do not account for possible positive externalities of education.

The results of this paper reveal that it is only the presence of educated females and not males which matters. Households that have more educated female members are less likely to incur catastrophic health payments, and they have a reduced risk of catastrophic health payments. This suggests that when it comes to OOP spending on health, the efficiency benefits of education (Grossman, 1999; Cowell, 2006) work through the effective use of modern medicine by female household members only. The gendered-effect of education perhaps reflects the fact women are primary care givers. In terms of policy, this finding means that efforts to increase the number of educated women, would go a long way in ensuring financial protection in health payments.

In conformity with other studies (e.g. Pal, 2012), the paper has found that increasing health care needs as measured by the number of young and elderly household members greatly increases the likelihood of spending on health, and conditional on spending, of incurring catastrophic health spending. It has also been found that the impact of health care needs on the mean and the variance of health spending emanating from young children is larger than that from elderly members. The policy implication of this finding is that the Malawi health care system needs to focus more on health care, promotion, and prevention which targets young children to reduce OOP health payments that might adversely affect households.

The role of infrastructure on OOP health payments has largely been ignored in the literature. Findings from this paper indicate that infrastructure, especially, health infrastructure influences health spending by reducing the likelihood of health payments, and the mean and variance of health spending. This means that interventions which improve access to and availability of health infrastructure in communities would lead to lower OOP health payments.

The findings also suggest that even after controlling for the availability of infrastructure, likelihood and mean share of health payments is higher for rural households. This spatial-differentiation perhaps reflect rural-urban price/cost differences in medical services especially low-end medical services such as medicines. It can also be explained by the possibility that the available health infrastructure itself might be of poor quality, which would then suggest that rural households have no choice but to cover medical expenses through out of pocket payments. Whatever the explanation, this finding has both short and long term implications for the existence and persistence of rural-urban poverty differentials. Poverty in Malawi is significantly higher in rural areas; for instance, poverty headcounts in 2011 were 56.6% and 17.3% for rural and urban areas respectively (NSO, 2012). Such catastrophic OOP health payments can throw rural households deeper into poverty either through sacrifice of current consumption, or through depletion of assets, dissavings or accumulation of debts (Russell, 2004; Wagstaff, 2006; Sparrow et al., 2013).

6 Concluding Comments

The existing literature on out-of-pocket (OOP) health payments has tended to use binary models to analyse the determinants of catastrophic health spending. In so doing, the literature ignores the fact that shares of out-of-pocket health care payments which are used to define the binary dependent variables are fractional with a mass point at zero. Further to this, the literature makes no distinction between factors which influence the level and the risk of catastrophic health payments. In order to address these shortcomings, this paper has departed from this approach, and used the zero-inflated beta regression instead. The paper has derived elasticity formulae for the zero-inflated beta regression. These elasticities allow one to talk about both the statistical, and economic significance of the different determinants of health nonpayment, catastrophic health spending, and the risk of catastrophe. Data from Malawi's Third Integrated Household survey are used. The empirical results have indicated that the same variable can have a different effect on the levels, and risk of catastrophic health spending as well as OOP health nonpayment.

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Figure 1. Incidence of catastrophic payments, 2005-2011

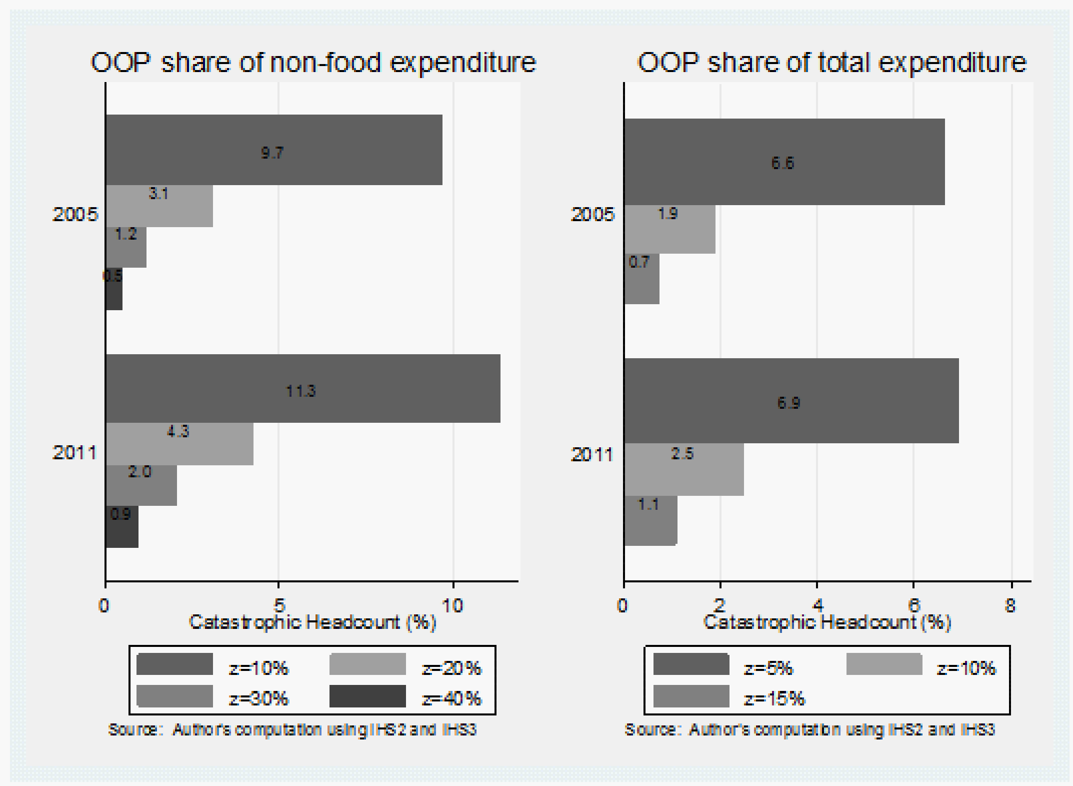

Figure 2. OOP share of non-food expenditure

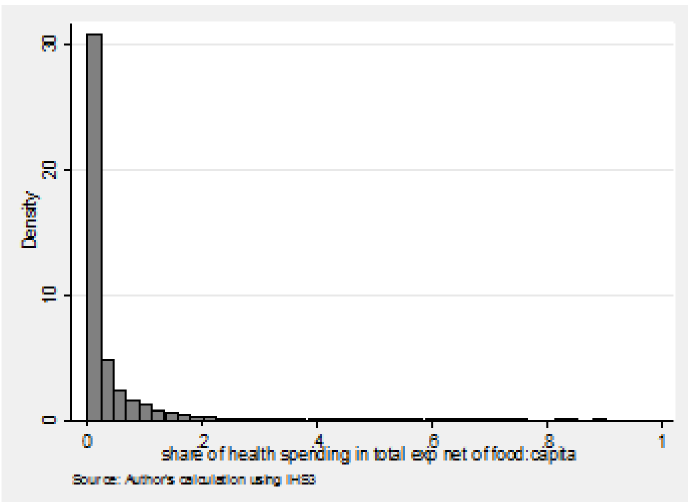

Table 1. OOP payments for health care as a percentage of non-food expenditure

Statistic	Share of non-food expenditure
Mean	3.690
Median	0.341
Proportion with zero OOP	0.476
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)	0.760	0.427
age	Age of household head in years	42.168	16.217
size	Household size	4.563	2.208
num_5	Number of members under 5 years old	0.909	0.916
num_60	Number of members over 60 years old	0.238	0.526
quartile1	Household in first quartile of asset index, (1=yes, 0=no), base	0.254	0.436
quartile2	Household in second quartile of asset index, (1=yes, 0=no)	0.291	0.454
quartile3	Household in third quartile of asset index, (1=yes, 0=no)	0.226	0.418
quartile4	Household in fourth quartile of asset index, (1=yes, 0=no)	0.229	0.420
jce_female	Number of females aged 20-59 with JCE	0.072	0.279
jce_male	Number of males aged 20-59 with JCE	0.110	0.335
msce_female	Number of females aged 20-59 with MSCE	0.040	0.215
msce_male	Number of males aged 20-59 with MSCE	0.092	0.316
chronic	Number suffering from chronic illness	0.239	0.533
shock	Household affected by health shock (1=yes, 0=no)	0.123	0.329
wall_durable	House has durable wall (1=yes, 0=no)	0.788	0.409
roof_durable	House has durable roof (1=yes, 0=no)	0.357	0.479
toilet	House has a toilet (1=yes, 0=no)	0.908	0.290
water	House uses clean water (1=yes, 0=no)	0.929	0.257
health_index	Index of health infrastructure	-0.796	1.171
econ_index	Index of economic infrastructure	-0.002	1.000
north	Regional dummy, north=1	0.188	0.390
centre	Regional dummy, centre=1	0.344	0.475
south	Regional dummy, south=1, base	0.469	0.499
rural	Rural-urban dummy, rural=1 if rural	0.818	0.386
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. Model selection criteria

OOP share of:	Model	lnL	AIC	BIC
Non-food expenditure	Beta regression without precision	-10852.60	21753.26	21585.02
	Beta regression with precision	-10989.40	22074.81	21751.78
	Zero-inflated beta without precision	-2786.20	5668.40	5304.67
	Zero-inflated beta without precision	-2572.77 [a]	5289.54 [b]	5155.66 [c]

[a] Preferred model based on the maximized log-likelihood (lnL) criteria.

[b] Preferred model based on Akaike information criteria (AIC); $\text{AIC} = -2\ln L + 2K$, where K is the number of estimated parameters.

[c] Preferred model based on Schwarz Bayesian criteria (SBC); $\text{SBC} = -2\ln L + K\ln N$, where N is the number of observations.

Table 4. Parameter estimates of the zero-inflated beta regression

Variable	Prob.	SE	Location	SE	Precision	SE
male	0.029	(0.050)	0.032	(0.048)	-0.072	(0.075)
age	0.008***	(0.002)	0.001	(0.002)	0.000	(0.003)
size	-0.100***	(0.011)	0.009	(0.011)	-0.017	(0.017)
num_5	-0.171***	(0.026)	0.040*	(0.023)	0.011	(0.036)
num_60	-0.177***	(0.055)	0.096*	(0.052)	-0.039	(0.075)
quartile2	0.154**	(0.061)	0.176***	(0.055)	-0.097	(0.084)
quartile3	0.171**	(0.067)	0.343***	(0.062)	-0.190**	(0.096)
quartile4	0.319***	(0.073)	0.480***	(0.069)	-0.362***	(0.100)
jce_female	-0.094	(0.076)	-0.170**	(0.075)	0.204*	(0.115)
jce_male	-0.031	(0.060)	0.070	(0.059)	-0.110	(0.091)
msce_female	0.185*	(0.097)	-0.255***	(0.095)	0.330**	(0.135)
msce_male	-0.000	(0.063)	-0.006	(0.074)	-0.101	(0.111)
chronic	-0.419***	(0.043)	0.208***	(0.036)	-0.199***	(0.054)
shock	-0.760***	(0.066)	0.395***	(0.052)	-0.404***	(0.076)
wall_durable	0.096	(0.060)	-0.210***	(0.046)	0.150**	(0.070)
roof_durable	0.067	(0.056)	-0.117**	(0.053)	0.051	(0.079)
toilet	0.125	(0.099)	-0.057	(0.070)	0.084	(0.114)
water	-0.103	(0.084)	-0.029	(0.069)	-0.109	(0.105)
health_index	0.015	(0.026)	-0.042*	(0.023)	-0.083**	(0.034)
econ_index	0.051*	(0.031)	0.016	(0.029)	-0.045	(0.041)
north	0.146**	(0.073)	-0.162**	(0.066)	0.268***	(0.103)
centre	-0.419***	(0.065)	0.108*	(0.058)	-0.183**	(0.085)
rural	-0.353***	(0.082)	0.218***	(0.080)	-0.180	(0.121)
constant	0.582***	(0.170)	-3.126***	(0.154)	2.978***	(0.242)
Chi-square			423.12			
Pseudo-R^2			0.44			
Observations			12271			

Notes: Prob. is the probability of zero health spending, Pseudo R^2 is McFadden's Pseudo R^2. Standard errors (SE) in parentheses are adjusted for clustering, *** indicates significant at 1%; ** at 5%; and, * at 10%.

Table 5. Elasticities of the zero-inflated beta regression

Variable	Prob.	SE	Location				Precision			
			Cond.	SE	Uncond.	SE	Cond.	SE	Uncond.	SE
male	0.011	(0.019)	0.023	(0.034)	0.012	(0.038)	-0.021	(0.022)	-0.010	(0.029)
age	0.174***	(0.040)	0.055	(0.068)	-0.115	(0.078)	0.002	(0.043)	0.176***	(0.059)
size	-0.232***	(0.027)	0.037	(0.047)	0.263***	(0.052)	-0.029	(0.030)	-0.261***	(0.040)
num_5	-0.079***	(0.012)	0.034*	(0.020)	0.111***	(0.023)	0.004	(0.013)	-0.075***	(0.017)
num_60	-0.021***	(0.007)	0.022*	(0.012)	0.042***	(0.013)	-0.004	(0.007)	-0.025***	(0.010)
quartile2	0.023**	(0.009)	0.048***	(0.015)	0.026	(0.018)	-0.011	(0.009)	0.012	(0.013)
quartile3	0.020**	(0.008)	0.073***	(0.013)	0.054***	(0.015)	-0.016**	(0.008)	0.003	(0.011)
quartile4	0.037***	(0.008)	0.103***	(0.015)	0.067***	(0.017)	-0.031***	(0.009)	0.005	(0.012)
jce_female	-0.003	(0.003)	-0.012**	(0.005)	-0.008	(0.006)	0.006*	(0.003)	0.002	(0.004)
jce_male	-0.002	(0.003)	0.007	(0.006)	0.009	(0.007)	-0.005	(0.004)	-0.006	(0.005)
msce_female	0.004*	(0.002)	-0.010***	(0.004)	-0.013***	(0.004)	0.005**	(0.002)	0.009***	(0.003)
msce_male	-0.000	(0.003)	-0.001	(0.006)	-0.001	(0.007)	-0.004	(0.004)	-0.004	(0.005)
chronic	-0.051***	(0.005)	0.047***	(0.008)	0.096***	(0.010)	-0.018***	(0.005)	-0.069***	(0.007)
shock	-0.047***	(0.004)	0.046***	(0.006)	0.092***	(0.008)	-0.019***	(0.004)	-0.066***	(0.005)
wall_durable	0.038	(0.024)	-0.155***	(0.034)	-0.193***	(0.042)	0.045**	(0.021)	0.083**	(0.032)
roof_durable	0.012	(0.010)	-0.039**	(0.018)	-0.051**	(0.021)	0.007	(0.011)	0.019*	(0.015)
toilet	0.057	(0.052)	-0.049	(0.060)	-0.105	(0.069)	0.029	(0.039)	0.086	(0.078)
water	-0.049	(0.039)	-0.026	(0.060)	0.022	(0.071)	-0.038	(0.037)	-0.087	(0.077)
health_index	0.006	(0.010)	-0.031*	(0.017)	-0.037*	(0.021)	0.025**	(0.010)	0.031**	(0.015)
econ_index	0.000*	(0.000)	-0.000	(0.000)	-0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
north	0.014**	(0.007)	-0.029**	(0.012)	-0.042***	(0.014)	0.019***	(0.007)	0.033***	(0.010)
centre	-0.073***	(0.011)	0.035*	(0.019)	0.106***	(0.023)	-0.024**	(0.011)	-0.097***	(0.016)
rural	-0.146***	(0.034)	0.168***	(0.061)	0.310***	(0.075)	-0.056	(0.038)	-0.202***	(0.051)

Notes: Prob. is the probability of zero health spending, standard errors (SE) in parentheses are adjusted for clustering, *** indicates significant at 1%; ** at 5%; and, * at 10%.