Effect of Health Insurance on Health Service Utilization among Households Affected by Non-communicable diseases in Busia County, Kenya.

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***Abstract*-** Non-Communicable Diseases (NCDs) are the most important agents of illness and death worldwide. In LMICs, NCDs will be the main agent of mortality projected to cause up to 75% of all deaths by the year 2030. Patients with NCDs go through lengthy and costly treatment regiments that consume a substantial portion of households' resources subsequently acting as a major barrier to access and utilization of available care. Kenya adopted the 2030 agenda for Sustainable Development Goals and committed to achieve SDG target 3.8 on Universal Health Coverage, so as to enhance access to services and deal with financial burden of illness. The Government made deliberate policy reforms at the National health insurer – NHIF aimed at building its capacity to provide cover for all households including those afflicted by NCDs. This study examined the effect of HI on out-patient and in-patient health service utilization among people with reported NCDs in Busia County.

Methods. A quasi experimental – (Pretest- posttest Nonequivalent control group) design using Propensity Score Matching method was conducted in Busia County among eligible households with HI cover (intervention group) and those without (comparison group), involving a total representative sample of 350 households. Interviewers conducted interviews at baseline and after one year among household heads. Ethical approval was obtained from Moi University Institutional Research and Ethics Committee (IREC).

Results. Utilization of outpatient and inpatient NCDs care was higher for insured households compared to uninsured households. We found evidence that utilization of outpatient care improved 1.24 (95% CI= 1.048-1.474), times more among insured households, (p=0.012). We also found evidence that utilization of inpatient care went up by 1.26 (95% CI = 0.965 -1.634) times, (p=0.004), among insured household

Conclusion. The Health Insurance program improved utilization of outpatient and inpatient health care among households affected by NCDs. To accelerate progress towards UHC, the national government should expand the program to target all households affected by NCDs across the Country. County governments in partnership with their development partners should strengthen the health system to ensure availability of essential commodities and adequate trained staff so as to accommodate the ever growing demand for holistic NCDs care.

***Index Terms*-** Busia County, Health Insurance, Health service utilization, NCDs care.

I. INTRODUCTION

Non-Communicable Diseases (NCDs) are the leading causes of morbidities and mortalities globally with LMICs facing the greatest burden [1]. In Kenya, the major NCDs are cardio-vascular diseases (CVDs), cancers, diabetes, and chronic respiratory diseases (CRDs) whose liability is greater than 50% of total hospitalizations and more than 39% of hospital deaths [2]. Out of Pocket (OOP) expenditure levied at service points in both public (cost-sharing) and private health institutions remains high and is a major barrier to accessing care. This is as a result of exorbitant costs, including often lifelong expensive NCDs treatment and inconsistent supply of essential medicine [3], partly contributed by inadequate government funding of public health institutions which are the main sources of care for majority of the population [4]. There is evidence suggesting that most patients with reported NCDs have unequal access to care including screening and treatment as a result of low capacity in health institutions charged with providing care [5].

In order to contain the upsurge of financial barriers on NCDs care and improve its utilization, Kenya Government adopted the 2030 agenda for Sustainable Development Goals (SDGs) and committed herself to achieve the SDG goal 3.8 on universal health coverage (UHC), by the year 2022. The Government integrated UHC into its health sector strategy goals with an aim of using it as a means for reducing financial hardship linked to illness in the country, subsequently improving utilization [6]. In 2017, the government initiated reforms at the National health insurer – NHIF in an effort to build its capacity to deliver UHC. The reforms entailed widening the benefit package where a new packages – 'the Supa cover' that address in-patient and out-patient NCDs care needs was introduced [7] although its level of uptake remained low [8]. All Kenyans are eligible to enroll into the scheme with a fixed monthly household premium for the informal sector. For the formally employed, a monthly premium graduated based on salary level is deducted from salary.

The NHIF contracts public and private health care facilities to provide care to its members and reimburse them using capitation and case based systems [7]. In 2018, the National Government through NHIF, initiated and rolled out a Pilot HI program in Kisumu, Machakos, Nyeri and Isiolo Counties targeting 3.2 million residents, with an aim of using the lessons learned to further scale up the program to all counties in Kenya [9]. Under this program, the county governments abolished user fees levied at level 4 and 5 government owned facilities while the national government refunded them the lost revenues. All residents of the 4 counties including those enrolled in other HI programs were eligible for registration. This initiative was later replicated by other County Governments in collaboration with their development partners. In Busia County for instance, a HI program was initiated by AMPATH, (a partnership between Moi University College of Health Sciences Moi Teaching and Referral Hospital and a consortium of North-American Universities lead by Indiana University) together with the County Government and NHIF. The program aims to scale up NCDs management in the region by strengthening the primary care services, linking patients to different levels of care and linking patients with NHIFs cover [10].

Effect of HI on NCDs care utilization in LMIC has been demonstrated by other published studies. Some have shown evidence that HI enhances the use of health interventions by people living with NCDs [11, 12 & 13] while other studies found evidence that HI has either a negative or insignificant effects on utilization of NCDs care [14 &15]. For instance, using a cross-sectional household survey, Nguyen concludes that HI significantly increased utilization of outpatient and inpatient NCDs care in Vietnam [11]. In contrast, Ngwira using a cross-sectional study design established that HI in Zambia had no statistically significant association with utilization of health services among people with NCDs [14]. A plausible explanation for the contradictory findings is the fact that these studies are implemented at different times in different health care set ups and with totally different HI policies.

In Kenya, given that most patients with reported NCDs have unequal utilization of available care as a result of financial barriers that limit access [5], there is urgent need for evidence whether the HI programs already in place have improved service utilization among the growing population of people with NCDs. Since studies in Kenya and other LMICs have reported that enrolment in a HI program does not necessarily translate to improved access and subsequent utilization of health care [7,16 & 42], there's need to evaluate local HI programs as the country embarks on the highly ambitious plan to attain UHC. Furthermore, to our knowledge, there's no evidence that the new NHIF reforms have addressed the needs of people with NCDs in relation to access and utilization of health care. This study aims to fill these gaps by assessing the effect of HI on health care utilization among the people with NCDs in Busia County and inform scale up plans for the rest of Kenya.

II. METHODS

Study Setting

Kenya is among the LMICs in the sub-Sahara Africa region. The hierarchy of Health delivery structure in Kenya is organized into three sub-systems: 1). Private for-profit institutions, 2). Government institutions which include facilities operated by County and those manned by the National Government, 3). Private not-for-profit institutions. According to the Ministry of Health, [17], government manned facilities are structured as follows: Level one: Community (no physical structure), Level two: Dispensary, Level three: Health center, Level 4: Primary referral facilities (former district hospitals), Level five: Secondary referral facilities (former provincial hospitals) and Level 6: National referral facilities. In the year 2013, upon the coming into effect of the Country's new constitution, delivery of health services was devolved to the County governments with an exception of the national referral facilities. The state department of health however, is still accountable for health policy, standards, regulation and training [18].

Implication of NCDs burden in Kenya

The country is experiencing a relatively high burden of disease, with CRDs, cancers, diabetes and CVDs constituting the greatest concern. It is foreseen that NCDs will be the most intense agent of death for the country by the year 2027 [2], a clear hint that the country needs to scale up her efforts in advancing her global health obligations [18].

According to the country-wide steps survey, CVDs are the top most agents of mortality, with a rate ranging from 6.1% to 8% of total deaths in the country, while cancer is responsible for 7% of all deaths annually. Diabetes with an estimated adult prevalence rate of 4.6% comes third, claiming up to 20,000 lives annually. These rates vary among communities and regions [19]. For instance, the prevalence of hypertension in western Kenya is high ranging from 13% in rural areas to 37% in urban areas [20]. Despite the fact that funds allocated for health services have shot up since health services were devolved in 2013, Kenya still dawdles behind in several global obligations in the health sector [18]. Disparities exist within the counties for instance, in 2015/16 financial year; Nyeri County spent 44.3% on health as a percentage of her total expenditure, compared to 17.3% spent by Busia County [18]. Inadequate government funding of public health institutions [4] contributes to persistent high OOP payments for care, a key challenge in the country that limits access to most patients, majority of who live with NCDs [5].

Study site

The study was implemented in Bunyala Sub County of Busia County. Busia County is situated in the western part of Kenya and serves as the gateway for Kenya to the republic of Uganda [21]. Busia County was purposively chosen because a HI program under implementation there targeting mainly the informal residents not covered by any Insurance scheme. AMPATH in partnership with the Ministry of Health and the County Government of Busia are implementing the HI program in Bunyala. Bunyala Sub County is located in the lower region of Busia County bordering Samia Sub County, Siaya County and the Republic of Uganda. The Sub County comprises of one constituency (Budalangi) and four administrative wards - Bunyala West, Bunyala Central, Bunyala South and Bunyala North. Fishing is the most dominant economic activity since part of Lake Victoria extends to the Sub County. Other complementing economic activities include rice farming under irrigation and subsistence farming [21]. Population parameters of Bunyala Sub County are comparatively indicated in table 1

Table 1. Population Parameters of study area.

Administrative unit	Population			Area (km2)	No. of Households	Household size	Pop density
	Male	Female	Inter sex				
Kenya	23,548,056	24,014,716	1,524	580,876	12,143,913	3.9	82
Busia	426,252	467,401	28	1,696.3	198,152	4.5	527
Bunyala	41,465	44,511	1	431.4	19,039	4.5	447

Source: *(Kenya National Bureau of statistics 2019).*

Study Objectives

Our work is part of a study that evaluates the effects of HI on Health service utilization and Economic burden of NCDs in Busia County using 4 objectives. This publication is however limited to the first 2 specific objectives: - 1). To assess the effects of HI on out- patient Health Service Utilization among people with reported NCDs and 2). To assess the effects of HI on in-patient Health service Utilization among people with reported NCDs.

Study Design

We conducted a quasi-experimental – (Pretest- posttest non-equivalent control group) design. When participants in a study are not randomized, the resulting groups are non-equivalent. This commonly happen when researchers want to evaluate effects of health care interventions, where ethical or logistical constraints rule out randomization [22 &23]. In this study, HI program was rolled out by the stakeholders hence randomization was not possible. Using a household register created during registration of beneficiaries, the study recruited households to an intervention group and a control group based on their HI status. The intervention group was interviewed for pretest before being enrolled for HI then a posttest was done after 1 year. At the same time, there was a non-equivalent comparison group which comprised households that had been enlisted to receive the NHIF cover (waiting group) but had not received the cover during study period. This group was also interviewed for pretest and a posttest was done after 1 year without the cover.

The study employed propensity score matching (PSM) to create a comparison group, by matching each intervention household to a comparison household of similar baseline characteristics based on calculated propensity scores.

Study population

Study population comprised households that had at least one member living with at least 1 among the 4 common NCDs in Kenya. Participants needed to have met the following inclusion criteria: - (1). Be a household head of an enrolled or an enlisted household having at least one household member living with one of the 4 common NCDs in Kenya. (2). The household needed to have sought at least one outpatient visit to a hospital in the 4 weeks preceding the survey or to have had at least one case of hospitalization the 12 months preceding the survey. (3). Household head should be willing to voluntarily consent to participate in the study. (4). Household head should be 18 years or older and (5) Household reside within the study area and would be available for the next 1 year.

Creation of comparison group

Randomization (considered to be the gold standard) ensures that on average, intervention subjects do not differ systematically from comparison subjects in baseline characteristics. On the other hand, non-randomization can introduce selection bias where by intervention subjects can be systematically different in baseline characteristics from comparison subjects.[24] In such a situation, PSM technique provides the best method for researchers whose objective is to estimate the effects of a program by controlling for variables related to self- selection into that particular program [24]. We used PSM to create a comparison group by matching each intervention unit to a non-intervention unit of similar baseline characteristics based on calculated propensity scores. We used control variables which included observed characteristics of the households before introduction of the HI program such as (age, gender, marital status, education level and occupation of household head, household size, income, geographical location, number of household members with NCDs and number of household members with NCDs comorbidity) to calculate propensity score of each household. Covariates were therefore selected following extensive literature review of similar studies as recommended by Stuart [25]. The propensity score for each household is the probability of that household participating in the health insurance program, given the set of baseline household characteristics included in the model. In this study, we used logistic regression to compute the scores whereas Nearest Neighbor Method (NNM) with caliper adjustment approach was used to create matches from propensity scores. Households were only matched when their propensity scores felt within the designated caliper or otherwise discarded.

In order to ensure the comparison group had a distribution of propensity scores similar to the intervention group, we assessed the quality of matches by comparing their balance visually and numerically. For numerical diagnosis of balance, we compared the absolute Standardized Mean Differences (SMD) and the Variance Ratios (VR) for the 2 groups as recommended by other studies [24, 26-29]. Similar to other studies [29 & 30], we considered covariate balance as an absolute SMD value less than 0.1 and a VR near 1. Using the formula in equation (1), we included four continuous covariates in calculation of SMD, this were age of household head, household size household income and household propensity score. For dichotomous variables, we used six variables in calculation of SMD, this were; gender of household head, marital status of household head, level of education for household head, geographical location of household residence, household NCD morbidity and household NCD comorbidity. The formula used to compute SMD for dichotomous variables is given in equation (2).

Equation (1).

$$\boldsymbol{SMD\ of\ X} = \frac{\left|\bar{\boldsymbol{X}}_{\boldsymbol{intervention}} - \bar{\boldsymbol{X}}_{\boldsymbol{comparison}}\right|}{\sqrt{\frac{\boldsymbol{Var}_{\boldsymbol{intervention}} + \boldsymbol{Var}_{\boldsymbol{comparison}}}{\mathbf{2}}}}$$

Where, $\bar{\boldsymbol{X}}_{\boldsymbol{intervention}}$ and $\bar{\boldsymbol{X}}_{\boldsymbol{comparison}}$ are the sample means for the intervention and comparison groups respectively. $\boldsymbol{Var}_{\boldsymbol{intervention}}$ and $\boldsymbol{Var}_{\boldsymbol{comparison}}$ are the sample variances for the intervention and comparison groups respectively.

Equation (2).

$$SMD\ of\ x = \frac{|\hat{p}_1 - \hat{p}_2|}{\sqrt{[\hat{p}_1(1-\hat{p}_1) + \hat{p}_2(1-\hat{p}_2)]/_2}}$$

Where, $\hat{p}_1$ and $\hat{p}_2$ were the prevalence of dichotomous variables in the intervention and comparison groups respectively.

For Visual diagnosis of balance, we used box plots and comparative Bar charts to diagnose propensity score balance between intervention versus comparison households as recommended in other studies [28, 31-33], illustrated in figure 2 and figure 3.

Sample size and sampling

Using a formula suggested by Sullivan [34], we estimated that a minimum sample size of 175 households per group would have power of 80% using a 2 sided alpha of 0.05 and a medium effect of 0.3. Power of 80% or greater is appropriate to establish a statistically significant difference [35]. To ensure the total sample size of 350 was available for analysis at 12 months, an additional 5% was added to each group to cater for those that would be lost during follow up.

Study variables

We formulated dependent variables based on research objectives. The first dependent variable related to utilization of outpatient NCD care, to evaluate the effect of HI on out-patient hospital care among the respondents. Similar to other studies evaluating the effects of HI on health care utilization [11, 14, 36 & 37], use of outpatient NCDs care services was measured using one indicator- the total number of out-patient hospital visits made by each household while seeking NCDs care in the last 4 weeks preceding the date of data collection.

The second dependent variable related to hospitalization, to evaluate the effect of HI in usability of in-patient hospital care among the respondent households. Just like in other related studies [11& 38], this variable was also measured using one indicator-the total number of hospital admissions encountered by each household while seeking NCDs care in the last 12 months prior to the survey date.

Data collection and analysis

Data was collected by trained research assistants at participants' residences using a structured questionnaire at baseline and the second wave after one year. We computed descriptive analysis so as to summarize data using percentages, means and median where applicable. Under inferential analysis, we run Negative Binomial regression to predict household outpatient and inpatient care visits from household HI status while controlling for baseline visits.

Study approval

Ethical approval was obtained from Moi University-Institutional Research and Ethics Committee (IREC). Approval to conduct research was obtained from Jomo Kenyatta University of Agriculture and Technology, National Commission of Science, Technology and Inovation.

III. RESULTS

Response Rate.

During baseline data collection, a total of 411 household heads were interviewed, (182 intervention group and 229 comparison group). All the 411 questionnaires were dully filled and coded. Since the study aimed at reaching a total minimum sample size of 350 households as described in the sample size section, the extra number of households included in the baseline survey was to cater for loss during matching and subsequent follow up. PSM resulted in a reduced sample size of 364 matched households, (182 in intervention and 182 in comparison groups). During the posttest wave of data collection, 350 questionnaires (175 in intervention and 175 in comparison group) were dully completed and matched, meaning that 3.8% of participating households were lost to follow up. The response rate therefore was 96.2%.

Socio-demographic and Economic Characteristics of Households

Matching of households based on their socio-demographic and economic characteristics closed the gap between the intervention and comparison groups averages for all household characteristics. Table 2 illustrates the households' socio-demographic and economic characteristics stratified by HI.

Table 2. Households' socio-demographic and economic characteristics.

COVARIATE	LEVEL	INTERVENTION		COMPARISON	
Dichotomous		**Freq.**	**%**	**Freq.**	**%**
Gender	Male	109	29.9	111	30.5

Marital status	Married	107	29.4	103	28.3
Education level	Not attained secondary	100	27.5	94	25.8
Residence location	Rural	140	38.5	138	37.9
NCD Morbidity	More than ONE in HH	14	4	13	3.7
NCD Comorbidity	Present in HH	33	9.4	34	9.7
Wealth quintiles (Monthly income in Kshs.).	1,000 to 5,000	80	22.7	79	22.6
	Over 5,000 to 9,000	62	17.7	67	19.1
	Above 9,000 to 14,500	33	9.4	29	8.3
Continuous	LEVEL	**Mean**	**SD**	**Mean**	**SD**
Age	Household head	55.40	12.61	56.0	12.25
No of people	Household	4.82	1.33	5.0	1.23
Monthly income	Household	6198.9	3033.87	6105.71	2643.36

Characteristics of NCDs affecting households in study area.

In this study, households were recruited to participate based on having at least one household member suffering from one or more than one (comorbid) of the 4 common NCDs in Kenya. Table 3 outlines **c**haracteristics of NCDs affecting households in the study area.

Association between household HI status and utilization of out-patient NCDs care

Our primary outcome of interest was household outpatient hospital visits to seek NCDs care. Study findings established that overall, households included in the study generally recorded improved out-patient hospital visits by up to (25.3%) during the study period. Insured households reported more outpatient visits by (18.6%) as compared to uninsured that reported increased utilization of (6.7%). Although improved utilization of outpatient NCDs care services was reported across the two groups, households with no cases of NCD comorbidity utilized outpatient care more compared to those with NCDs comorbidity. For instance, households with no comorbidity had a (22.3%) increase compared to only (3%) improvement reported by comorbid households. Uninsured households with cases of comorbidity reported a decline of (4.2%) in utilization of available care services compared to insured households with comorbid cases who reported improved utilization of (7.2%) for the same service. This finding could be attributed to the fact that insured households sought care multiple times without fear of incurring high costs of treatment as compared to their uninsured counterparts whose economic situation could possibly have denied them access to NCD care services especially when comorbidities exist, requiring costly specialist input.

Table 3: Characteristics of NCDs Affecting Households in the Study Area.

S/N	**NCD TYPE**	**Intervention**	**Comparison**	**Total (%)**	
		Frequency	Frequency	Total	%
1.	Cancer	11	10	21	6
2.	Diabetes	29	30	59	16.9
3.	CVDs	55	55	110	31.4
4.	CRDs	33	33	66	18.9
5.	Diabetes with CVDs	28	28	56	16
6.	CVDs with CRDs	11	11	22	6.3
7.	Diabetes with CRDs	5	5	10	2.8
8.	Cancer with CVDs	3	3	6	1.7
	TOTAL	175	175	350	100

For inferential analysis, since dependent variable is counts expressed as discrete positive values arising from counting, a common way to analyze discrete data is the use of Poisson regression models which are generalized linear models based on the Poisson distribution. Since data was over dispersed (variance greater than mean), Negative binomial regression was run to predict household outpatient visits from household HI status, presence of comorbidity and number of household members with NCDs, each independently, while controlling for household baseline (pretest) out-patient visits. We found evidence that generally, for every household with HI cover, utilization of outpatient NCDs care improved by 1.243 times (95% CI= 1.048, 1.474), (p=0.012) compared to households without HI. We also found evidence that utilization of outpatient NCDs care among insured household without

comorbidity improved by 1.803 (95%CI = 1.292 - 2.516) times, (p=0.003) compared to comparison household with comorbidity. We however did not find evidence that utilization of outpatient NCDs care was different across different wealth quintiles for both groups 0.970 (95% CI 0.862 - 1.092), (p=0.617). Table 5 illustrates the Negative binomial regression model output used to predict outpatient NCDs care services.

Table 4. Pretest and Posttest Out-patient care visits.

NCD TYPE	BASELINE			POSTTEST			CHANGE	
	Intervention	Comparison	Total	Intervention	Comparison	Total	Intervention	Comparison
Cancer.	10	8	18	19	16	35	9	8
Diabetes	27	23	50	35	37	72	8	14
CVDs	56	61	117	75	69	144	19	8
CRDs	31	29	60	44	46	90	13	17
Diabetes/CVD	53	45	98	76	41	117	23	-4
CVDs/CRD	23	23	46	26	17	43	3	-6
Diabetes/CRD	10	13	23	14	9	23	4	-4
Cancer/CVDs.	7	9	16	8	7	15	1	-4
TOTAL.	217	211	428	297	242	539	80	29

Table 5. Negative binomial regression model output to predict Outpatient NCDs care services.

Parameter Estimates

			95% Wald Confidence Interval		Hypothesis Test				95% Wald Confidence Interval for Exp(B)	
Parameter	B	Std. Error	Lower	Upper	Wald Chi-Square	df	Sig.	Exp (B)	Lower	Upper
(Intercept)	0.251	0.1527	-0.048	0.551	2.711	1	0.100	1.286	0.953	1.734
HH HI STATUS 1	0.217	0.0870	0.047	0.388	6.247	1	0.012	1.243	1.048	1.474
Baseline visits	-0.026	0.0890	-0.200	0.149	0.084	1	0.772	0.975	0.819	1.160
HH Comorbidity	0.400	0.1341	0.137	0.662	8.873	1	0.003	1.491	1.146	1.939
No. with NCDs	0.589	0.1700	0.256	0.923	12.011	1	0.001	1.803	1.292	2.516
Wealth quintiles	-0.030	0.0603	-0.148	0.088	0.250	1	0.617	0.970	0.862	1.092
(Scale)	1[a]									
(Negative binomial)	2.098E-9[b]	.	.	.						

Dependent Variable: HH Outpatient 2

Model: (Intercept), HH HI STATUS, Baseline visits, HH Comorbidity, No. with NCDs, Income groups

a. Fixed at the displayed value.

b. Hessian matrix singularity is caused by the scale or negative binomial parameter.

Association between household HI status and in-patient NCDs care

Households reported a 25% increase in utilization of in-patient NCD care across both groups during the study period. Insured households had 20.6% compared to 4.4% witnessed by uninsured households. The study further observed that utilization of inpatient NCDs care improved among the proportion of households with no cases of NCDs comorbidity by up to (18.9%) across both groups compared to households with cases of comorbidity (6.1%). Hospitalization aimed at seeking CVDs care was most frequently utilized irrespective of HI status, possibly due to its high prevalence in the study area. All households with cases of cancer witnessed increased hospitalizations possibly due to delayed diagnosis generally seen in LMICs where diagnosis is made when the disease has progressed to advanced stage prompting specialized care that require hospitalization. The study found evidence that hospitalization among insured households improved by 1.256 (95% CI= 0.965, 1.634), times compared to utilization by uninsured households (p=0.004). The study however did not find evidence that utilization of inpatient care among household with comorbidity was different for insured and uninsured households 1.230 (95% CI = 0.884 -1.712), p=0.219. We also found evidence that household with more than one members afflicted by NCDs had 1.9 times more admissions (95% CI 1.262-2.749) compared to households with only one member,

p=0.002). We did not find evidence for the difference in utilization across various income groups 0.776 (95% CI 0.637-0.946), p=0.072.

Table 6. Negative binomial regression model output to predict Inpatient NCDs care services.

Parameter Estimates

Parameter	B	Std. Error	95% Wald CI Lower	95% Wald CI Upper	Hypothesis Test Wald Chi-Square	df	Sig.	Exp(B)	95% Wald Confidence Interval for Exp(B) Lower	95% Wald Confidence Interval for Exp(B) Upper
(Intercept)	-0.530	0.2157	-0.953	-0.108	6.048	1	0.014	0.588	0.385	.898
HH HI STATUS	0.228	0.1343	-0.035	0.491	2.884	1	0.004	1.256	0.965	1.634
HH Comorbidity	0.207	0.1686	-0.123	0.537	1.509	1	0.219	1.230	0.884	1.712
No. with NCDs	0.622	0.1986	0.233	1.011	9.816	1	0.002	1.863	1.262	2.749
Income groups	-0.254	0.1009	-0.451	-0.056	6.317	1	0.072	0.776	0.637	0.946
In patient visits 1	0.419	0.1011	0.220	0.617	17.135	1	0.089	1.520	1.247	1.853
(Scale)	1[a]									
(Negative binomial)	4.988E-8[b]	.	.	.						

Dependent Variable: HH Inpatient 2

Model: (Intercept), HH HI STATUS, HH Comorbidity, No. with NCDs, Income groups, In patient visits

a. Fixed at the displayed value.

b. Hessian matrix singularity is caused by the scale or negative binomial parameter.

IV. Discussion

This study presents an analysis of the effects of HI on outpatient and inpatient care utilization among households with NCDs using a pretest and posttest non-equivalent control group, followed up for one year. First, the study found evidence that households with HI cover utilized outpatient NCDs care more compared to those without HI cover. Other studies have recorded similar findings elsewhere in Kenya [5] in Vietnam [11], South Africa [12], as well as in rural China [39]. For instance, to improve utilization of care among households with NCDs in Vietnam, the government undertook a series of modifications and significant investment in order to mobilize resources to the sector [11]. However, other studies in Zambia [14] and in Vietnam [15], reported that HI had no significant association with utilization of out-patient health services among people with NCDs. In Zambia for instance, the authors argued that the sample size for people with HI cover and those with NCDs was relatively small hence this limitation reduced the power of the study to detect the effect of HI [14]. In Vietnam, the authors stated that the study was conducted in the city, while most people stay in rural areas hence unable to access quality services [11].

Secondly, the study identified that there was increased utilization of outpatient NCDs care services across the 2 groups despite one group lacking HI cover. A similar finding has been reported by Mwenda et al, [40] that demand for NCDs care will likely rise in the country owing to population growth outpacing growth in supply of health facilities mainly due to the shifting epidemiological disease burden in the country.

Thirdly, the study found evidence that households with HI cover utilized in-patient NCD care more than those without HI cover. Other studies have recorded consistent results for example, applying the fixed-effects model with instrumental variables, Liu and Zhao [41] reported that a voluntary HI program in China increased the number of hospitalization. Similarly, Erlangga and team [38] established that Jaminan Kesehatan National HI program in Indonesia improved inpatient admissions for a voluntarily covered and a subsidized group. Likewise, using a cross-sectional study design, Nguyen and colleagues in Vietnam found out that household with NCDs covered by a voluntary HI were 2.5 times more likely to be hospitalized compared with households without any cover [11]. Despite the fact that we found a positive association between HI and hospitalization among NCDs patients, the study however did not found evidence for difference in utilization of NCDs care among comorbid households and those without comorbidity. Comorbidity is expected to increase utilization among the insured group due to reduction of cost since comorbidity is expensive to manage. This finding could be explained in relation awareness of the HI cover package entitlements by patients and hospital staff. Other studies have reported that inadequate awareness on the HI cover package entitlements among care givers and NCDs patients themselves can lead to denial of available services hence reducing utilization among insured patients [5 &42].

V. Conclusion

NCDs are a significant cause of illness and loss of live globally and in Kenya, liable for more deaths than all other causal agents combined. The government of Kenya has initiated reforms at the National health insurer – NHIF aimed at widening the benefit package so as to address out-patient and in-patient NCDs care needs. This study found evidence that HI improves out-patient health care utilization among households of people with NCDs. The study also found evidence that HI improves utilization of in-patient

NCDs care among households. The study observed that inadequate awareness on the HI cover package entitlements by care givers and patients can reduce utilization among insured households.

Policy recommendations

Based on our findings, we make the following recommendations.

First, the National government should prioritize rolling out HI programs countrywide targeting households with NCDs so as to enable more patients to access care.

Secondly, the County governments and their development partners should ensure health systems accommodate all HI covered NCDs care services.

Thirdly, the National insurer-NHIF should prioritize engaging with its members having NCDs, as well as hospital managers in relation to awareness of benefit package entitlements for NCDs care, so as to further improve utilization.

Strengths and limitation

The study utilized a pretest and posttest design, capable of capturing the effects of HI on NCDs care utilization over time. Other related studies often utilize cross sectional designs, unable to capture more insight on causality.

Selection bias was eliminated using study design - propensity score matching, - a statistical technique of matching each intervention household to a comparison household of similar baseline characteristics.

The study was implemented in Busia County western Kenya alone, although a few other counties have rolled out similar HI programs in anticipation for attainment of UHC. A larger study across several counties could yield more insights.

There could be minimal measurement errors since most questions were based on self-reporting by respondents, which could have led to recall bias. Effort was however made to minimize bias by requesting respondents to maintain a diary of care seeking events during the study period.

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Abbreviations

AMPATH.	Academic Model Providing Access to Healthcare.
CRDs.	Chronic Respiratory Diseases.
CVDs.	Cardio-vascular diseases.
HI.	Health Insurance.
LMICs.	Low and Middle Income Countries.
NHIF.	National Hospital Insurance Fund.
OOP.	Out of Pocket payments.
PSM.	Propensity Score Matching.
SDG.	Sustainable Development Goals.
UHC.	Universal Health Coverage.

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