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Comparative Analysis of Non-medical Consumption Pattern between Insured and Uninsured People in Ekiti State, Nigeria

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Abstract

Health Insurance (HI) brings about welfare improvement through improved health status and maintenance of non-medical consumption by ensuring that medical expenditures are smoothened over time. Notwithstanding, available data show that less than 4% of the Nigerian households are covered by national health insurance scheme.This implies weak ability to smoothen consumption over time whenever there is ailment. This paper aims at studying and evaluating the spillover effect of health insurance on non-medical consumption in Ekiti state. A propensity score matching estimation model was adopted to 1500 households across Ekiti state. This is the mean effect of an intervention through the mean difference in the outcomes of the treated and the control groups. The mean expenditure on non-medical consumption was N6947.03. In addition to that, the sign of the coefficient of the effect of health insurance on non-medical consumption is positive, showing that health insurance increases expenditure of insured households on non-medical consumption. Having recognized that insured households can be financially protected against unforeseen medical bill, federal government should encourage the expansion of health insurance by encouraging state government, local government and private sector to enroll their employees in health insurance programme. The paper concludes that health insurance is consumption increasing and therefore be expended to more people at local government areas to further redistribute income from the healthy to the sick.

Keywords: Health Insurance, Non-medical Consumption and Propensity Score Matching.

Introduction

The importance of insurance is embedded in its inherent purpose to offset financial risk in the face of adverse health outcomes [24]. With health insurance reducing households' exposure to risk, an insured households need not to save for precautionary motive, thus, the effect may differ in how they reallocate the newly 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 advance financing of health expenditure through contributions, premiums or taxes paid into a common pool to pay for all or part of health services specified by a policy or plan.[12] Other possible impact of health insurance is evidenced in the relevant literature.[1,24,28] Health insurance directly affects households by enhancing their access to medical care goods consumption regardless of the income and age group. Health insurance also brings about welfare improvement through improved health status and maintenance of non-health consumption goods by ensuring that health expenditure are smoothed over time and that there is no significant decline in household labour supply.[27] Other impacts of health insurance include economic benefits to cover the insured households from unforeseen medical expenditures, allowing individuals to access necessary medical treatment without suffering potentially crippling financial consequences. In addition, Insured households experience lower financial strain resulting from medical expenses, lower out-of-pocket expenditures, lower debt on medical bills, and lower rates of refused medical treatment because of medical debt than individuals who were not insured.[7] Through health insurance, consumption is more stable and higher, thereby positively affecting the health of all household members.[14]

Consumption of medical care can be catastrophic when its payment exceeds 40% non-food expenditure and leads the household to sacrifice consumption of other items that are necessary for their well-being such as shelter or education. For the households living close to the poverty line, even low levels 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.[29] Illness disrupts the pattern of household consumption via pressure on household income, and since consumption is a function of income, households need to be insured to be able to smoothen their consumption in the period of illness.[32] The possible impacts of health insurance in evidenced in relevant literature. For instance, Blanchet [34] found that health insurance programme in Ghana increased consumption of medical care by the insured households more than the uninsured households. The study showed that the insured women in Ghana consume more antenatal care than their uninsured counterparts. Also, study by Chou[30] on the effect of national health insurance on saving and consumption in Taiwan showed that health insurance reduces households' savings and in turn increases their consumption. The study showed that younger households are more sensitive to risk reduction associated in health insurance. This result is consistent with the empirical study by Kimball.[33] Carine[31] showed that health insurance had immediate and positiveeffects on three dimensions of health care consumption, namely, the probability of consuming healthcare, the number of consumption condition on consumption and the cost per consumption. One outstanding findings of the study is that health insurance has no relationship with moral hazard in terms of doctor's choice of medication but rather afford households access to trained medical personnel. According to Kai (2013), introduction of health insurance in China increased households' access to medical care in the event of health shocks. The findings also showed that health insurance increases investment in Agriculture and children's education, this is a form of increase non medical consumption. Notwithstanding, most studies that examined the effect of health insurance on consumption have focused generally on developed countries.[1,24,28,30] The few studies on health insurance consumption nexus in Nigeria focused mainly on medical consumption. Hence, the need for studies on the effect of health insurance on non-medical consumption in Nigeria.

Similar to other states in the Nigerian federation, health care services in Ekiti state is provided by both orthodox and traditional medical practitioners. In recent years, there has been a conscious effort by Ekiti State Ministry of Health to provide guidelines for the regulation and coordination of traditional medicine practice. However, there are two hundred and eighty three (340) primary health care facilities at the Local Government (LGA) level, i.e., basic health centres, comprehensive health centres, maternity centres/dispensary centres, while the state has 17 secondary health-care centres, 3 specialist health facilities and 2 tertiary health facility. One federal owned tertiary health facility is also located in the state. Furthermore, there exist one hundred and sixty three (142) registered private health facilities and about 7 mission health facilities in the state.

The State Ministry of Health provides the supervisory roles for the organization of health services in the state while also having the obligation for health manpower development and organization and operation of secondary health care. The State through the ministry of health also provides technical assistance to the local governments as regards primary health care and disease control. The Local Government on the other hand manages and implements primary health care activities at the local level and also has the responsibility of funding and coordinating service delivery at grassroots level. However, local governments have performed poorly in the funding and execution of primary health care programmes. This is sometimes hinged on the insincerity of responsible authorities and the lack of clear delineation of roles by the 1999 constitution. Thus, the responsibilities of local governments are sometimes taken over by the state government in order to provide succor to the people.

Notwithstanding of the initiative of the state geared towards improving the health status of the population, health indicators shows that the inequity which is the main bane of many health initiatives still persist. A sizeable proportion still lives below the poverty line while access to qualitative health care services in rural areas is still far from ideal. Many communities are still grappling with the double burden of diseases with infectious diseases in gridlock with non-communicable diseases in a poor environment. Data from the Planning Research and Statistics department of the ministry of health only presents an iceberg view of the true picture as the capacity for community generated data is still not adequate. However, the presently available data gives the Dipheria Pertusis Tetanus 3(DPT3) coverage as 71%, those fully immunized before the age of 12months as 32,881 and women with at least 2 doses of Tetanus toxoid as 38%. [5] This data though not too bad still falls short of expected standard for achieving the millennium development goals.

Table 1: Healthcare Facilities Distribution by Ownership

Healthcare Facility	**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

An overview of the available health infrastructure in Ekiti State is provided in Table 2. The table shows that there were 512 health facilities in the state. The distribution by ownership shows that 380 or 74.2% belongs to the public sector while private sector accounted for 25.8%. The distribution in terms of levels shows that majority belongs to the primary level accounting for 95.5%, secondary accounts for 4.1% while tertiary accounting for less than a unit percent of the total facilities.

Table 2: Healthcare Facilities Distribution by Levels

Healthcare facilities	Number of Healthcare Facilities	Percentage
Primary	489	95.5
Secondary	21	4.1
Tertiary	2	0.4
Total	512	100

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

Method

Population of the Study and Sampling Design

The survey research design was employed and purposive sampling technique was used to select hospitals that offer health insurance services across the sixteen local government areas (LGAs) of Ekiti state. A structured questionnaire was randomly administered to 95 patients per LGA except in Ado and Ido-Osi LGAs where 200 questionnaires were distributed. The reason for the concentration was based on the presence of teaching hospitals, and federal government parastatals and institutions while their workers are mostly covered by any 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 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 was the formal sector employees (private or public) and informal sector workers with or without health insurance coverage.

Table 3: Response Rate by Local Government of Residence

Local Government	Number of Distributed Questionnaires	Number of retrieved questionnaires	Percentage of Response
Ado	650	576	88.6
Efon Alaye	30	17	56.7
Ekiti East	30	23	76.7
Ekiti South/West	40	30	75.0
Ekiti West	40	30	75.0
Emure	30	20	66.7
Gbonyin	30	29	96.7
Ido-osi	200	141	70.5
Ijero	80	70	87.5
Ikere	80	53	66.3
Ikole	40	39	97.5
Ilejemeje	20	12	60.0
Irepodun	90	71	78.9
Ise/Orun	30	21	70.0
Moba	50	44	88.0
Oye	60	47	78.3
Total	1500	1223	81.5

Source: Computed from the Field Survey.

Administration and the collection of the Research Instrument

A purposive random sampling was adopted in which health facilities participating in health insurance scheme were selected. However, the process of respondents' selection 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 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's workers were entrusted to ensure the questionnaires were properly filled; they collected the questionnaires on regular basis for onward transfer to the enumerators. The enumerators assisted in supervising the households' respondent and also double-checked the questionnaires for consistency.

Description of Research Instrument

A well-structure questionnaire based on Vietnam Living Standards Survey (VLSS) is designed for this study. The reason for the choice of VLSS was because most of the variables required to proxy items in this study are not captured in Nigeria health living standard survey. It is a 45 items questionnaire containing questions regarding respondent household socio-demographic characteristics, health insurance status and rating, health status, health care expenditures and health care utilization, and household non-medical consumption (See questionnaire). A total of 1500 questionnaires were administered across the state. The survey for the study was conducted using trained enumerators. Facilities used in each local government are teaching hospitals, health centres, general hospitals, and private hospitals with health insurance facilities

Description of Variables

The dependent variable is household health insurance status. This refers to whether household is covered by health insurance or not. The variable is dichotomous. Other dependent variables 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, out of pocket health expenditure (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, non-medical consumption is measured by all expenses on all non-medical goods and services consumed during the sick period. The independent variables are household income during the sick period (YS) measured by income from employment, gifts and others, H is the households' health status which could be excellent, very good, good, fair, poor, or very poor, X are individual's household characteristics that can influence the purchase of health insurance such as the household size, level of education, employment status and marital status. Table 4 shows the variables and their definitions.

Table 4: Description of the Variables used in the Analysis

Variable	Definition	Description
Dependent Variables		
HIS	Health Insurance Status:Insured=1, Non-insured = 0	Dichotomous
Medical Consumption	Expenditure on medical consumption	Continuous
Non-Medical Consumption	Expenditure on non-medical consumption	Continuous
OOPHE	Expenditure on medical consumption plus other expenses associated like special food and drugs not prescribed	Continuous
Independent Variables		
Age	The age of the Respondents at the last birthday	Dichotomous
Gender	The sex of the Respondents: male=I, male =2	Categorical
Tribe	Tribe of the Respondents :Yoruba=1,Igbo=2,Hausa=3, Ebira =4, Igede =5, Others=6	Categorical
MSTSingle	Marital status :single=1, otherwise=0	Dichotomous
MSTMarried	Marita status: married=1, otherwise=0	Dichotomous
MSTDivorse/Seperated	Marital status: divorce/separated=1, otherwise=0	Dichotomous
MSTWidow/Widower	Marital status: widow/widower=1, otherwise=0	Dichotomous
Familytype	Type of family: momogamy=1, polygamy=	Categorical
Familysize	Number of people in a households	Continuous
HHHSTExcellent	Health status: EXCELLENT=1, otherwise=0	Dichotomous
HHHSTgood	Health Status:good=1,otherwise=0	Dichotomous
HHHSTfair	Health Status:fair=1,otherwisw=0	Dichotomous
HHHSTPoor	Health Satus:poor=1,otherwisw=0	Dichotomous
HHHSTVerypoor	Health Status: very poor=1, otherwisw=0	Dichotomous
HeadNFEDU	Head Education: No Formal Education=1, otherwisw=0	Dichotomous
HeadPRMEDU	Head Education; Primary School Education =1,otherwisw=0	Dichotomous
HeadSECOEDU	Head Education: Secondary Education =1, otherwise=0	Dichotomous
SpouseNFMEDU	spouse Education: No Formal Education =1, otherwise=0	Dichotomous
SpousePRMEDU	spouse Education: Primary Education=1,otherwise=0	Dichotomous
SpouseSECOEDU	spouse Education: secondary Education=1, otherwise=0	Dichotomous
HHOCUFPSWORKER	Head Occupation: Formal Private S.Worker =1,otherwise=0	Dichotomous
HHOCUTRADER	Head Occupation: Trader=1, otherwise=0	Dichotomous
HHOCUFARMER	Head Occupation: Farmer=1, otherwise=0	Dichotomous
HHOCUSELF_EMPL	Head Occupation: Self-employed=1, otherwise=0	Dichotomous
HHOCUUNEMLOYED	Head Occupation: Unemployed=1, otherwise=0	Dichotomous
InHincome	Log of Family income in the last four weeks	Continuous

Source: Author's Computation

Model Specification

The effect of health insurance on households' non-medical consumption is estimated using the following linear regression:

$$M^n = \alpha_1 + \alpha_2 HIS + B_3 X + \varepsilon \qquad (1)$$

Where M^n is the level of dependent variable of households, X a set of control variables at households level, ε, the error term which control for households unobservable variables affecting the consumption of non-medical goods. This refers to demographic and socioeconomic variables such as household size, household income, gender of the household head, age of the household head, highest level of qualification of the household head, occupation of the household head and the spouse etc. HIS connotes the participation of the treated households in health insurance programme

Method of Estimation

The propensity score matching (PSM) estimation model was employed to assess the impact of health insurance on household non-medical consumption in our study under the assumption that selection into the scheme is based on the observable characteristics alone[1]. The underlying strategy here was to assess the changes in various household consumption spending shares between the insured households (control group) and the uninsured households (treatment group).The major advantage of PSM estimation is that it allows policy evaluation by creating a counter-factual and addressing household adverse selection problem.[4] To compare levels of consumption between participants

[1] See [9,35-37] for evaluation of matching estimator

and non-participants using propensity score matching, we first predict the probability of participating in the scheme using a logit regression. The essence of the logit regression is to get the mean participation. As the determinants of participation in health insurance might not be the same for all households and as our specifications should be balanced[2], we use different specifications for all the households.

$$HIS = \beta_1 + \beta_2 Z + \varphi \quad (2)$$

Where HIS is the households' participation in health insurance, Z is a set of control variable and is the error term.

Main steps involved in the Application of Statistical Matching to Impact Evaluation

The main steps that are involved when employing propensity score matching estimation are listed as follows;

a) Estimating the propensity score
b) Matching the unit using the propensity score
c) Assessing the quality of the match
d) Estimating the impact.
e) Sensitivity analysis

Estimating the Propensity Score (PS)

The propensity score is defined as the conditional probability of receiving a treatment given pre-treatment characteristics.[21] This propensity score is estimated in order to indicate the presence (or absence) of the intervention with a number of households characteristics. In this case we estimate logit model to estimate propensity scores for matching purpose. The binary outcome for health insurance participation takes a value of one if the household has health insurance policy and zero otherwise. The propensity scores were computed using binary logit regression models given as:

$$P(X) = Pr\{D = 1/X\} = E\{D/X\} \quad (3)$$

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.

Matching the Unit Using the Propensity Score

Estimated propensity scores allow construction of comparison groups by matching propensity scores of the households with health insurance and households without health insurance. Once treatment groups are matched with control groups, the difference between the mean outcome of the program treatment and the mean outcome of the matched control groups can be measured. However, when estimating, propensity score matching requires different matching algorithms, but for the purpose of this study, kernel matching is employed.

Kernel Matching

The matching algorithms discussed so far have in common that only a few observations from the comparison group are used to construct the counterfactual outcome of a treated individual. However, in kernel matching every treated observation is matched with all the control observations where the control observations with the closest propensity score to that specific treated observation is assigned the biggest weight; the farther the propensity of the control observation from the specific treatment observation the smaller the weight. A drawback of these methods is that possibly observations are used that are bad matches. However, one major advantage of these approaches is the lower variance which is achieved because more information is used. A drawback of these methods is that possibly observations are used that are bad matches. Therefore, because of the possibility of observing two samples, one from treatment and other from control, with same propensity score in principle is zero, we select the kernel matching to overcome this problem. With kernel matching, all untreated observations are used to estimate the missing counterfactual outcome and greatest weight being given to observations with closer scores.

Moreover, estimation of average treatment effect on the treated (ATT) is sensitive to the sort order of the data if matching is performed without replacement. Since the weighted average of all samples from control group is used to construct the counterfactual outcome, kernel matching has an advantage of lower variance because more information is used.[9] Hence we decided to estimate ATT using kernel matching technique with a view to analysing the effect of health insurance interventions on households' consumption patterns in Ekiti State.

Assessing the Quality of the Match

In order to get the unbiased estimate of ATT and to assess the matching quality, balancing test is performed which is mainly concerned with the extent to which the difference in the covariates between the treated and control groups have been eliminated so that any difference in outcome variables between the two groups can be inferred as coming solely from the treatment group. There are two ways through which balancing of the covariates can be verified. The t stats of difference in means of covariates in the

[2] A balance propensity score function, p (x) must ensure that p(x) represents well the set of control variables.

treated and non-treated groups, before and after matching are used to examine the quality of the matching. Before matching, differences between the groups are expected; but after matching, the observed variables should be balanced in both groups and hence no significant differences should be discovered.[3]

Estimating the impact analysis

This involves estimating the effect of health insurance on all the outcome variables, i.e., estimating of 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 let M Insured and M Non-insured be the expenditure on medical and non-medical consumption (total consumption) for insured and uninsured households, respectively, and D ϵ {0,1} the indicator of enrollement status. The propensity score is defined by [21] as the conditional probability of participation, given observed characteristics:

$$p(X) = Pr(D = 1|X) = E(D|X) \quad (4)$$

where X is the vector of observe variables. Given the propensity score p(X), the Average effect of Treatment on the Treated (ATT) can be estimated as follows:

$$\begin{aligned} ATT &= E(\Delta M|\, D = 1, X) \\ &= E(M^{PART} - M^{NON-PART}|\, D = 1, X) \\ &= E(M^{PART} \mid D = 1, X) - E(M^{NON-PART} \mid D = 1, X) \\ &= E[M^{PART} \mid D = 1, p(X)] - E[M^{NON-PART} \mid D = 1, p(X)] \end{aligned} \quad (5)$$

where D = 1 indicates program participation (treatment) and X is a set of household characteristics on which the subjects will be matched. Equation (2) gives the average program impact under the conditional independence assumption (CIA)[3] and overlap assumption[4]. A unique advantage of PSM is that instead of matching subjects on a vector of characteristics, we only need to match on a single item, i.e., the propensity score that measures the probability of participating in the program.

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 has participated.

$$ATU = \frac{ATZ}{P\,(D=0)} - ATT * \frac{P(D=1)}{P(D=0)} \quad (6)$$

Where ATE is the effect on the individual drawn at random, Where P(D=1) is the probability that the sample population is with an intervention and P(D=0) is the probability that the sample population is without an intervention. (0, 1) is the treatment indicator. $(M^{PART} - M^{NON-PART})$ is the treatment effect. (0,1) is the treatment indicator, M is the observed outcome.

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:

$$ATE = ATT.P(D = 1) + ATU.P(D = 0) \quad (7)$$

Where P(D=1) is the probability that the sample population is with an intervention and P(D=0) is the probability that the sample population is without an intervention. Equation (4) shows the relationship between ATT (average treatment on the treated), ATE (average treatment effect on an individual) and ATU (average treatment on the untreated).

Sensitivity Analysis

Propensity-score matching estimators are not consistent estimators for treatment effects if the assignment to treatment is endogenous, i.e., if unobserved variables that affect the assignment processes are also related to the outcomes. In order to estimate the extent to which such "selection on unobservable" may bias our qualitative and quantitative inferences about the effects of health insurance. Rosenbaum[21] derives bounds on the Hodges-Lehmann point estimate of the treatment effect enabling the researcher to frame the sensitivity analysis in the more common metric of an interval of point estimates rather than in terms of implied significance levels for the estimated treatment effect. To arrive at an interval of plausible point estimates given a specific bias level γ, Rosenbaum defines the Hodges-Lehmann point estimate of the treatment effect. Assuming that the participation probability is given by

[3] Conditional independence assumption means that conditional on x, the outcomes are independence 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 may be observed and included in X. This allows the untreated units to be used to construct an unbiased counterfactual for the treatment group.

[4] overlap means that for each x, there are both treatred and control groups i.e. 0<pr(D=1|X|<1. 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

$$P(x_i, u_i) = P(D_i = 1) \parallel x_i = f(\beta x_i + \gamma u_i) \qquad (8)$$

Where x_i is the observed characteristics for individual i, u_i is the unobserved variable and γ is the effect of u_i on the participation decision. If the propensity score matching is free of hidden bias, γ will be zero and the participation probability will exclusively be determined by x_i. However, if there is hidden bias, two individuals with the same observed covariates x have differing chances of receiving treatment. Assuming we have a matched pair of individuals i and j and further assume that fis the logistics distribution. The odds that individuals receive treatment are then given by $\frac{P(x_i)}{(1-P(x_i))}$, and $\frac{P(x_j)}{(1-P(x_j))}$, and the odds ratio is given by:

$$\frac{\frac{P(x_i)}{1-P(x_i)}}{\frac{P(x_j)}{1-P(x_j)}} = \frac{P(x_i)(1-P(x_j))}{P(x_j)(1-P(x_i))} = \frac{exp(\beta x_j + \gamma u_j)}{exp(\beta x_i + \gamma u_i)} = exp[\gamma(u_i - u_j)] \ (9)$$

If both units have identical observed covariates as implied by the matching procedure the x vector is cancelled out. But still, both individuals differ in their odds of receiving treatment by a factor that involves the parameter and the difference in their unobserved covariates u. So, if there are either no difference in unobserved variables $(u_i = u_j)$ or if unobserved variables have no influence on the probability of participating (γ=0), the odds ratio is one, implying the absence of hidden or unobserved selection bias. Thus, the sensitivity analysis now evaluate how inference about the programme effect is altered by changing the values of γ and $u_i - u_j$.

Description of Variables

The dependent variable is household health insurance status. This refers to whether household is covered by health insurance or not. The variable is dichotomous. Other dependent variable is non-medical consumption; this is measured by all expenses on all non-medical goods and services consumed during the sick period. The independent variables are household income during the sick period (YS) measured by income from employment, gifts and others, H is the households' health status which could be excellent, very good, good, fair, poor, or very poor, X are individual's household characteristics that can influence the purchase of health insurance such as the household size, level of education, employment status and marital status. Table 5 shows the variables and their definitions.

Table 5: Description of the Variables used in the Analysis

Variable	Definition	Description
Dependent Variables		
HIS	Health Insurance Status: Insured=1, Non-insured = 0	Dichotomous
Non-Medical Consumption	Expenditure on non-medical consumption	Continuous
Independent Variables		
Age	The age of the Respondents at the last birthday	Dichotomous
Gender	The sex of the Respondents: male=I, male =2	Categorical
Tribe	Tribe of the Respondents :Yoruba=1,Igbo=2,Hausa=3, Ebira =4, Igede =5, Others=6	Categorical
MSTSingle	Marital status :single=1, otherwise=0	Dichotomous
MSTMarried	Marita status: married=1, otherwise=0	Dichotomous
MSTDivorce/Separated	Marital status: divorce/separated=1, otherwise=0	Dichotomous
MSTWidow/Widower	Marital status: widow/widower=1, otherwise=0	Dichotomous
Familytype	Type of family: momogamy=1, polygamy=	Categorical
Familysize	Number of people in a households	Continuous
HHHSTExcellent	Health status: EXCELLENT=1, otherwise=0	Dichotomous
HHHSTgood	Health Status:good=1,otherwise=0	Dichotomous
HHHSTfair	Health Status:fair=1,otherwisw=0	Dichotomous
HHHSTPoor	Health Satus:poor=1,otherwisw=0	Dichotomous
HHHSTVerypoor	Health Status: very poor=1, otherwisw=0	Dichotomous
HeadNFEDU	Head Education: No Formal Education=1, otherwisw=0	Dichotomous
HeadPRMEDU	Head Education; Primary School Education =1,otherwisw=0	Dichotomous
HeadSECOEDU	Head Education: Secondary Education =1, otherwise=0	Dichotomous
SpouseNFMEDU	Spouse Education: No Formal Education =1, otherwise=0	Dichotomous
SpousePRMEDU	Spouse Education: Primary Education=1,otherwise=0	Dichotomous
SpouseSECOEDU	Spouse Education: secondary Education=1, otherwise=0	Dichotomous
HHOCUFPSWORKER	Head Occupation: Formal Private S.Worker =1,otherwise=0	Dichotomous
HHOCUTRADER	Head Occupation: Trader=1, otherwise=0	Dichotomous
HHOCUFARMER	Head Occupation: Farmer=1, otherwise=0	Dichotomous
HHOCUSELF_EMPL	Head Occupation: Self-employed=1, otherwise=0	Dichotomous
HHOCUUNEMLOYED	Head Occupation: Unemployed=1, otherwise=0	Dichotomous
InHincome	Log of Family income in the last four weeks	Continuous

Source: Author's Computation

Results

The propensity score is the probability of receiving treatment (in this case, given access to health insurance progamme) conditional on the observed characteristics of the households. The propensity score was estimated with a logit regression model, which has a treatment dummy (that is, those household with health insurance is assigned 1, and those without is assigned 0) as the dependent variable, and a number of covariates as independent variables. Table 6 shows the first stage logistic regression results.

The value of odds for age implies that for a unit increase in age (i.e. one more year of age), the odds[5] of participating in health insurance increase by 0.8%. That is, older a household member becomes the higher the probability of been insured. This is because health deteriorates with age, so, in order to guide against unforeseen huge medical bill, it is expected that a risk averse household takes health insurance coverage against unforeseen medical expenses. Marital status shows that being single increase the odds of insurance participation by 51.12% relative to the married household members. The odds of income show that a unit increase in households' income increases the odds of being health insurance covered by 36.34%. The odds of family size is 0.876, which implies that for a unit increase in the family size, the odd of being insured increase by 12.42%. Gender coefficient shows that having additional female households increase the odds of being insured by 12.42% relative to additional male. The result further shows that being Igbo tribe increases the odd of participating in health insurance programme by 7.31% relative to the Yorubas. Similarly, being Hause, Ebira and other Tribes increase the participation in health insurance programme by 44.21%, 52.72% and 34.60% respectively.

Furthermore, the coefficient of households head with primary school education shows that for a unit increase in the level of education of households with primary school certificate increases the participation in health insurance programme by 9.70% relative to the households without any formal education. In the same vain, the coefficients of households head with secondary and post-secondary school levels of education show that a unit increase in their levels of education increase the odd of participation in health insurance programme by 81% and 423% relative to households without any formal education. The coefficient of spouse education shows that a unit increase in education of spouse with primary school certificate increase the odd of participating in health insurance programme by 32.96%.

Similarly, a unit increase in education of spouse with secondary school certificate and post-secondary school increases the odd of participation in health insurance programme by 4.34% and 25% respectively. Other variables of note include health status, which shows that for a unit increase in health status of households with "very good" rating category the odds of participation in health insurance programme increase by 15.75% relative to households with excellent rating category. Also, the coefficients of households with "good" and "fair" rating categories show that a unit increase in health increases the odd of participation by 32.24% and 3.63% respectively relative to the excellent rating category. As would be expected, the coefficient of the households in "very poor" shows that for a units increase in their health status, the odds of participation in health insurance increase by 66.58%. This is because households with deteriorating health status might see the need for regular medical consumption.

[5] The odds of "yes"=probability ("yes")/probability ("no")

Table 6: Summary Statistics of Logit Regression estimated for generating propensity scores

Health Insurance Status	Odds Ratio	P>|z|
Age	0.992051	0.194
Respondents' Marital Status (Reference Category: Married)		
MSTsingle	1.511165	0.026
lnHHINCOME		
Familytype	0.782532	0.348
Familysize	0.875832	0.001
Respondents' Gender (Reference Category: Male)		
Female	1.027338	0.871
Respondents' Tribe (Reference Category: Yoruba)		
Igbo	0.926922	0.821
Hausa	0.55788	0.614
Ebira	1.527184	0.586
Others	1.346697	0.749
Households' Head Highest Education (Reference Category: Post-Secondary)		
Primary School Educatio	0.90304	0.894
Secondary School Education	1.818741	0.351
Post-secondary School Education	5.234092	0.005
Households' Spouse Highest Education (Reference Category: Post-Secondary)		
Primary School Education	0.670428	0.499
Secondary School Education		
Post-secondary School Education	0.745871	0.433
Respondents' Health Status (Reference Category: Excellent)		
Verygood	0.566606	0.017
Good		
Fair	0.73703	0.427
Verypoor	8.335249	0.064
Households' Head Health Status (Reference Category: Excellent)		
Verygood	0.842505	0.434
Good	0.677555	0.16
Fair	0.963732	0.94
Verypoor	0.334217	0.484
Households' Head occupation (Reference Category: Government Worker)		
Formal Private Worker		
Trader	0.735682	0.387
Farmer	0.755229	0.616
Sele Employed	0.582368	0.028
Unemployed	0.485995	0.548
Others	0.375365	0.003
Spouses' Occupation(Reference Category: Government Worker)		
Formal Private Worker	0.14478	0
Trader	0.602571	0.148
Farmer	1.724832	0.318
Sele Employed	0.571	0.119
Unemployed	3.929706	0.114
Others	1	
_cons	0.017703	0.006

Source: author's computation

Balance Diagnostics

The basic idea behind statistical matching [23] is to recognize in a large pool of potential comparison observations a sufficient number of sample that closely resemble the treated units, i.e. to verify whether the observed group and matched control units have the same characteristics. Table 7 shows after-matching means of the covariates used in the logit regressions for enrolment in health insurance. In other words, we match each treated units using kernel matching algorithms. Following similar studies [13,19,20] the average treatment effect on the treated (ATT) i.e., the difference in the average health expenditure of the observed households and the matched control is the estimator of the impact of health insurance intervention. In general, since almost all the probability values of the covariates after matching is 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, the two categories are suitable for the analysis.

Table 7: Mean of Covariates and % Reduction Bias after Matching for the Treated and the Control Groupsa

Covariates	Treated	Control	P>|t|
	Matched	Matched	
Age	39.614	40.35	0.525
MSTSingle	.23102	.31996	0.014
MSTWidow/widower	.0066	.03062	0.029
InHincome	11.599	11.415	0.02
Familytype	1.099	1.0968	0.926
Familysize	4.1848	4.155	0.862
Female	.76238	.64144	0.001
Igbo	.05281	.05019	0.884
Hausa	.0033	.00538	0.697
Ebira	.0099	.00846	0.853
Others	.0132	.00316	0.171
HHHSTExcellent	.30033	.24408	0.12
HHHSTGood	.25083	.22081	0.385
HHHSTFair	.05611	.06503	0.646
HHHSTPoor	.0231	.01268	0.334
HHHSTVerypoor	.0231	.00172	0.017
HeadNFEDU	.0132	.01449	0.893
HeadPREDU	.0132	.0311	0.135
HeadSECOEDU	.11221	.11458	0.927
SpouseNFMEDU	.05611	.05355	0.89
SpousePRMEDU	.0264	.04547	0.208
HHOCUFPSWORKER	.08581	.13946	0.037
HHOCUTRADER	.0495	.06064	0.549
HHOCUFARMER	.0264	.02523	0.927
HHOCUSELE_EMPL	.10891	.09211	0.493
HHOCUUNEMPLOYED	.0033	.00266	0.885

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

Similarly, following Sianesi[16], we compare the pseudo R-square for unmatched and matched covariates to examine the quality of matching. Table 8 shows that matched pseudo R-square is much lower (0.064) than unmatched pseudo R-square (0.109). The significant reduction in the Pseudo R-square indicates a high quality of the match. In the same vain, likelihood ratio test of the joint significance is also insignificant suggesting that matching quality is good and therefore suitable for the analysis. It is clear from Table 8 that matching has achieved a substantial reduction in the observed mean bias as we can see the reduction in the mean bias from 16.7 when unmatched to 7.8 after matching.

Table 8: pseudo-R^2, LR x^2 and MeanBias Reduction

Sample	Ps R^2	LR chi^2	$p>chi^2$	MeanBias	MedBias	B	R	%Var
Unmatched	0.109	101.54	0	16.7	12.3	80.1*	0.51	75
Matched	0.064	39.38	0.045	7.8	4.9	56.5*	0.75	50

** if B>25%, R outside [0.5; 2], Source: author's computation*

To further corroborate the results of the quality of the match in Table 8, the visual analysis of the density distribution of the propensity score (PS) in Fig. 1 indicates sufficient overlap between the observed and the controls households.[6] The perfect overlap of the untreated and the treated on the horizontal line as depicted in 4.1 shows a high quality of match between the two groups.

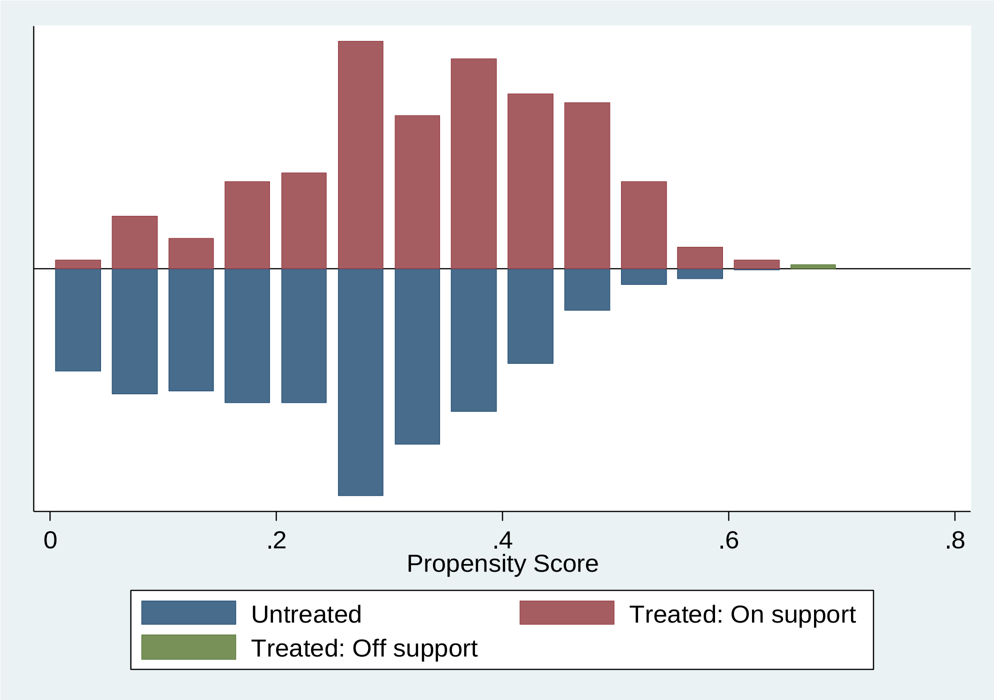

Figure 1: Density Distribution of the Propensity Score of the Treated and Control Groups.

Table 9 reports the average treatment effects on the treated for non-medical consumption outcome. The ATT is the difference in the mean expenditure on non-medical consumption for households with health insurance. Access to health insurance leads to a statistical increase in the amount expended on non-medical consumption by the insured households. The mean expense on nonmedical consumption of households with health insurance (treated group) is N6947.03 higher than the households in the control group. To put this in context, the odds of households without health insurance spending on non-medical consumption is N9805.43 lower than the households with health insurance. 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. This is because risk averse households without health insurance coverage and without access to financial institution could set aside a significant proportion of household income for contingencies in health. In addition to that, some items on nonmedical consumption like food, affordable clean housing can also have positive effects on households' health status thereby encouraging household to generate more money. The findings of this paper are consistent with.[28] Their finding suggests that Vietnam health insurance increased nonmedical consumption in Vietnem.

This paper also examine the impact of health insurance on sub-aggregates of households nonmedical consumption, these include food consumption and non-food consumption. Food consumption includes expenses on staple food, beverages, fruits, water, oil, meat and eggs. The result also show that food consumption increases with health insurance coverage status. However, the effect was more on nonfood consumption than food consumption.

Table 9: Average Treatment Effects of Health Insurance on the Treated (ATT): PMS Estimates

Variables	Sample	Treated	Controls	Differences	S.E	T-start
Non-Medical Consumption	Unmatched	104322.7	94517.3	9805.428	8050.22	1.22
	ATT	101357.1	94410.1	6947.031	9436.36	0.17

[6] Overlap means that for each X, there are both treated and control units.

Average Treatment Effects on the Untreated (ATU).

The result of the average treatment effects on the untreated is reported in Table 10. The ATU is the measure of treatment effect on the untreated. That is, the effect of health insurance on non-insured households if they have been insured. Having health insurance would have led N6667.72 increase in the expenditure of the control group if they have been insured.

Table 10: Average treatment effects of health insurance on the untreated (ATU): PMS Estimates

Variables	Sample	Treated	Controls	Differences	S.E	T-start
Non-Medical Consumption	Unmatched	104322.7	94517.3	9805.428	8050.22	1.22
	ATU	94517.3	101185	6667.724	.	.

NOTE: S.E. does not take into account that the propensity score is estimated

Average Treatment Effects (ATE)

Table 11 reports the average treatment effects for non-medical consumption. This is the difference in the mean of expenditure on non-medical consumption for households selected at random from the population sample. Having health insurance leads to N6741.05 increase in the amount expended on non-medical consumption by the households selected at random if they have been insured. In other words, the odds of households without health insurance spending on non-medical consumption is N9805.43 lower than the households with health insurance.

Table 11: Average Treatment Effects (ATE): PMS Estimates

Variables	Sample	Treated	Controls	Differences	S.E	T-start
Non-Medical Consumption	Unmatched	104322.7	94517.3	9805.428	8050.22	1.22
	ATE			6741.054		

NOTE: S.E. does not take into account that the propensity score is estimated

Robust Check: Sensitivity Analysis

In Table 12, the value of Gamma is interpreted as the odds of treatment assignment hidden bias. A change in the odds lower/upper bound from significance to non-significance indicates by how much the odds need to change before the statistical significance of the outcome shifts. For instance, in Table 12, 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 employed 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 leads to changes in significance compared to those that could be obtained if the study is free of bias.[21] Therefore, based on this result, health insurance participation in Ekiti State is insensitive to other unobservable predictors. And so, the result is robust to only observable characteristics.

Table 12: 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 unobserved factors
rbounds delta3, gamma (1 (0.1) 2)
Source: author's field work

Conclusion

The findings of this paper throw support to the debate that health insurance can improve health care consumption and at the same time expands non-medical goods. Based on our findings, access to health insurance leads to a statistical increase in the amount expended on non-medical consumption by the insured households. The results support Wagstaff[28] that submitted that health insurance improves health outcome and at the same time expand consumption of non-medical goods through the reduction in financial risk. The use of propensity score matching estimator allows us to reduce the risk of biases due to inappropriate model specification. The reality is that, majority of the households enrolled in social health insurance programme, therefore, insurance was not assigned randomly. The findings of this study suggest that access to food consumption, clean water and affordable hygienic environment reduce episodes of sickness being experienced by the insured households. This accounts for why there is no significant difference between the hospital visits of the insured and the uninsured. This is similar to Shi[38] that reported no significant impact of health insurance on inpatient service utilization. This is especially credible in a country where at the time (1993), a single visit to a public hospital cost on average the equivalent of 20% of a person’s annual non-food consumption.[2] Overall, the treatment effects suggest that health insurance coverage might have had some positive impact on several items of household non-medical consumption that may have a beneficial effect on health, particularly food consumption, clean water, and education expenditures, and investment in household durables.

Recommendation

Following the findings from this study and the positive relationships established between health insurance and consumption of non-medical goods in Ekiti State, it is pertinent to provide recommendations for policy makers with the aim of expanding health insurance to more people and improving their access to medical consumption at the same time, enable them to consume non-medical goods in the period of illness. Therefore, given the benefits accrued to the insured households in Ekiti State as a result of health insurance, health insurance should be extended to accommodate more people in Ekiti state especially the state government staffs, local government staffs, the private and the informal sectors of the state with little concern for ex-post moral hazard in health insurance.

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