Direct and Spillover Effects of Health Insurance on Household Consumption Patterns in Ekiti State, Nigeria

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Abstract

The report by the National Bureau of Statistics in 2017 that nearly 70 percent of Nigerians were living in poverty, using the dollar per day adjusted purchasing power parity as the criterion, implies weak ability to smoothen consumption over time for a large percentage of the population whenever there is an ailment. This study is therefore designed to examine the direct and spillover effects of health insurance (HI) on both medical and non-medical consumption in Ekiti State. A structured questionnaire was randomly administered to about 1500 respondents in all the hospitals that offer health insurance services in Ekiti State. A diagnostic test was performed to show the quality of match between insured and uninsured households, and their suitability for the study. The propensity score from logit regression at $\rho \leq 0.05$ was used to predict the probability of HI participation while the propensity score matching estimator was used to determine the direct and spillover effects of health insurance. The propensity score matching coefficient for medical consumption was 0.07 and positive, showing that medical consumption increased with health insurance status. The spillover effect of HI was 24,970 and it was positive indicating that health insurance increased non-medical consumption of the insured by ₦24,970 in the period of illness. This implies that health insurance increased the overall consumption of the insured households in the state.

Keywords: Direct effect, Spillover effect, Propensity Score Matching, Consumption patterns

Introduction

Low income and income inequality remain major barriers to consumption of medical care goods in less developed and developing nations of the world (Xu, Evans, Kawabata, Zeramdini, Klavus, & Murray, 2003; Preker & Carrin, 2004). According to Fatukasi and Ayeomoni (2015), income inequality and other health indicators have continued to be problematic in Nigeria despite the importance placed on the enhancement of health care facilities through equal distribution of income among the citizens. There are also reports about the growing profile of income inequality and the challenges it has posed to the health of Nigerians over the years which has brought about an increase in mortality rate, low life expectancy, low level of education and high unemployment rate. This situation is not different in Ekiti State where the majority of heads of household are civil servants and subsistence farmers. A report from the National Bureau of Statistics shows that Ekiti State has the lowest income level and the highest level of income inequality among the South West states (NBS, 2012), hence its choice for this study.

Coupled with this is the inability to effectively and efficiently mobilize and manage the scarce financial resources available for health care which, has always been sub-optimal in Ekiti State. Quite often, households find themselves at the receiving end of catastrophic health spending occasioned by many real and subtle "out-of-pocket" health expenses, in effect, a reduction in consumption of other non-medical goods. This implies that there is a need to promote health insurance which has the ability to offset financial risk in the event of adverse health outcomes (Sheu and Lu, 2014). With health insurance reducing households' exposure to risk, insured households need not save for precautionary motive, thus, the effect may differ in how they redistribute the additional funds.

Health insurance is a way of paying for health care which protects a household from paying the full cost of medical care expenses when sick or injured. In other words, it is a system of advanced financing of health expenditure through donations, premiums or taxes paid into a collective pool to settle all or parts of medical consumption specified by a policy or plan (NHIS, 2013). Among the significant direct effects of health insurance is the improved access to medical consumption notwithstanding income or age group (Cheng and Chiang, 1997). Health insurance further brings about welfare improvement through enhanced health status and maintenance of non-health consumption by ensuring that health expenditure is smoothened over time and that there is no significant decline in household labour supply (Varian, 1992; Townsend, 1994). Other impacts of health insurance include economic benefits to cover the insured households from unforeseen out-of-pocket health expenditures (OOPHEs); and allowing individuals to access necessary medical attention without suffering potentially crippling financial consequences. In addition, insured households experience lower financial tension resulting from medical expenses, lower out-of-pocket health expenditures, lower debt on medical bills, and lower rates of refused medical treatment because of medical debt than the uninsured (Finkelstein et al., 2011).

Also, health insurance, which often lays more emphasis on income redistribution, produces additional effect on a household's consumption distribution outside income protection. This effect of health insurance is termed "Spillover Effect", which goes beyond financial protection from unforeseen medical consumption. This has to do with the ability of the household to smoothen non-medical goods consumption even in the period of illness. The consumption pattern of a household is described as the combination of qualities, quantities, acts and tendencies characterizing a household, a community, or a human group's use of resources or commodities for survival, comfort and enjoyment (NBS, 2012). The types of commodities consumed vary from region to region and can be classified into food and non-food, durable and non-durable goods, and medical and non-medical goods.

In this study, consumption pattern is defined as how a household varies its consumption between medical and non-medical goods during periods of illness. This pattern of consumption is often altered when a member of the household is ill thereby leading to inability of the household to maintain its consumption pattern by sacrificing non-medical consumption goods for medical goods. Consumption of medical care can be catastrophic when its payment exceeds 40% of household income and leads the household to sacrifice consumption of other items that are necessary for its members' well-being (Uzochukwu and Uju, 2012). For households living close to the poverty line, even a low level of expenditure on health care may be sufficient to push them into poverty. This is because most households in such conditions are without full health insurance coverage, thereby facing the risk of incurring large medical expenditures whenever a member of the household falls ill. Therefore, during illness, health care consumption may depend on health insurance status, and the decision to be insured is driven by expected health care costs (Bolhaar, Lindeboom and van der Klaauw, 2012). Illness disrupts the pattern of household consumption via pressure on household income, and since consumption is a function of income (Keynes, 1936), households need to be insured to be able to smoothen their consumption patterns.

Hence, this study seeks to investigate the direct and spillover effects of health insurance on household consumption patterns using Ekiti State as a case study. Since expenditures on education and medical care are often regarded as important investments in human capital, the study focuses on examining the effects of health insurance on both medical and non-medical consumption patterns of the households. Thus, the research questions are as follows:

1. What is the effect of health insurance on medical consumption in the period of health shocks?
2. What is the spillover effect of health insurance on non-medical consumption goods during illness?
3. Can health insurance reduce households' out-of-pocket health expenditure in the period of illness?

In the light of these questions, this study sets out to examine the direct and spillover effects of health insurance on consumption of medical and non-medical goods within the context of Ekiti State.

The contributions of this paper emanate from expansion of this study to cover non-medical consumption which has not been done in the previous studies on the subject in Nigeria (Onyedibe, Goyit & Gomam, 2012; Obikeze et al. (2013); Olayiwola 2015). Also, some of the existing literature on this subject show that there is no consensus on the effect of health insurance on consumption (Nyman, 2003; Nyman, 2006). On a general note, the need to effectively and efficiently mobilise and manage the scarce financial resources available for health care which have been reported to always be sub-optimal in Nigeria demands extensive work on health financing. More often than not, the household is left at the receiving end of catastrophic health expenditure elicited by many real and subtle "out-of-pocket" health spending. Therefore, it is only by carrying out research on affordable contributory and innovative financing options such as health insurance that the expectations and targets for health care financing can be met. Hence, it is expected that the funding gaps identified in this research will be addressed through research work on the impact of health insurance programme. Thus, this paper contributes to the existing literature since it intends to use primary data from Nigeria to examine the causal effects of health insurance on consumption patterns among households in Ekiti State.

Background

Like any other state in Nigeria, orthodox and traditional medical experts provide healthcare services to the people of Ekiti State. The state government further made efforts to set the guidelines for the operation of traditional medical practitioners and the practice of traditional medicine in the state. Statistically, the state has two hundred and eighty-three (283) primary healthcare centres distributed among the local government areas. These primary healthcare centres include the basic health centres, comprehensive health centres, and maternity centres/dispensary centres. The state also boasts seventeen (17) secondary healthcare centres, three (3) specialist health facilities, two (2) tertiary health facilities; a federal government-owned tertiary health centre; one hundred and sixty-three (163) accredited private health facilities, and roughly 7 missionary health facilities.

The distribution of healthcare facilities in Ekiti State is presented in Table 1. The table shows that Ekiti State has 512 health facilities, out of which 380 belong to the public sector while the remaining 132 facilities are private-owned.

Table 1: Healthcare Facilities Distribution by Ownership

Healthcare Facilities	Number of Healthcare Facilities	Percentage
Public	380	74.2
Private	132	25.8
Total	512	100

Source: Computed based on data obtained from Planning, Research and Statistics Department, Ekiti State Ministry of Health, Ado-Ekiti.

Methods

Data source and description

The data for the study were collected using a purposive sampling survey carried out from December 2016 to February 2017 in the sixteen local government areas in Ekiti State though with concentration on Ado and Ido/Osi Local Government Areas. The reason for the concentration was the presence of teaching hospitals and federal government parastatals and institutions, while their workers are mostly covered by some type of health insurance. A purposive sample is one that is selected based on the knowledge of a population and the purpose of the study. In this case, a purposive sample was employed because those being interviewed fit a specific description (i.e. those who have health insurance and those who do not). The sixteen local government areas in Ekiti State are Ado, Efon, Ekiti-East, Ekiti/South-West, Ekiti-West, Emure, Gbonyin, Ido/Osi, Ijero, Ikere, Ikole, Ilejemeje, Irepodun/Ifelodun, Ise/Orun, Moba and Oye. The target population used in the study were formal sector employees (private or public) and informal sector workers with or without health insurance coverage.

The data was collected through a well-structure questionnaire following the Vietnam Living Standards Survey (VLSS) design. The choice of VLSS was because most of the variables required to proxy items in this study are not captured in the Nigeria Health Living Standard Survey. It is a 45-item questionnaire containing questions regarding respondent household socio-demographic characteristics, health insurance status and rating, health status, health care expenditure and health care utilization, and household non-medical consumption. A total of 1500 questionnaires were administered across the state while 1223 were retrieved. The survey for the study was conducted using trained enumerators. The facilities used in each local government were teaching hospitals, health centres, general hospitals, and private hospitals with health insurance facilities

Health facilities that were participating in health insurance schemes were purposively selected while selection of respondents in each facility was randomly done across all the departments. The departmental heads in the case of teaching and general hospitals, and chief Medical Director in private hospitals and matrons of the hospitals used were approached; their cooperation was solicited in view of the sensitive nature of the procedure. The enumerators, through the medical officers and nurses, administered the questionnaire to those who visited the facility during the survey period while the enumerators explained any part of the questions that appeared ambiguous to the respondents. The nurses in the health facilities and some other hospital workers were entrusted with ensuring that the questionnaires were properly filled; they also collected the questionnaires on regular basis for onward transfer to the enumerators. The enumerators assisted in supervising the households' respondents and also double-checked the questionnaires for consistency.

The questionnaire captured all the dependent and independent variables employed in the study. Health insurance status is the first dependent variable. It refers to whether a household is covered by health insurance or not. This variable is dichotomous. Other dependent variables in the equation are expenditure on medical consumption which is proxied by cost of all the medical goods and services consumed during the sick period in the last four weeks, OOPHE is measured by cost of medical care plus cost of non-prescribed medication, special drugs and meals and cost of transportation during the sick period, and non-medical consumption; this is measured by all expenses on all non-medical commodities consumed during the sick period. The independent variables in the equation are household income during the sick period measured by income from employment, gifts and others; the households' health status which could be excellent, very good, good, fair, poor, or very poor; and individual household characteristics which can influence the purchase of health insurance such as household size, level of education, employment status, marital status among others.

Model description

The propensity score matching (PSM) estimation model was adopted to assess the direct and spillover effects of health insurance on household consumption patterns in Ekiti State. The choice of PSM is its ability to analyse data without the baseline like the one employed in this study as a result of lack of national survey data for variables used. The major strength of the PSM technique is its capacity to redress bias by comparing how outcomes differ for participants (treated) relative to observationally similar non-participants (controlled) (Rosenbaum and Rubin, 1983). This method has turned out to be progressively mainstream and generally utilized as a part of the assessment of economic policy intervention (Becker and Ichino, 2002).

The basic idea behind propensity score matching (PSM) is to match each treatment (participant) with an identical control group (non-participants) and then measure the average difference in the outcome variable between the treatment and the control. Some of the studies that have employed this model include Wagstaff and Pradhan (2005), Sheu and Lu (2014), and Cheung and Padieu (2012), among others.

This estimation allows policy evaluation by creating a counterfactual and addressing the household adverse selection problem (Cheung and Padieu, 2012). To compare the level of consumption between participants and non-participants using propensity score matching, we first predict the probability of participating in the scheme using a logit regression. We evaluate the logit model to appraise propensity scores for matching purposes. Propensity score (PS) is the probability of receiving treatment (in this case, given access to health insurance programme), conditional on the observed characteristics of the household. It is interpreted by looking at the values of the odd ratios of all the observed variables generated in the logit model. The essence of the logit regression is to get the mean participation. Thus, it is specified as follows:

$$HI = \alpha_{3,i} + \delta_{i \cdot i} + \psi_i \tag{1}$$

where:

HI = the households' participation in health insurance

X_i = vector of other variables like households' income during illness, and other control variables which include age, gender, education, marital status among others that affect the demand for consumption goods

α_i = constant term

ψ_i = error term

This process is followed by generating propensity scores; this is the score assigned to the condition of likelihood of accepting a treatment given pre-treatment attributes (Rosenbaum and Rubin, 1983). This propensity score is assessed keeping in mind the end goal to show the presence (or non-appearance) of the intercession with various observable attributes. For this situation, we evaluate the logit model to appraise propensity scores for matching purposes. The binary outcome for health insurance participation takes a value of one (1) if the household has health insurance policy and zero (0) otherwise. The propensity scores were computed using binary logit regression models given as:

$$P(X) = Pr\{D = 1/X\} = E\{D/X\} \tag{2}$$

where, $D = \{0, 1\}$ is the indicator of introduction to participant characteristics (dependent variable). That is, D=1 if participated and D=0 if not participated, X is the multidimensional vector of observed characteristics. These independent variables are those which are expected to jointly determine the probability of participating in the scheme.

Given the assumption that selection into the scheme is based on observable characteristics alone[1], we matched the two groups to ensure their suitability for the analysis. Estimated propensity scores allowed construction of comparison groups by matching the propensity scores of the households with health insurance and households without health insurance. Once treatment groups were matched with control groups, the difference between

[1]See Dehejia and Wahba (1999), Heckman, Ichimura, Smith, and Todd (1998), Smith and Todd (2001) for evaluation of matching estimator.

the mean outcome of the programme treatment and the mean outcome of the matched control groups could be measured. However, when estimating, propensity score matching required different matching algorithms which included radius matching, nearest-neighbour, stratification matching and kernel matching.

We thereafter assessed the quality of match, keeping in mind the end goal to get an unbiased estimate and to survey the matching quality. In addition to this assessment, a balancing test was performed which was principally concerned about the degree to which the distinction in the covariates between the treated and control groups had been removed, so that, any distinction in result factors between the two groups could be surmised as coming exclusively from the treatment group. There are two different ways through which adjusting of the covariates can be confirmed. The t-stats of difference in means of observable characteristics are used to examine the quality of the matching before the match and after the match. Before matching, differences between the treated and the control groups are not unexpected; yet in the wake of matching, the observed covariates ought to be adjusted in both groups, and henceforth no huge contrasts ought to be found (Caliendo and Kopeinig, 2005).

Lastly, the impact was estimated. This involved estimating the effect of health insurance on all the outcome variables, i.e., estimating the average treatment effect on the treated (ATT), average treatment effect on the untreated (ATU), and average treatment effect (ATE).

Average Treatment Effect on the Treated (ATT)

This is the mean effect of an intervention through the mean difference in the outcomes of the matched pairs. Let Mc^{part} and $Mc^{non\text{-}part}$ be the expenditure on medical and non-medical consumption (total consumption) for insured and uninsured households, respectively, and D $\in$ {0,1} the indicator of enrollment status. The propensity score was defined by Rosenbaum and Rubin (1983) as the conditional probability of participation, given observed characteristics:

$$p(X) = Pr\ (D = 1 \mid X) = E\ (D \mid X)$$

where X is the vector of observed variables. Given the propensity score $p(X)$, the average effect of treatment on the treated (ATT) can be estimated as follows:

$$ATT = E(\Delta\, Mc \mid D = 1, X)$$

$$= E(Mc^{part} - Mc^{non\text{-}part} \mid D = 1, X)$$

$$= E(Mc^{part} \mid D = 1, X) - E(Mc^{non\text{-}part} \mid D = 1, X)$$

$$= E[Mc^{part} \mid D = 1, p(X)] = E[Mc^{non\text{-}part} \mid D = 0, p(X)] \quad (3)$$

where:

D = 1 denotes programme participation (treatment)

X is a set of conditioning variables on which the subjects will be matched and

$E(Mc^{non\text{-}part} \mid D = 1, X)$ is the mean of the counterfactual and denotes what the outcome would have been among participants had they not participated in the programme. However, PSM provides a way of estimating this counterfactual.

Equation (3) gives the average programme impact under the conditional independence assumption (CIA)[2] and overlap assumption[3]. A unique advantage of PSM is that instead of matching subjects on a vector of

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[2] Conditional independence assumption means that conditional on X, the outcomes are independent of treatment, i.e., after controlling for X, the assignment of units to treatment is 'as good as random.' This assumption is also known as selection on observables, and it requires that all variables relevant to the probability of receiving treatment be observed and included in X. This allows the untreated units to be used to construct an unbiased counterfactual for the treatment group.

[3] Overlap means that for each X, there are both treated and control groups, i.e. $0<pr(D=1|X|<1$. This implies that the probability of receiving treatment for each possible value of the vector X is strictly within the unit interval: as is the probability of not receiving treatment. This assumption of common support ensures that there is sufficient overlap in the characteristics of treated and untreated units to find adequate matches.

characteristics, we only need to match on a single item, i.e., the propensity score that measures the probability of participating in the programme.

Average Treatment Effect on the Untreated (ATU)

This is the measure of treatment effect on the untreated. That is, the effect of the intervention on non-participant if he/she had participated.

$$ATU = \frac{ATE}{P(D=0)} - ATT * \frac{P(D=1)}{P(D=0)} \qquad (4)$$

where:

ATE = the effect on the individual drawn at random,

P(D=1) = the probability that the sample population is with an intervention and

$P(D=0)$ = the probability that the sample population is without an intervention. (0, 1) is the treatment indicator.

Average treatment effect (ATE)

This is the average effect of the treatment for an individual drawn at random from the overall population. It is calculated as follows:

$$ATE = ATT\,.P(D = 1) + ATU\,.P(D = 0) \qquad (5)$$

Equation (5) shows the relationship between ATT (average treatment on the treated), ATE (average treatment effect on an individual) and ATU (average treatment on the untreated).

Balanced Diagnostics Test

The basic idea behind statistical matching (Rubin, 1974) is to recognize, in a large pool of potential comparison observation, a sufficient number of samples that closely resemble the treated units, that is, to verify whether the observed group and matched control units have the same characteristics. Table 2 shows after-matching means of the co-variates used in the logit regressions for enrolment in health insurance. In other words, we matched each treated unit using kernel matching algorithms.

In general, since almost all the probability values of the co-variates, after matching, are greater than the t-statistics (1%, 5% and 10%), it shows that there is no statistically significant difference between the characteristics of the observed and the control. This means that the two categories are suitable for the analysis.

Table 2: Mean of Co-variates and % Reduction Bias after Matching for the Treated and the Control Groups[a]

Co-variates	Treated Matched	Control Matched	P>|t|
Age	40.186	40.115	0.952
MSTsingle	0.76952	0.76168	0.831
Familytype	1.1004	1.0998	0.983
Familysize	4.2714	4.2587	0.941
Female	0.56134	0.50954	0.229
Igbo	0.05204	0.04585	0.74
Hausa	0.00372	0.00414	0.938
Ebira	0.01115	0.00776	0.685
Others	0.00743	0.00747	0.996
PREDU	0.01487	0.01902	0.71
SECEDU	0.05948	0.05806	0.944
POSECEDU	0.91078	0.90277	0.75
PRMEDU	0.02602	0.02563	0.977
SECOEDU	0.11524	0.12144	0.824
POSTSECOEDU	0.79554	0.78699	0.808
HSTVerygood	0.3197	0.31381	0.884
HSTGood	0.27138	0.24979	0.569
HSTFair	0.05576	0.05272	0.877
HSTVerypoor	0.00372	0.00288	0.866
HHSTVerygood	0.3829	0.36166	0.611
HHSTGood	0.16729	0.16243	0.88
HHSTFair	0.03346	0.02711	0.668
HHSTVerypoor	0.00372	0.00288	0.866
FPSWORKER	0.10037	0.08734	0.605
TRADER	0.05204	0.04721	0.797
FARMER	0.01859	0.02738	0.497

Co-variates	Treated Matched	Control Matched	P>|t|
SELF_EMPLOYED	0.11524	0.1121	0.909
UNEMPLOYED	0	0.00255	0.408
OTHERS	0.05204	0.05605	0.838
FPSCWORKER	0.03717	0.0446	0.664
TTRADER	0.04461	0.05545	0.565
TFARMER	0.0223		0.77
TSELF_EMPLOYED	0.04461	0.04049	0.813
TUNEMPLOYED	0.01115	0.00521	0.446
InHHINCOME	11.597	11.625	0.666

[a]if variance ratio outside [0.80; 1.25] for U and [0.79; 1.27] for M

Source: Author's computation.

Results and Discussion

Descriptive statistics and demographics

The summary statistics of the variables employed in the analysis for estimation are presented in Table 3. Health insurance status represented the dependent variable employed in this study. This was proxied by assigning 1 to the households with health insurance and 0 to the households without health insurance. The table shows that 27.4% of the households had health insurance coverage while 72.6% did not. Other variables used include income of the households, age of the respondents, family size, family type and other socio-demographic characteristics. The results show that the total monthly income of the households ranged from ₦18,000 to ₦1, 080,000 with average monthly income at ₦119, 779.40.

Another socio-demographic characteristic used in the analysis was gender. The result suggests that Ekiti people are not gender biased in terms of awareness about the use of hospitals as the figures were fairly even. Marital status results show the majority of heads of households were married (69.3%) while some were single (25.6), only a few were divorced or separated or widowed. Further, 69.5% of the household heads had post-secondary education, while only 8.5% had not had any type of formal schooling. Similarly, on the spouses' level of education, 67.7% had post-secondary education, and only 8.4% did not attend any formal school. This could be interpreted as an evidence that the majority of people working in the formal sector in Ekiti State had post-secondary school education.

Table 3: Summary Statistics of the Variables Used in the Estimation

Variables	Frequency	Percent	Cumulative %
HI Status			
Insured Households	335	27.4	27.4
Uninsured Households	888	72.6	100
Family Type			
Monogamy	1059	86.6	86.6
Polygamy	164	13.4	100
Gender Distribution			
Male	621	50.8	50.8
Female	602	49.2	100
Marital Status			
Single	313	25.6	25.6
Married	848	69.3	94.9
Divorce/Separated	7	0.6	95.5
Widow/Widower	55	4.5	100
Tribe Distribution			
Yoruba	1102	90.1	90.4
Igbo	79	6.5	96.9
Hausa	7	0.6	97.5
Ebira	17	1.4	98.9
Igede	5	0.4	99.3
Others	9	0.7	100
Family Head			
Father	1069	87.4	88
Mother	102	8.3	96.4
Brother	13	1.1	97.4
Sister	13	1.1	98.5
Self	26	2.2	100
Age Distribution			
Infant	506	41.4	41.4
Without Infant	717	58.6	100
Children	687	56.2	56.2

Variables	Frequency	Percent	Cumulative %
Without Children	536	43.8	100
Adult	1078	88.1	88.1
Without Adult	145	11.9	100
Old People	207	16.9	16.9
Without Old People	1016	83.1	100
Hospital Visits			
One Visit	779	63.7	63.7
Two Visits	333	27.2	90.92
Three Visits	102	8.3	99.26
Four Visits	8	0.7	99.92
Five Visits	1	0.1	100
Time Distribution			
0-10 minutes	153	13.3	13.3
11-30 minutes	703	55.1	68.4
31-60 minutes	237	20.5	88.9
Above 60 minutes	128	11.1	100
Household head			
No Education**	71	5.8	5.8
Primary Education	89	7.3	7.3
Secondary Education	133	10.9	10.9
Post-secondary Education	930	76	100
Spouse			
No Education **	104	8.5	8.5
Primary Education	88	7.1	7.1
Secondary Education	181	14.8	14.8
Post-secondary Education	850	69.5	100
Respondents			
No Education **	76	6.2	6.2
Primary Education	105	8.6	14.8
Secondary Education	202	16.5	31.3
Post-secondary Education	840	68.7	100
Government worker:(Household head)**	225	49.3	49.3

** shows the description of different variables in the table.

Source: Author's computation.

On household head's occupation, 49.3% were government workers, 11.2% were formal private sector workers, 8% were traders, 1.3% were transporters, 5.5% were farmers, about 13.8% were self-employed, while 0.7% fell within the others not specified category. This showed that the majority of the household heads were formal sector employees. However, the spouses' employment status was at variance with that of the household heads as 25% of the spouses were government employees, while 12.5% were private sector employees. Traders and self-employed spouse were the other categories to note, accounting for 8.4% and 6% of the sample size, respectively, with the exception of the spouses that were equally the household head accounting for about 40%. Similarly, the majority of the respondents worked in the formal sector, accounting for more than 50% of the sample. In addition to this category, trader, self-employed and students accounted for 11.7%, 11.4% and 15.5% respectively while the remaining categories together represented just about 11% of the sample. This distribution shows that the majority of households and respondents in this analysis were employed in the formal sector.

On the households' health status, there appears to be some level of consistency as both the respondents and the households showed dominance of very good health and excellent status, though not in absolute figures. Similarly, those with poor and very poor categories in both groups had the least proportions. This analysis revealed consistency in the respondent's health status perception. This shows that the respondent's health status actually reflected the household health status. Other variables employed in the study include medical consumption, non-medical consumption and out-of-pocket health expenditure.

Main results

The potential impacts of health insurance on medical consumption can be measured in several dimensions. In this study, medical consumption is measured in terms of hospital visits. As would be expected, the result shows that given the same socio-demographic characteristics and health status, households with health insurance, when sick, visit the hospital more regularly than their uninsured counterparts. This is because the barrier created due to low income and income inequality among households has been removed by health insurance as about 90% of the total health bill is reimbursed by health insurance with the exception of those treatments on the exclusion list. This finding shows that health insurance improves the consumption of both medical and non-medical goods among households in Ekiti State. From the result of non-medical consumption of households and health insurance reported in Table 4, access to health insurance leads to a statistically significant increase in the amount expended on non-medical consumption by the insured households. The mean expense on non-medical consumption of households with health insurance (treated group) was ₦6300 higher than the households in the control group. Intuitively, the result of ATT implies that health insurance increases non-medical consumption by reducing the uncertainty associated with future expense, thereby encouraging households to reduce savings. In other words, health insurance does have an impact on the insured households reducing their income risk and enabling them to access more consumption goods. Risk-averse households without health insurance coverage and without access to financial institution however, have to set aside a significant proportion of household income for health contingencies. In addition to that, some items on non-medical consumption, like food and affordable clean housing, can also have positive effects on households' health status thereby encouraging households to generate more money since investment in health has been proven to be one of the factors of production. The findings of this paper are consistent with Wagstaff and Pradhan (2005) and Cheung and Padieu (2012) whose findings also suggested that health insurance increased non-medical consumption.

This study further examined the impact of health insurance on sub-aggregates of households' non-medical consumption, which includes food consumption and non-food consumption. Food consumption includes expenses on staple foods, beverages, fruits, water, oil, meat and eggs. The result shows that food consumption increased with health insurance coverage status, thereby reducing the risk of unnecessary savings for medical consumption. This corroborates the findings by Gruber and Yelowitz (1999) that the parameters of the health insurance programme are major determinants of the savings behaviour of households. However, the effect was more on non-food consumption than food consumption. The study is similar to Glewwe, Gragnolati and Zaman (2000) in terms of what constitutes non-medical consumption items. This result further confirms the finding that health insurance has positive effects on household non-food consumption and per capita consumption (Dercon, Gunning & Andrew, 2012). Based on their report, households that take up health insurance are less likely to borrow from informal sources to cover medical costs.

Table 4: Average treatment effects of health insurance on non-medical consumption (₦)

Variable Sample	Kernel Matching					Radius Matching				
	Treated	Controls	Difference	S.E.	T-stat	Treated	Controls	Difference	S.E.	T-stat
NON-MED										
Unmatched	143450.3	128213.5	6300.632	19297.8	0.33	143450	128214	15236.79	19297.82	0.33
ATT	139587.9	133540.1	6047.806	25050.2	0.24	143450	128214	15236.79	26097	0.58
ATU	130388	161610	31221.98	.	.	128214	143450	15236.79	.	.
ATE			28196.75	.	.			15236.79	.	.
FOOD CONS.										
Unmatched	44785.16	40223.85	3569.236	3377.6	1.06	44785.2	40223.9	3569.236	3377.597	1.06
ATT	45958.57	42576.84	3381.731	3977.9	0.85	44785.2	40223.9	4561.308	3931.04	1.16
ATU	40398.05	46788.48	6390.429	.	.	40223.9	44785.2	4561.308	.	.
ATE			6028.869	.	.			4561.308	.	.

In addition, the study compared the result of kernel matching with radius matching algorithms. Though the results differed in terms of magnitude, the direction of the effect was similar. The result of the kernel matching using radius algorithm shows that the insured households increased their consumption by ₦6,300 as against ₦15,236. The result further shows the effect of health insurance on the uninsured households if they were insured. The findings show that households without health insurance could have increased their non-medical consumption by ₦6,047 with kernel matching and ₦15,236 with radius matching. Though the magnitude also differs, the direction of the effects is the same for both matching algorithms.

The effect of health insurance on out-of-pocket health expenditure (OOPHE) is reported in Table 5. The report shows that households that had health insurance spent ₦9,171.38 less on OOPHE when compared with those without health insurance though they had similar socio-demographic characteristics and health conditions. This study corroborates the finding by other authors such as Wagstaff (2007) and Yip and Hsiao (2008). On the contrary, however, Deb and Trivedi (2002) and Wagstaff, Lindelow, Junc, Ling & Juncheng (2007) found no significant correlation between health insurance and OOPHE. These findings further show that the impact of health insurance on OOPHE varies across countries depending on the type health insurance scheme. Whereas, in the current study, health insurance reduced out of pocket health expenditure, because two-thirds of the premium being paid by the insured was borne by the employers. The result also shows that the majority of the insured households were under NHIS.

However, comparing the results of kernel matching algorithm with radius matching algorithm shows some discrepancies in terms of the magnitude of the coefficient, but the direction of effects remains the same.

Table 6 reports the result of the effect of health insurance on medical consumption. Medical consumption comprises cost of consultation, drugs and laboratory tests, admission, medical checkup, caesarean section, surgical operations, among others. As would be expected, our findings show that insured households spent ₦10,207 less than the households without health insurance. This is consistent with other findings as reported in Wagstaff and Pradhan (2005). This implies that the majority of the items consumed during this survey were within the inclusive list of health insurance and so the insured households paid little money at the period of consumption.

Table 5: Average treatment effects of health insurance on OOPHE (₦)

Variable	Kernel Matching					Radius Matching				
Sample	Treated	Controls	Difference	S.E.	T-stat	Treated	Controls	Difference	S.E.	T-stat
OOPHE										
Unmatched	4968.71	14568.46	-8401.06	4465.293	-1.88	4968.71	14568.46	-8401.06	4465.293	-1.88
ATT	5378.571	13667.64	-8289.06	4279.692	-1.94	4968.71	14568.46	-9599.75	4101.352	-2.34
ATU	14232.8	6614.271	-7618.53	.	.	14568.5	4968.71	-9599.75	.	.
ATE			-7699.11	.	.			-9599.75	.	.

Table 6: Average Treatment effects of health insurance on medical consumption (₦)

Variable	Kernel Matching					Radius Matching				
Sample	Treated	Controls	Difference	S.E.	T-stat	Treated	Controls	Difference	S.E.	T-stat
Med Cons										
Unmatched	1420.323	13432.55	-10207.1	4265.375	-2.39	1420.323	13432.55	-10207.1	4265.375	-2.39
ATT	1450	12768.67	-11318.7	2521.419	-4.49	1420.323	13432.55	-12012.2	2643.213	-4.54
ATU	13141.68	2351.872	-10789.8	.	.	13432.55	1420.323	-12012.2	.	.
ATE			-10853.4	.	.			-12012.2	.	.

Robust Check: Sensitivity analysis

In Table 7, the value of gamma is interpreted as the odds of treatment assignment hidden bias. A change in the odds lower/upper bound from significant to non-significant indicates by how much the odds need to change before the statistical significance of the outcome shifts (Adeyemi and Lawanson, 2017). For instance, in this figure, the lower bound estimate changes from non-significant (0.9998) to non-significant (0.9988) when gamma is 1.0 and 1.1 respectively. Therefore, since moving from one level of gamma to another level does not show any level of significance, it then means that all the variables used in this analysis are strong enough to influence the outcome variables without any bias. A study is defined as sensitive if the values of gamma close to 1 lead to changes in significance compared to those that could be obtained if the study is free of bias (Rosenbaum, 2002). Therefore, based on this result, health insurance participation in Ekiti State is not sensitive to other unobservable predictors. Thus, the result is robust to only observable variables.

Table 7: Rosenbaum Sensitivity Test

Gamma	Upper bound significance level	Lower bound significance level
1	0.999896	0.999896
1.1	0.999994	0.998818
1.2	1	0.992573
1.3	1	0.970229
1.4	1	0.915596
1.5	1	0.817189
1.6	1	0.678956
1.7	1	0.52073
1.8	1	0.368
1.9	1	0.240249
2	1	0.145617

Note: Gamma is log odds of differential assignment due to un-observed factors rbounds delta3, gamma (1 (0.1) 2)

Source: Author's field work.

Summary and Conclusion

The study investigated the two major effects of health insurance vis à vis households' consumption patterns in Ekiti State. In view of the findings of this study, the following conclusions were drawn. In Ekiti State, 512 health care facilities exist with public and private hospital structures. These hospitals are classified into health insurance accredited and health insurance non-accredited, based on whether or not they provide health insurance services. In addition, the majority of hospitals are located in Ado-Ekiti, the state capital, and the number of health insurance, non-accredited hospitals are far more than the accredited hospitals. Furthermore, the state has two major teaching hospitals located in Ado-Ekiti and Ido-Ekiti. These hospitals provide health insurance services to more than half of the insured households in Ekiti State. Even though private hospitals are more than government-owned hospitals, the number of hospitals that are providing health insurance services are still very few and the level of patronage by the insured too is very low.

Overall, Ekiti State, like any other states of the federation comprises both insured and non-insured households. The number of hospital visits by these household groups varied, depending on their health insurance status. Similarly, the level of non-medical consumption among the two groups also varied, depending on their health insurance status. In view of the different relationships that exist between health insurance and medical consumption, and health insurance and non-medical consumption, it was concluded that health insurance has positive impacts on households' consumption. This scheme made the insured households visit hospitals as and when due more than the uninsured households.

Similarly, we conclude that health insurance increased the consumption of non-medicals of the insured since 90% of the bill that would have been paid by them is reimbursed by the scheme. The erstwhile income could then be redirected to consumption of non-medical goods. Furthermore, health insurance reduced the out-of-pocket health expenditure of the insured households. In other words, health insurance status is negatively correlated with OOPHE in the period of illness. Out-of pocket health expenditure comprises the cost of medication prescribed by doctors, non-prescribed medication and cost of special drugs and food that are associated with households' illness. Since 90% of the cost of prescribed medications that formed the bulk of the total OOPHE is often settled by the health insurance scheme, the study concluded that being enrolled in a health insurance scheme reduced insured households' OOPHE. This study further concluded that the findings that emanated from this study are robust enough. This is because the coefficients of the gamma in the sensitivity analysis which is the measurement parameter were not significant, implying that the variables employed in this study were strong enough to influence households' consumption without any bias. Finally, it was concluded that though health insurance increases access to medical care, it cannot wholly be an effective tool for the improvement of health care, unless the health care system as a whole is enhanced with reliable infrastructure, well-located health care facilities, competent health care providers, and proficient and accountable administration.

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