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Benjamin J.S. al-Haddad
Division of Epidemiology & Community Health
University of Minnesota

Elima Jedy-Agba, Emmanuel Oga, and Clement Adebamowo
Institute of Human Virology
Nigeria

April 2013

Working Paper No. 2013-03
https://doi.org/10.18128/MPC2013-03

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Benjamin J. S. al-Haddad, MSc.
Division of Epidemiology & Community Health
University of Minnesota
Elima Jedy-Agba, MSc., MD
Emmanuel Oga, MD
Clement Adebamowo, D.Sc., MD
Institute Human Virology, Nigeria

April 9, 2013

Abstract

Age heaping is an important source of demographic bias in many countries. There is little scholarship on the effect of age heaping on cancer rate estimation. We use Nigerian demographic and cancer registry data to (1) quantify age heaping in states and within cancer registries using the Myers Blended Index and (2) examine the effect of residual age heaping bias on age standardized cancer rates (ASRs). We find severe age heaping at the level of the state and within cancer registries which is more pronounced in the north than the south. Further, we find less age heaping among women in registries compared to both men in registries and to women in the general population. Lastly, we find little evidence of residual age heaping bias comparing ASRs estimated using the population data as given (Base) to Arriaga and Strong smoothed imputed populations. The geographic results likely reflect economic and educational disparities between the north and south. The gender difference may signify that higher educated women do more screening and seek care more often. Lastly, the absence of ASR differences between the Base and smoothed populations provides evidence that age heaping may not seriously bias ASRs in countries with severe age heaping.

1 Introduction

There is a dearth of scholarship on the effects of demography on cancer rate estimation in developing countries. Many challenges, including irregular censuses, internal migration and age heaping, present potentially important sources of demographic bias in estimating cancer rates [1].

Among demographic variables, age is among the most important. Population age structures are the essential foundation for estimates of standardized and comparable burdens of disease. In many countries, individuals do not know their exact age and estimate it when required. This leads to age heaping, a common phenomenon observed in multiple cultural and national contexts when a greater number of people state their age as a given multiple than would be expected if the rate of births and deaths was not cyclic on these multiples [2]. In many cultures, age heaping around ages ending in 0 and 5 years has been observed with a greater proportion of people claiming to be aged 40 or 45 than 39, 44, etc [3]. Different cultures may age heap on different multiples. For example, it has been observed that the Han Chinese age heap on 12 year multiples aligning with the zodiac cycle [4]. Age heaping has been found to be a useful measure of population numeracy and scholars continue to use indices of age heaping as proxies of quantitative reasoning ability [5].

Scholars have recognized the influence of age heaping on health, economic and demographic statistics in Africa at least since the late 1960s and early 1970s [6, 7]. Other recent work has examined age heaping in Nigeria [8]. Among African countries, Nigeria is the most populous; one in five Africans lives in Nigeria. As such, the country is tremendously diverse in ethno-linguistic and cultural groups [9]. There is historical anthropological evidence of a base 12 number system in the north of Nigeria that may influence age heaping tendencies [10].

While current methods of cancer age standardized rates (ASR) estimation attempt to account for bias from 0 to 5 year heaping, they do not attempt to address heaping on base 12 numbers. How age heaping might potentially affect ASR estimation depends not only on the number base heaped upon, but whether different segments of the population have differing tendencies to age heap, the real age structure of the population and the direction of the heaping (up or down). With so many variables, it is difficult to predict how precisely age heaping may affect ASRs.

People in any given decade of life are not likely to heap at random; cultural and other factors may influence the direction of heaping. Therefore, age heaping would seem likely to introduce bias to both age specific incidence (ASI) and ASRs and regardless of the multiples heaped upon.

At present, although there are methods to address the problem, there is little understanding of how age heaping, as an estimation bias problem in country specific contexts, affects cancer rate estimation. To investigate the role of age heaping on cancer rate estimation in Nigeria, we examine state population pyramids and numerical indices of age heaping at the state level and within individual cancer registries. Demographic methods are used to smooth the population distributions to permit appreciation of the effect of residual age heaping bias on cancer rate estimation using truncated ASRs.

2 Methods

In collaboration with the Institute for Human Virology, Nigeria [11] and the Federal Ministry of Health [12], ethical approval was sought and granted from the University of Minnesota Institutional Review Board [13] and the National Health Research Ethics Committee of Nigeria [14]. Twenty four Nigerian cancer registries were identified for potential inclusion in the study and invited to participate. Fourteen of these applied for and received permission to participate from their local health and or ethical authorities. From these 14 registries, 12 were deemed to have data of sufficient quality to be included in the study. The 12 registries were (1) University of Abuja Teaching Hospital Cancer Registry, (2) The Abuja Cancer Registry, National Hospital, Abuja, (3) University of Calabar Teaching Hospital Cancer Registry, (4) The Ibadan Cancer Registry, (5) Professor Olikoye Ransome-Kuti (Midwestern Nigeria) Cancer Registry, (6) Abeokuta Cancer Registry, (7) Cancer Registry, Federal Medical Centre, Ido Ekiti, (8) University of Nigeria Teaching Hospital Cancer Registry, (9) Ife Ijesha Cancer Registry, (10) Ilorin Cancer Registry, (11) Nnewi Cancer Registry and (12) University of Port Harcourt Teaching Hospital Cancer Registry.

2.1 Data

Participating cancer registries submitted registration data from years of their choice; among all registries these ranged from 1989 to 2011. Registries were also surveyed with a questionnaire to establish working catchment areas and to gather other pertinent meta data. Cancer case registry data from the 12 participating registries was cleaned and standardized. Some registries included standardized case addresses, which were used for case inclusion in working catchment areas. Three registries did not use CanReg4 [1] and did not code their cases using any internationally recognized pathological classification system. To address this problem, a professional cancer registrar was hired to code these cases using the International Classification of Diseases for Oncology, third edition (ICD-O-3) [15]. To examine systematic differences and coding fidelity, the professional registrar also recoded a previously ICD-O-3 coded registry that had been stripped of coding for comparison. Case data from both coded and uncoded registries was then harmonized for subsequent calculations of ASRs.

Population data from the 1991 and 2006 Censuses came from the Nigerian National Bureau of Statistics [16] and the National Population Commission of Nigeria [17].

2.2 Age Heaping Measure

There are several measures which have been developed to examine age heaping including Whipple's Index, the Bachi Index, the Carrier Index and the Ramachandran Index. However, the most widely used is the Myers Blended Index (MBI) which improves on the Whipple's Index and does not differ greatly in results compared to the other methods. The major improvement with the MBI comes from its use of blending to avoid a bias associated with the effect of mortality on ages ending in "0". The MBI was used for quantifying the degree of age heaping in both population data at the state level in 2006 and separately in individual cancer registries across all years of submission [2]. The index ranges from 0 to 100 (with 0 indicating no age heaping) and uses deviation from expected end digit ages for the estimation. It is

[1] CanReg4 is case registration software created and maintained by the International Agency for Research on Cancer

calculated as follows; an example is found in Siegel et al. 2008 [2].

> Step 1. Sum the populations ending in each digit over the whole range starting with the lower limit of the range (e.g., 10, 20, 30,...80; 11, 21, 31...81).
>
> Step 2. Ascertain the sum excluding the first population combined in step 1 (e.g., 20, 30, 40,...80; 21, 31, 41,...81).
>
> Step 3. Weight the sums in steps 1 and 2 and add the results to obtain a blended population (e.g., weights 1 and 9 for the 0 digit; weights 2 and 8 for the 1 digit).
>
> Step 4. Convert the distribution in step 3 into percentages.
>
> Step 5. Take the deviation of each percentage in step 4 from 10.0, the expected value for each percentage [2].

Additionally, we created population pyramids for each Nigerian state in 2006 as well as for Minnesota and the United States in 2010 for comparison.

2.3 Ecological Regression

The relationship between age heaping magnitude and population education has been previously established and the former has been used as a proxy of the latter in many studies [5]. To the our knowledge, literature has not been published on this relationship in Nigeria. We used univariate linear regression and correlation to examine the relationship between Nigerian state MBI and state literacy rates among those over 15 years old.

2.4 Population Imputation Method

Using only the population data from the censuses in 1991 and 2006 at the state and local government area (LGA) level, a linear model was used to impute the population growth from 1989 to 2011 [2]. These two years are the most recent two censuses in Nigeria. First, the ages were aggregated into five year groups (0-4...85+) for males and females. Then the average absolute change was calculated between 1991 and 2006 and used to impute the population from 1989 to 2011. In 1996, several new LGAs and some new states were created. Population imputation in these areas were handled either through aggregating the population of several LGAs together to match the 1991 LGAs or maintaining merged LGAs as separate entities by using the state growth and projecting the LGA populations forward and backwards from 1991. For this work, the 2009 and 2010 imputed populations were used.

2.5 Population Smoothing Methods

Although the age grouping by 5 year intervals is designed to remove bias from age heaping and other demographic data anomalies, there is often remaining residual bias. To examine the effect of age heaping on estimation of ASRs, the Arriaga and Strong age smoothing methods were employed to impute alternate population distributions for 2009 and 2010 [18].

Both the Arriaga and the Strong methods use all members of the population aged 0 to 79 for imputations. However the Arriaga method achieves "light" smoothing by not modifying the population in each 10 year age group, while the Strong method modifies these ten year groups assuming that age may be misreported by more than 10 years. In comparison to other light smoothing methods including the Carrier-Farrag, Karup-King Newton and United Nations methods, the Arriaga methods smooths from 0 to 79 years, compared to 10-69 years. This is desirable in cancer rate estimation since incidence increases with age. It also uses three decades at a time with different formulae for first three, last three and middle decades. Both the Strong and Arriaga formulae are given in Arriaga 2003 [18].

2.6 Age Standardized Rates

Cancer ASI rates were calculated by gender (not presented) and then used for estimation of the ASRs using the World Standard Population [19]. Although there is some controversy about whether the World Standard Population should be updated, most international cancer estimates use direct standardization and the traditional World Standard Population for rate calculation, as does this study [19, 20, 21].

The ASRs were calculated using the population as given (Base) with the ASI truncated at 80 years to make these rates comparable to those estimated using the Arriaga and Strong smoothed imputed populations. Subsequently, separate ASRs were calculated using the Arriaga and Strong smoothed imputed populations.

2.7 Software

STATA release 12 was used for data management, cancer rate calculations, population imputation and matrix and table management [22].

ArcGIS was used to develop choropleth maps of age heaping in the Nigerian states in 2006 for males, females and combined and the all the years of registries submission for males, females and combined [23].

The Population Analysis System (PAS) from the United States Census Bureau was used for the age heaping calculations, age smoothing and creating the population pyramids [24].

3 Results

The population pyramids for the 36 Nigerian states in 2006, the MBIs for age heaping at the state level, the MBIs for the cancer registries and the ASR tables for each registry by sex for 2009 and 2010 are all available on request.

3.1 Population Age Heaping

First, we will consider the age heaping results. Among Nigerian states, the MBI for males and females respectively ranges from 17.89 and 21.93 for Lagos State to 88.7 and 91.67 for Zamfara State. Among all states, the mean MBI was 52.25 for males and 55.22 for females. The median MBI was 48.36 for males and 51.9 for females. See figures 1 and 2. For comparison, the MBI for Minnesota males and females was 2.81 and 3.13 respectively.

In the state choropleths, we see that age heaping appears to be more severe in northern Nigeria than the south for both males and females.

3.2 Registry Age Heaping

Considering the age heaping within individual cancer registries, the MBI for males range from 14.14 for the National Hospital Abuja to 57.90 for the Ife Ijesha Cancer Registry. Similarly for females, the MBI range from 13.38 at the National Hospital Abuja to 63.13 at the Ilorin Cancer Registry. The mean registry MBI for males was 39.23 and the median was 41.54. For females they were 37.13 and 38.02 respectively. See Appendix D.

The registry choropleths do not show any discernible pattern.

3.3 Ecological Regression

When we regressed the state MBI on the state over 15 literacy rate in 2006, the coefficient for the literacy rate was -0.599 (95% CI: -0.831, -0.367). For every 1 percent increase in state over 15 year old literacy rate, the combined male and female state MBI decreases by 0.6. The two variables shared a correlation of -0.7615.

3.4 Age Standardized Rates

The ASR tables (per 100,000 person years) showing the three types of population imputation rate calculations for Ibadan Cancer Registry in 2009 are given in Tables 1 and 2. The other registry tables are available on request. These ASRs are all truncated at 80 years old to facilitate comparison amongst the population imputation methods; they are not comparable to typical ASRs. While the tables give the rates for cancers defined by ICD10 codes, here, I focus on the cancers considered to be the most important in Nigeria. Considering the Ibadan Cancer Registry in 2009 for males, the Base ASR for prostate cancer is 11.64, while using the Arriaga and Strong population smoothing methods yields rates of 11.46 and 11.25 respectively. For cancer of the liver and intra-hepatic bile ducts, the Base ASR is 2.50, while with the Arriaga and Strong methods, the rates are 2.45 and 2.42 respectively (see Table 1).

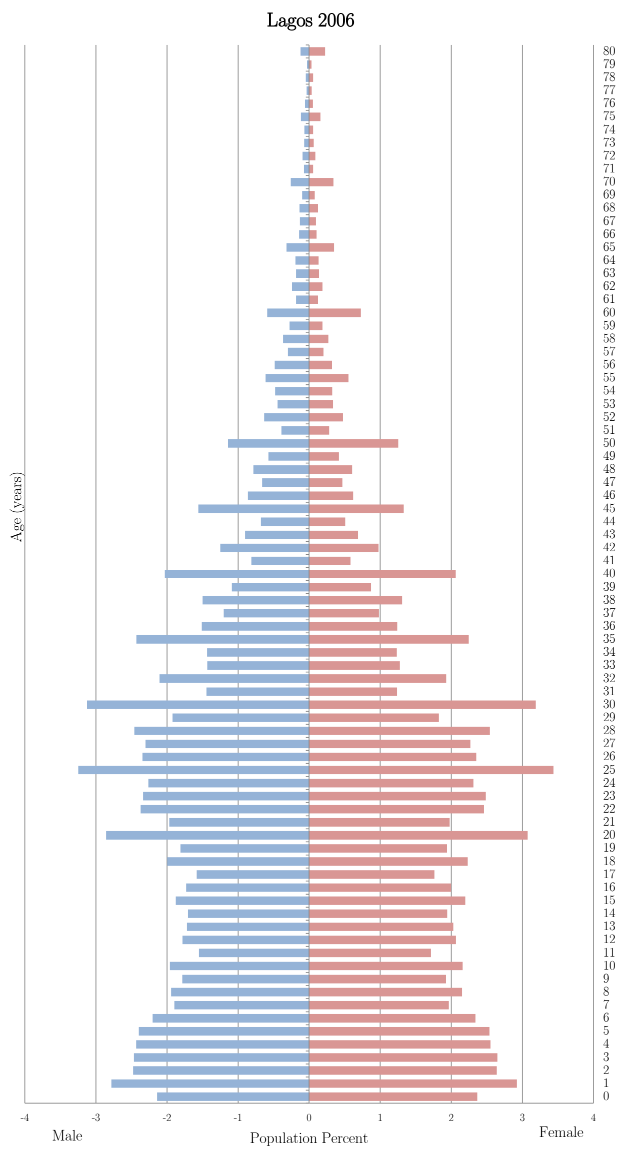

Figure 1: Population Pyramid for Lagos State in 2006

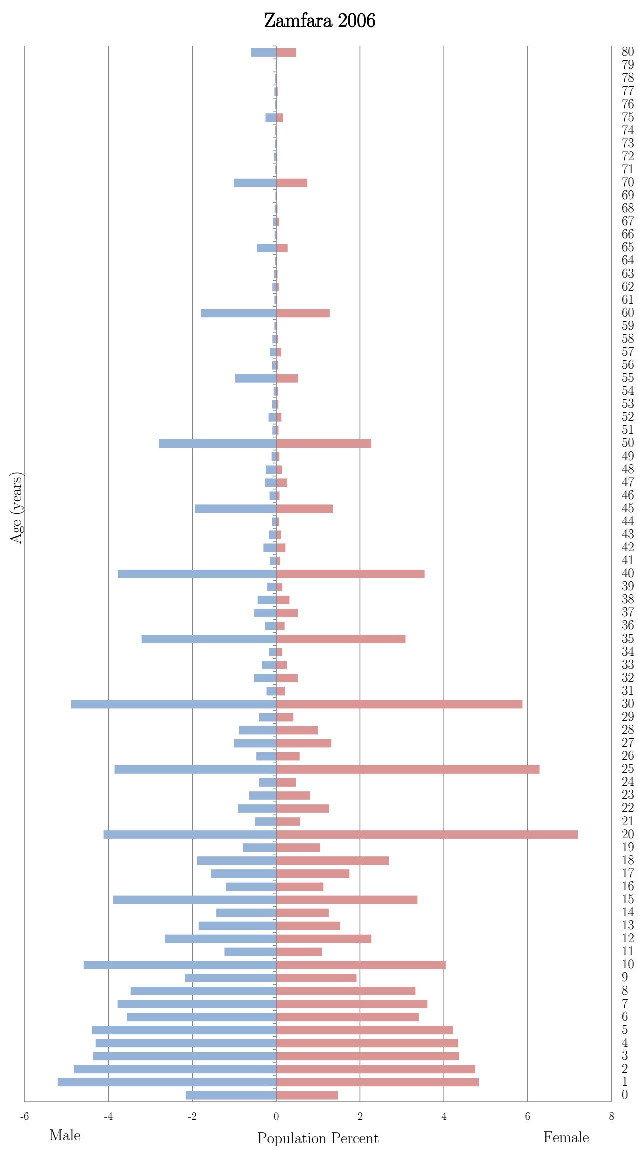

Figure 2: Population Pyramid for Zamfara State in 2006

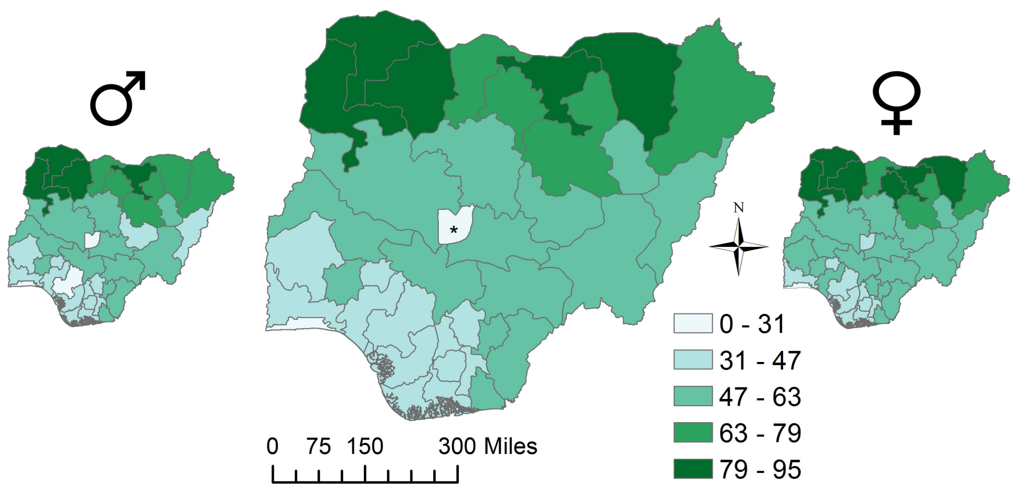

Figure 3: Age Heaping in Nigerian States in 2006. The center map depicts age heaping in the combined male and female populations. The map on the left only considers males, while the one on the right only depicts female age heaping.

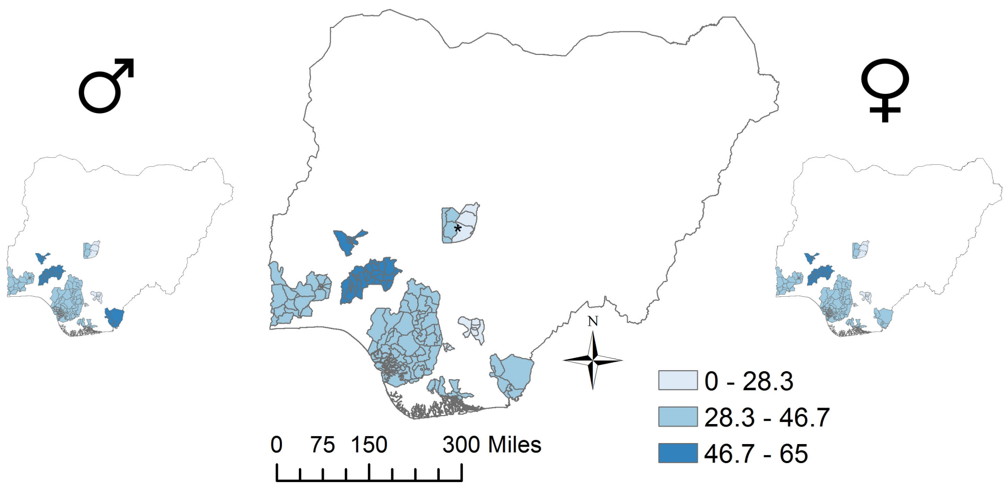

Figure 4: Map of Age Heaping in Nigerian Cancer Registries. The center map depicts age heaping in the combined male and female populations. The map on the left only considers males, while the one on the right only depicts female age heaping.

Table 1: Smoothed ASRs in the Ibadan Cancer Registry Males 2009

	Base ASR	95%	CI	Arriaga ASR	95%	CI	Strong ASR	95%	CI
All Cancers	41.66	37.19	46.13	40.80	36.47	45.14	40.17	35.91	44.43
Bladder	0.799	0	1.424	0.751	0	1.334	0.739	0	1.312
Brain & Nervous System	1.376	0	2.095	1.334	0	2.013	1.322	0	1.992
Colorectum	3.503	2.194	4.811	3.353	2.119	4.586	3.295	2.084	4.505
Esophagus	0.831	0	1.523	0.759	0	1.387	0.751	0	1.372
Gallbladder & Extrahepatic duct	0.382	0	0.817	0.374	0	0.800	0.375	0	0.803
Hodgkin Lymphoma	0.268	0	0.590	0.250	0	0.545	0.244	0	0.531
Kaposi Sarcoma	0.383	0	0.745	0.402	0	0.788	0.394	0	0.772
Kidney, Renal Pelvis & Ureters	0.262	0	0.582	0.276	0	0.621	0.272	0	0.609
Larynx	1.013	0	1.726	0.967	0	1.640	0.943	0	1.600
Leukemia	1.437	0	2.254	1.413	0	2.211	1.384	0	2.164
Lip & Oral	0.657	0	1.167	0.654	0	1.162	0.653	0	1.159
Liver & Intrahepatic ducts	2.495	1.432	3.559	2.448	1.423	3.472	2.416	1.406	3.427
Melanoma	0	0	0	0	0	0	0	0	0
Multiple Myeloma	0.996	0	1.754	0.900	0	1.577	0.877	0	1.536
Nasopharynx	1.107	0	1.794	1.086	0	1.749	1.081	0	1.739
Non-Hodgkin Lymphoma	3.425	2.184	4.667	3.296	2.124	4.469	3.253	2.099	4.408
Other Pharynx	0.262	0	0.579	0.248	0	0.542	0.241	0	0.524
Pancreas	1.015	0	1.752	1.015	0	1.744	0.992	0	1.704
Prostate	11.64	9.125	14.16	11.46	8.996	13.93	11.25	8.828	13.67
Stomach	1.947	0	2.906	1.919	0	2.856	1.891	0	2.814
Testis	0.125	0	0.299	0.125	0	0.299	0.125	0	0.298
Thyroid	0.185	0	0.444	0.183	0	0.440	0.183	0	0.440
Trachea, Bronchus & Lung	1.414	0	2.267	1.381	0	2.212	1.351	0	2.164

Among female cases registered at the Ibadan Cancer Registry in 2009, the Base ASR for breast cancer was 22.77, while the Arriaga and Strong ASRs were 22.46 and 21.81 respectively (see Table 2).

Table 2: Smoothed ASRs in the Ibadan Cancer Registry Females 2009

	Base ASR	95%	CI	Arriaga ASR	95%	CI	Strong ASR	95%	CI
All Cancers	71.36	65.56	77.16	70.32	64.68	75.97	68.78	63.27	74.30
Bladder	0.550	0	1.107	0.521	0	1.042	0.514	0	1.030
Brain & Nervous System	3.017	1.839	4.196	2.969	1.838	4.100	2.926	1.815	4.037
Breast	22.77	19.51	26.02	22.46	19.29	25.63	21.81	18.73	24.89
Cervix uteri	15.84	13.02	18.65	15.55	12.83	18.27	15.14	12.48	17.79
Colorectum	3.324	2.022	4.627	3.229	1.981	4.477	3.208	1.971	4.445
Corpus uteri	1.781	0	2.729	1.873	0	2.873	1.836	0	2.816
Esophagus	0.518	0	1.058	0.511	0	1.037	0.510	0	1.035
Gallbladder & Extrahepatic duct	0	0	0	0	0	0	0	0	0
Hodgkin Lymphoma	0.119	0	0.352	0.115	0	0.340	0.110	0	0.324
Kaposi Sarcoma	0.344	0	0.720	0.315	0	0.643	0.313	0	0.633
Kidney, Renal Pelvis & Ureters	0.713	0	1.272	0.707	0	1.263	0.693	0	1.234
Larynx	0.293	0	0.701	0.281	0	0.673	0.273	0	0.653
Leukemia	0.913	0	1.610	0.949	0	1.667	0.938	0	1.649
Lip & Oral	0.577	0	1.000	0.554	0	0.954	0.559	0	0.962
Liver & Intrahepatic ducts	1.859	0	2.758	1.856	0	2.751	1.808	0	2.679
Melanoma	0	0	0	0	0	0	0	0	0
Multiple Myeloma	0.309	0	0.747	0.268	0	0.643	0.262	0	0.631
Nasopharynx	0.608	0	1.113	0.620	0	1.139	0.606	0	1.113
Non-Hodgkin Lymphoma	1.668	0	2.466	1.654	0	2.439	1.639	0	2.413
Other Pharynx	0.119	0	0.352	0.115	0	0.340	0.110	0	0.324
Ovary	5.061	3.573	6.549	4.948	3.517	6.379	4.886	3.480	6.292
Pancreas	1.146	0	1.910	1.149	0	1.913	1.116	0	1.858
Stomach	0.548	0	1.005	0.565	0	1.035	0.549	0	1.002

In the 2009 combined estimations from the University of Abuja and National Hospital Abuja, the Base ASR for cancer of the cervix uteri is 31.96 while using the Arriaga and Strong methods yielded 31.15 and 27.25 respectively.

4 Discussion

4.1 Age Heaping

There were several interesting findings in re age heaping in Nigeria. First, although there is historical documentation of usage of a base 12 number system, examinations of the population pyramids for the northern states does not reveal any obvious heaping on 12, 24, 36 etcetera. There does appear to be fairly obvious heaping on 0 and 5 in all Nigerian states and this may be more pronounced after 20 years old. Like most countries in Africa, the population pyramids are bottom heavy indicating a large youth bolus.

After calculating the MBI at the state level and mapping them, it appears that the states in northern Nigeria generally have higher indices of age heaping than those in the south (see Figure 3. This is not surprising as age heaping has been established as a proxy for population numeracy and northern Nigeria is both less economically developed and has potentially more heterogeneity in quality of primary and secondary education compared to southern Nigeria.

The low MBI in Lagos state likely reflects the high numeracy of the population; similarly, the high MBI in Zamfara state likely reflects the low numeracy there. The high correlation (-0.76) between MBI and percentage of the population 15 years and older who are literate and associated regression results both lend support to the education hypothesis. It is also notable that with the exception of Anambra, Bayelsa, Ekiti, Jigawa, Katsina, Kogi, Niger and Osun States, the MBI is higher for women than men (see Figure 4). This may reflect poorer numeracy among women than men and the related educational outcomes gap. It could also reflect cultural norms in the north that may lead to census responses by proxies for women by male family members who are less knowledgeable about their ages [25].

In the cancer registry data, the mean and median MBI for women is lower than for men and this appears to be true for 8 of the 12 registries. This is interesting because it is the opposite of what is seen at the state level. There may be several explanations for this finding. We know that vastly more female cases are registered than male cases; better educated women may be more likely to both seek screening for cancer (e.g. breast and Papanicolaou exams) and seek care when they detect potential pathology in themselves. On the other hand, the difference seen between the population and registry data could be the result of the former being given by proxy and the latter given by patients themselves.

Of particular note, of the original 24 registries invited to participate, only 5 were located in the north. Two of these elected to participate but had data of such poor quality that they were not able to be included. As is evinced by the age heaping results and other development indicators, the infrastructure of the north of the country is less developed than the south and this has tangible impacts on cancer rate estimation.

The other major element of interest in Figure 4 is the divergence of MBI between the University of Abuja registry and the National Hospital Abuja registry. These registries, although both located in the Federal Capitol Territory (starred in Figure 4) are 1-2 hours apart and may likely have dramatically different populations presenting for care. It is possible that more highly educated patients may seek treatment at the National Hospital Abuja which is located near central Abuja, while the patients seeking care at University of Abuja 1 to 2 hours away may be less numerate. Because these two registries' catchment areas abut each other, their cases are aggregated into one larger catchment area covering the entire Federal Capitol Territory for subsequent ASR estimation.

Lastly, enumerators in the 2006 Nigerian census were not allowed to accept an unknown age from respondents. As is common in other country contexts, they were trained to use recollection of milestone life events and historical events [26, 17].

The challenge of unknown ages is not unique to Nigeria or to cancer rate estimation [27]. There have been several other studies in African countries with age heaping findings, however these are usually treated as a nuisance to be addressed rather than a finding in their own right [28]. A study in Sierra Leone examining age heaping in multiple years of census data found a mean MBI of 23 for two censuses 9 years apart [29]. In studies of age heaping over time, the magnitude has been found to decrease with time in multiple populations [30, 31]. Perhaps this reflects the effect of increased development and education.

4.2 Effect of Population Age Heaping on Cancer Rate Estimation

Considering the tables of ASRs, it is apparent that the residual bias from the age heaping does not appreciably alter the estimates of ASR. There are several potential explanations for this. First, the majority of the age heaping observed occurred on the 0 and 5 digits, which is greatly addressed by grouping cases and denominator in 5 year age groups. Second, from the population pyramids, there does not appear to be important heaping on 12 year intervals in either the north or the south of the country.

It is notable that the smoothed rates are slightly, but consistently lower than the Base rates. This may be due to the other considerations of whether certain segments of the population are more likely to age heap and whether they heap up or down. These factors seem to be mostly inconsequential since the population smoothed ASRs greatly resemble the Base versions. Because the denominator (person-years) is so many orders of magnitude larger than the numerator (cases of cancer), it makes sense that modifying the distribution of the denominator would not have large effects on the estimated ASRs. However, this could be examined by completing a series of modeling exercises with different reference populations.

4.3 Necessary Assumptions & Limitations

This work and these conclusions are based on several assumptions. First, not all of the registries under study consider themselves population based and I have defined hypothetical catchment areas in collaboration with them for this and associated studies in the full knowledge that many of these catchment areas are at least partially contrived. Second, while some registries have standardized methods for recording the address of a given case, most registries do not. This means that for those that do not, we must assume that all cases registered should fall into the associated catchment area. These two major assumptions are clearly fallacious - to be a population-based registry, a registry must not only have a clearly defined catchment area, but they must have the resources and personnel to be able find and record all cases in the area. Even among Nigerian registries with defined populations, the regular and complete ascertainment of all cases is an ongoing challenge made more difficult by insufficient resources, personnel, geography and strife.

However, because the present study is using truncated non-standard ASRs with the as given (Base) and imputed data to study the effects of age heaping bias and not the incidence of cancer in the country, the data interpretations given here are robust to these limitations.

4.4 Conclusions

To conclude, we find evidence of significant age heaping at both the level of the state and within individual Nigerian cancer registries. Most age heaping occurs on the 0 and 5 digits; there was no evidence of age heaping on a base 12 number system in any state. Because of the high correlation of age heaping with numeracy and by extension education, we interpret these results as indicating lower levels of numeracy in the north of Nigeria. Further, we find lower levels of age heaping among female cases in Nigerian cancer registries compared to both men in the registries and men and women in the general population. This may be evidence of increased screening and care seeking among higher educated Nigerian women compared to both men and Nigerian women generally.

There appears to be very little residual bias due to age heaping as evidenced by the similar ASRs produced using the Base, Arriaga and Strong imputed populations. We find that the ASRs produced from the population smoothed data are consistently lower than those from the Base data; future modeling studies with different magnitudes of age heaping in particular sections of the population and different reference populations may shed light on this finding. This empirical evidence lends increased confidence to ASRs estimated using population data with moderate to severe age heaping.

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