The effect of household income on child welfare clinic attendance in Ghana

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Abstract: This paper examines the effect of household income on child welfare clinic attendance in Ghana using the Ghana Living Standards Survey round six (GLSS 6) data. In order to choose the model that best fits the data, the corrected versions of the Vuong test were used and the ZIP model was chosen over the PRM. The paper finds evidence that other things being equal, a child in a household that gets a GH¢1 increase in income is 0.023 more likely to be sent for child welfare clinic service and this will in turn, lead to an improvement in the child's health. It is recommended that the government should provide mobile child welfare clinics around the country and also design cash transfer policies in order to provide financial support for poor caregivers to be able to attend child welfare clinics regularly.

Keywords: household income; Poisson regression; child health; child welfare clinic.

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1 Introduction

According to the 2015 World Health Organisation (WHO) report, the risk of a child dying before completing five years of age in the WHO African Region is still highest (81 per 1000 live births) about seven times higher than that in the WHO European Region (11 per 1000 live births). In Ghana, childhood immunisation status remains low. Majority of children do not receive all the recommended 15 vaccine doses before 1 year of age

(Adokiya et al., 2017). The 2014 Ghana Demographic and Health Survey report reveals that one in every 24 Ghanaian children dies before reaching age 1, and one in every 17 does not survive to his or her fifth birthday (GSS, 2015). In order to reduce this phenomenon to the barest minimum, the WHO recommends that vaccination and immunisation must be administered during the first five years of a child's life within a specified schedule and time range (WHO, 2015, 2016).

In Ghana, child welfare clinics are a part of the health care system and provide invaluable health care services to children under-five years of age. These clinics are set up throughout the country and run as facility-based, community-based and outreach clinics. There are three core activities conducted at the child welfare clinics. These include child weighing and charting of the weight-for-age Z scores, identification of growth faltering and counselling of caregivers on age appropriate infant and young child feeding (Agbozo et al., 2018). Other child health activities at the child welfare clinics include growth monitoring, immunisation against childhood killer diseases, vitamin A supplementation, treatment of minor ailments and referral of complicated illnesses, health promotion and counselling of mother and caregivers on health issues (Adu-Gyamfi and Adjei, 2013). Caregivers/mothers are required to send their children below five years old on monthly basis to the child welfare clinics for these services.

According to Adu-Gyamfi and Agyei (2013), there is a greater chance of child's survival, growth and development if she/he attends child welfare clinic regularly up to age 59 months. For instance, regular child welfare clinic attendance enables caregivers to track changes in their children's weight. Additionally, it raises awareness on the significance of growth charts and their interpretation (Agbozo et al., 2018). Furthermore, regular child welfare clinic attendance contributes to early identification of growth faltering, increases vaccination coverage and provides avenues for education on health and nutrition.

In Ghana, all services provided at child welfare clinics are free of charge. However, the participation rate of some mothers/caregivers tends to be low. Over the years, the main challenges that have confronted some mothers/caregivers are unavailability of and inaccessibility to child welfare clinics leading to high participation drop outs and slow progress in reducing malnutrition rates (GHS, 2008). The reasons often cited include financial constraints and transportation difficulties (Agbozo et al., 2018).

Gething (2004), Davies (2011) and Adu-Gyamfi and Agyei (2013) found evidence that the distance between the residence of a mother and the child welfare clinic influences child welfare clinic attendance. In addition, some mothers prefer to take their children to well established clinics and hospitals for these services rather than relying on temporal child welfare clinics normally established in various communities. This is because most of these temporal clinics lack basic facilities such as furniture for the caregivers/mothers to sit and wait for the services to be provided for their children (Adu-Gyamfi and Agyei, 2013).

In the light of this, it is reasonable to investigate the extent to which household income[1] can influence child welfare clinic attendance in the country. In other words, how can household income make a difference in the number of times that a child attends child welfare clinic in the context of the current healthcare system in Ghana?

So far, relatively little sustained academic scholarship addresses the effect and implications of household income on child welfare clinic attendance especially, in Africa and in the Ghanaian case, such studies are almost non-existent. In the health economics literature, a number of studies have come close to the present study by investigating the effect of household income on child health (see Case et al., 2002; Currie and Stabile, 2003; Burgess et al., 2004; Chen et al., 2010; Malone, 2014). However, none of these studies has specifically addressed the effect of household income on child welfare clinic attendance. Also, none of these empirical studies is on any African economy. Thus, this current study provides the first empirical attempt on the effect of household income on child welfare clinic attendance both at the national and continental level.

In Ghana, the effect of household income on child welfare clinic attendance is particularly important for two reasons. First, quite a number of children in the country are living below the poverty line. According to UNICEF (2015), almost three out of ten children in Ghana live in poverty. The situation is not different in other developing countries. Second, even though child welfare clinic services are free, public health care systems are generally poorly equipped and the availability of public health care is very heterogeneous across the country. The uneven distribution of health care centres makes it difficult for some mothers to seek quality child welfare clinic services for their children. In order for them to have such services, they would have to travel far away from their homes to places where those services are available. This certainly involves transport cost.

It is important to note that households, not doctors, are primarily responsible for their children's health. Households make choices about the amount and quality of health care their children receive, their nutritional levels, the amount of physical activity they engage in, the amount of emotional support they receive, and the quality of their environments. All these choices are conditioned by the household's economic resources and these resources include household income, household members' knowledge of health practices and programs and the characteristics of the communities in which they reside.

Although many factors unrelated to socioeconomic status also affect health outcomes, children's health is heavily influenced by the characteristics of the households into which they are born. Thus, children in poorer households are more likely to develop a variety of serious health problems than children in richer households. The disparities in health status between children in richer and poorer households increase through childhood, so that children in poorer households enter adulthood with the disadvantage of worse health (Case and Paxson, 2002). In this regard, the role played by household income in influencing the health of the child cannot be overemphasised.

The remainder of the paper is structured as follows. The next section discusses the theoretical mechanisms through which household income can influence child welfare clinic attendance in the context of the existing body literature. This is followed by a section that describes the method and data source while we discuss the results of the study in the next section. The conclusion and policy recommendations are presented in the final section.

2 Linking household income to child health

We derive our theoretical model for the analysis from household production theory which originated in the work of Becker (1965) and adopted by Grossman (1972) to analyse the accumulation and depreciation of health capital. In this model, it is assumed that the individual inherits an initial stock of health that depreciates overtime. It is further assumed that the individual may positively influence the stock of health capital via gross investments. According to the model, individual utility can be characterised as a function of health in all periods that individuals maximise subject to a budget constraint. Households choose infant health (H), leisure (L), and consumption of goods and services (C) and they are assumed to maximise a unitary household utility function which can be represented as follows:

$$U = f(H, L, C, X) \tag{1}$$

where X is a vector of household characteristics such as the household income, the age of the household head, the size of the household, the gender of the household head, whether the head of the household is employed or not, whether the mother is educated or not, etc. The health status of a child H is a normal good that depends on nutritional and medical inputs, biologic endowments and some household characteristics including household income.

The utility function is subject to a budget constraint stated as follows:

$$P'G = \sum_n l_n$$

where P represents the price vector, G is the commodity consumption of all household members and l_n denotes the household income accruing to individual $n\,(=1,\ldots,N)$

Thus, the health status H_i, of child *i,* at any point in time can be modelled as the following health production function:

$$H_i = f\left(\mathrm{M}_i, \mathrm{X}_i, \varepsilon_i\right) \tag{2}$$

where M_i represents the medical inputs into the health of infant i, X_i represents some household characteristics; and ε_i represents random health shocks. The health of the child is expected to improve as the income of the household increases.

At the empirical level, the debate on whether family/household income improves child welfare clinic attendance and child health is unending. Overall, the results are inconclusive even for some country-specific studies, which motivate further studies on the subject. While one section of the literature argues in favour of the potential of household income to improve child health, the other side of the literature argues against that position.

According to Case et al. (2002), in the USA, children from poorer families tend to have worse health than children in richer families. Using US cross-sectional data they find a strong positive relationship between parental income and children's subjective health, low income children are more likely to have chronic health conditions, and the impact of chronic conditions on parent of chronic conditions on parent-assessed general health is worse than for children of high income parents. Similarly, in Canada Currie and Stabile (2003) found that a strong positive relationship exists between family income and child health. Again, Currie et al. (2007) found evidence of a positive relationship between family income and child health in England. This relationship is, however, weak.

In England, healthcare provision is available and virtually free to the entire population and so this may have accounted for the weak relationship between family income and child health. In this regard therefore, income is not really a major determinant of child health.

Case et al. (2005) found that even after conditioning on parental background, UK children in poor health have worse health outcomes at the beginning of adulthood. Similarly, Malone (2014) empirically examined the income health gradient for the USA using 2009–2012 National Health Interview Survey (NHIS) data and finds evidence that there is a positive relationship between family income and child health.

Again, a study by Reinhold and Jürges (2012) on Germany reveals that wealthier children are able to manage their chronic conditions better than poorer children.

In contrast, Dowd (2007) used data from the 1988 US National Maternal and Infant Health Survey and the 1991 follow-up to test whether maternal health status and health behaviours during pregnancy and early infancy can explain the relationship between family income and subjective health status at the age of three years. The author finds no significant relationship between household income and child health. Again, Khanam et al. (2009) investigated the gradient in Australia, using the first two waves of the Longitudinal Study of Australian Children (LSAC). Their interest was to establish whether the income gradient increases with child age. These results suggest that in Australia the gradient does not reflect any causal effect of income on health, but unobserved heterogeneity.

Finally, Propper et al. (2007) found evidence that the relationship between household income and child health disappeared when controls for parental health were used. Specifically, the mother's mental health plays an important role in their models and effectively reduces the estimated effect of income per se to zero.

Based on the above, there is no gainsaying the fact that overall, the empirical findings regarding the effect of household income on child health is mixed and provides grounds for further study into the causal relationship between the two variables.

3 Method and data source

Equation (1) in which health capital is conceived as the output of a multivariate production process (Grossman, 1972; Liebowitz and Friedman, 1979; Strauss and Thomas, 1995) provides the basis for our empirical strategy. The econometric model assumes that the household decision to spend on child welfare clinic attendance and for that matter child health is based on the objective of utility maximisation as earlier discussed in the theoretical model.

3.1 Regression for household income and child welfare clinic attendance

Since child welfare clinic attendance is used as the dependent variable in the study, count data models are employed for analysis. In view of the fact that there could be the possibility of over dispersion of excess zeros in the child welfare clinic attendance variable leading to inconsistent and biased estimates, this study employs both the Poisson Regression Model (PRM) and the Zero-Inflated Poisson (ZIP). Additionally, a decision is made on the technique that best fits the data by using the Vuong test. A statistically significant uncorrected Vuong test, AIC-corrected and BIC-corrected Vuong test values implies that the ZIP model best fits the data. Thus, the model can correct for over-dispersion of zeros and give reliable estimates (Vuong, 1989; Greene, 1994).

3.2 Poisson regression and zero-inflated Poisson models

According to Gujarati and Porter (2009), a Poisson regression will treat the number of visits to the child welfare clinic as a Poisson random variable with an intensity hypothesised to depend on posited exogenous variables. The key assumption underlying the Poisson regression model is the fact that, the variance and the mean are the same. Thus, $E(Y) = \mu$ and $\operatorname{var}(Y) = \mu$. The probability distribution function of the Poisson distribution is given by

$$f(Y_i) = \frac{\mu^Y \ell^{-\mu}}{Y!} \tag{3}$$

The count process is denoted by $Y = 0, 1, 2, 3, \ldots$.

where $f(Y)$ represents the probability that the variable Y takes non-negative integer values, and $Y! = Y \times (Y-1) \times (Y-2) \times 2 \times 1$.

Since the count variable is the number of times the child is sent to child welfare clinic in a year, this number will depend on variables such as income of the household, whether the mother is educated or not, the gender of the household head, the age of the household head, location of the household, the number of migrants from the household, household size, whether the household head is employed or unemployed etc. If the number of times a child visits child welfare clinic is known, then according to the Poisson specification, we have

$$CW_i = \frac{\mu^{CW_i} \exp^{(-u)}}{\mathrm{CW}_i!} \tag{4}$$

where $\mu > 0$ and $CW = 1, 2, 3, \ldots$ denotes the intensity of the Poisson process.

In a sample where there are households with children attending child welfare clinics, $(CW_i, \ldots, CW_n)$, the corresponding log-likelihood function is the logarithm of the product of the marginal probabilities.

In a real world situation, a count variable may contain excess zeros thereby, causing a higher probability of zero values than is consistent with the Poisson regression model. In that regard, it could be assumed that zeros and positive values do not come from the same data generating process (Winkelmann, 2013) which means that employing a Poisson regression model on such data will result in biased and unreliable estimates. In order to address this excess zeros problem, the Zero-inflated Poisson model can be employed to accommodate both data generating processes (Koomson, 2017).

In the Zero-inflated Poisson model, two different data generating regimes are allowed: the outcome of regime 1 (R1) which is always zero and the outcome of regime 2 (R2) which is generated by a Poisson process (Lambert, 1992; Greene, 1994; Bauer and Sinning, 2010; Cameron and Trivedi, 2010). In the Zero-inflated model, the unconditional expectation of the dependent variable involves the conditional probability of observing regime 2 and the conditional expectation of the zero-truncated density. This is stated in equation (5).

$$\begin{cases} \Pr\left(LR_i = 0 \middle| X_i\right) = \Pr\left(R1\right) + \Pr\left(LR_i = 0 \middle| X_i, R2\right)\Pr\left(R2\right) \\ \Pr\left(LR_i = j \middle| X_i\right) = \Pr\left(LR_i = j \middle| X_{i,} R2\right)\Pr\left(R2\right), j = 1,2,3....... \end{cases} \tag{5}$$

The conditional probability of regime 1 is specified by Lambert (1992) as a Logit model and stated as follows:

$$\Pr\left(R1 \middle| X_i\right) = \frac{\exp\left(\gamma Z_i\right)}{1 + \exp\left(\gamma Z_i\right)} \tag{6}$$

where γ represents the parameter vector to be estimated and Z_i contains the covariates of the conditional probability of excess zeros. Additionally, the unconditional mean of the dependent variable is stated in equation (7) as

$$S\left(\beta_i^{ZIP}, X_i\right) = \frac{i}{N_g}\sum_{i=1}^{N}\left[1 - \left(\Pr\left(R_i\right)\middle| X_i\right)\right]\mu_i = \frac{1}{N}\sum_{i=1}^{N}\frac{\exp\left(\beta_i^{ZIP}, X_i\right)}{1 + \exp\left(\gamma Z_i\right)} \tag{7}$$

R1 is generated through a binary process and takes account of households that have children who are taken to child welfare clinics for child health services. R2 is generated through a Poisson process and takes into account both genuine and certain zeros in addition to counts above zero. The genuine zero is where the household has children but has no child that qualifies to attend child welfare clinic. The age range for child welfare clinic attendance is children under five years old. The certain zero is the household that may either have no child in the house or has children who are either five years old or above and for this reason, will certainly report zero for the number of children regardless of the condition. The variable that generates the logit process is whether a household has a child who is within the age limit of attending child welfare clinic or not and is used as a source of inflation to model the Zero-inflated Poisson. Both the Poisson regression model and Zero-inflated model are ran and the uncorrected Vuong test is conducted in addition to the AIC-corrected and BIC-corrected tests so as to determine the model which best fits the data.

3.3 The Vuong test

The Vuong test for non-nested models is the standard test employed in choosing between the Poisson regression model and the Zero-inflated Poisson model. In the context of testing for zero inflation, the Vuong test is used to test whether the mean observation-wise difference between the log-likelihood contribution to the zero inflation model and the contribution to the Poisson regression model is on average, greater than zero (Desmarais and Harden, 2013). For example, let $\hat{\beta}$ represent the estimate of β when the zero inflation component is excluded from the model and $\hat{\gamma}$ represent the estimate of γ. Furthermore, let us represent the vector of length *N* with *dl* such that the *i*-th element is the *i*-th individual log-likelihood difference. Thus, we have

$$dl_i = \ln\left\{l\left(y_i \middle| x_i, z_i, \hat{\beta}, \hat{\gamma}\right)\right\} - \ln\left\{f\left(y_i \middle| x_i{}'\hat{\beta}\right)\right\} \tag{8}$$

$$\text{The Vuong test} = \left(sdl\sqrt{n}\right)^{-1} \sum_{i=1}^{n} dl_i \tag{9}$$

Where sdl represents the standard deviation of dl. Research has shown that the Vuong test statistic is a biased estimator of the differences in the average of the count model.

Using Monte Carlo simulations, Desmarais and Harden (2013) indicated that the Vuong test does not provide any correction for additional parameters estimated in the inflation equation and is biased toward favouring the zero-inflated model. To address this, the corrected versions of the Vuong test have been provided and include all the functionalities of the old Vuong test. These are the AIC-corrected Vuong test and the BIC – corrected Vuong test. Essentially, the AIC and BIC-based correction factors adjust for extra parameters in the zero-inflated component (Hilbe, 2014). In this paper, it is these corrected versions of the Vuong test which have been used in choosing between the Poisson regression model and the zero-inflated model. According to Desmarais and Harden (2013), the AIC corrected test is better at conclusively supporting the more extensively specified zero-inflated model while the BIC correction is better at conclusively supporting the more parsimonious single equation model when it is appropriate.

3.4 *Empirical Poisson model for child welfare clinic attendance*

An empirical model is estimated for both the Poisson regression model and zero-inflated Poisson model by regressing child welfare clinic attendance on household income and other household level variables. The corrected versions of the Vuong test are then used to choose the best – fit model. It can be seen from Table 3 that all the three versions (uncorrected version of Vuong test, AIC-corrected and BIC corrected Vuong test statistics) are statistically significant at 1% in favour of the zero-inflated Poisson model. It also indicates that the child welfare clinic attendance variable is over-dispersed and the use of the Poisson regression model technique will result in biased and reliable estimates. Thus, the empirical model for the study is stated as follows:

$$\begin{aligned} E\left(CW_i / X_i\right) &= b_0 + b_1 \ln \text{hhinc}_i + b_2\text{loc}_i + b_3\text{hhsize}_i \\ &+ b_4\text{age}_i + b_5\text{gender}_i + b_6\text{Migrant}_i + b_7\text{Medu\_bin}_i \\ &+ b_8\text{employed}_i + b_9\text{Region}_i + \varepsilon_i \end{aligned} \tag{10}$$

where CW is child welfare clinic attendance, $\ln hhinc$ is the natural log of household income, loc represents the location of the household, age is the age of the household head, $gender$ is the gender of the household head, medu_bin is a dummy variable representing whether the mother of the child is educated or not, $employed$ is another dummy variable representing whether the head of the household is employed or unemployed, $migrant$ represents the number of migrants from the household, $hhsize$ is household size and Region represents regional dummies and ε is the error term.

The definition and measurement of variables in equation (5) are indicated in Table 1.

Table1 Definition and measurement of explanatory variables

Variable	*Definition*	*a priori Sign*
ln hhinc	Natural log of household income	Positive
Gender	Gender of the household head	indeterminate
age	Age of the economic head of the household	indeterminate
Employed	Dummy variable indicating whether the household head is engaged in economic activity or not	Positive
migrant	The number of household members who have migrated to work elsewhere	Positive
medu_bin	Binary variable indicating whether the mother (caregiver) is educated or not	
loc (rural=1, urban=0)	The location of the household	Indeterminate
Region	Categorical variable to capture regional effects	Indeterminate

Source: Compiled from literature and theories

3.5 Data source

This study uses a cross-sectional data constructed from the Ghana Living Standards Survey Round 6 (GLSS 6). The GLSS 6 is a nationwide household survey carried out by the Ghana Statistical Service (GSS) from 18th October 2012 to 17th October 2013 which was designed to generate information on living conditions in Ghana using the multi-stage approach. The GLSS 6 focuses on the household as the key socio-economic unit and provides information on living conditions of households in Ghana. Out of a total of 18,000, 16,722 households were enumerated successfully and this led to a response rate of 93.2% (GSS, 2014). After merging files from various sections of the data, finding the natural logarithm of household income and running the regression, there were missing observations in some rows and columns and this reduced the total number of observations to 2919.

Table 2 shows the summary statistics of variables used in the study. The average number of times a child is sent for child welfare clinic services in a year is 6 with a standard deviation of 4. Again, about 18% of the mothers who send their children for child welfare clinic attendance are educated. The data also indicates that about 19.5% of the household heads are females and 6.2% are employed. Obviously, some household members who are not heads may be employed and for this reason, the average household income totalled GH¢4,072 with a standard deviation of GH¢3.90. Again, the average age of the household heads is about 41 years with a standard deviation of about 13 years. Table 2 also shows that the average size of a household is 6 and the maximum is 29. This implies that the average number of people in the household that depend on household income is high and this could have a negative effect on the ability to improve child health trough child welfare clinic attendance.

Table 2 Summary statistics

Variable	*Mean*	*Std. Dev.*	*Min*	*Max*
CW	6.12	4.65	0	48
hhinc	4072.45	3.90	0.24	624,688
Medu_bin	0.180	0.384	0	1
Gender (female=1, male=0	0.195	0.396	0	1
hhsize	6	3	2	29
age	40.89	12.74	17	80
loc(rural=1, urban=0)	0.34	0.47	0	1
Employed	0.062	0.241	0	1
Migrants	0.066	0.382	0	6
Region				
Central	0.074	0.261	0	1
Greater Accra	0.074	0.261	0	1
Volta	0.112	0.315	0	1
Eastern	0.098	0.3	0	1
Ashanti	0.105	0.306	0	1
Brong Ahafo	0.093	0.291	0	1
Northern	0.119	0.324	0	1
Upper East	0.098	0.297	0	1
Upper West	0.104	0.306	0	1

Source: Computed from GLSS 6, 2012/2013

4 Results and discussion

Based on the reported values for the uncorrected version, AIC-corrected and BIC-corrected Vuong test results, the zero-inflated Poisson regression model was chosen over the Poisson regression model. Thus, the results are presented in Table 3 with both the Incidence Rate Ratio (IRR) and the Marginal Effects (ME) for comparison purpose. However, the analyses are done using the marginal effects.

In Table 3, the results from the zero-inflated Poisson model indicate that there is a direct effect of household income on the number of child welfare clinic visits per year. The marginal effects show that a child in a household that experiences a GH¢1 increase in household income is 0.022 (2.2%) more likely to be sent for child welfare clinic services, holding all other variables constant. This result is statistically significant at 1%. The positive influence of household income on child welfare clinic attendance may be because of the fact that some mothers need to spend money on transport to be able to visit a child welfare clinic. A regular visit to child welfare clinic by a child is likely to lead to an improvement of the child's health (Adu-Gyamfi and Agyei, 2013). This result is therefore, consistent with the findings by Malone (2014) which conclude that an increase in household income leads to improvement in child health in the USA. The result also coincides with the findings by Currie et al. (2007). These authors conclude that household income seem to be much more effective in improving health outcomes for children belonging to the richest households. As noted earlier by Adu-Gyamfi and Agyei (2013), transportation difficulties may hinder a caregiver's ability to send her child to a child welfare clinic and so an increase in household income will lead to an increase in child welfare clinic attendance, *ceteris paribus*.

Table 3 Results of Zero-Inflated Poisson Model and Poisson Regression Model for the effect of household income on child welfare clinic attendance

Dependent variable: child welfare clinic attendance	*Zero-inflated Poisson model*		*Poisson regression model*	
	IRR	*ME*	*IRR*	*ME*
lnhhinc	1.023*** (0.006)	0.023*** (0.006)	1.022** (0.011)	0.021** (0.011)
medu_bin (educated=1; uneducated=0)	1.076*** (0.022)	0.073*** (0.021)	1.072* (0.041)	0.69* (0.0410
Gender(female=1; male=0)	0.963* (0.020)	– 0.037* (0.021)	0.958 (0.035)	–0.043 (0.036)
hhsize	0.994* (0.004)	–0.007* (0.004)	0.993 (0.006)	–0.008 (0.006)
age	1.002*** (0.001)	0.002*** (0.001)	1.002* (0.001)	0.002* (0.001)
loc(rural=1; urban=0)	0.941*** (0.016)	–0.061*** (0.017)	0.947 (0.033)	–0.054 (0.035)
employed(employed=1; unemployed=0)	1.056* (0.034)	0.055* (0.032)	1.049 (0.059)	0.048 (0.059)
migrant	1.104*** (0.0191)	0.099*** (0.017)	1.106*** (0.038)	0.101*** (0.034)
Region				
Central	0.974 (0.036)	–0.026 (0.037)	0.974 (0.059)	–0.026 (0.061)
Greater Accra	1.115*** (0.040)	0.109*** (0.036)	1.126* (0.062)	0.119* (0.055)
Volta	1.351*** (0.034)	0.301*** (0.030)	1.359*** (0.064)	0.307*** (0.047)
Eastern	1.036 (0.034)	0.036 (0.033)	1.039 (0.057)	0.038 (0.055)
Ashanti	0.928** (0.031)	–0.075** (0.034)	0.934 (0.045)	–0.068 (0.048)
Brong Ahafo	1.367*** (0.043)	0.313*** (0.031)	1.374*** (0.110)	0.318*** (0.080)
Northern	0.995 (0.033)	–0.005 (0.033)	0.990 (0.049)	–0.010 (0.050)

Table 3 Results of Zero-Inflated Poisson Model and Poisson Regression Model for the effect of household income on child welfare clinic attendance (continued)

Dependent variable: child welfare clinic attendance	*Zero-inflated Poisson model*		*Poisson regression model*	
	IRR	*ME*	*IRR*	*ME*
Upper East	1.110*** (0.037)	0.104*** (0.034)	1.110** (0.058)	0.105** (0.052)
Upper West	1.204*** (0.039)	0.185*** (0.033)	1.201*** (0.060)	0.183*** (0.050)
constant	4.451*** (0.329)	1.531*** (0.079)	4.439*** (0.619)	1.533*** (0.151)
Inflate				
CW	–57.824 (0.340)	–57.824 (0.340)		
constant	33.338 (0.334)	33.338 (0.334)		
Observations	2919	2919	2919	2919
Non-zero observations		2910		
Zero observations		10		
Hosmer-Lemeshow: Prob> chi^2		0.625		
Link test				
_hat		0.000		
_hatsq		0.114		
Log-likelihood		–9081		
Vuong test				
ZIP versus standard Poisson z		3.10		
Pr>z		0.0010		
AIC(Akaike) correction z		2.99		
Pr>z		0.0014		
BIC (Shwarz) correction z		2.67		
Pr>z		0.0038		
Standard errors in parentheses				

Source: Computed from GLSS 6, 2012/2013 **p*<0.10 ***p*<0.05****p*<0.01.

Another factor that can influence child welfare clinic visits is the formal education of the child's mother. According to Adu-Gyamfi and Agyei (2013), the more educated the mother, the higher the level of immunisation of the child. The ZIP results indicate that holding other factors constant, a child is 0.073 more likely to be sent for child welfare clinic services if the mother of the child is educated. This result is statistically significant at 1% and consistent with the findings by Baye and Fambon (2009) which find a positive effect of parental education on child health in Cameroon. It also corroborates the findings by Case and Paxson (2002) which state that children with educated mothers are more likely to be in excellent or very good health than children whose mothers are not educated. Thus, more educated mothers may be better informed about the availability and use of health care, or have better health behaviour that confers benefits to their children.

The age of the household head also influences child welfare clinic attendance. All other factors being equal, a child is 0.002 more likely to be sent for child welfare clinic services if the head of the household is older by one year. This result is statistically significant at 1%. The implication is that as the head of the household grows older, he/she becomes more aware of the importance of the services provided at child welfare clinics and therefore encourages caregivers in the household to seek those services for their children on regular basis.

Again, migration influences child welfare clinic attendance. The ZIP results show that all other things being equal, if the number of migrants in a household increases by one, a child in the household is 0.099 (i.e. 9.9%) more likely to be sent for child welfare clinic attendance. This is statistically significant at 1% and consistent with the findings by Hildebrandt and McKenzie (2005) which state that migrant family members tend to increase mothers' health knowledge. The authors assert that the health knowledge of a family member increases as he/she migrates to the urban centre or to a more endowed place to work. Thus, the health knowledge acquired by the migrant is likely to be shared amongst members of his household including nursing mothers.

The gender of the household head also influences the number of times the child visits the child welfare clinic per year. The ZIP results indicate that a child in a female-headed household is 0.037 less likely to visit child welfare clinic than a child in a male-headed household *ceteris paribus*. This result is statistically significant at 10%.

Furthermore, the ZIP estimates indicate that the location of the household in which the child resides has influence on the number of times the child visits child welfare clinic. All things being equal, a child residing in the rural area of Ghana is 0.061 less likely to visit a child welfare clinic than a child residing in the urban centre and this is statistically significant at 1%. This result corroborates the study by Ray and Amar (2013) which states that the rate of stunting and wasting are lower among urban children in Tripura (India) indicating a better nutritional status for them than their rural counterparts.

The employment status of the head of the household head can also influence the number of times a child visits child welfare clinic. The ZIP results indicate that all other things being equal, if the head of the household is employed, a child in that household is 0.055 more likely to visit child welfare clinic than a child whose household head is unemployed. This result is statistically significant at 10% and is consistent with the study by Mörk et al. (2014). Analysing the extent to which health outcomes of Swedish children are affected by the employment status of their parents, the authors conclude that parental unemployment does hurt child health.

Again, the size of the household in which a child resides can influence the number of times the child visits child welfare clinic. The ZIP results show that all other things being equal, a child in a household whose size has increased by one person is 0.007 less likely to visit child welfare clinic and this is also statistically significant at 10%. This finding in consistent with the study by Ajao et al. (2010) which shows that larger family size is associated with lower nutritional status of under-five children in Ile-Ife in Nigeria.

Regional dummies have some effect on child welfare clinic attendance. For instance, the ZIP results in Table 3 show that all other factors being equal, a child in a household in the Greater Accra region is 0.109 more likely to attend child welfare clinic with his/her mother than a child in a household in the Western region. This is statistically significant at 1% and it is probably due to the fact that there appears to be more health centres in the Greater Accra region than in the Western region.

Similarly, a child in a household in the Volta region is 0.301 more likely to be sent by his/her mother for child welfare clinic services than a child in a household in the Western region and this is also statistically significant at 1%. Several reasons may account for this result in the Volta region among which are greater public education on child welfare clinic attendance, availability of child welfare clinics and easy accessibility of child welfare clinics.

The ZIP results further indicate that all other factors remaining constant, a child living with the mother in a household in the Brong Ahafo region is 0.313 more likely to access child welfare clinic services than a child in the Western region and it is statistically significant at 1%.

Again, the study results show that all other factors held constant, a child living with his/her mother in a household in the Upper East region is 0.104 more likely to attend child welfare clinics than a child living with the mother in a household in the Western region and this is statistically significant at 1%.

Furthermore, it is also evidenced in the study results in Table 3 that holding other factors constant, a child in a household in the Upper West region is 0.185 more likely to attend child welfare clinics with the mother than a child in a household in the Western region. This result is statistically significant at 1%. The Upper West region is a relatively small region and so it is easier to provide child welfare clinic services to children in that region than in the Western region.

Finally, the ZIP results indicate that a child residing in a household in the Ashanti region is 0.075 less likely to access child welfare clinic services than a child residing in a household in the Western region, *ceteris paribus*. This result is statistically significant at 5%.

Since the _haq is 0.000 and _hatsq is 0.114 and for that matter insignificant, it implies that the link function is correctly specified. Thus, we can only by chance, find additional predictors that are statistically significant. The Hosmer-Lemeshow goodness of fit test has a large *p*-value of 0.625 indicating that the model fits the data and adequately estimates the effect of household income on child welfare clinic attendance.

5 Conclusions and policy recommendations

The current paper presents the first econometric evidence on the household income-child welfare clinic attendance relationship in Ghana using the GLSS round 6 data. Because the child welfare attendance variable was over-dispersed, both the uncorrected and the corrected versions of the Vuong test were employed to choose between the zero-inflated Poisson and the Poisson regression models. The test results were all in favour of the zero-inflated Poisson model and so that was the regression technique used in estimating the model. The study results indicate that there is a positive and statistically significant effect of household income on child welfare clinic attendance in Ghana and this is consistent with the findings by Malone (2014). There is also evidence that the education of the mother has a positive and significant influence on child welfare clinic attendance. A number of empirical studies have shown that mothers' education is the critical determinant of child health and survival in the first five years of life (Abuya, Onsomu, Kimani and Moore, 2011) and this could be due to educated mothers' stronger link to hygienic health behaviours and management of illness. It is clear from this result that besides household income, other household characteristics could have significant influence on child welfare clinic attendance.

From a policy perspective, it is important to note that the positive household income effect on child welfare clinic attendance implies that a social intervention programme such as the Livelihood Empowerment Against Poverty (LEAP) that increases income for the poor may be an effective way to improve the child welfare clinic attendance of children from poorer families in Ghana. Thus, the government of Ghana could design cash transfer policies in order to increase the amount given to poor households on the LEAP programme. This will afford caregivers/ mothers in these poor households the opportunity to visit hospitals/clinics regularly for child welfare clinic services so as to improve child health in the country. It is also important that the Ministry of Health provides mobile child welfare clinics all over the country so as to enable more children to access these services.

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Note

1 There is no household income file in the Ghana Living Standards Survey (GLSS) Round 7 data, hence, the use of the GLSS 6 data for the analysis.