New memory-based ratio estimator in survey sampling

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Abstract:

This study proposes a new estimator based on the Exponential Weighted Moving Average (EWMA) statistic by following the concept of Noor-ul-Amin (2021). The EWMA model consumed contemporary and empirical data to enhance the competence of the population mean estimation. The memory type estimate is proposed with a twofold utilisation of Auxiliary Information (AUI) in alignment with the sampling type, i.e., Simple Random Sampling (SRS). A detailed numerical study and analysis are conducted to estimate the projected efficiency. This study provides an efficient estimator for population mean in the occurrence of time series data. The extra advantage of using EWMA statistics instead of classical statistics is that we can get better effectiveness of the mean estimate of the population under SRS by altering the significance of the smooth constant \( \lambda \), as the cost of the smoothing constant \( \lambda \) decreases from one towards zero, and we gain the efficiency of the suggested estimator. For \( \lambda = 1 \), the proposed estimator performs the same as their comparative estimator. This expands incompetence over the presented ones statistically demonstrated in mean square error and relative effectiveness. Previous research is also accessed with everyday life information that indicates the conclusions of the simulation investigation.

Keywords: Simple random sampling, Auxiliary information, Ratio estimator, Memory type estimate, Smoothing constant, Mean square, Relative efficiency, New estimator, Simulation.

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1. Introduction

The relevant estimation procedure supplies estimation with more precision. The Auxiliary Information (AUI) is integrated into these estimation procedures to obtain improved estimators. This auxiliary variable is also used at the beginning stages of designing or evaluation. Cochran (1940) suggests applying AUI at the estimate stage in the form of a ratio estimator, which is specified by Equation (1).

$$\bar{y}_r = \frac{\bar{y}}{\bar{x}}$$

Whereas the sample mean of the research variable is $\bar{y}$, $\bar{x}$ is the auxiliary mean sample auxiliary for the variable and $\bar{X}$ is the mean of the population for the auxiliary variable, and it is known and understandable. Numerous statisticians used AUI as a regression estimator, as presented by Equation (2).

$$\bar{y}_{reg} = \bar{y} + b(\bar{X} - \bar{x})$$

The $b$ is the least square estimate of the coefficient of population regression as $\beta$. Similarly, Kadilar and Cingi (2004) utilised the auxiliary variable and recommended the ratio estimator estimate as presented in Equation (3).

$$\bar{y}_{dr} = \frac{\bar{y} + b(\bar{X} - \bar{x})}{\bar{x}} = \frac{\bar{y}_{reg} \bar{X}}{\bar{x}}$$

The respective MSE expressions of Equations (1-3) are as follows.

$$MSE(\bar{y}_r) \approx \theta \bar{Y}^2 \left[ C_y^2 - 2 \rho C_y C_x + C_x^2 \right],$$

$$MSE(\bar{y}_{reg}) \approx \theta \bar{Y}^2 C_y^2 \left( 1 - \rho^2 \right),$$

And,

$$MSE(\bar{y}_{dr}) \approx \theta \bar{Y}^2 \left[ C_x^2 + C_y^2 \left( 1 - \rho^2 \right) \right]$$

Where $\theta = \frac{1 - n/N}{n}$, $n$ is the sample size, $N$ is the population size, $C_y$ is the variation coefficient for the variable of study, $C_x$ is the auxiliary variable variation coefficient. Furthermore, $S_y^2$, $S_x^2$ are the sample inconsistency of variables both investigated and auxiliary correspondingly, and $\rho$ is the coefficient of correlation stuck between the study and the auxiliary variables.

The rest of the research paper has the following structure: The Section 2 describes the literature review along with the research gap. The Section 3 explains the memory type estimator. Section 4 presents the proposed estimator. The Section 5 presents a numerical study related to the
proposed estimator. The Section 6 discusses the study's main findings. The Section 7 illustrates an application of the proposed estimator. Concluding remarks are provided in the Section 8 of this research paper.

2. Literature review

The ratio estimate accuracy has been improved by numerous researchers, as presented in Equations (1) and (2), by amending them in dissimilar situations. Like, Sisodia and Dwivedi (1981) extended the classical ratio estimator by incorporating the variation of coefficient with the variable of auxiliary, while the extension in the estimation of Sisodia and Dwivedi (1981) was made by Upadhyaya and Singh (1999). Bahl and Nain (1999) proposed a generalised estimator motivated by Ray and Singh (1981). Kadilar et al. (2007) proposed estimators using robust regression. Jhajj and Walia (2012) proposed a comprehensive disparity cum estimate for ratio type in twofold sampling. A dissimilarity cum estimate of exponential type was given by Shabbir et al. (2014), and a modified exponential type of estimator under Simple Random Sampling (SRS) was given by Kadilar (2016). Jhajj and Walia (2012) proposed a universal estimation of the ratio for a mean of the population in the occurrence of non-response. An estimation of the ratio and product type for the known coefficient of variation via the modified maximum likelihood method was projected by Kumar and Chhaparwal (2019).

The literature review about estimates is only helpful in cross-sectional field studies. Consequently, the efficiency of the ratio estimator could be enhanced for investigations in which gathered data rely on a time scale. For such circumstances, the estimation for ratio and product with simple random type for time series statistics was proposed by Aslam et al. (2021), titled estimations for memory type ratio and product by using the EWMA statistic. During 2020 and 2021, memory type ratio estimations mean of the population for sampling types of stratified and ranked correspondingly was utilised by (Aslam et al., 2020; 2021). Qureshi et al. (2022) provided estimations for the memory type ratio for variance of a population. Chhaparwal and Kumar (2022) improved the effectiveness of memory type ratio estimations using EWMA fusion. Zahid et al. (2023) proposed estimations for memory type ratio and product under extensive statistics of EWMA. To measure the mean, Bhushan et al. (2023) gave an estimate for memory type logarithm. In this manuscript, we are modifying the methodology of Noor-ul-Amin (2021) to advance the competence of estimation of the population’s mean for times-scaled surveys and suggesting a new memory base ratio type estimator employing auxiliary information twice.

3. Memory type estimator

Roberts (1959) was the first to utilise the statistics of EWMA by involving the previous and existing data to improve the competence of estimates and is presented as

\[ Z_t = \lambda \bar{y}_t + (1-\lambda)Z_{t-1} \quad \text{where} \quad t > 0 \]  

(7)

Whereas \( \bar{y}_t \) is the sample's mean at the moment in time \( t \), \( \lambda \) is the parameter for weight and smoothing constant of clarification. Its value lies between 0-1. The bigger the importance of \( \lambda \) then the heavier weight is specified for the newest worth and the lesser weight to the earlier period.
values, while the less significant the value of \( \lambda \), the superior weight is prearranged for the empirical data and small weight to the most recent data. For \( \lambda = 1 \), the EWMA statistic becomes equal to the conventional mean of the sample. Whereas \( Z_{t-1} \) specifies the statistics of old data. The early value (\( Z_0 \)) of \( Z_t \) is the anticipated mean, which may be obtained from the pilot survey (Noor-ul-Amin (2021)). The anticipated assessment and inconsistency of EWMA statistics is presented as:

\[
E(Z_t) = \bar{Y} \quad \text{and} \quad \text{Var}(Z_t) = \frac{\sigma^2_y}{n} \left[ \frac{\lambda}{2-\lambda} \left( 1 - (1-\lambda)^2 \right) \right],
\]

where, \( \bar{Y} \) and \( \sigma^2_y \) is the variable of interest’s mean and variance. The restrictive type of variance is illustrated by Equation (8).

\[
\text{Var}(Z_t) = \frac{\sigma^2_y}{n} \left[ \frac{\lambda}{2-\lambda} \right]. \quad (8)
\]

The proposed estimate for the memory type ratio of Noor ul Amin (2021) is given by Equation (9).

\[
yrt^M = \frac{Z_{yt} E_{xt}}{E_{xt}}, \quad (9)
\]

Where \( Z_{yt} = \lambda \bar{y}_t + (1-\lambda)Z_{yt-1} \), \( E_{xt} = \lambda \bar{x}_t + (1-\lambda)E_{xt-1} \) are the statistics of memory type for study and auxiliary variable, respectively.

4. Proposed memory type estimator

In this section, we proposed memory based estimator by modifying the estimator suggested by Kadilar and Cingi (2004) for time scale survey. The EWMA statistic, as given in Equation (7), is utilized to propose an estimation of memory type. For the projected estimation, the EWMA statistic at time \( t \) for study variable (\( y \)), represented by \( E_{yt} \) is obtained by using the regression estimator in Equation (7) and is given below:

\[
E_{yt} = \lambda \bar{y}_{regt} + (1-\lambda)E_{yt-1} \quad (10)
\]

Where \( \bar{y}_{regt} \) is given in Equation (2) at time \( t \) and EWMA statistic for variable of auxiliary (\( x \)) signified as \( E_{xt} \) such that.

\[
E_{xt} = \lambda \bar{x}_t + (1-\lambda)E_{xt-1} \quad (11)
\]

Where \( \bar{x}_t \) is the mean per unit estimate under SRS plan at period \( t \). The planned estimation for memory type ratio in SRS is designed as follows:
The estimated expression of MSE for the projected estimate of the ratio is presented by Equation (13).

\[
\text{MSE}\left(\tilde{y}_{\text{dr}}^M\right) \approx 2\hat{Y}^2 \frac{\lambda}{2-\lambda}\left[\text{C}^2_y\left(1-\rho^2\right)+\text{C}^2_x\right]
\]

(Detailed proof of MSE is shown in the Appendix).

5. Numerical study

A broader statistical investigation is done to assess the efficiency of the estimation under study. The presented MSEs are founded on fifty thousand repeated attempts to project estimation. The MSE is measured for the proposed estimator by utilising the method specified in Equation (14).

\[
\text{MSE}(a) = \frac{1}{50,000} \sum_{i=1}^{50,000} (a_i - \bar{Y})^2
\]

Where \( a = Y_n, Y_{\text{dr}}, Y_{\text{dr}}^M, Y_{\text{dr}}^M \) and \( \mu_a \) is the mean with 50,000 samples. Equation (15) provides the Relative Efficiencies (REs) for mean per unit estimates.

\[
RE(a) = \frac{\text{MSE}(\bar{Y})}{\text{MSE}(a)},
\]

The projected MSE values are given in Table-1, and the outcomes of REs are presented in Table-2. The outcomes of MSE and REs are obtained for various values of coefficient correlations, i.e. 0.25, 0.50, 0.75, .95. To observe the effect of smoothing constant, different values of \( \lambda \), like .05, .10, .25, .50, .75, 1.0 have been used.

Subsequent instructions have been used to measure the values of MSEs and REs for the projected ratio of memory type with SRS.

- A populace size of 10000 is generated from a distribution of bivariate normal with parameters \((Y, X) \sim N_2(1,50,1,1,\rho)\).
- Select the random sample of size \( n=10-30, 50, 200, \text{ and } 500.\)
- Calculate the statistics of EWMA presented in (10-11) with diverse options for smoothing constants.
- Measure the estimations of the ratio presented in Equation (12).
- Replicate steps (i) to (iv) for fifty thousand times.
- The projected MSE is measured using formula given in Equation (14), and the outcomes are formed in Table-1.
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- We got REs for each size of sample size with the application of Equation (15), which is given in Table-2.

6. Main findings

The premeditated outcomes of MSEs and REs for the projected type are illustrated in 1 and 2 Tables. The proportional investigation for projected MSE and REs of memory type estimate with twice application of AUI placed on SRS phase are presented in Tables-1 and 2 and the foremost conclusions of the proposed estimation are:

- It is prominent in Table-1 that MSEs of the projected estimate of memory type given in (12) are smaller than the estimator given in (1), (3) and (9). Consider for example, for $\lambda = 0.05$, $\rho = 0.75$ and $n = 30$, MSE of (1) is 0.0324, (3) is 0.0147, (9) is 0.0009 and the proposed estimator (12) is 0.0004. This shows that the proposed estimator (12) performs better than (1), (3), and (9).

- The REs of the planned estimate is given Table-2, these REs are higher than (1), (3), and (9). Consider for example, for $\lambda = 0.50$, $\rho = 0.75$ and $n = 50$, RE of (1) is 1.0306, (3) is 2.3003, (9) is 3.0791, and the proposed estimator (12) is 6.7745. This establishes the competence of the planned ratio estimation with respect to classical and other corresponding ratio estimators.

- As $\rho$ i.e. coefficient of correlation among variable of study and auxiliary rises from .25 to .95, the figures of MSEs shift downward to augment the competency of the planned estimation (12). For example, consider $\lambda = 0.50$, $n = 50$, as $\rho$ increases from 0.50 to 0.75, and then for (1), MSE decreases from 0.0195 to 0.0194, with corresponding RE increases from 1.0199 to 1.0306. For (3), MSE decreased from 0.0149 to 0.0087, and the corresponding RE increased from 1.3343 to 2.3003. For (9), MSE decreased from 0.0066 to 0.0065 with corresponding RE increases from 3.0644 to 3.0791 and for (12), MSE decreased from 0.0051 to 0.0030 with corresponding RE increases from 3.9723 to 6.7745. Increase in $\rho$ From 0.50 to 0.75, the decrease in MSE for (1), (3), (9), and (12) is 0.0001, 0.0062, 0.0001, and 0.0021, respectively, with an increase in the corresponding RE of 0.0107, 0.9660, 0.0147, and 2.8022. This shows that the proposed estimator excels at performance compared to (1), (3), and (9). Hence, the utilization of AUI enlarges the effectiveness of the estimate.

- For unchanging lambda value and correlation coefficient, as the size of sample enlarges, it means that $n$ opt values 10, 20, 30, 50, 100, 200, 500, the MSEs decreased with each improved value of the size of sample e.g. consider $\lambda = 0.05$, $\rho = 0.75$, as $n$ increases from 30 to 50, the corresponding MSE decreases from 0.0324 to 0.0195, 0.0147 to 0.0087, 0.0009 to 0.0005, and 0.0004 to 0.0002 for (1), (3), (9), and (12), respectively.

- To use the previous outcomes, align with the existing information, a smoothing constant $\lambda$ is used. For example, fix $\rho = 0.75$, $n = 30$ as $\lambda$ decreases from 0.25 to 0.10, then MSE decreases from 0.0047 to 0.0017 and 0.0021 to 0.0008 for (9) and (12), respectively. This shows that as $\lambda$ decrease, weight for past information increase and weight decrease for current information. This can guide the competence of the anticipated estimate and is given in Tables-2. Finally, $\lambda =1$ shows that only the existing data is used and that there is no consumption of previous data. This can be seen from the last two columns of table-2 that the EWMA-based planned estimation will rely upon recent information only to
approximate the mean just like (3). Hence, the performance of the (12) will be equally suitable for $\lambda = 1$.

Figure 1: Comparison of proposed estimator with other ratio estimators for the production of wheat

7. Conclusion

During a time-scaled field study, utilising the existing and previous information about the sample is significant. To handle such a problem, the Noor-ul-Amin model helped to use ratio estimates by applying the statistics of EWMA for the cross-sectional field studies. In the current study, we try to improve the competence of the model mentioned above by double-using auxiliary information differently. We scrutinise the projected estimate by doing an extensive investigation. It is concluded from the numerical research and actual life use that the projected estimation showed better outcomes for error of mean square and efficiency of relativism than the proportional estimate. Therefore, it is further concluded that the anticipated memory type estimation under SRS is more well-organized than their comparative estimations deliberated and shown in the numerical investigation.
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References


Appendix:

In order to derive the MSE of the proposed estimator, we define the following notations such as:

\[ e_{st} = \frac{E_{st} - \bar{Y}}{\bar{Y}} \quad \text{and} \quad e_{sr} = \frac{E_{sr} - \bar{X}}{\bar{X}} \]

\[ E(e_{st}) = 0, \quad E(e_{sr}) = 0, \]

\[ E(e_{st}^2) = \frac{Var(E_{st})}{\bar{Y}^2} = \frac{1}{\bar{Y}^2} \left[ \frac{\lambda}{2 - \lambda} \right] Var(\bar{y}_{reg}) \]

Further we have,

\[ E(e_{st}e_{sr}) = \frac{1}{XY} Cov(E_{st}, E_{sr}) = \frac{1}{XY} \left[ \frac{\lambda}{2 - \lambda} \right] Cov(\bar{y}_{reg}, \bar{x}_t). \]

Where \( Var(\bar{y}_{reg}) = \theta \frac{S_y^2}{n} (1 - \rho^2) \), \( Var(\bar{x}_t) = \theta \frac{S_x^2}{n} \) and \( Cov(\bar{y}_{reg}, \bar{x}_t) = 0. \)

To derive the MSE expression put the value of \( E_{st} \) and \( E_{sr} \) into (12) and then simplifying by Taylor series approximation, we have.

\[ \bar{y}_{dat}^M = \bar{Y} \left( 1 + e_{st} \right) \left( 1 + e_{sr} \right)^{-1}, \]

Further simplifying and ignoring the higher-order terms, the approximate expression is obtained as follows.

\[ \bar{y}_{dat}^M \approx \bar{Y} \left( 1 + e_{st} \right) \left( 1 - e_{sr} \right), \]

The approximate mean square error expression is given by.

\[ MSE\left( \bar{y}_{dat}^M \right) \approx \bar{Y}^2 \left[ Var(E_{st}) + R \left( Var(E_{sr}) - 2 R Cov(E_{st}, E_{sr}) \right) \right] \]

\[ MSE\left( \bar{y}_{dat}^M \right) \approx \frac{\lambda}{2 - \lambda} \left[ Var(\bar{y}_{reg}) + R^2 Var(\bar{x}_t) - 2 R Cov(\bar{y}_{reg}, \bar{x}_t) \right] \]

\[ MSE\left( \bar{y}_{dat}^M \right) \approx 0 \frac{\lambda}{2 - \lambda} \left[ S_y^2 \left( 1 - \rho^2 \right) + R^2 S_x^2 \right] \]

\[ MSE\left( \bar{y}_{dat}^M \right) \approx 0 \frac{\lambda}{2 - \lambda} \left[ C_y^2 \left( 1 - \rho^2 \right) + C_x^2 \right] \]
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Table 1: MSEs of proposed and under study estimators

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<th>λ</th>
<th>n</th>
<th>[\hat{y}_n]</th>
<th>[\hat{y}_{dn}]</th>
<th>[\hat{y}_M]</th>
<th>[\hat{y}_{dn}]</th>
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Note: *0.0000 is approximately zero up to 4 decimal places, but RE is possible to calculate.

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Table-2: REs of proposed and under study estimators

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<th>$\lambda$</th>
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Table 3: Summary results of illustrative example

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