# On The Estimation of Population Mean in Current Occasion in Two- Occasion Rotation Patterns 

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Received: 19 Feb. 2015, Revised: 10 Apr. 2015, Accepted: 12 Apr. 2015.
Published online: 1 Jul. 2015.


#### Abstract

The present work is an effort to develop some estimators of current population mean in two-occasion successive sampling utilizing the known population mean $\bar{Z}$ alongwith known correlation coefficient $\rho_{y z}$ and coefficient of kurtosis $\beta_{2}(z)$ of the auxiliary variable $z$ on both occasions in successive sampling. Optimum replacement policy relevant to the proposed estimators has been discussed. Numerical illustration is carried out and appropriate recommendations are made.


Keywords: Auxiliary variable, Study variable, Bias, Mean square error, Efficiency Comparison.

## 1 Introduction

The problem of sampling on two successive occasions was first considered by Jessen [1] who introduced the idea of sampling on two occasions by using the information gathered on the previous occasions to improve the precision of the current estimate. Later several authors including Patterson [2], Narain [3], Eckler [4], Rao and Graham [5], Gordon [6], Arnab and Okafor [7] and Singh et al. [8], among others have developed the theory of successive sampling. Sen [9] applied this theory in designing the strategies for estimating the population mean on the current occasion using information on two auxiliary variables. Sen $[10,11]$ extended his work for multiple auxiliary variables. Fen and Zou [12] and Biradar and Singh [13] used the auxiliary information on both occasions for estimating the current population mean in the successive sampling. Singh [14], Singh and Vishwakarma [15, 16, 17] have used the auxiliary information on both occasions and envisaged several estimators for estimating the population mean on current (second) occasion in two - occasion successive (rotation) sampling.
Recently Singh and Pal $[18,19]$ have suggested some estimators utilizing the known population mean $\bar{Z}$ alongwith known coefficient of variation $C_{z}$ and Standard deviation $S_{z}$ of the auxiliary variable $z$ on both occasions in successive sampling for estimating the current (second) population mean in two occasion successive sampling. Motivated by Singh and Pal [18, 19], Singh and Tailor [20] and Singh et al. [21] we have suggested some estimators utilizing the known population mean $\bar{Z}$ alongwith known correlation coefficient $\rho_{y z}$ and coefficient of kurtosis $\beta_{2}(z)$ of the auxiliary variable $z$ on both occasions in successive sampling for estimating the current (second) population mean in two occasion successive sampling.

## 2 The Suggested Class of Estimators

Let $U=\left(U_{l}, U_{2} \ldots U_{N}\right)$ be the finite population of size $N$ units, which has been sampled over two occasions. The character under study be denoted by $x(y)$ on the first (second) occasion respectively. It is assumed that information on population coefficient of Kurtosis $\beta_{2}(z)$ of an auxiliary variable $z$ along with known population mean $\bar{Z}$ is available for the both the occasions. As pointed by Singh and Tailor [20] and Sahai and Sahai [22] the population correlation coefficient $\rho_{y z}$ between the study variable $y$ and auxiliary variable $z$ can also be made known from the post data or experience gathered in due to course of time. So we have assumed that $\rho_{y z}$ is also known along with the population mean $\bar{Z}$ of an auxiliary
variable $Z$ on both occasions. In such situation, we have to proposed two combined classes of estimators of the population mean $\bar{Y}$ on the current (second) occasion, one is based on ( $\rho_{y z}, \bar{Z}$ ) and second on ( $\left.\beta_{2}(z), \bar{Z}\right)$.

A simple random sample of $n$ units is drawn without replacement (WOR) on the first occasion. A random sub sample of $m$ ( $=n \lambda$ ) units is retained (matched) from the sample drawn on the first occasion for its use on the current (second) occasion, while a fresh sample of size $u=(n-m)=n \mu$ units is drawn on the current (second) occasion, from the entire population by simple random sampling without replacement (SRSWOR) method so that the sample size on the current (second) is also $n$. The fractions of the matched and fresh samples are respectively designated by $\lambda$ and $\mu$ such that $\lambda+\mu=1$.

The following notations have been used throughout the paper.
$\bar{X}, \bar{Y}, \bar{Z}$ : The population means of the variables $x, y$ and $z$ respectively.
$\bar{x}_{m}, \bar{x}_{n}, \bar{y}_{u}, \bar{y}_{m}, \bar{z}_{u}, \bar{z}_{n}$ : The sample means of the respective variables based on the sample sizes indicated in suffices.
$C_{x}, C_{y}, C_{z}$ : The coefficients of variation of the variables $x, y$ and $z$ respectively,
$\rho_{y x}, \rho_{y z}, \rho_{x z}:$ The correlation coefficients between the variables shown in suffices .
$S_{x}^{2}=(N-1)^{-1} \sum_{i=1}^{N}\left(x_{i}-\bar{X}\right)^{2}, S_{y}^{2}=(N-1)^{-1} \sum_{i=1}^{N}\left(y_{i}-\bar{Y}\right)^{2}, S_{z}^{2}=(N-1)^{-1} \sum_{i=1}^{N}\left(z_{i}-\bar{Z}\right)^{2}$ are
The population mean squares of $x, y$ and $z$ respectively,
$f=n / N$ : The sampling fraction.
For estimating the population mean $\bar{Y}$ on the second (current) occasion two different sets of estimators are proposed. One set of estimators $\tau_{u}=\left\{\tau_{1 u}, \tau_{2 u}\right\}$ based on sample size $u(=n \mu)$ drawn afresh on the second occasion and the second set of estimators $\tau_{m}=\left\{\tau_{1 m}, \tau_{2 m}\right\}$ based on the sample size $m(=n \lambda)$ common with both occasions. Estimators of sets $\tau_{u}$ and $\tau_{m}$ are given below:

$$
\begin{align*}
\tau_{1 u} & =\bar{y}_{u}\left(\frac{\bar{Z}+\rho_{y z}}{\bar{z}_{u}+\rho_{y z}}\right)  \tag{2.1}\\
\tau_{2 u} & =\bar{y}_{u}\left(\frac{\bar{Z}+\beta_{2}(z)}{\bar{z}_{u}+\beta_{2}(z)}\right) \tag{2.2}
\end{align*}
$$

And

$$
\begin{align*}
\tau_{1 m} & =\bar{y}_{m}\left(\frac{\bar{x}_{n}}{\bar{x}_{m}}\right)\left(\frac{\bar{Z}+\rho_{y z}}{\bar{z}_{n}+\rho_{y z}}\right),  \tag{2.3}\\
\tau_{2 m} & =\bar{y}_{m}\left(\frac{\bar{x}_{n}}{\bar{x}_{m}}\right)\left(\frac{\bar{Z}+\beta_{2}(z)}{\bar{z}_{n}+\beta_{2}(z)}\right) . \tag{2.4}
\end{align*}
$$

Where $\left(\rho_{y z}, \beta_{2}(z)\right)$ are known correlation coefficient between $y$ and $x$ and coefficient of kurtosis.
Combining the estimators of sets $\tau_{u}$ and $\tau_{m}$, we have the following estimators of the population mean $\bar{Y}$ at the second (current) occasion:
(i) when $\rho_{y z}$ is known along with population mean $\bar{Z}$ :

$$
\begin{equation*}
\tau_{1}=\varpi_{1} \tau_{1 u}+\left(1-\varpi_{1}\right) \tau_{1 m} \tag{2.5}
\end{equation*}
$$

(ii) when $\beta_{2}(z)$ is known along with population mean $\bar{Z}$ :

$$
\begin{equation*}
\tau_{2}=\varpi_{2} \tau_{2 u}+\left(1-\varpi_{2}\right) \tau_{2 m} \tag{2.6}
\end{equation*}
$$

In short, we can define the estimators (2.5) and (2.6) as:

$$
\begin{equation*}
\tau_{i}=\varpi_{i} \tau_{i u}+\left(1-\varpi_{i}\right) \tau_{i m},(i=1,2) ; \tag{2.7}
\end{equation*}
$$

Where $\varpi_{i}(i=1,2)$ are unknown constants to be determined under certain criterion.

## 3 Bias and Mean Squared Errors of Suggested Estimators $\tau_{i}(\mathbf{i}=1,2)$

The biases and mean squared errors of the class of estimators $\tau_{i}(i=1,2)$ are given in the following Theorems 3.1 and 3.2.
Theorem 3.1 Biases of the proposed estimators $\tau_{i}(i=1,2)$ to the first order of approximation are given by

$$
\begin{equation*}
B\left(\tau_{i}\right)=\varpi_{i} B\left(\tau_{i u}\right)+\left(1-\varpi_{i}\right) B\left(\tau_{i m}\right) \tag{3.1}
\end{equation*}
$$

Where

$$
\begin{gather*}
B\left(\tau_{i u}\right)=\bar{Y}((1 / u)-(1 / N)) \delta_{i}\left(\delta_{i} C_{z}^{2}-\rho_{y z} C_{y} C_{z}\right),(i=1,2),  \tag{3.2}\\
B\left(\tau_{i m}\right)=\bar{Y}\left[((1 / m)-(1 / N))\left(C_{x}^{2}-\rho_{y x} C_{y} C_{x}\right)+((1 / n)-(1 / N)) \delta_{i}\left(\delta_{i} C_{z}^{2}-\rho_{y z} C_{y} C_{z}\right)\right],  \tag{3.3}\\
\delta_{1}=\bar{Z} /\left(\bar{Z}+\rho_{y z}\right) \text { And } \delta_{2}=\bar{Z} /\left(\bar{Z}+\beta_{2}(z)\right) .
\end{gather*}
$$

Proof is simple so omitted.
Theorem 3.2 The mean squared errors of the suggested combined class of estimators $\tau_{i}(i,=1,2)$ to first degree of approximation are given by

$$
\begin{equation*}
M\left(\tau_{i}\right)=\left[\varpi_{i}^{2} M\left(\tau_{i u}\right)+\left(1-\varpi_{i}\right)^{2} M\left(\tau_{i m}\right)+2 \varpi_{i}\left(1-\varpi_{i}\right) \operatorname{Cov}\left(\tau_{i u}, \tau_{i m}\right)\right],(i=1,2), \tag{3.4}
\end{equation*}
$$

Where

$$
\begin{align*}
M\left(\tau_{i u}\right) & =\bar{Y}^{2}((1 / u)-(1 / N))\left[C_{y}^{2}+\delta_{i}\left(\delta_{i} C_{z}^{2}-2 \rho_{y z} C_{y} C_{z}\right)\right], \\
& =\bar{Y}^{2}((1 / u)-(1 / N))\left(C_{y}^{2}+\omega_{i}\right)  \tag{3.5}\\
M\left(\tau_{i m}\right) & =\bar{Y}^{2}\left[(1 / m) \omega+(1 / n)\left(C_{y}^{2}-\omega+\omega_{i}\right)-1 / N\left(C_{y}^{2}+\omega_{i}\right)\right], \\
& =\bar{Y}^{2}\left[(1 / m) \omega+(1 / n) \omega_{i}^{*}-1 / N\left(C_{y}^{2}+\omega_{i}\right)\right],  \tag{3.6}\\
\operatorname{Cov}\left(\tau_{i u}, \tau_{i m}\right) & =-\left(\bar{Y}^{2} / N\right)\left(C_{y}^{2}+\omega_{i}\right),(i=1,2),  \tag{3.7}\\
\omega & =\left(C_{y}^{2}+C_{x}^{2}-2 \rho_{y x} C_{y} C_{x}\right),  \tag{3.8}\\
\omega_{i} & =\delta_{i}\left(\delta_{i} C_{z}^{2}-2 \rho_{y z} C_{y} C_{z}\right),  \tag{3.9}\\
\omega_{i}^{*} & =\left(C_{y}^{2}-\omega+\omega_{i}\right)  \tag{3.10}\\
& =\left\{2 \rho_{y x} C_{y} C_{x}-C_{x}^{2}+\delta_{i}\left(\delta_{i} C_{z}^{2}-2 \rho_{y z} C_{y} C_{z}\right)\right\} ;(i=1,2) .
\end{align*}
$$

## 4 Minimum Mean Squared Error of Proposed Estimators $\tau_{i}(\mathbf{i}=\mathbf{1}, \mathbf{2})$

Differentiating $M\left(\tau_{i}\right)$ at (3.4) with respect to $\varpi_{i}$ and equating to zero we get the optimum value of $\varpi_{i}$ as

$$
\begin{gather*}
\varpi_{\text {iopt }}=\frac{\left[M\left(\tau_{i m}\right)-\operatorname{Cov}\left(\tau_{i u}, \tau_{i m}\right)\right]}{\left[M\left(\tau_{i u}\right)+M\left(\tau_{i m}\right)-2 \operatorname{Cov}\left(\tau_{i u}, \tau_{i m}\right)\right]}, \\
=\frac{\mu_{i}\left(A_{i}-\mu_{i} B_{i}\right)}{\left(A_{i}-\mu_{i}^{2} B_{i}\right)}, \tag{4.1}
\end{gather*}
$$

Where $A_{i}=\left\{1+\delta_{i}\left(\delta_{i}-2 \rho_{y z}\right)\right\}$ and $B_{i}=\left\{2 \rho_{y x}-1+\delta_{i}\left(\delta_{i}-2 \rho_{y z}\right)\right\}$.
Thus the resulting minimum $\operatorname{MSE}$ of $\tau_{i}(i=1,2)$ is given by

$$
\begin{align*}
\min . M\left(\tau_{i}\right)= & \frac{\left[M\left(\tau_{i u}\right) M\left(\tau_{i m}\right)-\left\{\operatorname{Cov}\left(\tau_{i u}, \tau_{i m}\right)\right\}^{2}\right]}{\left[M\left(\tau_{i u}\right)+M\left(\tau_{i m}\right)-2 \operatorname{Cov}\left(\tau_{i u}, \tau_{i m}\right)\right]}, \\
& =\frac{S_{y}^{2}}{n} \frac{A_{i}\left[(1-f) A_{i}-\mu_{i} B_{i}+f \mu_{i}^{2} B_{i}\right]}{\left(A_{i}-\mu_{i}^{2} B_{i}\right)} . \tag{4.2}
\end{align*}
$$

## 5 Optimum Replacement Policy

To obtain the optimum value of $\mu_{i}$ (fraction of a sample to be drawn afresh on the second occasion) so that the population mean $\bar{Y}$ may be estimated with maximum precision. Differentiating $\min . M\left(\tau_{i}\right)$ at (4.2) with respect to $\mu_{i}$ and equating it to zero we get

$$
\begin{equation*}
B_{i} \mu^{2}-2 A_{i} \mu+A_{i}=0,(i=1,2) \tag{5.1}
\end{equation*}
$$

Solution of the above equation is given by

$$
\begin{equation*}
\mu_{i o}=\frac{A_{i} \pm \sqrt{2\left(1-\rho_{y x}\right) A_{i}}}{B_{i}},(i=1,2) \tag{5.2}
\end{equation*}
$$

From (5.2) two values of $\mu_{i 0}$ are possible, hence to choose a value of $\mu_{i 0}$, it should be recommended that $0 \leq \mu_{i 0} \leq 1$, all other values of $\mu_{i 0}$ are inadmissible. Substituting the value of $\mu_{i 0}$ from equation (5.2) into equation (4.2), we have

$$
\begin{equation*}
\min \cdot M\left(\tau_{i}\right)_{o p t}=\frac{S_{y}^{2}}{n} \frac{A_{i}\left[(1-f) A_{i}-\mu_{i 0} B_{i}+f \mu_{i 0}^{2} B_{i}\right]}{\left(A_{i}-\mu_{i 0}^{2} B_{i}\right)},(i=1,2) \tag{5.3}
\end{equation*}
$$

## 6 Efficiency Comparison

The percent relative efficiencies(PREs) of the suggested estimators ' $\tau_{i}$ ' with respect to usual unbiased estimator $\bar{y}_{n}$, when there is no matching and the estimator $\hat{\bar{Y}}=\psi \bar{y}_{u}+(1-\psi) \bar{y}_{m}^{\prime}$, when no auxiliary information is used at any occasion, where $\bar{y}_{m}^{\prime}=\bar{y}_{m}+\beta_{y x}\left(\bar{x}_{n}-\bar{x}_{m}\right)$ and $\beta_{y x}$ is the known population regression coefficient; have been obtained for various choices $\rho_{y x}, \rho_{y z}$ and $\delta_{i}$.

Following Sukhatme et al. [23], the variance of usual unbiased estimator $\bar{y}_{n}$ and optimum variance of $\hat{\bar{Y}}$ are respectively given by

$$
\begin{equation*}
V\left(\bar{y}_{n}\right)=(1-f) \frac{S_{y}^{2}}{n} \tag{6.1}
\end{equation*}
$$

And

$$
\begin{equation*}
V(\hat{\bar{Y}})=\left[(1 / 2)\left(1+\sqrt{\left(1-\rho_{y x}^{2}\right)}\right)-f\right] \frac{S_{y}^{2}}{n}, \tag{6.2}
\end{equation*}
$$

For $\mathrm{N}=1000, \mathrm{n}=100$ and the various choices $\rho_{y x}, \rho_{y z}, \overline{\mathrm{Z}}$ and $\beta_{2}(z)$, Table 6.1 and Table 6.2 depicts the optimum values $\mu_{i 0}$ of $\mu_{i}(i=1,2)$ and the percent relative efficiencies (PREs) $E_{i}^{(1)}$ and $E_{i}^{(2)}$ of the suggested estimator $\tau_{i}(i=1,2)$ with respect to $\bar{y}_{n}$ and $\hat{\bar{Y}}$ respectively by using the following formulae:

$$
\begin{align*}
E_{i}^{(1)} & =\frac{V\left(\bar{y}_{n}\right)}{\min \cdot M\left(\tau_{i}\right)_{o p t}} \times 100 \\
& =\frac{(1-f)\left(A_{i}-\mu_{i 0}^{2} B_{i}\right)}{A_{i}\left[(1-f) A_{i}-\mu_{i 0} B_{i}+f \mu_{i 0}^{2} B_{i}\right]} \times 100, \tag{6.3}
\end{align*}
$$

And

$$
\begin{align*}
& E_{i}^{(2)}=\frac{V(\hat{\bar{Y}})_{o p t}}{\min \cdot M\left(\tau_{i}\right)_{o p t}} \times 100 \\
&\left.\left.=\frac{\left[\left(\frac{1}{2}\right)\left(1+\sqrt{\left(1-\rho_{y x}^{2}\right.}\right)\right.}{}\right)-f\right]\left(A_{i}-\mu_{i 0}^{2} B_{i}\right)  \tag{6.4}\\
& A_{i}\left[(1-f) A_{i}-\mu_{i 0} B_{i}+f \mu_{i 0}^{2} B_{i}\right]
\end{align*} 100, ~ \$
$$

Findings are shown in Table 6.1 and 6.2. To make the numerical values obtained for (PREs).
In Table 6.1 and 6.2 more comprehensible to the readers we have represented these through figures 6.1 and 6.2 respectively.
Table 6.1: The percent relative efficiencies (PREs) of $\tau_{i}(i=1,2)$ with respect to $\bar{y}_{n}$ and $\hat{\bar{Y}}$ for different values of $\rho_{y x}, \rho_{y z}$ and $\bar{Z}$.

| $\rho_{y x}$ | $\rho_{y z}$ | $\bar{Z}$ | $\mu_{10}$ | $E_{1}^{(1)}$ | $E_{1}^{(2)}$ | $\bar{Z}$ | $\mu_{10}$ | $E_{1}^{(1)}$ | $E_{1}^{(2)}$ | $\bar{Z}$ | $\mu_{10}$ | $E_{1}^{(1)}$ | $E_{1}^{(2)}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0.50 | 0.60 | 10.0 | 0.4654 | 121.87 | 112.80 | 20.0 | 0.4686 | 119.69 | 110.79 | 30.0 | 0.4697 | 118.92 | 110.07 |
| 0.50 | 0.70 | 10.0 | 0.4291 | 149.54 | 138.41 | 20.0 | 0.4325 | 146.72 | 135.80 | 30.0 | 0.4338 | 145.69 | 134.84 |
| 0.50 | 0.80 | 10.0 | 0.3801 | 196.99 | 182.33 | 20.0 | 0.3832 | 193.50 | 179.10 | 30.0 | 0.3845 | 192.11 | 177.81 |
| $\mathbf{0 . 5 0}$ | $\mathbf{0 . 9 0}$ | $\mathbf{1 0 . 0}$ | $\mathbf{0 . 3 0 3 7}$ | $\mathbf{3 0 5 . 8 7}$ | $\mathbf{2 8 3 . 1 1}$ | $\mathbf{2 0 . 0}$ | $\mathbf{0 . 3 0 5 4}$ | $\mathbf{3 0 2 . 9 4}$ | $\mathbf{2 8 0 . 3 9}$ | $\mathbf{3 0 . 0}$ | $\mathbf{0 . 3 0 6 3}$ | $\mathbf{3 0 1 . 1 9}$ | $\mathbf{2 7 8 . 7 7}$ |
| 0.60 | 0.60 | 10.0 | 0.4932 | 129.96 | 115.52 | 20.0 | 0.4964 | 127.59 | 113.42 | 30.0 | 0.4976 | 126.75 | 112.67 |
| 0.60 | 0.70 | 10.0 | 0.4566 | 160.09 | 142.30 | 20.0 | 0.4601 | 157.02 | 139.57 | 30.0 | 0.4613 | 155.89 | 138.57 |
| 0.60 | 0.80 | 10.0 | 0.4067 | 212.01 | 188.45 | 20.0 | 0.4099 | 208.18 | 185.05 | 30.0 | 0.4112 | 206.66 | 183.70 |
| 0.60 | 0.90 | 10.0 | 0.3278 | 331.84 | 294.97 | 20.0 | 0.3295 | 328.60 | 292.09 | 30.0 | 0.3305 | 326.67 | 290.38 |
| 0.70 | 0.60 | 10.0 | 0.5292 | 140.55 | 118.23 | 20.0 | 0.5324 | 137.92 | 116.02 | 30.0 | 0.5335 | 136.99 | 115.24 |
| 0.70 | 0.70 | 10.0 | 0.4925 | 174.04 | 146.40 | 20.0 | 0.4959 | 170.61 | 143.52 | 30.0 | 0.4972 | 169.36 | 142.46 |
| 0.70 | 0.80 | 10.0 | 0.4418 | 232.09 | 195.23 | 20.0 | 0.4451 | 227.80 | 191.62 | 30.0 | 0.4464 | 226.09 | 190.19 |
| 0.70 | 0.90 | 10.0 | 0.3603 | 367.23 | 308.91 | 20.0 | 0.3620 | 363.56 | 305.83 | 30.0 | 0.3631 | 361.38 | 303.99 |
| 0.80 | 0.60 | 10.0 | 0.5792 | 155.58 | 121.01 | 20.0 | 0.5823 | 152.58 | 118.67 | 30.0 | 0.5834 | 151.51 | 117.84 |
| 0.80 | 0.70 | 10.0 | 0.5431 | 194.09 | 150.96 | 20.0 | 0.5465 | 190.13 | 147.88 | 30.0 | 0.5478 | 188.69 | 146.76 |
| 0.80 | 0.80 | 10.0 | 0.4922 | 261.47 | 203.36 | 20.0 | 0.4956 | 256.46 | 199.47 | 30.0 | 0.4969 | 254.47 | 197.92 |


| 0.80 | 0.90 | 10.0 | 0.4082 | 420.42 | 326.99 | 20.0 | 0.4100 | 416.07 | 323.61 | 30.0 | 0.4112 | 413.49 |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| 0.90 | 0.60 | 10.0 | 0.6606 | 180.78 | 124.13 | 20.0 | 0.6635 | 177.10 | 121.60 | 30.0 | 0.6645 | 175.80 |
| 0.90 | 0.70 | 10.0 | 0.6270 | 228.37 | 156.80 | 20.0 | 0.6302 | 223.46 | 153.43 | 30.0 | 0.6314 | 221.66 |
| 0.90 | 0.80 | 10.0 | 0.5782 | 313.12 | 214.99 | 20.0 | 0.5815 | 306.77 | 210.63 | 30.0 | 0.5828 | 304.25 |
| 0.90 | 0.90 | 10.0 | 0.4938 | 518.23 | 355.82 | 20.0 | 0.4957 | 512.55 | 351.92 | 30.0 | 0.4969 | 509.17 |



Figure 6.1: The percent relative efficiencies (PREs) of $\tau_{i}(i=1,2)$ with respect to $\bar{y}_{n}$ and $\hat{\bar{Y}}$ for fixed values of $\rho_{y x}=0.5, \bar{Z}=10$ and different values of $\rho_{y z}$.

Table 6.2: The percent relative efficiencies of (PREs) $\tau_{i}(i=1,2)$ with respect to $\bar{y}_{n}$ and $\hat{\bar{Y}}$ for different values of $\rho_{y x}, \rho_{y z}$, $\bar{Z}$ and $\beta_{2}(z)=5.0$.

| $\rho_{y x}$ | $\rho_{y z}$ | $\beta_{2}(z)$ | $\bar{Z}$ | $\mu_{20}$ | $E_{2}^{(1)}$ | $E_{2}^{(2)}$ | $\bar{Z}$ | $\mu_{20}$ | $E_{2}^{(1)}$ | $E_{2}^{(2)}$ | $\bar{Z}$ | $\mu_{20}$ | $E_{2}^{(1)}$ | $E_{2}^{(2)}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0.50 | 0.50 | 5.0 | 10.0 | 0.4686 | 119.67 | 110.76 | 20.0 | 0.4782 | 113.31 | 104.88 | 30.0 | 0.4837 | 109.84 | 101.66 |
| 0.50 | 0.60 | 5.0 | 10.0 | 0.4453 | 136.54 | 126.37 | 20.0 | 0.4519 | 131.52 | 121.73 | 30.0 | 0.4566 | 128.09 | 118.56 |
| 0.50 | 0.70 | 5.0 | 10.0 | 0.4169 | 160.17 | 148.25 | 20.0 | 0.4190 | 158.30 | 146.51 | 30.0 | 0.4224 | 155.31 | 143.75 |
| 0.50 | 0.80 | 5.0 | 10.0 | 0.3807 | 196.32 | 181.71 | 20.0 | 0.3750 | 202.70 | 187.62 | 30.0 | 0.3761 | 201.49 | 186.50 |
| $\mathbf{0 . 5 0}$ | $\mathbf{0 . 9 0}$ | $\mathbf{5 . 0}$ | $\mathbf{1 0 . 0}$ | $\mathbf{0 . 3 3 0 8}$ | $\mathbf{2 6 0 . 8 8}$ | $\mathbf{2 4 1 . 4 6}$ | $\mathbf{2 0 . 0}$ | $\mathbf{0 . 3 0 9 0}$ | $\mathbf{2 9 6 . 4 4}$ | $\mathbf{2 7 4 . 3 7}$ | $\mathbf{3 0 . 0}$ | $\mathbf{0 . 3 0 4 6}$ | $\mathbf{3 0 4 . 3 3}$ | $\mathbf{2 8 1 . 6 8}$ |
| 0.60 | 0.50 | 5.0 | 10.0 | 0.4965 | 127.57 | 113.39 | 20.0 | 0.5061 | 120.66 | 107.26 | 30.0 | 0.5116 | 116.89 | 103.90 |
| 0.60 | 0.60 | 5.0 | 10.0 | 0.4730 | 145.92 | 129.70 | 20.0 | 0.4797 | 140.45 | 124.85 | 30.0 | 0.4844 | 136.73 | 121.53 |
| 0.60 | 0.70 | 5.0 | 10.0 | 0.4442 | 171.70 | 152.62 | 20.0 | 0.4464 | 169.65 | 150.80 | 30.0 | 0.4498 | 166.39 | 147.90 |
| 0.60 | 0.80 | 5.0 | 10.0 | 0.4073 | 211.28 | 187.80 | 20.0 | 0.4015 | 218.27 | 194.02 | 30.0 | 0.4026 | 216.95 | 192.84 |
| 0.60 | 0.90 | 5.0 | 10.0 | 0.3560 | 282.23 | 250.87 | 20.0 | 0.3333 | 321.43 | 285.71 | 30.0 | 0.3287 | 330.14 | 293.46 |
| 0.70 | 0.50 | 5.0 | 10.0 | 0.5324 | 137.89 | 115.99 | 20.0 | 0.5420 | 130.25 | 109.57 | 30.0 | 0.5474 | 126.08 | 106.06 |
| 0.70 | 0.60 | 5.0 | 10.0 | 0.5089 | 158.26 | 133.13 | 20.0 | 0.5156 | 152.19 | 128.02 | 30.0 | 0.5203 | 148.05 | 124.54 |
| 0.70 | 0.70 | 5.0 | 10.0 | 0.4800 | 186.98 | 157.29 | 20.0 | 0.4821 | 184.70 | 155.37 | 30.0 | 0.4856 | 181.06 | 152.30 |
| 0.70 | 0.80 | 5.0 | 10.0 | 0.4424 | 231.27 | 194.54 | 20.0 | 0.4365 | 239.12 | 201.15 | 30.0 | 0.4376 | 237.63 | 199.89 |
| 0.70 | 0.90 | 5.0 | 10.0 | 0.3896 | 311.14 | 261.72 | 20.0 | 0.3660 | 355.44 | 299.00 | 30.0 | 0.3612 | 365.31 | 307.29 |
| 0.80 | 0.50 | 5.0 | 10.0 | 0.5824 | 152.54 | 118.64 | 20.0 | 0.5917 | 143.81 | 111.85 | 30.0 | 0.5970 | 139.05 | 108.15 |
| 0.80 | 0.60 | 5.0 | 10.0 | 0.5593 | 175.91 | 136.82 | 20.0 | 0.5659 | 168.93 | 131.39 | 30.0 | 0.5706 | 164.18 | 127.70 |
| 0.80 | 0.70 | 5.0 | 10.0 | 0.5306 | 209.05 | 162.59 | 20.0 | 0.5327 | 206.41 | 160.54 | 30.0 | 0.5362 | 202.20 | 157.26 |
| 0.80 | 0.80 | 5.0 | 10.0 | 0.4929 | 260.51 | 202.62 | 20.0 | 0.4868 | 269.67 | 209.75 | 30.0 | 0.4880 | 267.94 | 208.39 |
| 0.80 | 0.90 | 5.0 | 10.0 | 0.4387 | 354.16 | 275.46 | 20.0 | 0.4142 | 406.46 | 316.14 | 30.0 | 0.4092 | 418.14 | 325.22 |


| 0.90 | 0.50 | 5.0 | 10.0 | 0.6635 | 177.06 | 121.57 | 20.0 | 0.6721 | 166.38 | 114.24 | 30.0 | 0.6769 | 160.57 | 110.25 |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0.90 | 0.60 | 5.0 | 10.0 | 0.6422 | 205.82 | 141.31 | 20.0 | 0.6484 | 197.20 | 135.40 | 30.0 | 0.6527 | 191.35 | 131.38 |
| 0.90 | 0.70 | 5.0 | 10.0 | 0.6152 | 247.05 | 169.62 | 20.0 | 0.6172 | 243.74 | 167.35 | 30.0 | 0.6205 | 238.48 | 163.74 |
| 0.90 | 0.80 | 5.0 | 10.0 | 0.5788 | 311.91 | 214.16 | 20.0 | 0.5729 | 323.55 | 222.15 | 30.0 | 0.5741 | 321.34 | 220.63 |
| 0.90 | 0.90 | 5.0 | 10.0 | 0.5251 | 432.00 | 296.62 | 20.0 | $*$ | - | - | 30.0 | 0.4948 | 515.25 | 353.77 |



Figure 6.2: The percent relative efficiencies (PREs) of $\tau_{i}(i=1,2)$ with respect to $\bar{y}_{n}$ and $\hat{\bar{Y}}$ for fixed values of $\rho_{y x}=0.5, \beta_{2}(z)=5.0, \bar{Z}=10$ and different values of $\rho_{y z}$.

From Table 6.1 it is observed that:
(i) For fixed values of $\left(\rho_{y x}, \rho_{y z}\right)$, the values of $\mu_{i 0}$ increases as the value of $\bar{Z}$ increases while the values of $E_{i}^{(1)}$ and $E_{i}^{(2)}$ decrease.
(ii) for fixed values of $\left(\rho_{y x}, \bar{Z}\right)$, the values of $\mu_{i 0}$ decreases as the value of $\rho_{y z}$ increases

While the values of $E_{i}^{(1)}$ and $E_{i}^{(2)}$ increase.
(iii) For fixed values of $\left(\bar{Z}, \rho_{y z}\right)$, the values of $\mu_{i 0}, E_{i}^{(1)}$ and $E_{i}^{(2)}$ increase with increasing value of $\rho_{y x}$. This behavior is in agreement with Sukhatme et al. [23], results which explained that more the value of $\rho_{y x}$, more the fractions of fresh sample required at the current occasion.
(iv) minimum value of $\mu_{10}$ is $0.3037(\cong 0.30)$ which shows that the fraction to be replaced at the current occasion is as low as about 30 percent of the total sample size leading to a reduction of considerable amount in the cost of the survey.

Similar trend and conclusions can be drawn from Table 6.2.

In addition to these it is observed from Tables 6.1 and 6.2 that there is appreciable gain in efficiencies by using the proposed estimators $\tau_{i}(i=1,2)$ over usual unbiased estimator $\bar{y}_{n}$ and the estimator $\hat{\bar{Y}}$. Thus we infer that the use of auxiliary information at the estimation stage is highly rewarding in terms of the proposed estimator $\tau_{i}(i=1,2)$.

We also note from Table 6.1 (and Figure 6.1) and Table 6.2 (and Figure 6.2) that the proposed estimators $\tau_{1}$ and $\tau_{2}$ yield more gain over $\bar{y}_{n}$ as compared to $\hat{\bar{Y}}$.

## 7 Conclusion

In this article, an efficient estimation procedure has been developed utilizing the known population mean $\bar{Z}$ alongwith known correlation coefficient $\rho_{y z}$ and coefficient of kurtosis $\beta_{2}(z)$ of the auxiliary variable $z$ on both the occasions for estimating the current (second) population mean in two occasion successive sampling. From numerical illustrations, it may be concluded that the suggested classes of estimators is more useful in estimation of the population mean of the study variable at the current occasion in two-occasion successive sampling. Finally looking on the good performance of the envisaged estimator, our suggestion is to use the proposed classes of estimators in practice.

## 8 Acknowledgements

The authors are highly grateful to the Editor-in-Chief and learned referees for their excellent comments which helped us to improve the previous draft of the paper.

## References

[1] R. J. Jessen, Statistical investigation of a sample survey for obtaining form facts. Iowa Agricultural Experiment Station Road Bulletin no. 304: Ames, USA, (1942).
[2] H.D. Patterson, Sampling on successive occasions with partial replacement of units. Jour. Roy. Statist. Assoc, B, 12, 241-255, (1950).
[3] R. D. Narain, On the recurrence formula in sampling on successive occasions. Journal of the Indian society of agriculture statistics, 5, 96-99, (1953).
[4] A.R. Eckler, Rotation sampling. Ann. Math. Statist. 26, 664-685, (1955).
[5] J.N.K. Rao, and J.E. Graham, Rotation design for sampling on repeated occasions. Jour. Amer. Statist. Assoc., 59, 492509, (1964).
[6] L. Gordon, Successive sampling in finite population. The Annals of statistics, 11(2), 702-706, (1983).
[7] R. Arnab, Okafor, F.C., A note on double sampling over two occasions. Pakistan Journal of Statistics, 8, 9-18, (1992).
[8] H.P. Singh, H.P. Singh and V.P. Singh, A generalized efficient class of estimators of population mean in two-phase and successive Sampling. Int. Jour. Manage. Systems, 8(2), 173-183, (1992).
[9] A .R. Sen, Successive sampling with two auxiliary variables. Sankhya, B, 33, 371- 378, (1971).
[10] A .R. Sen, Successive sampling with $\mathrm{p}(\mathrm{p} \geq 1)$ auxiliary variables, Ann. Math., 43, 2031-2034, (1972).
[11] A .R. Sen, Theory and application of sampling on repeated occasions with several auxiliary variables. Biometrics, 29: 381-385, (1973).
[12] S. Feng and G. Zou, Sampling rotation method with auxiliary variable. Commun. Statist. Theo. Meth., 26(6): 14971509, (1997).
[13] R. S. Biradar and H.P. Singh, Successive sampling using auxiliary information on both the occasions. Calcutta Statist. Assoc. Bull., 51, 243-251, (2001).
[14] G.N. Singh, on the use of chain type ratio estimator in successive Sampling Statistics in Transition - new series, 7(1), 21-26, (2005).
[15] H. P. Singh, and G.K. Vishwakarma, Modified exponential ratio product estimators for finite population mean in double sampling. Austrian Jour. Statist., 36(3), 217 - 225, (2007a).
[16] H.P. Singh, and G.K. Vishwakarma, A general class of estimators in successive sampling. Metron, 65(2), 201-227, (2007b).
[17] H.P. Singh, and G.K. Vishwakarma, A general procedure for estimating population mean in successive sampling. Commun. Statist. Theo. Meth., 38, 293-308, (2009).
[18] H. P. Singh and S. K. Pal, on the estimation of population mean in successive sampling. Int. Jour. Math. Sci. Applica., 5(1), 179-185, (2015a).
[19] H. P. Singh and S. K. Pal, on the estimation of population mean in rotation sampling. Jour. Statist. Applica. Pro. Lett. 2(2), 131-136, (2015b).
[20] H.P. Singh and R. Tailor, Use of known correlation coefficient in estimating the finite population mean. Statistics in Transition, 6 (4), 555-560, (2003).
[21] H.P. Singh, Tailor, Rajesh, Tailor, Ritesh and M. S. Kakran, An improved estimator of population mean using power transformation. Journal of the Indian Society of Agricultural Statistics, 58 (2), 223-230, (2004).
[22] A. Sahai and A. Sahai. An efficient use of auxiliary information. Jour. Statist. Plan.Inf.12, 203-212, (1985).
[23] P. V. Sukhatme, B. V. Sukhatme, and C. Ashok. Sampling theory of surveys with applications, 3rd ed. Ames, IA, Iowa State University Press, (1984).

