International Journal of Mathematics and Statistics Invention (IJMSI)
E-ISSN: 2321 – 4767 P-ISSN: 2321 - 4759
www.ijmsi.org Volume 6 Issue 3 || March, 2018 || PP-57-64

Ratio Estimation of Teacher to Students In Junior Secondary School In Gombe Local Government Area

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ABSTRACT: *This research is an attempt to assess the ratio of teacher to students on one and the ratio of male to female enrolment, based on junior secondary school enrolment. The data was obtained from the enrolment of junior secondary school student under Ministry of Education Authority Gombe state, was subjected to analysis using the ratio, regression and stratified estimators. The analysis shows that the ratio of male and female is 1:1 in all arms of the schools where the study was carried out. We discovered that the ratio of teacher to student in JSS1 is 1:70, JSS2 is 1:60 and JSS3 is 1:50 which is very high compared to the millennium development goal of 1:35. The comparison of the three methods used for the estimation shows that the regression estimator has the minimum variance, which is more efficient in estimation of male and female students while in estimation of teacher to student the ratio estimator is more efficient.*

KEYWORDS*: Ratio Estimation, Males, Females, Junior School, Gombe, Nigeria*

DATE OF SUBMISSION: 31-05-2018 DATE OF ACCEPTANCE: 15-06-2018

I. INTRODUCTION

Secondary schools are mostly state or federally owned; although in 2001 the federal government began encouraging the return of former church mission schools. The federal government promised to continue paying teacher salaries. Generally, the federal government funds and manages two federal government colleges (secondary schools) in each state. In addition, each state owns and operates secondary schools. In 1996, there were 7,104 secondary schools with 4,448,981 students. The teacher-students ratio was approximately 1:32. The government pays most of the fees for students, but students must pay incidental costs and sometimes part of their board or other expenses that can amount to $200 a year, a considerable amount in a nation where the average annual income was only about $300 in 2000.Students attend junior secondary school for grades seven through nine. At this point, the majorities of students are at least 15-years-old and are no longer required to attend school. In the ninth grade, students take the Junior Secondary Certificate Examination (JSCE) to qualify for the limited number of openings in senior secondary schools. Those who do well on the exam may continue at the same institution or transfer to a different school if they qualify.

StateUniversity.com http://education.stateuniversity.com/pages/1104/Nigeria-SECONDARY-EDUCATION.html#ixzz3YhyJ7OmQ, 2015. In stratified sampling, the researcher first identified the strata of interest and then randomly draws a specified number of subjects from each stratum either by taking equal number from each stratum or by proportion to the size of the stratum in the population Ary et al (2002). Popham (1993) warns, however, not to simply subdivide a population into ages, sex and socioeconomic subgroups unless the researcher believe these dimensions are relevant to the things being measured. According to Ary, et al. (2002) an advantage of stratified sampling is that it allows the researcher to study differences among various subgroups of a population and guarantees representation of defined groups in the population. In addition Fraenkel and Wallen (2006), content that stratified random sampling increases the likelihood of representativeness, especially if the sample in not very large. They suggest that the disadvantage is that it requires more effect on the part of the researcher. Popham (1993) purports that stratified random sampling is seen as a more define method of sampling over simple random sampling. Mukhpahay (1998) the population under consideration in the empirical study was the 2000 Academic Performance Index (API) Base data file. These data contain performance scores and ethnic and socio-economic information for the schools in the State of California, USA. The data file in question may be useful for academic purposes, as it is publicly available and contain many variables. In our application, a natural stratification variable was school type (elementary, high, middle or small). We show that stratified sampling plans may give a more insightful analysis since they allow us to obtain a separate estimation for each school type. Furthermore, the stratification variable helped to reduce the variance of the logistic regression estimator. Our analysis shows that incorporating auxiliary information into a suitable model may substantially enhance the efficiency of estimating proportions, demonstrating that the appropriate modeling of survey data may result in more suitable procedures. In National Center for Education Statistics (NCES) surveys, ordinary post stratification and raking ratio adjustment are commonly used techniques for improving the precision and reducing the bias of estimators. Generally speaking, post stratification refers to any method of data analysis which involves forming units into homogeneous groups after observation of the sample, especially for those cases where additional information, external to the sample, is available for the subgroups. While the ordinary post stratified estimator (or ratio-adjusted estimator) is a special case of regression estimator, raking ratio adjustment can be extended to log linear models for weighting. One disadvantage is that no simple formula for its variance is available Bethlehem and Keller (1987). The regression estimator and raking ratio adjusted estimator, however, are both special cases of a more general class of estimators—the calibration estimator Deville and Sarndal (1992). More importantly, any other member of the calibration estimator class is asymptotically equivalent to the regression estimator and, as a consequence, all members of the calibration estimator class share the same asymptotic variance Deville and Sarndal (1992).In this study, we first present the Horvitz-Thompson estimator in matrix form in order to compare it with the regression estimator. In discuss the unconditional variance of the regression estimator and compare it to the unconditional variance of the Horvitz-Thompson estimator. Our intention in discussing the regression estimator here is to throw some light on a more complicated estimator—the raking ratio adjusted estimator. The raking ratio adjusted estimator, although its variance formula is hard to find, shares the same asymptotic variance with the regression estimator. Since conditional variance estimates are preferred, we reviewed a recent study conducted by Yung and Rao (1996) raking ratio adjustment was performed on the estimates of 1993 National Household Education Survey (NHES:93) School Readiness component. We compare variance estimates which incorporated the raking ratio adjustment to variance estimates which did not incorporate the adjustment. Enrolment in school represents the largest component of the investment in human capital in most society Schultz (2002). Education, schooling, and human capital development and often used interchangeably in the literature. The human resources of a nation are considering being the engine of growth of the country. These most how ever be adequately develop and efficiently utilized. Education bestow on the recipients, a deposition for a lifelong acquisition of knowledge, values, attitude, competent and skills Fafunwa (2001). Hence rapid socio-economic development of a nation has observed to depend on the caliber human capital in the country. Education is thus central to the development process. Net enrolment rate is the ratio of children of official age who are enrolled in school to the population of the corresponding official school age. Secondary education completes the provision of basic education that began at primary level, and aims at laying the foundations for lifelong learning and human development, by offering more subjects or oriented institution using more specialized teachers (Institute for statistics). Small discrepancies in the reported age of children may occasionally cause net enrolment rate to exceed 100 percent.

II. METHODOLOGY

2.1 Source of Data

The source of these data is a secondary source that is collected from the ministry of education of Gombe state authority. A stratified sampling method is adopted for this study. In this case, the schools levels are regarded as strata and in each stratum, a sample of size n_h comprising of students and teachers. The method of selection used is proportional allocation. This method gives equal opportunity to a large number of student/teachers being included in the general sample. The method is simply explain as follows

$$n_h \alpha N_h$$

$$n_h = \lambda N_h$$

Where n_h is the students/teachers selection from a particular stratum and N_h are the total teacher/student of the stratum and λ is a constant known as sampling fraction. Muhkpahay. P (1998).

2.2 Stratified Sampling

Stratified sampling, is a sampling techniques in the population is divided into K strata such that the units belonging to a particular strata is homogeneous and there is maximum difference between units belonging to another stratum. A simple random sample is perform in stratum such that the units selected using a simple random sample are representative of the stratum by some allocation procedure such as proportional allocation procedure.

N_h: Total number of unit in a stratum
n_h: Unit sample in each stratum
F_h: Sampling fraction in each stratum

W_h: Sampling weight in each stratum
S_h: The standard deviation in each stratum

Theorem: Using simple random sampling in each stratum, the mean of the stratified sampling can be obtained by the formula.

$$E(y_{st}) = \bar{Y}$$

Proof: $\bar{y}_{st} = \sum_{h=1}^{L} W_h \bar{y}_h$

$$\therefore E(\bar{y}_{st}) = E\left[\sum_{h=1}^{L} W_h \bar{y}_h\right]$$

$$= \sum_{h=1}^{L} W_h E(\bar{y}_h) = \sum_{h=1}^{L} W_h \bar{Y}_h = \bar{Y} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

If the following terms are known, then the variance of stratified sampling can be obtained using the formula.

Theorem: for stratified random sampling, the variance of the estimate is

$$\mathrm{v}(\bar{y}_{st}) = \sum_{h=t}^{l} w^2 \frac{s_h^2}{n_h}(1- f_h)$$

Proof: $\bar{y}_{st} = \sum_{h=1}^{L} W_h \bar{y}_h$

$$\Longrightarrow Var(\bar{y}_{st}) = Var\left(\sum_{h=1}^{L} W_h \bar{y}_h\right)$$

$$= \sum_{h=1}^{L} W_h{}^2 Var(\bar{y}_h)$$

$$= \sum_{h=1}^{L} W_h{}^2 (1 - f_h) \frac{S_h{}^2}{n_h} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Corollary: if the sampling fraction ${}^{n_h}\!/\!{}_{N_h}$ are negligible in all strata,

$$\mathrm{v}(\bar{y}_{st}) = \sum_{h=t}^{l} \frac{w_h^2 s_h^2}{n_h} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(3)$$

And with proportion allocation, we substitute

$$n_h = \frac{nN_h}{N}$$

The variance reduce to

$\mathrm{v}(\bar{y}_{st}) = \frac{1-f}{n} \sum_{h=t}^{l} w_h s^2$ also, if sampling is proportional and the variances in all strata have the same value variance Mukhpahay (1998).

2.3 The Ratio Estimator

In the ratio method, an auxiliary variable denoted by x_i correlated with study variable y_i is obtained for each unit in the sample. The population total X of x_i must be known. In practice, x_i is often the value of y_i at some previous time when a complete census is taken? The aim in this method is to obtain increase precision by taken the advantage of the correlation between y_i and x_i. At present we assume simple random sampling. The ratio estimate of Y total population is given by;

$$\hat{Y}_R = \frac{y}{x} X = \frac{\bar{y}}{\bar{x}} X \;;$$

Where y, x are the sample total of the x_i and y_i respectively. If x_i is the value of y_i at some previous time, the ratio method uses the sample to estimate the relative change Y/X that has occurred since that time. P.S.R.S Rao and J.N.K Rao (1971) The estimated relative change y/x is multiplied by the known population total X on the previous occasion to provide an estimate of high precision. If the quantity to be estimated is $\bar{Y}$ that is the mean, the populations mean value of y_i, the ratio estimate is; $\hat{\bar{Y}}_R = \frac{y}{x}\bar{X}$

Frequently, we wish to estimate ratio rather than total or mean.

, we obtain v($\bar{y}$) = $\frac{s^2h}{n}$ ($\frac{N-n}{N}$)

2.4 Ratio Estimator in Stratified Random Sampling

In stratified sampling, there are two ways of forming the ratio estimator of a population total. This give;

I. A separate ratio estimator.

II. A combined ratio estimate.

Separate Ratio Estimators

If the regression of y on x approximately passes through the origin in each of the stratum and the slop of the regression line differs from stratum to stratum then in such a situation we use the separate ratio estimators for each of the stratum and then add this estimate, the ratio estimate for population total Y is given by;

- Total estimate: $\hat{Y}_{RS} = \sum_{h=1}^{L} \frac{\bar{y}_h}{\bar{x}_h} X_h$.
- Mean estimate: $\hat{\bar{Y}}_{RS} = \sum_{h=1}^{L} W_h \frac{\bar{y}_h}{\bar{x}_h} \bar{X}_h$

The corresponding variance of the population mean is

$$V\left(\hat{\bar{Y}}_{RS}\right) = \sum_{h=1}^{L} W^2{}_h \left(\frac{1-f_h}{n_h}\right)\left[S^2{}_{yh} - 2R_h S_{xy} + R^2{}_h S^2{}_x\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4)}$$

Combine Ratio Estimate

If the ratio R_h for the strata does not differ much, it is possible first to obtain the common ratio as R_c = $\bar{y}_{st}/\bar{x}_{st}$. Therefore the population mean estimate for the combine ratio is given by;

$$\hat{\bar{Y}}_{CR} = R_C \bar{X}$$

For large samples, the bias of the estimate disappears or vanishes and its variance is approximately

$$V\left(\hat{\bar{Y}}_{RS}\right) = \sum_{h=1}^{L} W^2{}_h \left(\frac{1-f_h}{n_h}\right)\left[S^2{}_{yh} - 2R_C \rho_h S_x S_y + R^2{}_c S^2 x\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(5).}$$

Hansen, at el (1946).

2.5 The Regression Estimator

I. When the auxiliary variable X is a predetermined (non-random) variable, we can obtained an alternative estimator to the ratio estimator.

II. It is based on concept of least square method and it is known as regression.

III. Assuming there is a liner relationship between X and Y

   a. $\hat{y} = a + bx_i = \bar{y} + b(x_i - \bar{x})$

IV. With paired observations (x_i, y_i) for i= $1, \ldots, n$. Then the estimator of population mean μ_y is

V. $= \bar{y} + b\hat{\mu}_{yL}(\mu_x - \bar{x})$.

VI. The estimated variance of $\hat{\mu}_{y\,L}$ is

VII. $\widehat{Var}\left(\hat{\mu}_{yL}\right) = \left(\frac{N-n}{Nn}\right)\left(\frac{1}{n-2}\right)\left[\sum_{i=1}^{n}(y_i - \bar{y})^2 - b^2\sum_{i=1}^{n}(x_i - \bar{x})^2\right]$

VIII. $= \left(\frac{N-n}{Nn}\right).MSE$

IX. Where MSE is the mean square error from the standard simple linear regression.

X. In general, the ratio estimator is most appropriate when the relationship between x and y is linear through the origin. Otherwise, in general, it is better to use regression estimators.

XI. To obtain an estimate of $V(\bar{y}_r)$.

$V(\bar{y}_r) = V(\bar{\upsilon})$ Where $\bar{\upsilon}$ is the simple random sample mean of the variance υ with the value $\upsilon_i = Y_i + B(x_i - \bar{x})$, i= 1…N. Hence a variance estimator is

$$\upsilon(\bar{y}_r) = \frac{1-f}{n(n-1)}\sum_{i=1}^{n}(\upsilon_i - \bar{\upsilon})^2$$

$$= \frac{1-f}{n(n-1)}\sum_{i=1}^{n}\left[y_i - B(x_i - \bar{x}) - \bar{y}\right]^2$$

$$= \frac{1-f}{n(n-1)}\sum_{i=1}^{n}\left[y_i - \bar{y} - b(x_i - \bar{x}) + (b-B)(x_i - \bar{x})\right]^2$$

$$= \frac{1-f}{n(n-1)}\sum_{i=1}^{n}\left[y_i - \bar{y} - b(x_i - \bar{x})\right]^2$$

$$= \frac{1-f}{n(n-1)}\left\{\sum_{i=1}^{n}(y_i - \bar{y})^2 - \frac{\left[\sum_{i=1}^{n}(y_i - \bar{y})(x_i - \bar{x})\right]}{\sum_{i=1}^{n}(x_i - \bar{x})^2}\right\}$$

2.6 Regression Estimates When b Is Computed From the Sample

It is suggested that if b is computed from a sample (the increase in y per unit increase in x)as on the case of this, the least square estimate of B is

$$b = \frac{\sum_{i=0}^{n}(y_i - \bar{Y})(x_i - \bar{X})}{\sum_{i=0}^{n}(x_i - \bar{X})^2} \quad \text{………………………………………………………….(6)}$$

The theory of linear regression plays a prominent part in statistical methodology. The standards result of this theory is not entirely suitable for samples surveys because they acquire the assumptions that the population regression of y on x is linear, and that the residual error variance of y about the linear regression constant, and that the population is infinite. If the first two assumptions are violently wrong, a linear regression estimate will probably not to be used. However in surveys in which the regression of y on x is although to be approximately linear, it is helpful to be able to use y_{ls} without having to assume exact linearity or constant residual variance.Consequently, we present an approach that no assumption of any specific relation between y_i and x_i . As in the analogous theory for the ratio estimator only large sample result are obtained. With b as in the linear regression estimates of $\hat{Y}$ in simple random sample Douglas (2003).

$$\hat{Y}_{lr} = \hat{Y} + b(x_i - \bar{X})$$

2.7 Regression Estimate in Stratified Sampling

As the ratio estimator, two types of regression estimate can be made in stratified random sampling.

I. A separate regression estimator.

II. A combined regression estimator.

Separate regression estimator

Assume β is known, say β_o. Then

$$\hat{\hat{Y}}_{sreg} = \sum_{i=1}^{k} W_i\,[\bar{y}_i + \beta_{0i}(\bar{X}_I - \bar{x}_i)]$$

$$E\left(\hat{\bar{Y}}_{sreg}\right) = \sum_{i=1}^{k} W_i\left[E(\bar{y}_i) + \beta_{0i}\left(\bar{X}_i - E(\bar{x}_i)\right)\right]$$

$$= \sum_{i=1}^{k} W_i[\bar{Y}_i + (\bar{Y}_i - \bar{Y}_i)]$$

$$= \bar{\boldsymbol{Y}}$$

$$Var\left(\hat{\bar{Y}}_{sreg}\right) = E\left[\hat{\bar{Y}}_{sreg} - E\left(\hat{\bar{Y}}_{sreg}\right)\right]^2$$

$$= E\left[\sum_{i=1}^{k} w_i\bar{y}_i +_i + \sum_{i=1}^{k} w_i\beta_{0i}(\bar{X}_i - \bar{x}_i) - \bar{Y}\right]^2$$

$$= E\left[\sum_{i=1}^{k} w_i\,(\bar{y}_i - \bar{Y}) - \sum_{i=1}^{k} w_i\,\beta_{0i}(\bar{x}_i - \bar{X}_i)\right]^2$$

$$=\sum_{i=1}^{k} w_i^2\,E(\bar{y}_i - \bar{Y}_i)^2 + \sum_{i=1}^{k} w_i^2\beta_{0i}^2\quad E\,(\bar{x}_i - \bar{X}_i)^2 - 2\sum_{i=1}^{k} w_i^2\ \beta_{0i}E(\bar{x}_i - \bar{X}_i)(\bar{y}_i - \bar{Y}_i)$$

$$=\sum_{i=1}^{k} w_i^2\,Var(\bar{y}_i) + \sum_{i=1}^{k} w_i^2\,\beta_{0i}^2\,Var(\bar{x}_i) - 2\sum_{i=1}^{k} w_i^2\beta_{0i}Cov(\overline{x_i}, \bar{y}_i)$$

$$=\sum_{i=1}^{k} \frac{w_i^2 f_i}{n_i}\,(s_{iY}^2 + \beta_{oi}^2 s_{iX}^2 - 2\beta_{0i}s_{iXY}).$$

$\boldsymbol{Var}\left(\hat{\bar{\boldsymbol{Y}}}_{\boldsymbol{sreg}}\right)$ is minimum when $\beta_{0i} = \frac{S_{iXY}}{S_{iX}^2}$ and so substituting β_{0i}, we have

$V_{min}\ \left(\hat{\bar{Y}}_{sreg}\right) = \sum_{i=1}^{k}\left\lfloor\frac{w_i^2 f_i}{n_i}(S_{iY}^2 - \beta_{0i}^2 S_{iX}^2)\right\rfloor$ Where $f_i = \frac{N_i - n_i}{N_i}$

Since SRSWOR is followed in drawing the samples from each stratum, so

E $(s_{ix}^2) = S_{iX}^2$

E$\left(s_{iy}^2\right) = S_{iY}^2$

E$\left(s_{ixy}\right) = S_{iXY}$

Thus an unbiased estimator of variance can be obtained by replacing S_{iX}^2 *and* S_{iY}^2 by their respective unbiased estimators S_{iX}^2 *and* S_{iY}^2 respectively as

$\widehat{Var}\left(\hat{\bar{Y}}_{sreg}\right) = \sum_{i=1}^{k}\left\lfloor\frac{w_i^2 f_i}{n_i}(s_{iy}^2 + \beta_{oi}^2 s_{ixy})\right\rfloor$ and

$\widehat{Var}_{min}\left(\hat{\bar{Y}}_{sreg}\right) = \sum_{i=1}^{k}\left\lfloor\frac{w_i^2 f_i}{n_i}(s_{iy}^2 - \beta_{oi}^2 s_{ix}^2)\right\rfloor$

Combined regression estimators

Assume β is known, say β_0. Then $\hat{\bar{Y}}_{creg} = \sum_{i=1}^{k} w_i\bar{y}_i + \beta_0(\bar{X} - \sum_{i=1}^{k} w_i\bar{x}_i)$

$$E\left(\hat{\bar{Y}}_{creg}\right) = \sum_{i=1}^{k} w_i\,E(\bar{y}_i) + \beta_0\left[\bar{X} - \sum_{i=1}^{k} w_i E(\bar{x}_i)\right]$$

$$= \sum_{i=1}^{k} w_i\bar{Y}_i + \beta_0\left[\bar{X} - \sum_{i=1}^{k} w_i\bar{X}_i\right]$$

$$= \bar{Y} + \beta_0(\bar{X} - \bar{Y})$$

$$= \bar{Y}$$

Thus $\hat{\bar{Y}}_{creg}$ is an unbiased estimator of $\bar{Y}$.

$$Var\left(\hat{\bar{Y}}_{creg}\right) = E\left[\bar{Y}_{creg} - E(\bar{Y}_{creg})\right]^2$$

$$= E\left[\sum_{i=1}^{k} w_i\,\bar{y}_i + \beta_0\left(\bar{X} - \sum_{i=1}^{k} w_i\bar{x}_i\right) - \bar{Y}\right]^2$$

$$= E\left[\sum_{i=1}^{k} w_i(\bar{y}_i - \bar{Y}) - \beta_0\sum_{i=1}^{k} w_i(\bar{x}_i - \bar{X}_i)\right]^2$$

$$= \sum_{i=1}^{k} w_i^2\,Var(\bar{y}_i) + \beta_0^2\sum_{i=1}^{k} w_i^2 Var(\bar{x}_i) - 2\sum_{i=1}^{k} w_i^2\beta_0 Cov(\bar{x}_i, \bar{y}_i) = \sum_{i=1}^{k}\frac{w_i^2 f_i}{n_i}\left\lfloor s_{iy}^2 + \beta_0^2 S_{iX}^2 - 2\beta_0 S_{iXY}\right\rfloor$$

$Var(\hat{\bar{Y}}_{creg})$ is minimum when

$$\beta_0 = \frac{Cov(\bar{x}_{st}, \bar{y}_{st})}{Var(\bar{x}_{st})}$$

$$= \frac{\sum_{i=1}^{k} \frac{w_i^2 f_i}{n_i} s_{iXY}}{\sum_{i=1}^{k} \frac{w_i^2 f_i}{n_i} S_{iX}^2}$$

And the minimum variance is given by

$$Var_{min}\left(\hat{\hat{Y}}_{creg}\right) = \sum_{i=1}^{k} \frac{w_i^2 f_i}{n_i} (S_{iY}^2 - \beta_0^2 S_{iX}^2).$$

Since SRSWOR is followed to draw the sample from strata, so using

$$E(S_{ix}^2) = S_{iY}^2 \ and \ E(S_{ixy}) = S_{iXY},$$

We get the estimate variance as

$$\widehat{Var}\left(\hat{\hat{Y}}_{creg}\right) = \sum_{i=1}^{k} \left[\frac{w_i^2 f_i}{n_i} (s_{iy}^2 + \beta_o^2 s_{ix}^2 - 2\beta_{0i} s_{ixy})\right]$$

And

$$\widehat{Var}_{min}\left(\hat{\hat{Y}}_{creg}\right) = \sum_{i=1}^{k} \left[\frac{w_i^2 f_i}{n_i} (s_{iy}^2 - \beta_{oi}^2 s_{ix}^2\right]$$

Comparison of $\hat{\hat{Y}}_{sreg} \ and \ \hat{\hat{Y}}_{creg}$:

Note that

$$Var\left(\hat{\hat{Y}}_{creg}\right) - Var\left(\hat{\hat{Y}}_{sreg}\right) = \sum_{i=1}^{k} (\beta_{io}^2 - \beta_0^2) \frac{w_i^2 f_i}{n_i} S_{iX}^2$$

$$= \sum_{i=1}^{k} \frac{f_i}{n_i} (\beta_{io} - \beta_0)^2 w_i^2 S_{iX}^2 \quad \geq 0$$

Which is always true. So if regression line of y on x is approximately linear and the regression coefficients do not vary much among strata, then separate regression estimate is more efficient than combined regression estimator.

III. EMPIRICAL ANALYSIS

TABLE 1: The distribution of mean, variance and ratio estimates of male to female in the stratum

Class (stratum)	Male Mean $(\bar{X})$	Female Mean $(\bar{Y})$	Male Variance (S_x^2)	Female variance (S_y^2)	Male to Female Ratio (R)
1	270	198.13	18107.75	2046.11	1.36
2	202.16	158.20	5285.36	1500.50	1.28
3	166	141.25	2926.75	2302.19	1.18

From the above table, the analysis of gender shows that the ratio of male to female is approximately 1:1 in all arms of the schools were the data was collected. Hence there is no significant difference between the male and female.

TABLE 2: The distribution of mean, variance and ratio estimates of teacher to student

Class (stratum)	Student Mean $(\overline{X+Y})$	Teacher Mean $\bar{Z}$	Student Variance $S^2{}_{(X+Y)}$	Teacher Variance $S^2{}_Z$	Student to Teacher (R)
JSS 1	468.13	6.50	29820.11	1.50	72.02
JSS 2	380.63	6.00	11391.73	2.50	60.10
JSS 3	294.75	5.88	9788.94	1.11	50.88

From the above table, the result shows that the ratio of teacher to student is approximately 1:70 in JSS 1, approximately 1:60 in JSS 2 and approximately 1:50 in JSS 3 of the school consider in study.

Table 3. Comparing the efficiency of stratified, regression and ratio estimators of male and female ratio

Male and Female	Stratified Estimator	Regression Estimator	Ratio Estimator
Mean	386.91	2111.28	1324.58
Variance	859.59	219.58	492.95

From the above table, we observed that the variances estimate for stratified, regression and ratio estimators are 859.59, 219.58 and 492.95 respectively. This indicates that the regression estimate has the minimum variance; hence it is more efficient than any of the two.

Table 4.Comparing the efficiency of stratified, regression and ratio estimators of teacher to student ratio

Student to Teacher	Stratified Estimator	Regression Estimator	Ratio Estimator
Mean	396.30	49141.98	49.51
Variance	275.75	6354.44	269.20

From the above table, we observe that the variance estimate for stratified, regression and ratio estimator are 275.75, 6354.44 and 269.20 respectively. This indicates that the ratio estimate has the minimum variance; hence it is more efficient than any of the two.

IV. CONCLUSION

4.1 Conclusion

The main aim of this research was to estimate the ratio of teacher to student in junior secondary schools and to estimate the enrollment of male and female. The data collected for this research was obtain from 8 selected junior secondary school in Gombe local government area for 2013/2014session.The enrolment was stratified into three strata each stratum contain male, female and their respective teachers that is, the first stratum contains all JSS 1, the second contains all the JSS 2 and the third contains all the JSS 3 in the 8 junior secondary schools considered in this study. The first part of the analysis deals with estimation of male to female ratio using the method of stratified, regression and ratio estimators. In table 1, the ratio of male to female was found to be approximately 1:1. That is, for every female there is one male enrolled for the particular session in consideration. In the second part of the analysis, we estimated the ratio of both male and female to their teachers and the result shows that there are approximately 70 student per teacher estimated in JSS1, 60 student per teacher in JSS2, while it is approximately 50 student per teacher in JSS3. The variance of the regression estimator is minimum compared to those of stratified and ratio estimators in the first part of the analysis while the ratio estimator is minimum and hence efficient on the second part of the analysis. This was due to large variation between the student and teachers in the observed data on the analysis of ratio of teacher to student when compared with the data collected of males and females. On the basis of the conclusion, shows that the ratio of male and female is almost the same compare with the usual report that the male children are allow to go to school than the female children. On average the ratio of teacher to student are 1:70 JSS 1, 1:60 JSS 2 and 1:50 JSS 3 which is higher than the millennium development Goal (MDG's) recommendation of 1:35.

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Abubakar Bello." Ratio Estimation of Teacher to Students In Junior Secondary School In Gombe Local Government Area." International Journal of Mathematics and Statistics Invention (IJMSI) , vol. 06, no. 03, 2018, pp. 57–64.