PREDICTING COMMUNITY-BASED HEALTHCARE CLAIMS USING INTERNATIONAL CLASSIFICATION OF PRIMARY CARE CODES

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Abstract

As in many other developing countries, affordability and accessibility to health care in Nigeria have always been a matter of great concern. The hope of the average Nigerian to have reliable and affordable healthcare delivery system was brightened with the take-off of the National Health Insurance Scheme (NHIS) in 2005. However, Social Health Insurance Schemes like other forms of health insurance have both health and financial risks. This study applied the International Classification of Primary Care codes to develop diagnostic-based risk adjustment model for predicting future claims in a Community Based Social Health Insurance Programme using claims data of 23,735 enrollees. Results show the adequacy of the diagnostic-based risk adjustment model with a predictive performance of 52% and MAPE of 53%. The expectation is that implementation of risk adjustment model will correct prevalence of risk selection cream-skimming at the community level of the healthcare system.

Keywords: Risk-adjustment, Risk Selection, NHIS, Primary Care, Health Insurance.

บทคัดย่อ

เช่นเดียวกับประเทศกำลังพัฒนาหลายประเทศ ความสามารถในการจ่ายเงินและการเข้าถึงการดูแลสุขภาพในประเทศไนจีเรียเป็นเรื่องที่น่าเป็นห่วง ความหวังของชาวไนจีเรียที่จะมีระบบการจัดส่งการดูแลสุขภาพที่เชื่อถือได้และราคาไม่แพงเริ่มสดใสขึ้นเมื่อมีการนำเอาประกันสุขภาพแห่งชาติ (NHIS) มาใช้ในปี พ.ศ. 2548 อย่างไรก็ตามโครงการประกันสุขภาพในระดับสังคมก็เผชิญความเสี่ยงทางด้านสุขภาพและความเสี่ยงด้านการเงินเช่นเดียวกับการประกันสุขภาพในรูปแบบอื่น การศึกษานี้ใช้เลขรหัส International Classification of Primary Care ในการพัฒนารูปแบบแบบจำลองที่มีการปรับปรุงความเสี่ยงเพื่อคาดการณ์การเรียกร้องค่าสินไหมทดแทนในอนาคตในโครงการ Community Based Social Health Insurance Programme โดยใช้ข้อมูลการเรียกร้องค่าสินไหมทดแทนจำนวน 23,735 ราย ผลการวิจัยแสดงให้เห็นถึงความเพียงพอของแบบจำลองที่มีการปรับปรุงความเสี่ยงโดยมีผลการพยากรณ์ร้อยละ 52 และ ค่า MAPE เท่ากับ ร้อยละ 53 การนำแบบจำลองที่มีการปรับปรุงความเสี่ยงไปใช้ในการแก้ไขความชุกของการคัดเลือกความเสี่ยงในระดับชุมชนของระบบการดูแลสุขภาพ

คำสำคัญ: การปรับปรุงความเสี่ยง การคัดเลือกความเสี่ยง NHIS การบริการระดับปฐมภูมิ ประกันสุขภาพ

1.INTRODUCTION

Evidences from literatures suggest that many people in the developing countries lack healthcare from which they could benefit greatly (O'Donnell, 2007). But concerned about healthcare accessibility and affordability in these countries including Nigeria, are of great interest (Yohersor, 2004). The expectations of average Nigerian to access efficient and affordable healthcare delivery system were enhanced with the introduction of the National Health Insurance Scheme (NHIS, 2005; Dotun, 2009; Ibiwoye & Adeleke, 2007). One of the programmes designed by the NHIS scheme is Community Based Social Health Insurance Programme (CBSHIP). This is a relatively new approach in the provision of health services to the poor (Tundui & Macha, 2014). The emergence of CBSHIP stem from the failures of the microcredit programmes and conventional health insurance plans to protect low-income households and vulnerable rural population from health shocks and non-use of health services (Ekman, 2004; Carrin, Waelkens, & Criel, 2005; Donfouet & Mahieu, 2012). However, Social Health Insurance Scheme like other forms of health insurance has some risks, both health and financial risks. Literatures had confirmed that the distribution of risk among members of any population in any society is highly skewed, with a few members using disproportionate amounts of resources, and the large majority using more moderate resources (Duncan, 2011; Dunn, *et al*., 1996; Cumming, Knutson, Cameron & Derrick, 2002). Therefore, an important modeling challenge to health analysts and actuaries is the prediction of those members of the population whose experience will place them in the tail of the distribution with low frequency but high severity. For viability of the programme, there is need for regular evaluation of the financial stability and sustainability of the scheme. Actuaries have conventionally modeled risk using age and sex, and other factors (such as geography and employer industry) to predict resource use in healthcare. However, to eliminate the bias introduced by employing demographic factors in health risk selections, this study explores the use of diagnoses in building predictive model for future healthcare claims based on the International Classification of Primary Care (ICPC) codes. This approach is expected to assess the enrollee(s) based on the morbidity risks that he or she brings into the pool. To this end, the goal is to apply International Classification of Primary Care (ICPC) codes to develop diagnostic-based health risk adjustment model in order to predict expected claims among the enrollees of a CBSHIP for the Nigeria Medical Care Organizations or Health Maintenance Organizations (HMOs) for them to be in business and not be insolvent.

The remainder of this article is organized as follows: section 2 presents a review of literatures in the area of health-based risk adjustment model, section 3 discusses the methodology employed in the study while results and discussion of findings are presented in section 4.Section 5 presents the conclusion.

2. LITERATURES

The predictive power of claims data became a topic of research in the 1980s (Zhao *et al*. 2005) and numerous studies have since established the potency of administrative data models on health-care costs (Ash *et al*. 2000; Zhao *et al*. 2001; Farley, Harley and Devine, 2006; Zhao *et al*. 2005). Overview of the developments in risk-based predictive modeling and evaluation of different risk models developed in the insurance industry for both assessment

and population health-care cost prediction have been extensively discussed (Van de Ven and Ellis 2000; Cumming *et al*. 2002). Several studies concentrated on using classical regression models when predicting total health-care costs while logistic regression models are used to identify high-risk members. Often these regression models are pooled with heuristic classification rules and there are significant works in creating co-morbidity scores from administrative data (Bertsimas, *et al*. 2008; Zhao *et al*. 2001; Powers *et al*. 2005; LaVange *et al*. 1986; Roblin *et al*. 1999; Klabunde, Warren & Legler, 2002). Studies that predict health-care costs, based on data other than claims data, are also available; see the works of Fleishman *et al*. (2006) and Pietz *et al*. (2004). Mesike, Adeleke & Ibiwoye (2011) construct predictive models that can be used in forecasting future healthcare costs of inpatient diagnoses with high incidence of occurrence for effective health care intervention. The study employed various forecasting techniques, such auto-regressive-integrated-moving-average (ARIMA) and regression to find the best fit for data for various health conditions to determine out-of-sample forecast. Ojikutu (2009) explores the use of regression model to examine the prevalence of cardiovascular diseases. The use of correspondence analysis, actuarial loss model and discriminant functions and also explored in modeling healthcare data (Ojikutu, Adeleke,Yusuf & Ajijola, 2010; Adeleke, Hamadu & Ibiwoye,2012; Ojikutu, Yusuf, Obalola, Adeleke, Ajijola & Mesike, 2012).

Significant literatures on how to compare and evaluate risk adjustment models have been developed over the years. Different metrics for model performance and evaluation have been defined and used for evaluating risk adjustment models (Ash *et al*, 1989; Cumming *et al*, 2002). In addition to the individual R^2 metric, the grouped R^2, which measured how well the models perform for mutually exclusive partitions is also a common measure of model performance. Other predictive ratios are Mean absolute deviation (MAD) Mean Absolute Prediction Error (MAPE), Cumming Prediction Error (CPM) and the standard error of the regression. An ideal model would have predictive ratios close to one for every group of possible interest. Health risk assessment and health risk adjustment are key components of any national health insurance restructurings (Rosenblatt *et al*, 1993; American Academy of Actuaries, 1994). While health risk assessment is a procedure for determining objectively the comparative risks of individuals or group of individuals, health risk adjustment on the other hand uses the outcomes of risk assessment to determine carrier transfer and also a mean of reducing the effect of risk selection from health insurance premiums to a health care plan. Risk adjustment is also a mechanism to recompense for differences among patients that may affect their health care outcomes (Holohan & Charns, 1997). It is away to level the playing field by accounting for illness, demographic and other factors that patients bring to a health care encounter. Mehmud & Yi (2012) define claimed based risk assessment in healthcare as the process of determining the relative costs of a person based on their medical history. They explain that a typical process claimed based risk assessment is to group the diagnoses and/or prescription drug history of a patient into condition categories. Until the mid-1970s, most morbidity data collected in primary care settings for statistics and research was classified using the International Classification Diseases (ICD) (Beasley *et al*, 2004). The important advantage of this classification is attainment of international recognition, thus aiding the comparability of data from different countries. However, the disadvantage was that the many symptoms and non-disease conditions that are presented in primary care were problematic to code using this classification, which was originally designed for application to mortality statistics, and with a disease-based structure (Beasley *et al*, 2004). Identifying the glitches associated with the ICD and the need for an internationally recognized classification for general practice, the World Organization of Family Doctors (WONCA) Classification Committee (now the WONCA International Classification Committee (WICC)) designed the

International Classification of Primary Care (ICPC). In this classification, the reason for encounter (RFE) is classified as well as the diagnostic processes, interventions, preventions, administrative procedures, and the diagnosis. This classification is different from the International Classification of Disease (ICD) format, in which the axes of the chapters vary from body systems to aetiology and others (Fleming, Cross & Barley, 2005). Fleming, Cross & Barley (2005) further argue that this mixture of axes creates confusion, since diagnostic entities can be classified into more than one chapter with equal logic. Ayankogbe *et al* (2009) uses the International Classification of Primary Care to document the pattern of illnesses presenting in general/family physician practices in Lagos, Nigeria.

3. MATERIAL AND METHODS

3.1 Data

The data used for this study includes claim and enrollment information for Community Based Social Health Insurance Scheme (CBSHIP) in Lagos State. The scheme targets low-income beneficiaries located in markets in Lagos State. The data is restricted to those members continuously enrolled from April 1, 2012 to September 30, 2012 for which medical and pharmacy claim data and enrollment information, including age and gender, are available.The data were sourced from a Health Management Organization (HMO) through National Health Insurance database. The scheme covered 23,735 individuals both sponsors (principals) and dependants Market Men and Women in four market places where merchandise is exposed for sale at Agege, Ikotun, Daleko and Ojuwoye. The markets are distributed across the four most populated local governments of Agege, Alimosho, Oshodi/Isolo and Mushin respectively in Lagos urban metropolis (National Population Commission, 2006). However, the target population consists of 92,000 men and women and their family members. The enrollees in the scheme consist of individuals involved in retail trading of consumer goods, food products, textile, utensils and house hold items. For this study, only 15,666 enrollees who made claims are considered for the analysis. Of the 15,666 enrollees in the base period (April, May and June), 68.98% (10,806) are female, over 50% of the enrollees are in the age bracket of 0 to 34 years old and 33.55% of the medical claims is below ₦5,000. In addition, 65.8% (10,308) of the enrollees are sponsors or principals while 34.2% (5,358) of the enrollees are dependants. Furthermore, 13.75% (2,154) of the enrollees who made claims are under five years old while 8.52% (1,336) of the enrollees who made claims are sixty five years old and above.The percentage of medical claims that is ₦5,000 and below also shows that most community based health insurance claims are due to primary care.

3.2 Design

Actuaries generally model health care costs and claims using trend factors (Rosenberg & Farrell, 2008). The advantage of using trend factors is the simplicity of their application to predict the next year's aggregate claims. The disadvantage of this method is that it does not incorporate the movement of individuals in and out of a group; depending on their level of utilization this movement would impact the projections. A splits trend factors design was used for the study to allow for the development and testing of calibrated risk weights (Cumming *et al*, 2002). Specifically, each member was randomly assigned to one of two subsets: (1) the calibration data base period of April, May and June subset and (2) the validation data prediction period of July, August and September subset, placing all the

enrollees who made claims in each subset. This design was used to avoid over-fitting the data, which could exaggerate the goodness of the fit and various other measures of predictive accuracy (Cumming et al. 2002).The calibration data subset was used to develop a new set of risk weights using the study data. Specifically, each member was randomly assigned to one of two subsets. All the enrollees who made claims in the base period (April, May and June) were used for the calibrated risk weights to calculate the risk scores. Risk score or total risk score is the sum of the demographic and condition risk weights. Usually, risks scores are stated relative to 1.0, with 1.0 being equal to the average expected risk score across the entire population. In order to obtain correct estimates for the overall population, the following sampling weights were used based on the proportion of the CBSHIS affiliates residing in different Local Government of the Scheme. First, the data were selected accordingly and their population age and gender structure used to estimate sampling weights. Secondly, a dataset of individuals was constructed based on; (i) registered completely or partially from 1 April 2012 until 30 September 2012, and (ii) born before 30 September 2012. Finally, the dataset was sorted by gender and five-year interval age-groups. A random sample was drawn from each age-gender group by the health care providers. Microsoft Excel macros, pivot table and vlookup were used to do the sorting.

3.3 Method

The most important risk adjusters discussed in the literatures on alternative risk adjustment models are the following: age and gender (or "demographic" adjusters); diagnosis-based risk adjustment; information from drug prescriptions; self-reported health information; mortality; disability and functional health status (Holly, Gardiol, Eggli, Yalcin & Ribeiro, 2003). Van de Ven and Ellis (2000) discussed an extensive analysis of the advantages and disadvantages of all these risk-adjusters. However, Beck (1999) observes that an insured person who has received inpatient treatment generates treatment costs that are seven times higher in the subsequent year than those who did not receive inpatient treatment. The main conclusion of Beck (1999) is that inclusion of prior hospitalization as a risk adjuster has a strong impact on risk selection profits. To this end, this study examines three types of risk adjustment models, which we call the demographic model, demographic, and hospitalization model as well as demographic, hospitalization and ICPC diagnoses model. The models were compared by using measure of predictive performance (R-Square, MAPE, CPM and Predictive Ratio) under concurrent and prospective risk assessment. The concurrent risk assessment consists of predicting expenditures in the current period (t) for the same period (t) . Prospective risk assessment on the other hand consists of predicting claims expenditures in the current period (t), for the next period $(t+1)$. In general, to calculate the risk weights for a particular risk adjuster, the following multivariate linear regression models is used for the three models:

Demographics Risk Adjustment Model

$$P = \sum_i (RWAG_i \times AG_i) \qquad (1)$$

where:

$P = total\ claim\ payment\ for\ period\ t\ \ (including\ medical\ and\ pharmacy)$

$RWAG_i = risk\ weight\ for\ age/gender\ category\ i$

$AG_i = indicator\ variable(0\ or\ 1)\ age/gender\ category\ i$

Demographics and Hospitalization Risk Adjustment Model

$$P = \sum_i (RWAG_i \times AG_i) + \sum_i (RWH_i \times MH_i) \quad (2)$$

where:

$P = total\ claim\ payment\ for\ period\ t\ \ (including\ medical\ and\ pharmacy)$

$RWAG_i = risk\ weight\ for\ age/gender\ category\ i$

$AG_i = indicator\ variable(0\ or\ 1)\ age/gender\ category\ i$

$RWH_i = risk\ weight\ for\ hospitalization\ category\ \ i$

$MH_i = indicator\ variable(0\ or\ 1) for\ hospitalization\ category\ i$

Demographics, Hospitalization and ICPC Diseases Risk Adjustment Model

$$P = \sum_i (RWAG_i \times AG_i) + \sum_i (RWH_i \times MH_i) + \sum_i (RWMCC_i \times MCC_i) \quad (3)$$

where:

$P = total\ claim\ payment\ for\ period\ t\ \ (including\ medical\ and\ pharmacy)$

$RWAG_i = risk\ weight for\ age/gender\ category\ i$

$AG_i = indicator\ variable(0\ or\ 1)\ age/gender\ category\ i$

$RWH_i = risk\ weight\ for\ hospitalization\ category\ i$

$MH_i = indicator\ variable(0\ or\ 1) for\ hospitalization\ category\ i$

$RWMCC_i = risk\ weight\ for\ medical\ condition\ category\ i$

$MCC_i = indicator\ variable(0\ or\ 1) for\ medical\ condition\ category\ i$

The paid claims and health plan encounter data of the enrollees were collected, and then the ICPC codes were applied to group the diagnoses information into risk categories. Duplicate risk categories were removed and highest risk categories within a disease group were selected by using stepwise regression analysis. Stepwise regression is a semi-automated process of building a model by successively adding or removing variables based solely on the t-statistics of their estimated coefficients (Anderson, Sweeney and Williams, 2003).Stepwise regression essentially does multiple regressions a number of times, each time removing the weakest correlated variable. At the end, the variables that explain the distribution best are left. The only requirements are that the data is normally distributed (or rather, that the residuals are), and that there is no correlation between the independent variables (known as collinearity). The enrollees were grouped into age/gender categories (Female 0-4, 5-9,……80+; Male 0-4, 5-9……..80+). Individual enrollees risk weights were applied and summed it up to obtain the risk score. The models were assessed by R-Square, MAPE, CPM and Predictive Ratio for measure of goodness of fit under concurrent and prospective risk assessment. The concurrent risk assessment consists of predicting expenditures in the current period (t) for the same period (t) . Prospective risk assessment on the other hand consists of predicting claims expenditures in the current period (t), for the next period $(t + 1)$.

4.Results and Discussion

The frequency distributions of International Classification of Primary Care (ICPC) diagnoses categories of the enrollees were obtained. General and unspecified diagnoses

categories that consist of Fever, Tuberculosis, Measles, Malaria, Chickenpox among others accounted for 31.13% (20,721) of claims made by the enrollees. Pregnancy, child bearing and family planning related conditions accounted for 16.05% (10,684) of the claims while cardiovascular related conditions accounted for 14.67% (9,765) of the claims made by the enrollees. Social problems related conditions accounted for only 0.01% (6) of the claims. The ICPC process condition categories of the enrollees revealed that other diagnoses, infections and symptoms/complains accounted for 48.52% (32,295), 40.29% (26,815) and 10.06% (6,695) respectively of the claims made by enrollees. Of the 26,815 infections conditions categories 38% (10,071) are as a result of Malaria. The total claim from Malaria alone is ₦5,201,375.00. Tables 1 to 3 show the stepwise regression results for demoraphic model, demographic and hospitalization model and demographic, hospitalization and ICPC diagnoses model respectively. The models were used to determine the individual risk score for the concurrent risk assessment as well as individual relative risk score for the prospective risk assessment.

From the "Demographic Model" stepwise regression results in Table 1, 25 of the 34 (74%) age/gender groupings are significant ($p < 0.001$). Females in age bracket 5 to 14 are not significant while Males in age bracket 5 to 39 are not significant. This result further confirmed that women use more health care services than men (Mechanic & Greenley, 1982; Hibbard & Pope, 1982; Waldron, 1983; Verbrugge & Wingard, 1987). Table 2 shows the stepwise regression results of the "Demographics and Hospitalization model" in order to predict the expected claims of enrollees. From these results in table 2, hospitalization of enrollees is significant at ($p < 0.001$) in addition to 26 of the 34 (76%) age/gender groupings. Twenty five (25) of these age/gender grouping are significant at 1% confidence level ($p < 0.001$) while a male in 35-39 years age group is significant at 5% confidence level ($p < 0.05$). Females in age bracket 5 to 14 and Males in age bracket 5 to 34 are not significant hence removed by the stepwise regression procedures. The Demographics, Hospitalization and ICPC disease categories model in table 3 shows that 29 (85%) of age/gender grouping is significant. Twenty two (22) of these age/gender groupings are significant at 1% ($p < 0.001$) while 7 are significant at 5% ($p < 0.05$). In addition 13% (67 out of 498) ICPC diagnoses conditions are significant as well as hospitalization of the enrollees. Abdominal hernias, Asthma, Malaria, Complicated labour delivery, Diabetis insulin dependent, Pregnancy related conditions among others are 40 diagnoses that are significant at 1% ($p < 0.001$) while the remaining 27 diagnoses like: Abnormal cervix smear, Allergic rhinitis Diabetis non-insulin dependent, Fear of sexually transmitted disease are significant at 5% confidence level.

Table 1
Stepwise Linear Regression Results for Demographic Model

Variable Label	Parameter Estimate	Standard Error	P-value
(Constant)	5962.52	250.04	0.0000
A Female in 0-4 Age Group	2138.37	438.98	0.0000
A Female in 15-19 Age Group	3917.01	835.60	0.0000
A Female in 20-24 Age Group	9617.99	539.60	0.0000
A Female in 25-29 Age Group	11198.49	387.23	0.0000
A Female in 30-34 Age Group	10971.64	372.24	0.0000
A Female in 35-39 Age Group	7183.47	437.99	0.0000
A Female in 40-44 Age Group	4037.22	511.29	0.0000
A Female in 45-49 Age Group	4514.64	546.16	0.0000
A Female in 50-54 Age Group	5486.44	495.60	0.0000
A Female in 55-59 Age Group	6704.85	490.97	0.0000
A Female in 60-64 Age Group	7782.48	532.66	0.0000
A Female in 65-69 Age Group	8701.43	610.84	0.0000
A Female in 70-74 Age Group	7792.20	820.11	0.0000
A Female in 75-79 Age Group	8408.85	1312.09	0.0000
A Female in 80 and Above Age Group	8032.04	1636.68	0.0000
A Male in 0-4 Age Group	2364.82	430.34	0.0000
A Male in 40-44 Age Group	1523.77	675.90	0.0000
A Male in 45-49 Age Group	3235.12	772.02	0.0000
A Male in 50-54 Age Group	4447.09	796.32	0.0000
A Male in 55-59 Age Group	5208.21	756.34	0.0000
A Male in 60-64 Age Group	6425.73	710.08	0.0000
A Male in 65-69 Age Group	8986.52	739.36	0.0000
A Male in 70-74 Age Group	7379.83	955.40	0.0000
A Male in 75-79 Age Group	6624.59	1416.33	0.0000
A Male in 80 and Above Age Group	5980.18	2144.13	0.0000
Dependent Variable: Total Amount it Cost to Treat The Enrollee			

Source: Author's Computation, 2017

Table 2
Stepwise Linear Regression Results for Demographic and Hospitalization Model

Variable Label	Parameter Estimate	Standard Error	P-value
Constant	5024.13	246.29	0.0000
Hospitalization Variable			
Whether the enrollee was Hospitalized or not	20520.78	305.08	0.0000
Age/Gender Variables			
A Female in 0-4 Age Group	1859.26	401.94	0.0000
A Female in 15-19 Age Group	3033.47	744.20	0.0000
A Female in 20-24 Age Group	6624.67	490.00	0.0000
A Female in 25-29 Age Group	7837.55	362.11	0.0000
A Female in 30-34 Age Group	7987.11	348.90	0.0000
A Female in 35-39 Age Group	5371.46	402.14	0.0000
A Female in 40-44 Age Group	3655.57	463.54	0.0000
A Female in 45-49 Age Group	4812.88	493.36	0.0000
A Female in 50-54 Age Group	5789.60	450.05	0.0000
A Female in 55-59 Age Group	7050.78	446.11	0.0000
A Female in 60-64 Age Group	8520.67	481.84	0.0000
A Female in 65-69 Age Group	8890.21	549.03	0.0000
A Female in 70-74 Age Group	8086.44	730.54	0.0000
A Female in 75-79 Age Group	8596.48	1160.72	0.0000
A Female in 80 and Above Age Group	8970.44	1445.60	0.0000
A Male in 0-4 Age Group	2044.96	394.63	0.0000
A Male in 35-39 Age Group	1208.80	551.57	0.0284
A Male in 40-44 Age Group	2164.76	605.32	0.0004
A Male in 45-49 Age Group	3610.20	688.71	0.0000
A Male in 50-54 Age Group	4868.16	709.85	0.0000
A Male in 55-59 Age Group	5992.89	675.13	0.0000
A Male in 60-64 Age Group	6697.86	634.91	0.0000
A Male in 65-69 Age Group	9340.70	660.33	0.0000
A Male in 70-74 Age Group	7933.46	848.54	0.0000
A Male in 75-79 Age Group	7562.99	1252.19	0.0000
A Male in 80 and Above Age Group	6234.55	1891.47	0.0010
Dependent Variable: Total Amount it Cost to Treat The Enrollee			

Source: Author's Computation, 2017

Table 3

Stepwise Linear Regression Results for Demographic, Hospitalization and Diseases Model

Variable Label	Parameter Estimate	Standard Error	P-value
Constant	5363.76	196.23	0.0000
Hospitalization Variable			
Whether the enrollee was Hospitalized or not	14825.85	268.68	0.0000
Age/Gender Variables			
A Female in 5-9 Age Group	-1774.90*	570.84	0.0019
A Female in 10-14 Age Group	-2005.41*	737.94	0.0066
A Female in 20-24 Age Group	4120.91	385.74	0.0000
A Female in 25-29 Age Group	5279.64	272.53	0.0000
A Female in 30-34 Age Group	5024.91	260.64	0.0000
A Female in 35-39 Age Group	2632.84	308.55	0.0000
A Female in 40-44 Age Group	769.71	362.83	0.0339
A Female in 45-49 Age Group	1583.53	389.36	0.0000
A Female in 50-54 Age Group	2014.64	353.51	0.0000
A Female in 55-59 Age Group	2908.24	350.88	0.0000
A Female in 60-64 Age Group	3986.62	382.82	0.0000
A Female in 65-69 Age Group	4229.35	441.14	0.0000
A Female in 70-74 Age Group	3168.54	594.77	0.0000
A Female in 75-79 Age Group	3995.43	953.65	0.0000
A Female in 80 and Above Age Group	4605.35	1188.85	0.0001
A Male in 5-9 Age Group	-1560.83*	493.31	0.0016
A Male in 10-14 Age Group	-1701.38*	715.48	0.0174
A Male in 15-19 Age Group	-2822.51*	821.64	0.0006
A Male in 20-24 Age Group	-1967.21*	796.18	0.0135
A Male in 25-29 Age Group	-2051.18*	595.59	0.0006
A Male in 30-34 Age Group	-1513.28*	436.96	0.0005
A Male in 35-39 Age Group	-924.73*	438.36	0.0349
A Male in 50-54 Age Group	1067.07	574.78	0.0634
A Male in 55-59 Age Group	1978.96	546.66	0.0003
A Male in 60-64 Age Group	2409.83	513.10	0.0000
A Male in 65-69 Age Group	3852.01	538.28	0.0000
A Male in 70-74 Age Group	3491.92	693.85	0.0000
A Male in 75-79 Age Group	2621.72	1029.52	0.0109
A Male in 80 and Above Age Group	3363.19	1558.16	0.0309

Source: Author's Computation, 2017

** The value is set to zero for risk score computation.*

Table 3
Stepwise Linear Regression Results for Demographic, Hospitalization and Diseases Model(Cont'd)

Variable Label	Parameter Estimate	Standard Error	P-value
ICPC Diagnoses Variables			
Abdominal hernia, other	29369.71	2616.71	0.0000
Abdominal pain localized, other	4176.64	1208.92	0.0006
Abnormal cervix smear	8550.08	4245.22	0.0441
Abortion spontaneous	4483.82	1185.40	0.0002
Acute bronchitis/bronchiolitis	5939.21	1589.84	0.0002
Acute otitis media/myringitis	3473.78	1074.00	0.0012
Allergic rhinitis	2372.87	1134.69	0.0365
Anaemia other/unspecified	6437.49	1079.43	0.0000
Anaemiavit B12/folate deficiency	7807.48	3824.80	0.0412
Anal fissure/perianal abscess	5908.01	2831.76	0.0371
Animal/human bite	9122.17	4254.98	0.0321
Antepartum bleeding	7930.88	3015.84	0.0086
Asthma	4770.12	572.10	0.0000
Benign neoplasm breast female	2016.02	906.07	0.0261
Blood/lymph/spleen disease, other	6836.76	792.65	0.0000
Boil/carbuncle	2134.81	463.56	0.0000
Burn/scald	4935.73	1618.37	0.0022
Bursitis/tendinitis/synovitis NOS	13395.34	4908.55	0.0064
Chlamydia infection genital female	26060.56	8576.49	0.0024
Complicated labour/delivery livebirth	50564.20	826.84	0.0000
Complication of medical treatment	47803.25	6000.89	0.0000
Complications of puerperium, other	52345.48	3211.79	0.0000
Congenital anomaly complicating pregnancy	15350.74	4905.20	0.0000
Conjunctivitis infectious	2690.29	518.75	0.0000
Constipation	2483.14	1075.01	0.0209
Cough	1986.19	691.89	0.0041
Cystitis/urinary infection, other	2615.75	485.02	0.0000
Deafness	8316.01	2686.65	0.0012
Dermatitis contact/allergic	1983.99	590.72	0.0008
Dermatitis/atopic eczema	3487.76	1277.84	0.0064
Diabetes insulin dependent	7163.82	1433.22	0.0000
Diabetes non-insulin dependent	11116.68	262.27	0.0000
Diarrhoea	1538.30	611.67	0.0119
Disease digestive system, other	4528.86	638.86	0.0000
Disorder of pregnancy/delivery, other	7916.83	671.80	0.0000
Dyspepsia/indigestion	3074.11	505.15	0.0000
Ear/mastoid disease, other	12684.21	997.44	0.0000
Fear of sexually transmitted disease male	5617.81	2691.12	0.0369
Fear of urinary disease, other	18492.01	8483.64	0.0293
Foreign body in skin	12886.78	6035.60	0.0328

Source: Author's Computation, 2017

Table 3
Stepwise Linear Regression Results for Demographic, Hospitalization and Diseases Model (Cont'd)

Variable Label	Parameter Estimate	Standard Error	P-value
Genital disease male, other	-5181.27*	2271.70	0.0226
Haemorrhoids	3886.25	1640.61	0.01786
Hair/scalp symptom/complaint, other	9809.84	4903.81	0.0455
Hypertension complicated	932.91	294.96	0.0016
Inguinal hernia	2083.74	989.41	0.0352
Injury digestive system, other	-7154.02*	3466.39	0.0391
Injury eye, other	14715.73	6007.76	0.0143
Injury respiratory, other	-11265.04*	4957.51	0.0231
Lactation symptom/complaint	15079.22	6000.85	0.0121
Lumps/swellings generalized	10693.54	4898.88	0.0291
Malaria	629.36	145.86	0.0000
Malignant neoplasm stomach	9354.13	3797.33	0.0138
Neoplasm digestive system benign/unspecified	11067.94	4244.25	0.0091
Pain general/multiple sites	1428.92	394.07	0.0003
Pityriasisrosea	7209.46	3213.90	0.0249
Post-partum symptom/complaint, other	7339.73	2065.88	0.0004
Pregnancy	1195.13	207.03	0.0000
Pregnancy high risk	4947.16	1673.90	0.0031
Psoriasis	9934.54	3794.67	0.0089
Sexual function symptom/complaint male	8701.40	3811.43	0.0225
Skin injury, other	3630.71	1667.31	0.0295
Sprain/strain of knee	13161.91	6001.86	0.0283
Teeth/gum disease	4972.56	2358.42	0.0351
Uncomplicated labour / delivery live birth	1506.94	388.50	0.0001
Unexplained abnormal white cells	22093.13	8502.03	0.0094
Upper respiratory infection acute	511.23	158.14	0.0012
Worms/other parasites	1866.31	769.85	0.0154
Dependent Variable: Total Amount it Cost to Treat The Enrollee			

Source: Author's Computation, 2017
** The value is set to zero for risk score computation.*

4.1 Predictive Performance for Individual Level

The mean absolute prediction error (MAPE) is a single summary measure of predictive accuracy (Cumming *et al*, 2002; Winkelman & Mehmud, 2007). On the positive side, it does not square the prediction errors and, so, is not overly sensitive to large claims (Cumming *et al*, 2002). However, it is not articulated on a standardized scale, so comparisons across studies are grim to make. Therefore, for purposes of this study, we have expressed MAPE as a percentage of the average per member per month (PMPM) cost. Lower MAPE indicates a better fits. As shown in Table 4 under the concurrent risk assessment, as additional variable is added the predictive performance is increasing. Demographic model explains 68%; demographic and hospitalization model explain 60% and demographic, hospitalization and ICPC diagnoses model explain 53%. The same scenario played out when

R^2 and Cumming Predictive Measure (CPM) were used with $R^2 = 10\%,\ 30\%\ and\ 52\%$ for demographic; demographic and hospitalization; and demographic, hospitalization and ICPC diagnoses risk adjustment model respectively. The higher the R^2 and CPM, the better the predictive performance. For prospective risk assessment in Table 5, the performance is relatively low compare to concurrent risk assessment with MAPE of 63%, 65% and 52% for demographic model, demographic & hospitalization model and demographic, hospitalization and ICPC diagnoses model respectively. As earlier explained, the higher the MAPE values the weaker the prediction performance. However demographic, hospitalization and ICPC diagnoses model outperformed the other two models. Table 5 also shows that with $R^2 =$ 49% and CPM=22% the ICPC grouper model outperform the other two models.

4.2 Predictive Performance for Group Level

Grouped results are presented using predictive ratios, which are simply the ratio of the average predicted cost to the average actual cost for a particular group of individuals. Predictive ratios (PR) closer to 100 percent (or 1) are desirable (Winkelman & Mehmud, 2007)). As shown in the Table 6, predictive ratios are generally 100 percent except age/gender, hospitalization and ICPC diagnoses model which is 102%. This is somewhat expected under concurrent applications since risk adjusters generally over-predict costs for higher cost individuals (Winkelman & Mehmud, 2007). Table 7 shows the PR under the prospective risk assessment applications. It is interesting to see that demographic model outperformed the other two models with PR=1. This result is not surprising since an ICPC diagnosis-based criterion was adopted for creating the disease groups rather than one based on ICD codes. This example further highlights the importance of correct tool usage.

Table 4
Summary of Individual Predictive Performance - Concurrent Risk Assessment

	MAPE	R-Square	CPM
Demographic Model	68%	10%	6%
Demographic and Hospitalization Model	60%	30%	17%
Demographic, Hospitalization and ICPC Diagnoses Model	53%	52%	27%

Source: Author's Computation, 2017

Table 5
Summary of Individual Predictive Performance - Prospective Risk Assessment

	MAPE	R-Square	CPM
Demographic Model	63%	9%	5%
Demographic and Hospitalization Model	65%	19%	2%
Demographic, Hospitalization and ICPC Diagnoses Model	52%	49%	22%

Source: Author's Computation, 2017

Table 6
Summary of Group Predictive Performance - Concurrent Risk Assessment

	Actual Claims	Predicted Claims	Predictive Ratio
Demographic Model	185,559,267.00	185,559,267.00	1
Demographic and Hospitalization Model	185,559,267.00	185,559,267.00	1
Demographic, Hospitalization and ICPC Diagnoses Model	185,559,267.00	189,238,490.62	1.02

Source: Author's Computation, 2017

Table 7
Summary of Group Predictive Performance - Prospective Risk Assessment

	Actual Claims	Predicted Claims	Predictive Ratio
Demographic Model	94,568,308.00	94,568,308.00	1.00
Demographic and Hospitalization Model	94,568,308.00	108,135,373.43	1.14
Demographic, Hospitalization and ICPC Diagnoses Model	94,568,308.00	99,588,722.04	1.05

Source: Author's Computation, 2017

5. Conclusion

The objective of primary health care (PHC) was to provide accessible health for all. Unfortunately, this is yet to be achieved in Nigeria and seems to be unrealistic in the next decade (Abdulraheem, Olapipo & Amodu, 2011). Determined to change the country's poor health rating, the Federal Government through the National Health Insurance Scheme has continued to advance policies and programmes aimed at ensuring that a greater number of Nigerians including the rural poor have access to quality health care. One of such health programmes is the Community Based Health Insurance Programme (CBHIP). The task before the healthcare analyst and actuary is how to review typical actuarial models and then evaluate their potential for increasing the relevance and accuracy of risk prediction. For this study typical actuarial health risk adjustment models were reviewed by using medical condition-based models especially at the primary level of healthcare services or micro-health insurance among the enrollees in the National Health Insurance Scheme especially, the Community Based Social Health Insurance Programme. To predict expenditures at the individual level of CBHIP, the risk adjustment models obtained from an Ordinary Least Squares (OLS) regression was use to combine the expenses associated with ICPC diagnostic groupings and age/sex cohorts. The individual level predictive performance was measured by using individual R^2 and the mean absolute prediction error (MAPE). The group level predictive performance was assessed by using predictive ratios (PR) of expenditure quintiles. The R^2 measures the model fit and describes the percentage of the individual variance in actual expenditure explained by the model. MAPE is the mean of the difference between actual and predicted expenditures for all individuals. The predictive ratio of expenditure quintiles is a group measure calculated as the ratio or the aggregated predicted expenditure for a given group of beneficiaries, over the aggregated actual expenditure for the same group of people.

The results from the ICPC risk assessment model have broadly confirmed that the demographic only risk adjustment model is inadequate; it does not fully provide incentives to prevent cream skimming. Indeed, apart from the fact that it is a retrospective model, it does not use health-related risk adjusters; it assumes that health care costs are only correlated with the two variables "age" and "gender", and therefore does not properly take into account, for example, young people with very costly illnesses or, the elderly in good health. It was observed that the predictive power of this "demographic variable" is extremely poor and thus, leaves a lot of room for risk selection by sickness insurance funds. The primary reason for implementing risk adjustment is to correct for risk selection problems and to prevent "cream skimming". This selection may occur because community rating implies predictable profits on low-risk consumers and predictable losses on high-risk consumers, and thus NHIS funds have an incentive to avoid bad risks and appeal to good risks. Furthermore, as illustrated with the results above, this incentive is reinforced by the fact that health expenditures are very

highly concentrated in relatively few individuals. From the results above, the demographic, hospitalization and ICPC risk adjustment model developed in this study is a powerful and much needed tool in the health insurance marketplace. The risk adjusters will allow health insurance programs to measure the morbidity of the members within different groups and pay participating health plans fairly especially in CBSHIP. In turn, health plans can better protect themselves against adverse selection and are arguably more likely to remain in the marketplace. In conclusion, the main objective of this study, which is to apply ICPC codes to a diagnostic based health risk adjustment model in order to estimate future claims of HMOs under a CBSHIP, has been achieved. Hence this model is proposed for Nigeria CBSHIP because it will assist in appropriate premium determination, mitigate the impact of potential adverse selection and cream skimming and stabilize premiums in the individual and small group market like CBSHIP.

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