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Income and health insurance effects on modern health-seeking behaviours in rural Ghana: nature and extent of bias involved

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Received 1 April 2023
Revised 8 July 2023
25 August 2023
Accepted 3 October 2023

Abstract

Purpose – This study examined the influence of income and health insurance on the health-seeking behaviour of rural residents, addressing the concerns of endogeneity and heterogeneity bias.

Design/methodology/approach – A two-stage residual inclusion was utilised to correct self-selection-based endogeneity problems arising from health insurance membership.

Findings – This study provides support for Andersen's behavioural model (ABM). Income and health insurance positively stimulate rural residents' use of modern healthcare services, but the effect of insurance risks a downward bias if treated as exogenous. Further, the effect of health insurance differs between males and females and between adults and the elderly.

Originality/value – This study advances the literature, arguing that, within the ABM framework, enabling (i.e. income and insurance) and predisposing factors (i.e. age and gender) complement each other in explaining rural residents' use of modern health services.

Peer review – The peer review history for this article is available at: https://publons.com/publon/10.1108/IJSE-03-2023-0223

Keywords Health-seeking behaviours, Heterogeneity, Ghana, Income, National health insurance scheme, Two-stage residual inclusion

Paper type Research paper

1. Introduction

The right to good health is a human rights issue. Meanwhile, the development of human capital critically depends on people's health status (Sun and Lyu, 2020). Healthcare access and utilisation are at the core of disease prevention, detection, diagnosis and treatment of sickness. In addition, healthcare access and utilisation are crucial for increasing quality of life, avoiding needless deaths and improving life expectancy (Healthy People 2020, 2022). Preferably, rural residents should be able to access and use modern health services with ease and confidence. However, access to and availability of adequate healthcare services for people living in rural areas is a major problem, and this has become a global public health concern (World Health Organization, 2018). Inequitable access to basic, fundamental, primary and specialist health care is a problem in rural communities. This situation is worrying, particularly in sub-Saharan Africa, where 70% of the population are low-income earners and reside in rural areas (Archibong *et al.*, 2020). Improving access to healthcare is and will

JEL Classification — C21, C31, I12, I13

The authors are grateful to both the Economic Growth Centre at Yale University and the Institute of Statistical, Social and Economic Research (ISSER) at the University of Ghana to use the Ghana Socioeconomic Panel Survey dataset.

International Journal of Social Economics
Vol. 51 No. 6, 2024
pp. 800-818

0306-8293
DOI 10.1108/IJSE-03-2023-0223

continue to be an essential issue in rural health globally. This situation raises a legitimate research need to improve healthcare access and utilisation. In this study, we examined the influence of income and health insurance on rural residents' decision to use modern health care facilities in Ghana.

Ghana's case is fascinating for several reasons: First, despite falling short of the World Health Organisation's recommended minimum threshold of the doctor-to-population ratio of 1:1,320, Ghana stands tall relative to other African countries in terms of medical personnel (doctors, nurses, midwives) density (Asemota, 2019). Second, Ghana is the first in sub-Saharan Africa to promote universal healthcare (Fusheini, 2020) through the National Health Insurance Scheme (NHIS). The NHIS is a flagship social protection programme that seeks to increase healthcare access and service quality, especially for the most vulnerable and underprivileged (Kusi *et al.*, 2018). The NHIS ensures that those in the formal and informal sectors of the economy and the agricultural and rural populations have access to healthcare (World Health Organization, 2012). Additionally, the Community-based Health Planning Services (CHPS) programme has been in place since the late 1990s and the early 2000s as part of the Government of Ghana's strategy to provide essential health care to people in rural and remote areas, as well as other hard-to-reach communities (Adam *et al.*, 2021).

Despite these interventions, there are still obstacles and impediments related to healthcare access and utilisation, particularly for people in rural areas (Aseweh-Abor *et al.*, 2011). This raises the legitimate question of whether an NHIS stimulates healthcare access and utilisation. The most common critique of Ghana's NHIS is that it is not a pro-poor solution to healthcare challenges as it disenfranchises a significant number of rural residents (Polychronis, 2015). A study by Kwarteng *et al.* (2020) underscored the low enrolment and coverage of rural people. As most Ghanaians reside in rural areas, uninsured rural people become more vulnerable.

In addition, according to a study on the progressivity of healthcare financing in Ghana, the distribution of overall gains from utilising healthcare is pro-rich. Estimates show that the benefits received by the wealthiest quintile were nearly double (24%) those of the poorest quintile (13%). Evidence further revealed that the richest two quintiles received about half of the total healthcare benefits, whilst the poorest two quintiles received less than a third of the total public and private healthcare benefits (Akazili *et al.*, 2012). These results demonstrate that income influences the degree of health-seeking behaviour amongst rural inhabitants in Ghana. This is because individuals with higher economic status have more advantages and opportunities to receive better healthcare than those with lower incomes.

The current study contributes to the literature on drivers of healthcare utilisation by examining how enabling factors such as income and health insurance affect healthcare utilisation in Ghana, accounting for endogeneity and heterogeneity bias. Andersen (1968) identified three drivers of healthcare utilisation: predisposing, enabling and needing factors. This study argues that the effect of enabling factors (i.e. income and health insurance) may be influenced by other predisposing factors (i.e. age and gender). Whilst health insurance reduces the risk of medical expenses and increasing income enhances purchasing ability, the effects of these factors, to a large extent, depend on the gender and age of the health decision-making agent. The decision to use healthcare services may be influenced by differences in risk factors and health-seeking behaviours between males and females and young and old individuals.

There is substantial empirical evidence on the influence of health insurance and income on healthcare utilisation (Ekman, 2007; Geitona *et al.*, 2007; Hullegie and Klein, 2010; Nketiah-Amponsah *et al.*, 2013; Liu and Zhao, 2014; O'Connor, 2015; Saeed *et al.*, 2015; Gotsadze *et al.*, 2017; Mwami and Oleche, 2017; Madyaningrum *et al.*, 2018; Sengupta and Rooj, 2019; Kumara and Samaratunge, 2019; Archibong *et al.*, 2020; Sanogo and Yaya, 2020). However, we note that a significant gap exists regarding how the effect of enabling factors (i.e. income and insurance) differ, considering different predisposing factors such as gender and age. This is particularly critical because the differing risk attributes and health-seeking behaviours associated with males and females, and the young and old, have implications for health decision-making. The current literature raises possible concerns of heterogeneity bias. This study fills this gap by examining how the effects of income and health insurance on healthcare utilisation differ for different genders and age groups.

A second important issue regarding the literature on healthcare utilisation is the endogeneity of health insurance. Access to health insurance depends on household characteristics, suggesting a possible self-selection bias. This violates the identification conditions and creates inconsistent and biased estimates. Whilst some previous studies have ignored this concern (Ekman, 2007; Geitona *et al.*, 2007; Fenny *et al.*, 2014; O'Connor, 2015), others have addressed this concern of self-selection bias (Waters, 1999; Hullegie and Klein, 2010; Gajate-Garrido and Ahiadeke, 2013; Liu and Zhao, 2014; Bonfrer *et al.*, 2016; Gouda *et al.*, 2016). Interestingly, even for studies that address endogeneity concerns, little is known about the extent and nature of bias induced by the self-selection bias problem. This study addressed endogeneity using a two-stage residual inclusion (2SRI) methodological approach. The identification strategy involves using the formal sector work as an external instrument for health insurance. In addition, we report the extent and nature of the bias involved in the relationship between healthcare utilisation and health insurance.

2. Theoretical framework

Andersen's behavioural model (ABM) of health service utilisation provides a theoretical framework for this study (Andersen, 1968). The model identifies three factors that influence how people use health services: predisposing, enabling and need factors. The model is based on analytical causal ordering, in which predisposing factors (i.e. social structure, health beliefs and demography) are exogenous, as they are not directly related to medical usage, but have an impact on the likelihood of use (Andersen, 1995). Enabling factors relate to the resources (i.e. community, personal or family) that enable or impede use (Andersen, 1995). Need factors (i.e. perceived or evaluated) represent ones need for care (Andersen, 1995).

Since ABM was developed, it has been widely used to explain healthcare services utilisation in advanced and developing countries (Han-Kim and Lee, 2016; Li *et al.*, 2016; Gotsadze *et al.*, 2017; Başar *et al.*, 2021). For instance, Başar *et al.* (2021) applied the model to analyse the usage of outpatient and inpatient treatment services in Turkey. In China, Li *et al.* (2016) employed the model to examine how people in rural areas in Guangxi use health services, notably hospitalisation and physician visits. To apply ABM to the current study, we tested the effects of income and health insurance, which are enabling factors, on rural residents' health-seeking behaviours and how predisposing factors such as age and gender influence the relationship. By this, we claim that within the Anderson framework, enabling and predisposing factors could act as complementary factors in influencing the healthcare utilisation behaviour of household — women compared to their male counterparts, are more likely to use health services (Cleary *et al.*, 1982; Bertakis *et al.*, 2000).

3. Methodology

3.1 Data

This study utilised data from the Ghana Socioeconomic Panel Survey (GSPS) (Yale Economic Growth Center, 2018). The study used the second and third waves (2014/2015 and 2018/2019) of GSPS, because there was difficulty in generating the household expenditure variable from the first wave, which serves as a proxy measure of income for this study. Data on predisposing, enabling and need factors were merged after excluding observations on key variables with missing values. Urban residents were excluded from the sample to focus on rural residents.

3.2 Empirical model

The empirical model is derived from Andersen's health utilisation framework (Andersen, 1968). We model health utilisation as a function of enabling factors (*E*), predisposing factors (*P*) and need factors (*N*). Equation (1) specifies the empirical model, where *HU* is a measure of health utilisation, *E* is an n x 1 vector of enabling factors, *P* is an n x 1 vector of predisposing factors, *N* is an n x 1 vector of need factors and ε_i is the stochastic term assumed to be white noise. Patient's recent visit to a modern health facility is used as the proxy variable for HU (Başar *et al.*, 2021).

$$HU_i = \alpha + \beta_1 E_i + \beta_1 N_i + \beta_1 P_i + \varepsilon_i \tag{1}$$

This study considered four enabling factors in the vector of enabling factors: literacy, income, health insurance and savings (Archibong *et al.*, 2020; Başar *et al.*, 2021). Household consumption spending is used as a proxy for income. Income quartiles were constructed. The vectors of predisposing factors used in this study were gender, age and household size (Cleary *et al.*, 1982; Bertakis *et al.*, 2000; Başar *et al.*, 2021). Need factors used in this study were obesity, risky behaviour, self-assessment of health status, chronic illness and type of illness (Başar *et al.*, 2021). The outcome variable (i.e. health utilisation) is dichotomous; therefore, we employed a logit regression to estimate Equation (1). If we let the vector "y" denote the probability of observing the outcome variable of interest and collect all the independent variables into a vector X and the corresponding parameters into the parameter vector β, the logit regression version of Equation (1) can be expressed as

$$Pr(Y_i) = F(\alpha_i + X_i\beta + \varepsilon_i)\,;\ i = 1, 2, \ldots, n; \tag{2}$$

where $Pr(Y_i)$ stands for the probability of selecting one of the response outcomes (visit to modern healthcare facilities). α_i is intercept; β is vector of parameter estimates; X_i is vector of explanatory variables consisting of predisposing, enabling and need factors; ε_i is error term and F is the cumulative logistic distribution of the form

$$F(z) = \frac{\exp(z)}{1 + \exp(z)} \tag{3}$$

The identification condition requires that the expected value of the vector X, conditional on the vector of the error term, should be zero. However, this is unlikely for health insurance. This is because health insurance membership is a voluntary decision resulting in self-selection-based endogeneity. Insured and uninsured individuals may differ in their health behaviours, the propensity to utilise healthcare and baseline health status, amongst other things (Meer *et al.*, 2004; Sengupta and Rooj, 2019). These unobserved factors can affect health insurance membership and future healthcare utilisation. People with poor health status may decide to acquire health insurance in anticipation of increased healthcare utilisation. In addition, a person's spirituality and cultural values can influence their decision to access modern healthcare and possess health insurance. Spirit beings are believed to have the power to affect the well-being/health of those alive. This causes increased dependence on traditional solutions such as seeking help from witch doctors or religious leaders, decreasing the likelihood to patronise health insurance. This negative correlation between spirituality/culture and ownership of health insurance can create a downward bias in the coefficient of health insurance. Moreover, individuals who own durable assets may see themselves as more secured and therefore reluctant to buy health insurance. This could also introduce negative bias in the health insurance coefficient. Failing to address endogeneity concern can create biased results and invalidate inferences.

To address this concern, our identification strategy involves estimating a two-stage residual inclusion [2SRI] model (Terza *et al.*, 2008). Compared to the generalised method of moment (GMM) estimator, Koladjo *et al.* (2018) noted that the 2SRI is less biased and yields satisfactory confidence intervals. As a control function technique, 2SRI introduces an extra regressor to break the correlation between the endogenous independent variable and unobserved heterogeneities affecting the outcome variable (Wooldridge, 2010).

This study followed the explicit instructions for modelling the 2SRI provided by Terza (2017). The first stage of 2SRI involves predicting the residual of the endogenous regressor. Using a logit model, this requires estimating the probability of health insurance enrolment as a function of the instrument variable(s) and other exogenous covariates as.

$$NHIS\ \mathrm{enrolment}_i = \alpha_0 + \alpha_1 T_i + \alpha_2 X_i + \mu_i \tag{4}$$

where $NHIS$ enrolment$_i$ takes the value of one (1) if an individual decides to enrol in NHIS and zero (0) otherwise, T_i is a vector of the instrumental variables, X_i denotes a set of exogenous explanatory variables hypothesised to influence NHIS enrolment and ε_i is the error term. The predicted residuals from Equation (4) is used in the second-stage regression. The following conditions must be met by the elements in T: first, the instrumental variable(s) cannot be correlated with μ_i; second, the instrumental variable(s) must be adequately correlated with the endogenous variable (i.e. NHIS enrolment); and finally, the instrumental variable(s) can neither have a direct influence on the outcome variable (i.e. visits to a modern healthcare facility) nor be correlated with the error term in (1). In addition, there must be at least as many elements in T as there are endogenous regressors in (1).

This study used formal sector work (T) as the instrumental variable. Ghana's law requires all formal sector workers to contribute to the Social Security and National Insurance Trust (SSNIT). As a result, practically, all formal sector employees pay for the SSNIT. The statute that established Ghana's NHIS made it mandatory for workers to contribute 2.5% of their SSNIT contributions to support the NHIS. The law also requires SSNIT contributors to enrol in the NHIS without paying a premium. Therefore, we reasoned that our instrument (i.e. formal sector work) would be a good predictor of NHIS enrolment. However, being a formal sector worker do not directly affect one's decision to visit a modern healthcare facility. Therefore, we expect the instrumental variable to satisfy the external validity condition. To test this claim, we performed a pseudo-regression of healthcare utilisation on the instrument variable, controlling for other factors that influence healthcare use (see Table A2).

The second stage of the 2SRI model involved fitting a logit model of the outcome (visits to modern healthcare facilities) on all other covariates, including the residuals from the first-stage regression as a regressor. The model for the second stage is as follows:

$$Pr(Y_i) = F\left(\alpha_i + X_i\beta + \delta_i Res + \varepsilon_i^{2SRI}\right);\ i = 1, 2, \ldots, n; \tag{5}$$

where Res represents the estimated residuals from the first-stage regression and ε_i^{2SRI} is the error term in the second stage. The standard errors provided at this stage were incorrect, but correct standard errors were retrieved using bootstrapped standard errors.

4. Results and discussion

4.1 Descriptive statistics

Table 1 displays descriptive statistics for the entire sample. Approximately, 6.9% of the respondents in the overall sample had visited a modern health facility during their most

Variable name	Measurement	Mean	SD
Dependent variables			
Visits to modern health facility	Dummy: 1 = Visits to modern healthcare facility; 0 = otherwise	0.069	0.254
Independent variables			
NHIS enrolment	Dummy: 1 = currently insured; 0 = otherwise	0.577	0.494
Gender	Dummy: 1 = male; 0 = otherwise	0.489	0.500
Age	Continuous: positive whole numbers in years	35.775	20.641
Literacy	Dummy: 1 = if an individual can read and write in English; 0 = otherwise	0.389	0.488
Household size	Continuous: positive whole numbers of the number of persons in the household	5.336	2.858
Obesity	Dummy: 1 = if Body Mass Index ≥30; 0 = otherwise	0.071	0.257
Risky behaviour	Dummy: 1 = if consume alcoholic beverages and/or smoke or chew tobacco; 0 = otherwise	0.247	0.431
Chronic illness	Dummy: 1 = if exposed to chronic illness (sores, irritations and/or numbness); 0 = otherwise	0.342	0.475
Household expenditure	Continuous: positive numbers in Ghana cedis	523.21	483.59
Self-assessed health	Ordinal: unhealthy = 1, somewhat unhealthy = 2, somewhat healthy = 3 and Very healthy = 4	3.663	0.622
Fever	Dummy: 1 = if suffered fever; 0 = otherwise	0.061	0.239
Cold or cough	Dummy: 1 = if suffered cold or cough; 0 = otherwise	0.015	0.121
Diarrhoea	Dummy: 1 = if suffered diarrhoea; 0 = otherwise	0.006	0.079
Other illnesses	Dummy: 1 = if suffered from other illnesses; 0 = otherwise	0.035	0.185
Savings	Dummy: 1 = if household head saves with banking institutions and others; 0 = otherwise	0.210	0.408

Note(s): SD is the standard deviation
Source(s): Authors' own creation

Table 1. Variables, measurement and descriptive statistics

recent visit. Almost 58% of rural residents were enrolled in the NHIS. This statistic is impressive because it shows that many rural inhabitants had valid NHIS cards at the time of the survey. The average monthly household expenditure was Ghana cedis (GHS) 523.21.

4.2 Baseline regression

Failure to account for endogeneity in the model can introduce severe bias in the coefficient estimates, undermining the causal ability of the estimated model and inferences. To understand the severity of the bias involved when one ignores the endogeneity problem, we first performed a baseline regression, where the assumption of exogenous regressors was imposed. As discussed, spirituality, culture and family or household collateral can negatively influence health insurance enrolment decisions, thereby introducing negative bias in the coefficient. Table 2 presents the results of the baseline regression. We observe that health insurance increases the likelihood of utilising modern healthcare. The estimated baseline marginal effect is 0.059, indicating that having health insurance at the margin increases the likelihood of utilising modern health facilities by 5.9%. The different income quartiles show positive effects, suggesting that income is a significant predictor of modern healthcare utilisation. All predisposing factors (age, gender and household size) exerted a statistically significant effect on the usage of modern healthcare. In addition, all need factors, except obesity, have a statistically significant effect on modern healthcare use.

The 2SRI provides a simple approach to test the hypothesis that the endogenous explanatory variable is indeed endogenous by observing the residuals. The residual coefficient is negative and statistically significant, demonstrating that the NHIS variable is

Variable	Coefficient	Marginal effects
NHIS enrolment	1.123***	0.059***
	(0.097)	(0.005)
Second income quartile	0.202*	0.011*
	(0.114)	(0.006)
Third income quartile	0.307**	0.016**
	(0.124)	(0.007)
Fourth income quartile	0.415***	0.022***
	(0.133)	(0.007)
Gender (male)	−0.401***	−0.021***
	(0.091)	(0.005)
Age	0.007***	0.000***
	(0.002)	(0.000)
Literacy	0.085	0.004
	(0.093)	(0.005)
Household size	−0.071***	−0.004***
	(0.018)	(0.001)
Obesity	−0.047	−0.002
	(0.138)	(0.007)
Self-assessed health	−0.777***	−0.041***
	(0.057)	(0.003)
Chronic illness	0.411***	0.022***
	(0.088)	(0.005)
Risky behaviour	−0.235**	−0.012**
	(0.102)	(0.005)
Fever	2.094***	0.110***
	(0.107)	(0.006)
Cold or cough	1.647***	0.086***
	(0.210)	(0.011)
Diarrhoea	2.244***	0.118***
	(0.346)	(0.018)
Savings	0.198*	0.010*
	(0.104)	(0.005)
Constant	−1.259***	
	(0.307)	
Observations	12,314	
Wald χ^2	1,118.62***	
Log likelihood	−2,401.72	
Pseudo R^2	0.226	
Model classification	93%	

Note(s): Bootstrapped standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.10$
Source(s): Authors' own creation

Table 2.
Logit results assuming exogeneity of model regressors

endogenous (Table 3). A negative coefficient indicates that the latent factors influencing the probability of NHIS membership reduce the likelihood of using modern healthcare facility. This suggests that the coefficient of NHIS in the baseline regression is likely to suffer from downward bias. Consequently, inferences based on the baseline regression are misleading. This raises caution regarding the causal ability of previous studies that ignored endogeneity. Later, we commented on the severity of the bias involved.

4.3 Test for the instrumental variable

This study tested the validity, relevance and strength of the instrument using serial diagnostics. First, the t-value for the instrumental variable (i.e. a formal sector work) is 8.7 (i.e. 0.825/0.095), well above the rule of thumb value of at least 3.2, in the case of a single instrumental variable and a single endogenous regressor. This demonstrates the relevance and strength of the instrument (see the results in Appendix Table A1). Lastly, the effect of formal sector work is statistically insignificant in the second-stage regression, confirming that it does not directly influence the utilisation of modern healthcare services (see Appendix Table A2). This suggests that the instrumental variable satisfies the external validity condition.

4.4 The determinants of modern healthcare utilisation

Table 3 presents the 2SRI estimated results. The corrected standard errors for the second-stage estimations were calculated using bootstrapping, as suggested by Palmer *et al.* (2017).

Variable	Coefficient	Marginal effects
NHIS enrolment	1.843***	0.097***
	(0.385)	(0.020)
Second income quartile	0.190	0.010
	(0.116)	(0.006)
Third income quartile	0.328***	0.017***
	(0.117)	(0.006)
Fourth income quartile	0.372***	0.020***
	(0.125)	(0.007)
Gender (male)	−0.319***	−0.017***
	(0.098)	(0.005)
Age	0.006***	0.000***
	(0.002)	(0.000)
Literacy	0.037	0.002
	(0.099)	(0.005)
Household size	−0.070***	−0.004***
	(0.017)	(0.001)
Obesity	−0.092	−0.005
	(0.140)	(0.007)
Self-assessed health	−0.765***	−0.040***
	(0.059)	(0.003)
Chronic illness	0.422***	0.022***
	(0.088)	(0.005)
Risky behaviour	−0.226**	−0.012**
	(0.103)	(0.005)
Fever	2.092***	0.110***
	(0.100)	(0.005)
Cold or cough	1.659***	0.087***
	(0.210)	(0.011)
Diarrhoea	2.252***	0.118***
	(0.303)	(0.016)
Savings	0.192*	0.010*
	(0.098)	(0.005)
Residuals	−0.352*	−0.018*
	(0.181)	(0.010)
Constant	−1.737***	
	(0.396)	
Observations	12,314	
Wald χ^2	1,247.37***	
Log likelihood	−2,399.739	
Pseudo R^2	0.2265	
Model classification	93.02%	

Note(s): Bootstrapped standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.10$
Source(s): Authors' own creation

Table 3. Two-stage residual inclusion estimates for modern healthcare utilisation

The estimates were bootstrapped with 1,000 replications. The diagnostics of the estimated model was the starting point for discussing the empirical results. The Wald chi-squared test rejects the hypothesis that all regression coefficients are jointly equal to zero, suggesting that the model fits the data reasonably well. Additionally, 93% of visits to a modern health facility were correctly predicted.

The coefficients of NHIS enrolment and income significantly determine visits to a modern healthcare facility. The effect of NHIS enrolment is positive and statistically significant at the 1% level. This result implies that insured people in rural areas are more likely to use modern healthcare facilities when they are sick than when they uninsured. The marginal effect estimate shows that rural persons with NHIS are 9.7% more likely to visit a modern health facility when ill than their uninsured counterparts. One possible explanation is that insurance reduces the financial strain on individuals by lowering the cost of care, even if individuals have to travel vast distances to seek care. The positive influence of insurance on healthcare use is consistent with previous studies' findings (Fenny *et al.*, 2014; Liu and Zhao, 2014; Madyaningrum *et al.*, 2018; Van Der Wielen *et al.*, 2018). In a study of older persons in rural Ghana, Van Der Wielen *et al.* (2018) discovered that NHIS members were 6% and 9% more likely than non-members to receive inpatient and outpatient treatments, respectively. According to Madyaningrum *et al.* (2018), people with health insurance are 1.38 times more likely than their counterparts to seek outpatient services in Indonesia. Our findings, however, contradict those of Kumara and Samaratunge (2019) in Sri Lanka, which revealed that having health insurance reduced the likelihood of using public healthcare facilities for non-communicable diseases and acute illnesses. Compared to the baseline coefficient, our estimate demonstrates a 3.8% point downward bias in the coefficient of NHIS, confirming the earlier claim that failing to account for the endogeneity of NHIS can introduce downward bias.

Except for the second income quartile, which was statistically insignificant, our findings revealed an increasing rate of modern healthcare visits with income. The marginal effect results show that the probabilities of utilising modern healthcare increased by 1.7% and 2% in the third and fourth income quartiles, respectively, compared to the first income quartile. As modern healthcare is not cost-free, its use is determined by an individual's economic capacity, as measured by income. Rural residents' income levels are often low, resulting in many financial difficulties in seeking modern healthcare services. Gotsadze *et al.* (2017) obtained similar results in Georgia. This finding, however, contradicts that of Mwami and Oleche (2017). These authors used a wealth index as a proxy for income and discovered a negative influence of income on healthcare utilisation in Kenya.

Another enabling factor that determines rural inhabitants' health-seeking behaviours is savings. The coefficient of savings is positive and statistically significant. This result indicates that for persons from households where the head saves, the probability of visiting a modern healthcare facility increases by one percentage point. Families that save could rely on their past savings to seek medical attention at a modern healthcare facility if a member becomes sick.

All predisposing factors (i.e. gender, age and household size) significantly influenced rural residents' health-seeking behaviours. The gender (male) variable negatively predicts rural residents' modern health-seeking behaviours, suggesting that males are 1.7% points less likely to seek modern healthcare compared to that of their female counterparts. This finding supports earlier studies conducted in Ghana (Fenny *et al.*, 2014), Kenya (Mwami and Oleche, 2017) and Korea (Han-Kim and Lee, 2016). Age is positively associated with visits to modern healthcare facilities, suggesting that the elderly compared to the young adult are more likely to seek modern healthcare services. This is consistent with the findings of Li *et al.* (2016) and Mwami and Oleche (2017) but contradicts the findings of O'Connor (2015) and Han-Kim and Lee (2016). Finally, household size is a negative driver of health-seeking behaviours amongst rural residents. Large family sizes often characterise rural households in Ghana. Medical expenses increase with family size and with competing demands against lower income, families with large size numbers find it challenging to afford modern healthcare facilities. This finding is supported by those of previous studies (Li *et al.*, 2016; Mwami and Oleche, 2017).

Amongst the need factors, only obesity did not influence rural residents' utilisation of modern healthcare services significantly. Self-assessed health is a negative predictor of rural residents' use of modern healthcare services, suggesting that the more rural residents rate their health status as very good, the lower the likelihood of them using modern healthcare facilities. This observation is consistent with the findings of other studies (Madyaningrum *et al.*, 2018; Grustam *et al.*, 2020). Chronic illness is a positive determinant of modern healthcare utilisation. The marginal effect shows that rural residents with chronic illnesses exhibit 2.2% points higher likelihood to utilise modern healthcare facilities. This result reinforces the results of studies in China (Li *et al.*, 2016) and Indonesia (Madyaningrum *et al.*, 2018). Risky behaviour is negatively and significantly related to modern healthcare visits. The results suggest that for persons who smoke or drink in rural areas, the probability of using a modern healthcare facility decreased by 1.2% points. Lastly, the type of illness is a positive determinant of modern healthcare use (i.e. fever, cold/cough and diarrhoea). These results suggest that rural residents suffering from fever, cold/cough, or diarrhoea exhibit a higher probability of visiting a modern healthcare facility compared to other illnesses. This result is consistent with the findings of Sekyi and Domanban (2012) in Ghana.

4.5 Heterogeneous results

A heterogeneity analysis was also performed to explore the effects of income and health insurance on modern healthcare utilisation by splitting the sample based on gender and age. The estimated results for these subpopulations are presented in Table 4.

Regarding gender subpopulations, the effect of health insurance on modern healthcare utilisation is statistically significant and positive for both males and females (see Columns 2 and 3). These findings imply that the likelihood of utilising modern healthcare increases for males and females who are insured relative to their uninsured counterparts. Further observation suggests that insured females are more likely than their insured male counterparts to use modern healthcare. Compared to their insured male counterparts, insured females at the margin had a 13.6% point higher likelihood of using modern healthcare. The lower part of Table 4 provides the test results on whether these effects are statistically different. These tests were conducted following the methods described by Clogg *et al.* (1995) and Paternoster *et al.* (1998). The results demonstrate that health insurance exerts heterogeneous effects on modern healthcare utilisation, depending on gender group. Comparatively, men are known to care less about their health and only do so when they find themselves in a critical condition. According to Landro (2019), more men avoid visiting their physicians, skip recommended screenings and practice risky behaviours compared to women. In a case study of knowledge and periodic visits to medical centres, in Accra, Ghana, it was found that women tend to visit medical centres more than men (Appiah, 2019). Based on the supported literature, it is reasonable to conclude, based on our findings, that given that both men and women hold valid NHIS cards, utilisation of modern healthcare is likely to be higher for women than for men. Men have generally blamed their infrequent visits to medical facilities for their busy work schedules, fear of knowing and discomfort of medical examinations (Centers for Disease Control and Prevention, 2001).

Regarding income, we find that only the third income quartile has a statistically significant (but weak) and positive influence on modern healthcare utilisation. However, the effect was positive and statistically significant at all income levels for females. This result suggests that increased income for women of different classes will significantly influence

Table 4. Heterogeneity analysis for modern healthcare utilisation by gender and age subpopulation

Variable	Male		Female		Adults (18–59 years old)		The elderly (60 and above)	
	Coefficient	ME	Coefficient	ME	Coefficient	ME	Coefficient	ME
NHIS enrolment	1.509***	0.055***	2.016***	0.136***	1.910***	0.108***	2.813***	0.259***
	(0.537)	(0.020)	(0.479)	(0.033)	(0.473)	(0.027)	(0.759)	(0.069)
Second income quartile	0.012	0.000	0.271*	0.018*	0.142	0.008	0.195	0.018
	(0.196)	(0.007)	(0.139)	(0.009)	(0.160)	(0.009)	(0.196)	(0.018)
Third income quartile	0.357*	0.013*	0.294*	0.020*	0.319**	0.018**	0.285	0.026
	(0.204)	(0.008)	(0.152)	(0.010)	(0.160)	(0.009)	(0.236)	(0.022)
Fourth income quartile	0.178	0.007	0.456***	0.031***	0.266	0.015	0.539**	0.050**
	(0.219)	(0.008)	(0.160)	(0.011)	(0.165)	(0.009)	(0.265)	(0.025)
Gender (male)	–	–	–	–	−0.393***	−0.022***	0.120	0.011
	–	–	–	–	(0.140)	(0.008)	(0.194)	(0.018)
Age	0.012***	0.000***	0.002	0.000	–	–	–	–
	(0.004)	(0.000)	(0.003)	(0.000)	–	–	–	–
Literacy	0.129	0.005	−0.054	−0.004	−0.078	−0.004	0.115	0.011
	(0.163)	(0.006)	(0.137)	(0.009)	(0.121)	(0.007)	(0.214)	(0.020)
Household size	−0.096***	−0.004***	−0.058***	−0.004***	−0.044**	−0.002**	−0.118***	−0.011***
	(0.031)	(0.001)	(0.021)	(0.001)	(0.021)	(0.001)	(0.037)	(0.003)
Obesity	−0.538	−0.020	−0.004	−0.000	−0.207	−0.012	−0.036	−0.003
	(0.408)	(0.015)	(0.156)	(0.011)	(0.176)	(0.010)	(0.277)	(0.025)
Self-assessed health	−0.729***	−0.027***	−0.786***	−0.053***	−0.867***	−0.049***	−0.686***	−0.063***
	(0.099)	(0.004)	(0.069)	(0.005)	(0.071)	(0.004)	(0.087)	(0.008)
Chronic illness	0.467***	0.017***	0.398***	0.027***	0.438***	0.025***	0.280	0.026*
	(0.150)	(0.006)	(0.109)	(0.007)	(0.112)	(0.006)	(0.171)	(0.016)
Risky behaviour	−0.371**	−0.014**	−0.198	−0.013	−0.316***	−0.018***	−0.248	−0.023
	(0.161)	(0.006)	(0.133)	(0.009)	(0.122)	(0.007)	(0.180)	(0.016)
Fever	2.308***	0.085***	1.987***	0.134***	1.899***	0.108***	2.054***	0.189***
	(0.178)	(0.007)	(0.132)	(0.009)	(0.141)	(0.008)	(0.214)	(0.018)
Cold or cough	2.025***	0.074***	1.428***	0.096***	1.632***	0.092***	1.140***	0.105***
	(0.341)	(0.013)	(0.276)	(0.019)	(0.257)	(0.015)	(0.407)	(0.038)
Diarrhoea	2.773***	0.102***	1.814***	0.122***	2.504***	0.142***	1.248*	0.115*
	(0.442)	(0.017)	(0.466)	(0.032)	(0.451)	(0.026)	(0.719)	(0.067)

(continued)

Table 4.

Variable	Male Coefficient	Male ME	Female Coefficient	Female ME	Adults (18–59 years old) Coefficient	Adults (18–59 years old) ME	The elderly (60 and above) Coefficient	The elderly (60 and above) ME
Savings	−0.081	−0.003	0.329***	0.022***	0.200	0.011	0.038	0.004
	(0.171)	(0.006)	(0.126)	(0.009)	(0.127)	(0.007)	(0.225)	(0.021)
Residuals	−0.208	−0.008	−0.414*	−0.028*	−0.450**	−0.025**	−0.557*	−0.051*
	(0.251)	(0.009)	(0.224)	(0.015)	(0.226)	(0.013)	(0.292)	(0.027)
Constant	−2.063***		−1.692***		−0.956**		−2.275***	
	(0.616)		(0.431)		(0.424)		(0.645)	
Observations	6,025		6,289		7,068		1,923	
Wald χ^2	520.28***		587.29***		617.12***		219.35***	
Log likelihood	−869.482		−1,517.670		−1,480.702		−590.132	
Pseudo R^2	0.2384		0.2071		0.1940		0.2216	
Model classification	95.39%		90.65%		92.56%		86.90%	

Test for heterogeneity in the effects of NHIS and income by gender and age subgroups

Variables	Male–female comparison Z-statistics	The elderly – Adult comparison Z-statistics
NHIS enrolment	−2.099122**	−2.0379371**
Second income quartile	−1.5787044	−0.49690399
Third income quartile	−0.5466082	−0.33656253
Fourth income quartile	−1.7645151*	−1.31724238

Note(s): ME is marginal effects; bootstrapped standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$ and $^{*}p < 0.10$
Source(s): Authors' own creation

their decision to utilise modern healthcare. According to the results, the marginal effects depict 1.8, 2 and 3.1% increases in the probability of using modern healthcare for the second, third and fourth income quartiles, respectively, relative to the first quartile. A test on whether the effect of income differs by gender revealed weak evidence to confirm the claim that income does not exert a heterogeneous effect on visits to modern healthcare facilities amongst females.

By age subgrouping, Table 4 reveals that insured elderly are 15.1% points more likely to utilise modern healthcare than insured adults. The test of whether health insurance exerts a different influence on the decision to use modern healthcare, based on age grouping, revealed that the effect is statistically different from zero. This result suggests a failure to accept the null hypothesis that the influence of health insurance on modern healthcare utilisation is homogeneous for all age categories. Older people suffer more health-related issues and are therefore more likely to visit their doctors. Moreover, because they are no longer part of the working class, it is reasonable to assume that the working hours for these age groups will not compete with the hours they must spend at medical facilities. This situation might not be the case for the adult population, who may exhibit a higher opportunity cost for their time spent at health facilities. The effect of different income quartiles is positive but not very robust statistically. For adults, it is only statistically significant in the third income quartile, whereas for the elderly, it is statistically significant in the fourth income quartile. The test of the heterogeneous effect on income for adults and the elderly shows no statistically significant difference, suggesting that the influence of income is homogeneous for adults and the elderly.

Our results highlight that the heterogeneity in effect by gender and age group is more robust for health insurance and not for income. Thus, failure to account for heterogeneity can be another important source of bias.

5. Conclusion

This study examined the effects of health insurance and income on rural household healthcare utilisation in Ghana. A two-stage residual inclusion method was used to address self-selection-based endogeneity whilst subgroup regression was used to address heterogeneity bias. The results support the Andersen framework, suggesting that healthcare utilisation is influenced by predisposing, enabling and need factors. Thus, for rural people to use modern healthcare, they should be predisposed to use, expressed the need for care and have the right enabling environment. Specifically, we demonstrated that health insurance and increased income exert significant positive effects on healthcare utilisation in rural households. Generally, the results show that the effect of health insurance risks a downward bias of approximately 3.8% points when it is treated as exogenous. This finding raises vital caution regarding the causal ability of studies that failed to address the endogeneity of health insurance. Heterogeneity bias is another crucial form of bias discovered in this study. This study has illustrated that women and men and adults and the elderly, exhibit different likelihoods of utilising modern healthcare when having national health insurance. However, income generally does not suffer from significant heterogeneity bias.

The results of our study have the following implications for public policy. In order to improve rural residents' access to modern healthcare, amongst other things, policymakers should create the enabling condition to use modern healthcare. This study has emphasised the importance of having national health insurance. The Ministry of Health through the Ghana National Health Insurance Authority should expand NHIS coverage. Amongst other things, this might require breaking the financial barrier as related to premium rates that often inhibit rural people folks from either enrolling into or re-subscribing to the scheme. Creating a special premium dispensation to take care of the rural people could prove critical. However, the existing heterogeneity bias in the effect of NHIS suggests that such scale-ups engineered by special premium rates should be more targeted. For example, males and adult groups in rural communities may require complementary interventions, in addition to having NHIS, to promote awareness and education about their health. This could help consolidate the benefits of having national health insurance related to men's health and their use of modern healthcare. Regarding this, the Ministry of Health should partner with other agencies (public or private) to intensify health awareness creation amongst males. For women, who are economically disadvantaged, interventions that break women's financial barriers to NHIS enrolment could also help consolidate the benefits of the scheme to women's health. In this regard, the Ministry of Gender, Children and Social Protection should pursue income-generating activities or programmes that are widespread and inclusive. Next, this study presents important implications for the literature and future studies. Evidence of downward and heterogeneity bias in the effect of health insurance raises serious caution about the causal ability of insurance in explaining healthcare use in previous studies. Thus, future studies that fail to address endogeneity and heterogeneity issues risk suffering from serious bias.

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Appendix

Variable	Coefficient	p-value
Gender (male)	−0.534*** (0.037)	0.000
Age	0.000 (0.001)	0.898
Education	0.336*** (0.032)	0.000
Marriage	−0.004 (0.045)	0.921
Obesity	0.363*** (0.076)	0.000
Chronic illness	−0.045 (0.041)	0.266
Physical inactivity	0.562*** (0.059)	0.000
Household expenditure	0.000*** (0.000)	0.000
Formal sector work	0.825*** (0.095)	0.000
Constant	0.214*** (0.049)	0.000
Observations	12,666	
LR χ^2	618.21***	
Log likelihood	−8,314.898	
Pseudo R^2	0.0358	
Model classification	60.55%	

Note(s): Standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$
Source(s): Authors own creation

Table A1. Predictors of NHIS membership or enrolment

Variable	Coefficient
NHIS enrolment	1.118***
	(0.098)
Second income quartile	0.182
	(0.120)
Third income quartile	0.323***
	(0.121)
Fourth income quartile	0.393***
	(0.133)
Gender (male)	−0.398***
	(0.088)
Age	0.007***
	(0.002)
Literacy	0.076
	(0.101)
Household size	−0.070***
	(0.018)
Obesity	−0.044
	(0.132)
Self-assessed health	−0.778***
	(0.056)
Chronic illness	0.413***
	(0.087)
Risky behaviour	−0.232**
	(0.098)
Fever	2.092***
	(0.103)
Cold or cough	1.646***
	(0.209)
Diarrhoea	2.247***
	(0.326)
Savings	0.194*
	(0.105)
Formal sector work	0.137
	(0.173)
Constant	−1.273***
	(0.296)
Observations	12,314
Wald χ^2	1,161.98***
Log likelihood	−2,401.449
Pseudo R^2	0.2260
Model classification	92.96%

Note(s): Bootstrapped standard errors in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$
Source(s): Authors own creation

Table A2. Second-stage regression results for modern healthcare utilisation

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