

A Simulation Study for Unit Non Response under Double Sampling

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Received: 21 Jul. 2014, Revised: 18 Aug. 2014, Accepted: 21 Aug. 2014

Published online: 1 Jan. 2015

Abstract: This paper suggests a new class of estimators under the general framework of two phase sampling scheme using auxiliary information where there is non-response on study as well as auxiliary variables. The expressions of bias and mean squared error (MSE) of the suggested class of estimators were obtained. Some estimators are also derived from the proposed class of estimators by allocating the suitable values of constants used. It has been shown that the proposed estimator is more efficient than the usual unbiased estimator and other estimators. Moreover, these theoretical findings are supported by simulation.

Keywords: Efficiency, Exponential estimator, Mean squared error, Ratio estimator, Simulation.

1 Introduction

The variable which is highly correlated with the study variable is popularly known as auxiliary variable which may be fruitfully utilized either at planning stage or at design stage or at the information stage to arrive at improved estimator compared to those without auxiliary information. Cochran (1942) pioneered the use of auxiliary information for forming ratio and regression method of estimation. When full information on auxiliary variable is available, and the auxiliary variable is highly correlated with the study variable, then it is well known that ratio and regression estimators provide more efficient estimates of the population mean of study variable. However, when the information on population mean \bar{X} of the auxiliary variable x is unknown, it is sometimes relatively cheap to take a large preliminary sample in which auxiliary variable alone is measured. The aim of this sample is to obtain a good estimate of the population mean or total of the auxiliary variable or its frequency distribution (Prabhu-Ajgaonkar, 1975). This technique is well known as double sampling or two phase sampling.

In general, conducting a mail survey, the problem of non-response often happens due to the refusal of the subject, absenteeism and sometimes due to the lack of information. Hansen and Hurwitz (1946) pioneered the treatment of non-response, assumes that a sub sample of initial non respondents is recontacted with a more expensive method; they suggested the first attempt by mail questionnaire and the second attempt by a personal interview. Sodip and Obisesan (2007) have studied the problem of estimating the population mean in the presence of non-response, in sample survey with full response of an auxiliary variable x . In general, it has been observed that the population mean of the auxiliary variable is not known. In such cases two phase (Double) sampling can be used for estimating the population mean of the auxiliary character. Cochran (1977), Foradari (1961), Upadhyaya et. al (1985), Rao (1986, 1987), Srdal, C. E. and Swensson, B. (1987), Khare and Srivastava (1993, 1995, 1997), Okafor and Lee (2000), Khare and Sinha (2004, 2007), Tabasum and Khan (2004, 2006), Singh et. al (2006), Singh and Kumar (2008, 2009, 2010), Kumar et. al (2011) and Kumar (2012) have studied the problem of non-response under double (or two phase) sampling.

Consider a finite population $U = (U_1, U_2, \dots, U_N)$, a large first phase sample of size n' is selected by simple random sampling without replacement (SRSWOR). From n' units, a second phase sample is selected of size n by SRSWOR. Non response occurs on the second phase sample of size n in which n_1 units respond and n_2 units do not respond. From the n_2

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non respondents, a sample of $r = (n_2/k)$; $k > 1$ units is selected by SRSWOR, where k is the inverse sampling rate at the second phase sample of size n . It is assumed that all the r units respond this time round.

Hansen and Hurwitz (1946) proposed an unbiased estimator for the population mean \bar{Y} of the study variable y as

$$\bar{y}^* = w_1 \bar{y}_1 + w_2 \bar{y}_{2r}, \quad (1)$$

where $w_i = (n_i/n)$; $i = 1, 2$; $\bar{y}_1 = \frac{1}{n_1} \sum_{i=1}^{n_1} y_i$ and $\bar{y}_{2r} = \frac{1}{r} \sum_{i=1}^r y_i$.

The variance of \bar{y}^* is given by

$$\text{Var}(\bar{y}^*) = \bar{Y}^2 \left\{ \left(\frac{1}{n} - \frac{1}{N} \right) C_y^2 + \frac{W_2(k-1)}{n} C_{y(2)}^2 \right\}, \quad (2)$$

where $S_y^2 = \frac{1}{N-1} \sum_{i=1}^N (y_i - \bar{Y})^2$; $S_{y(2)}^2 = \frac{1}{N_2-1} \sum_{i=1}^{N_2} (y_i - \bar{Y}_2)^2$; $C_y = \frac{S_y}{\bar{Y}}$; $C_{y(2)} = \frac{S_{y(2)}}{\bar{Y}_2}$;

$\bar{Y} = \frac{1}{N} \sum_{i=1}^N y_i$; $\bar{Y}_2 = \frac{1}{N_2} \sum_{i=1}^{N_2} y_i$; $W_i = \frac{N_i}{N}$; $i = 1, 2$; N_1 and N_2 are the sizes of the responding and non-responding units from the finite population of size N .

Let x denote an auxiliary variable with population mean $\bar{X} = \frac{1}{N} \sum_{i=1}^N x_i$. Let $\bar{X}_1 = \frac{1}{N_1} \sum_{i=1}^{N_1} x_i$ and $\bar{X}_2 = \frac{1}{N_2} \sum_{i=1}^{N_2} x_i$ denote the population means of the responding and non-responding units. Let $\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i$ denote the mean of all the n units. Let $\bar{x}_1 = \frac{1}{n_1} \sum_{i=1}^{n_1} x_i$ and $\bar{x}_2 = \frac{1}{n_2} \sum_{i=1}^{n_2} x_i$ are the means of the responding and non responding units. Further, let $\bar{x}_{2r} = \frac{1}{r} \sum_{i=1}^r x_i$ denotes the mean of the sub sampled units of size r . With this background, one can define an unbiased estimator of population mean as

$$\bar{x}^* = w_1 \bar{x}_1 + w_2 \bar{x}_{2r}, \quad (3)$$

with variance

$$\text{Var}(\bar{x}^*) = \bar{X}^2 \left\{ \left(\frac{1}{n} - \frac{1}{N} \right) C_x^2 + \frac{W_2(k-1)}{n} C_{x(2)}^2 \right\}, \quad (4)$$

where $S_x^2 = \frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{X})^2$; $S_{x(2)}^2 = \frac{1}{N_2-1} \sum_{i=1}^{N_2} (x_i - \bar{X}_2)^2$; $C_x = \frac{S_x}{\bar{X}}$; $C_{x(2)} = \frac{S_{x(2)}}{\bar{X}_2}$.

In the present study, a new class of estimators for estimating the population mean of the study variable under the framework of two phase sampling scheme when there is non-response occurs on both the variables i.e. study as well as auxiliary variable is proposed which includes the estimators/classes of estimators and its properties are studied.

2 The proposed class of estimators

A class of estimators is define when there is non-response on the study and auxiliary variable as

$$t^* = \omega_1 \bar{y}^* \left\{ \frac{\bar{X}''}{\alpha \bar{x}^1 + (1-\alpha) \bar{X}''} \right\}^g + \omega_2 \bar{y}^* \exp \left\{ \frac{\delta (\bar{X}'' - \bar{x}^1)}{\bar{X}'' + \bar{x}^1} \right\}, \quad (5)$$

where $\bar{X}'' = a\bar{x} + b$; $\bar{x}^1 = a\bar{x}^* + b$; and $a (\neq 0)$, b are either real numbers or functions of the known parameters of the auxiliary variable x such as the standard deviation (S_x), Coefficient of Variation (C_x), Coefficient of Skewness $\{\beta_1(x)\}$, Coefficient of Kurtosis $\{\beta_2(x)\}$, and Correlation coefficient (ρ_{yx}) of the population, α is a suitable constant, (g, δ) being constants which take values $(0, 1, -1)$ for deriving the different estimators, and (ω_1, ω_2) are suitably chosen constants to be determined such that $MSE(t^*)$ is minimum.

(i) for $(\omega_1, \omega_2) = (1, 0)$, the class of estimators t^* reduces to

$$t_1^* = \bar{y}^* \left\{ \frac{\bar{X}''}{\alpha \bar{x}^1 + (1-\alpha) \bar{X}''} \right\}^g; \quad (6)$$

(ii) for $(\omega_1, \omega_2) = (\omega_1, 0)$, the class of estimators t^* reduces to

$$t_2^* = \omega_1 \bar{y}^* \left\{ \frac{\bar{X}''}{\alpha \bar{x}^1 + (1-\alpha) \bar{X}''} \right\}^g; \quad (7)$$

(iii) for $(\omega_1, \omega_2) = (0, 1)$, the class of estimators t^* reduces to

$$t_3^* = \bar{y}^* \exp \left\{ \frac{\delta (\bar{X}'' - \bar{x}^1)}{\bar{X}'' + \bar{x}^1} \right\}; \tag{8}$$

(iv) for $(\omega_1, \omega_2) = (0, \omega_2)$, the class of estimators t^* reduces to

$$t_4^* = \omega_2 \bar{y}^* \exp \left\{ \frac{\delta (\bar{X}'' - \bar{x}^1)}{\bar{X}'' + \bar{x}^1} \right\}; \tag{9}$$

(v) for $(\omega_1, \omega_2, \delta) = (0, 1, 1)$, the class of estimators t^* reduces to

$$t_5^* = \bar{y}^* \exp \left\{ \frac{(\bar{X}'' - \bar{x}^1)}{\bar{X}'' + \bar{x}^1} \right\}; \tag{10}$$

The different estimators are defined in Appendix (A1-A8) are the members of the proposed estimators $t^*, t_1^*, t_2^*, t_3^*, t_4^*, t_5^*$, respectively. To obtain the bias and MSE of the proposed class of estimators, let $\bar{y}^* = \bar{Y}(1 + \epsilon_0)$, $\bar{x}^* = \bar{X}(1 + \epsilon_1)$ and $\bar{x}' = \bar{X}(1 + \epsilon_1')$ such that

$$E(\epsilon_0) = E(\epsilon_1) = E(\epsilon_1') = 0;$$

and

$$E(\epsilon_0^2) = \left\{ \left(\frac{1}{n} - \frac{1}{N} \right) C_y^2 + \frac{W_2(k-1)}{n} C_{y(2)}^2 \right\}; E(\epsilon_1^2) = \left\{ \left(\frac{1}{n'} - \frac{1}{N} \right) C_x^2 + \frac{W_2(k-1)}{n} C_{x(2)}^2 \right\};$$

$$E(\epsilon_1'^2) = \left(\frac{1}{n'} - \frac{1}{N} \right) C_x^2; E(\epsilon_1 \epsilon_1') = \left(\frac{1}{n'} - \frac{1}{N} \right) C_x^2; E(\epsilon_0 \epsilon_1) = \left(\frac{1}{n} - \frac{1}{N} \right) C_{yx} + \frac{W_2(k-1)}{n} C_{yx(2)};$$

$$E(\epsilon_0 \epsilon_1') = \left(\frac{1}{n'} - \frac{1}{N} \right) C_{yx},$$

where $S_{yx} = \frac{1}{N-1} \sum_{i=1}^N (y_i - \bar{Y})(x_i - \bar{X})$; $S_{yx(2)} = \frac{1}{N_2-1} \sum_{i=1}^{N_2} (y_i - \bar{Y})(x_i - \bar{X})$; $C_{yx} = \frac{S_{yx}}{YX}$;

$$C_{yx(2)} = \frac{S_{yx(2)}}{YX}.$$

Expand t^* in terms of ϵ' s, we obtain

$$t^* = \omega_1 \bar{Y}(1 + \epsilon_0) \left\{ 1 + \frac{\alpha v (\epsilon_1 - \epsilon_1')}{(1 + v \epsilon_1')} \right\}^{-g} + \omega_2 \bar{Y}(1 + \epsilon_0) \exp \left\{ \frac{v \delta}{2} (\epsilon_1 - \epsilon_1') \left(1 + \frac{v}{2} (\epsilon_1 + \epsilon_1') \right)^{-1} \right\} \tag{11}$$

where $v = \frac{a\bar{X}}{a\bar{X} + b}$.

Expanding the right hand side of (11), neglecting terms of ϵ' s having power greater than two and subtracting \bar{Y} from both sides, we get

$$(t^* - \bar{Y}) = \bar{Y} \left[\omega_1 \left\{ 1 - g \alpha v (\epsilon_1 - \epsilon_1' - v \epsilon_1 \epsilon_1' + v \epsilon_1'^2) + \frac{g(g+1)}{2} \alpha^2 v^2 (\epsilon_1^2 + \epsilon_1'^2 - 2 \epsilon_1 \epsilon_1') + \epsilon_0 - g \alpha v (\epsilon_0 \epsilon_1 - \epsilon_0 \epsilon_1') \right\} + \omega_2 \left\{ 1 + \frac{v \delta}{2} (\epsilon_1' - \epsilon_1) - \frac{v^2 \delta}{4} (\epsilon_1'^2 - \epsilon_1^2) + \frac{1}{2} \left(\frac{v \delta}{2} (\epsilon_1' - \epsilon_1) - \frac{v^2 \delta}{2} (\epsilon_1'^2 - \epsilon_1^2) \right)^2 + \epsilon_0 + \frac{v \delta}{2} (\epsilon_0 \epsilon_1' - \epsilon_0 \epsilon_1) \right\} - \right] \tag{12}$$

The bias of t^* to the first degree of approximation is obtained by taking expectations on both sides of (12) as

$$B(t^*) = \bar{Y} \left[\omega_1 \left\{ 1 + g \alpha v ((\lambda - \lambda') ((g+1) \alpha v C_x^2 - C_{yx})) - \theta C_{yx(2)} - \lambda (g+1) \alpha v C_x^2 \right\} + \omega_2 \left\{ 1 + (\lambda - \lambda') \frac{v \delta}{8} (v(2 - \delta) C_x^2 - 4 C_{yx}) + \frac{v \delta}{8} \theta (v(2 - \delta) C_{x(2)}^2 - 4 C_{yx(2)}) \right\} \right] \tag{13}$$

where $\lambda = \left(\frac{1}{n} - \frac{1}{N}\right)$; $\lambda' = \left(\frac{1}{n'} - \frac{1}{N}\right)$; $\theta = \frac{W_2(k-1)}{n}$.

By squaring and taking expectations of both sides of (12), we have the MSE of t^* to the first degree of approximation as

$$MSE(t^*) = \bar{Y}^2 (1 + \omega_1^2 A + \omega_2^2 C - 2\omega_1 B - 2\omega_2 E + 2\omega_1 \omega_2 D), \quad (14)$$

where

$$A = 1 + (\lambda - \lambda') \{C_y^2 + (g^2 \alpha^2 v^2 + g(g+1) \alpha^2 v^2) C_x^2 - 4g\alpha v C_{yx}\} + \lambda' C_y^2 \\ + \theta \{C_{y(2)}^2 + (g^2 \alpha^2 v^2 + g(g+1) \alpha^2 v^2) C_{x(2)}^2 - 4g\alpha v C_{yx(2)}\};$$

$$B = 1 + (\lambda - \lambda') \left\{ \frac{g(g+1)}{2} \alpha^2 v^2 C_x^2 - g\alpha v C_{yx} \right\} + \theta \left\{ \frac{g(g+1)}{2} \alpha^2 v^2 C_{x(2)}^2 - g\alpha v C_{yx(2)} \right\};$$

$$C = 1 + (\lambda - \lambda') \left\{ C_y^2 + v^2 \left(\frac{\delta^2 + \delta}{2} \right) C_x^2 - 2v\delta C_{yx} \right\} + \lambda' C_y^2 + \theta \left\{ C_{y(2)}^2 + v^2 \left(\frac{\delta^2 + \delta}{2} \right) C_{x(2)}^2 - 2v\delta C_{yx(2)} \right\};$$

$$D = 1 + (\lambda - \lambda') \left\{ C_y^2 + \frac{v^2}{8} \left\{ (2g\alpha + \delta)^2 + 2(2g\alpha^2 + \delta) \right\} C_x^2 - (2g\alpha + \delta) v C_{yx} \right\} + \lambda' C_y^2 \\ + \theta \left\{ C_{y(2)}^2 + \frac{v^2}{8} \left\{ (2g\alpha + \delta)^2 + 2(2g\alpha + \delta) \right\} C_{x(2)}^2 - (2g\alpha + \delta) v C_{yx(2)} \right\};$$

$$E = 1 + (\lambda - \lambda') \left\{ v^2 \left(\frac{\delta^2 + 2\delta}{8} \right) C_x^2 - \frac{v\delta}{2} C_{yx} \right\} + \theta \left\{ v^2 \left(\frac{\delta^2 + 2\delta}{8} \right) C_{x(2)}^2 - \frac{v\delta}{2} C_{yx(2)} \right\}.$$

The MSE (t^*) is minimum, when

$$\omega_1 = \frac{BC - ED}{AC - D^2} = \omega_{1(opt)} \quad (15)$$

and

$$\omega_2 = \frac{AE - BD}{AC - D^2} = \omega_{2(opt)}. \quad (16)$$

By substituting the optimum values of ω_1 and ω_2 from (15) and (16), we get the minimum MSE of the class of estimators t^* as

$$\min.MSE(t^*) = \bar{Y}^2 \left\{ 1 - \frac{B^2 C - 2BDE + AE^2}{AC - D^2} \right\}. \quad (17)$$

Thus, the following theorem to the first degree of approximation:

Theorem 1. $MSE(t^*) \geq \bar{Y}^2 \left\{ 1 - \frac{B^2 C - 2BDE + AE^2}{AC - D^2} \right\}$ with equality holding if $\omega_1 = \frac{BC - ED}{AC - D^2} = \omega_{1(opt)}$ and $\omega_2 = \frac{AE - BD}{AC - D^2} = \omega_{2(opt)}$.

The MSE of the estimators t_1^* , t_2^* , t_3^* , t_4^* and t_5^* , respectively obtained by substituting the different values of ω_1 , ω_2 and δ , as follows:

$$MSE(t_1^*) = \bar{Y}^2 \left[(\lambda - \lambda') (C_y^2 + g^2 \alpha^2 v^2 C_x^2 - 2g\alpha v C_{yx}) + \lambda' C_y^2 + \theta (C_{y(2)}^2 + g^2 \alpha^2 v^2 C_{x(2)}^2 - 2g\alpha v C_{yx(2)}) \right], \quad (18)$$

$$MSE(t_2^*) = \bar{Y}^2 (1 + \omega_1^2 A - 2\omega_1 B), \quad (19)$$

$$MSE(t_3^*) = \bar{Y}^2 \left[(\lambda - \lambda') \left(C_y^2 + \frac{v^2 \delta^2}{4} C_x^2 - v\delta C_{yx} \right) + \lambda' C_y^2 + \theta \left(C_{y(2)}^2 + \frac{v^2 \delta^2}{4} C_{x(2)}^2 - v\delta C_{yx(2)} \right) \right], \quad (20)$$

$$MSE(t_4^*) = \bar{Y}^2 (1 + \omega_2^2 C - 2\omega_2 E), \quad (21)$$

$$MSE(t_5^*) = \bar{Y}^2 \left[(\lambda - \lambda') \left(C_y^2 + \frac{v^2}{4} C_x^2 - v C_{yx} \right) + \lambda' C_y^2 + \theta \left(C_{y(2)}^2 + \frac{v^2}{4} C_{x(2)}^2 - v C_{yx(2)} \right) \right]. \quad (22)$$

The MSE of t_i^* ; $i = 1(1)5$ are respectively, minimized for

$$\alpha = \frac{(\lambda - \lambda') C_{yx} + \theta C_{yx(2)}}{(\lambda - \lambda') C_x^2 + \theta C_{x(2)}^2} = \alpha_{(opt)}, \tag{23}$$

$$\omega_1 = \frac{B}{A} = \omega_{1(opt)}^*, \tag{24}$$

$$\delta = \frac{2 \{ (\lambda - \lambda') C_{yx} + \theta C_{yx(2)} \}}{v \{ (\lambda - \lambda') C_x^2 + \theta C_{x(2)}^2 \}} = \delta_{(opt)}, \tag{25}$$

$$\omega_2 = \frac{E}{C} = \omega_{2(opt)}^* \tag{26}$$

and

$$v = \frac{2 \{ (\lambda - \lambda') C_{yx} + \theta C_{yx(2)} \}}{\{ (\lambda - \lambda') C_x^2 + \theta C_{x(2)}^2 \}} = v_{(opt)}. \tag{27}$$

Substituting $\alpha_{(opt)}$, $\omega_{1(opt)}^*$, $\delta_{(opt)}$, $\omega_{2(opt)}^*$ and $v_{(opt)}$, from (23) to (27) in the expressions of MSE of t_i^* ; $i = 1(1)5$ respectively, we obtain the *min.MSE* of t_i^* ; $i = 1(1)5$, to the first degree of approximation, as

$$\min.MSE(t_1^*) = \min.MSE(t_3^*) = \min.MSE(t_5^*) =$$

$$\bar{Y}^2 \left\{ (\lambda - \lambda') C_y^2 + \theta C_{y(2)}^2 - \frac{\{ (\lambda - \lambda') C_{yx} + \theta C_{yx(2)} \}^2}{(\lambda - \lambda') C_x^2 + \theta C_{x(2)}^2} + \lambda' C_y^2 \right\}, \tag{28}$$

$$\min.MSE(t_2^*) = \bar{Y}^2 \left(1 - \frac{B^2}{A} \right), \tag{29}$$

$$\min.MSE(t_4^*) = \bar{Y}^2 \left(1 - \frac{E^2}{C} \right). \tag{30}$$

3 Particular Case: When $\omega_1 + \omega_2 = 1$

For $\omega_1 + \omega_2 = 1$, the proposed class of estimators t^* reduces to

$$t_c^* = \omega_1 \bar{y}^* \left\{ \frac{\bar{X}''}{\alpha \bar{x}^1 + (1 - \alpha) \bar{X}''} \right\}^g + (1 - \omega_1) \bar{y}^* \exp \left\{ \frac{\delta (\bar{X}'' - \bar{x}^1)}{(\bar{X}'' + \bar{x}^1)} \right\}. \tag{31}$$

The expression of MSE of t_c^* , to the first degree of approximation, respectively, given as

$$MSE(t_c^*) = \bar{Y}^2 \{ 1 + C - 2E + \omega_1^2 (A + C - 2D) - 2\omega_1 (C + B - E - D) \}, \tag{32}$$

which is minimum, when

$$\omega_1 = \frac{C + B - E - D}{A + C - 2D} = \omega_{1(opt)}^{**}.$$

Thus, the minimum MSE of t_c^* is given by

$$\begin{aligned} \min.MSE(t_c^*) &= \bar{Y}^2 \left\{ 1 + C - 2E - \frac{(C + B - E - D)^2}{A + C - 2D} \right\} \\ &= \bar{Y}^2 \left[(\lambda - \lambda') C_y^2 + \theta C_{y(2)}^2 - \frac{\{ (\lambda - \lambda') C_{yx} + \theta C_{yx(2)} \}^2}{(\lambda - \lambda') C_x^2 + \theta C_{x(2)}^2} + \lambda' C_y^2 \right] \\ &= \min.MSE(t_1^*) = \min.MSE(t_3^*) = \min.MSE(t_5^*). \end{aligned} \tag{33}$$

Thus, the following theorem to the first degree of approximation is stated as

Theorem 2. $MSE(t_c^*) \geq \bar{Y}^2 \left\{ 1 + C - 2E - \frac{(C+B-E-D)^2}{A+C-2D} \right\}$ with equality holding if $\omega_1 = \frac{C+B-E-D}{A+C-2D} = \omega_{1(opt)}^{**}$.

Table 1: PRE of t_{Ri}^* , t_{Pi}^* , t_{Rei}^* and t_{Pei}^* ($i = 1, 2, \dots, 13$) with respect to \bar{y}^* .

Variance of $\bar{y}^* = 0.01514224$			
Ratio-type estimator	$PRE(\bar{y}^*, .)$	Product-type estimator	$PRE(\bar{y}^*, .)$
t_{R1}^*	114.2102	t_{P1}^*	116.2246
t_{R2}^*	118.3532	t_{P2}^*	109.9654
t_{R3}^*	116.7055	t_{P3}^*	114.1994
t_{R4}^*	109.6878	t_{P4}^*	97.4185
t_{R5}^*	117.3161	t_{P5}^*	113.1566
t_{R6}^*	104.8072	t_{P6}^*	104.7134
t_{R7}^*	115.7877	t_{P7}^*	115.2462
t_{R8}^*	117.7448	t_{P8}^*	111.914
t_{R9}^*	114.7163	t_{P9}^*	98.5811
t_{R10}^*	118.5042	t_{P10}^*	109.0759
t_{R11}^*	118.9836	t_{P11}^*	103.2461
t_{R12}^*	116.1492	t_{P12}^*	114.8503
t_{R13}^*	106.6251	t_{P13}^*	97.4487
Ratio-product-type exponential estimator		Product-ratio-type exponential estimator	
t_{Re1}^*	119.2562	t_{Pe1}^*	110.218
t_{Re2}^*	117.121	t_{Pe2}^*	99.7700
t_{Re3}^*	118.9385	t_{Pe3}^*	105.1443
t_{Re4}^*	104.1556	t_{Pe4}^*	97.5439
t_{Re5}^*	118.6169	t_{Pe5}^*	103.3413
t_{Re6}^*	101.3611	t_{Pe6}^*	102.0961
t_{Re7}^*	119.1775	t_{Pe7}^*	107.4332
t_{Re8}^*	118.0704	t_{Pe8}^*	101.6841
t_{Re9}^*	106.7859	t_{Pe9}^*	96.8283
t_{Re10}^*	116.5425	t_{Pe10}^*	99.1211
t_{Re11}^*	112.0671	t_{Pe11}^*	96.8456
t_{Re12}^*	119.0801	t_{Pe12}^*	106.5048
t_{Re13}^*	102.8637	t_{Pe13}^*	98.1200

4 Efficiency comparison

For comparison of the proposed class of estimators t^* with usual unbiased estimator \bar{y}^* , the usual ratio estimator $\bar{y}_R^* = \bar{y}^* \frac{\bar{X}^*}{\bar{X}}$ and the usual product estimator $\bar{y}_P^* = \bar{y}^* \frac{\bar{X}^*}{\bar{X}}$; the expression of MSE's to the first degree of approximation respectively, as

$$Var(\bar{y}^*) = \bar{Y}^2 \left\{ (\lambda - \lambda') C_y^2 + \theta C_{y(2)}^2 + \lambda' C_y^2 \right\}, \tag{34}$$

$$MSE(\bar{y}_R^*) = \bar{Y}^2 \left\{ (\lambda - \lambda') (C_y^2 + C_x^2 - 2C_{yx}) + \theta (C_{y(2)}^2 + C_{x(2)}^2 - 2C_{yx(2)}) + \lambda' C_y^2 \right\}, \tag{35}$$

$$MSE(\bar{y}_P^*) = \bar{Y}^2 \left\{ (\lambda - \lambda') (C_y^2 + C_x^2 + 2C_{yx}) + \theta (C_{y(2)}^2 + C_{x(2)}^2 + 2C_{yx(2)}) + \lambda' C_y^2 \right\}. \tag{36}$$

From (17), (28), (29), (30), (33), (34), (35) and (36), we have

$$Var(\bar{y}^*) - \min.MSE(t_1^* \text{ or } t_3^* \text{ or } t_5^* \text{ or } t_c^*) = \frac{\{(\lambda - \lambda') C_{yx} + \theta C_{yx(2)}\}^2}{(\lambda - \lambda') C_x^2 + \theta C_{x(2)}^2} \geq 0, \tag{37}$$

$$MSE(\bar{y}_R^*) - \min.MSE(t_1^* \text{ or } t_3^* \text{ or } t_5^* \text{ or } t_c^*) = \frac{\{(\lambda - \lambda') (C_x^2 - C_{yx}) + \theta (C_{x(2)}^2 - C_{yx(2)})\}^2}{(\lambda - \lambda') C_x^2 + \theta C_{x(2)}^2} \geq 0, \tag{38}$$

$$MSE(\bar{y}_P^*) - \min.MSE(t_1^* \text{ or } t_3^* \text{ or } t_5^* \text{ or } t_c^*) = \frac{\{(\lambda - \lambda') (C_x^2 + C_{yx}) + \theta (C_{x(2)}^2 + C_{yx(2)})\}^2}{(\lambda - \lambda') C_x^2 + \theta C_{x(2)}^2} \geq 0, \tag{39}$$

Table 2: PRE of t_{RRi}^* , t_{PPi}^* , t_{RPi}^* and t_{PRi}^* ($i = 1, 2, \dots, 13$) with respect to \bar{y}^* .

Variance of $\bar{y}^* = 0.01514224$			
Ratio-ratio type exponential estimator	PRE(\bar{y}^* , .)	Product-product type exponential estimator	PRE(\bar{y}^* , .)
t_{RR1}^*	72.88283	t_{PP1}^*	54.4895
t_{RR2}^*	119.1121	t_{PP2}^*	118.6979
t_{RR3}^*	118.8514	t_{PP3}^*	119.2595
t_{RR4}^*	109.618	t_{PP4}^*	104.187
t_{RR5}^*	118.9539	t_{PP5}^*	119.1989
t_{RR6}^*	109.0434	t_{PP6}^*	108.6556
t_{RR7}^*	118.6964	t_{PP7}^*	119.2745
t_{RR8}^*	119.0066	t_{PP8}^*	119.029
t_{RR9}^*	114.808	t_{PP9}^*	108.951
t_{RR10}^*	119.121	t_{PP10}^*	118.4505
t_{RR11}^*	118.8057	t_{PP11}^*	115.5702
t_{RR12}^*	118.7521	t_{PP12}^*	119.2637
t_{RR13}^*	106.2542	t_{PP13}^*	101.913
Ratio-product-type exponential estimator		Product-ratio-type exponential estimator	
t_{RP1}^*	118.3666	t_{PR1}^*	119.1826
t_{RP2}^*	112.1377	t_{PR2}^*	70.6831
t_{RP3}^*	94.8842	t_{PR3}^*	62.2368
t_{RP4}^*	110.4339	t_{PR4}^*	90.9394
t_{RP5}^*	101.4054	t_{PR5}^*	64.8927
t_{RP6}^*	93.9754	t_{PR6}^*	98.1167
t_{RP7}^*	85.6730	t_{PR7}^*	58.8636
t_{RP8}^*	106.2526	t_{PR8}^*	67.3112
t_{RP9}^*	115.1801	t_{PR9}^*	86.7157
t_{RP10}^*	113.5166	t_{PR10}^*	71.8743
t_{RP11}^*	119.1379	t_{PR11}^*	79.6060
t_{RP12}^*	89.2789	t_{PR12}^*	60.1875
t_{RP13}^*	107.5185	t_{PR13}^*	93.3973

$$\min.MSE(t_2^*) - \min.MSE(t^*) = \bar{Y}^2 \frac{(AE - BD)^2}{A(AC - D^2)} \geq 0, \tag{40}$$

$$\min.MSE(t_4^*) - \min.MSE(t^*) = \bar{Y}^2 \frac{(BC - DE)^2}{C(AC - D^2)} \geq 0, \tag{41}$$

$$\min.MSE(t_c^*) - \min.MSE(t^*) = \bar{Y}^2 \frac{\{C(B - A) + D(D - B) + E(A - D)\}^2}{(AC - D^2)(A + C - 2D)} \geq 0, \tag{42}$$

From (39)-(44), the following inequalities holds,

$$\min.MSE(t^*) \leq \min.MSE(t_2^*) \leq \min.MSE(t_1^*), \tag{43}$$

$$\min.MSE(t^*) \leq \min.MSE(t_4^*) \leq \min.MSE(t_3^*), \tag{44}$$

$$\min.MSE(t^*) \leq \min.MSE(t_1^* \text{ or } t_3^* \text{ or } t_5^* \text{ or } t_c^*) \leq MSE(\bar{y}_R^*) \leq MSE(\bar{y}^*). \tag{45}$$

From (43), (44) and (45), it is noted that the proposed class of estimator t^* at its optimum is the best among all the discussed estimators.

5 Simulation Study

In this section we demonstrate the performance of different types of estimators fallen under the proposed class of estimators mentioned in (5). Basically we compared all the estimators with the usual unbiased estimator \bar{y}^* by an

Table 3: PRE of t_{1Ri}^* , t_{1Pi}^* , t_{2Ri}^* and t_{2Pi}^* ($i = 1, 2, \dots, 13$) with respect to \bar{y}^* .

Variance of $\bar{y}^* = 0.01514224$			
Ratio- type estimator, $(\alpha, g) = (1, 1)$	PRE(\bar{y}^*, \cdot)	Product-type estimator, $(\alpha, g) = (1, -1)$	PRE(\bar{y}^*, \cdot)
t_{1R1}^*	32.8621	t_{1P1}^*	16.8928
t_{1R2}^*	96.0705	t_{1P2}^*	42.0280
t_{1R3}^*	58.4124	t_{1P3}^*	26.3190
t_{1R4}^*	111.9331	t_{1P4}^*	85.8688
t_{1R5}^*	70.0109	t_{1P5}^*	30.6321
t_{1R6}^*	82.2834	t_{1P6}^*	87.5777
t_{1R7}^*	45.7031	t_{1P7}^*	21.6785
t_{1R8}^*	80.6888	t_{1P8}^*	35.0751
t_{1R9}^*	116.4345	t_{1P9}^*	77.9212
t_{1R10}^*	100.1586	t_{1P10}^*	44.5980
t_{1R11}^*	118.348	t_{1P11}^*	62.4593
t_{1R12}^*	50.2727	t_{1P12}^*	23.3932
t_{1R13}^*	108.8982	t_{1P13}^*	90.0502
Ratio-type estimator, $(\alpha, g) = (1, 1)$		Product-type estimator, $(\alpha, g) = (1, -1)$	
t_{2R1}^*	0.2288	t_{2P1}^*	0.0835
t_{2R2}^*	0.5449	t_{2P2}^*	0.0802
t_{2R3}^*	0.2982	t_{2P3}^*	0.0805
t_{2R4}^*	1.9323	t_{2P4}^*	0.1676
t_{2R5}^*	0.3430	t_{2P5}^*	0.0799
t_{2R6}^*	0.2602	t_{2P6}^*	0.2611
t_{2R7}^*	0.2600	t_{2P7}^*	0.0817
t_{2R8}^*	0.4043	t_{2P8}^*	0.0796
t_{2R9}^*	3.2945	t_{2P9}^*	0.1255
t_{2R10}^*	0.6180	t_{2P10}^*	0.0809
t_{2R11}^*	1.9482	t_{2P11}^*	0.0924
t_{2R12}^*	0.2732	t_{2P12}^*	0.0812
t_{2R13}^*	1.2337	t_{2P13}^*	0.2065

exemplary simulation study. The whole simulation process, i.e. drawing a two-phase sample on interest variable Y and auxiliary variable X from the pseudo population and calculating the estimates was repeated 5000 times.

The pseudo population size (*N units*) is 2000 and all the sample and sub-sample sizes are considered here to run this empirical study are $n' = 500$, $n = 100$, $n_1 = 70$, $n_2 = n - n_1 = 30$, $r = 20$. Now, we assume that the relationship between Y and X is linear with drift 3 and slope 1.5 and the auxiliary information on variable X has been generated from $N(0.5, 0.3)$ population. We have also employed an additive noise factor in the model $Y = 3 + 1.5X$, by random ϵ following $N(0, 1)$. This type of population is very relevant in mostly all socio-economic situations with one interest and one auxiliary variable.

We have computed the PRE of t_{Ri}^* , t_{Pi}^* , t_{Rei}^* , t_{Pei}^* , t_{RRi}^* , t_{PPi}^* , t_{RPi}^* , t_{PRi}^* , t_{1Ri}^* , t_{1Pi}^* , t_{2Ri}^* , t_{2Pi}^* , t_{3Rei}^* , t_{3Pei}^* , t_{4Rei}^* , t_{4Pei}^* and $Var(\bar{y}^*)$, where $i = 1, 2, \dots, 13$. The results are shown in tables (1-4).

Note: The estimator t_5^* : ($\omega_1 = 0, \omega_2 = 1, \delta = 1$) is same as t_3^* for $\delta = 1$.

The following points are to be noted from tables (1-4) :

- 1.The ratio estimator t_{R11}^* , t_{Re1}^* , t_{RR2}^* , t_{RR10}^* , t_{RP11}^* , t_{1R11}^* and t_{3Re2}^* have the large efficiency with respect to the usual unbiased estimator \bar{y}^* among the class of estimators t_1^* , t_2^* , t_3^* and t_4^* respectively.
- 2.Among all the proposed ratio-type class of estimators, the estimator t_{Re1}^* (i.e. Ratio type exponential estimator with parameters $g = 0, \delta = 1, a = 1$ and $b = 0$) is performing well in terms of PRE with respect to usual unbiased estimator \bar{y}^* .
- 3.The product-product type exponential estimator t_{PP3}^* ($\alpha = 1, g = -1, \delta = -1, a = \beta_2(x), b = C_x$) is more efficient with respect to usual unbiased estimator \bar{y}^* among all the proposed class of estimators.
- 4.The performance of t_{1Ri}^* , t_{1Pi}^* , t_{2Ri}^* , t_{2Pi}^* , t_{3Ri}^* , t_{3Pi}^* , t_{4Ri}^* and t_{4Pi}^* ($i = 1, 2, \dots, 13$) estimators are worst compared to the usual unbiased estimator for population considered in the present simulation study.

Table 4: PRE of t_{3Ri}^* , t_{3Pi}^* , t_{4Ri}^* and t_{4Pi}^* ($i = 1, 2, \dots, 13$) with respect to \bar{y}^* .

Variance of $\bar{y}^* = 0.01514224$				
Ratio-type exponential estimator $\delta = 1$	PRE(\bar{y}^* , .)	Product-type exponential estimator $\delta = -1$	PRE(\bar{y}^* , .)	
t_{3Re1}^*	88.5738	t_{3Pe1}^*	38.4703	
t_{3Re2}^*	118.7231	t_{3Pe2}^*	66.1256	
t_{3Re3}^*	109.6319	t_{3Pe3}^*	50.9517	
t_{3Re4}^*	106.4449	t_{3Pe4}^*	93.0202	
t_{3Re5}^*	114.3062	t_{3Pe5}^*	55.6612	
t_{3Re6}^*	93.9335	t_{3Pe6}^*	97.6524	
t_{3Re7}^*	101.6158	t_{3Pe7}^*	45.2421	
t_{3Re8}^*	116.7272	t_{3Pe8}^*	60.0671	
t_{3Re9}^*	109.6907	t_{3Pe9}^*	88.9766	
t_{3Re10}^*	118.5368	t_{3Pe10}^*	68.2052	
t_{3Re11}^*	115.3762	t_{3Pe11}^*	80.3392	
t_{3Re12}^*	104.8377	t_{3Pe12}^*	47.4486	
t_{3Re13}^*	104.6520	t_{3Pe13}^*	95.0889	
Ratio-type exponential estimator, $\delta = 1$		Product-type exponential estimator, $\delta = -1$		
t_{4Re1}^*	2.3228	t_{4Pe1}^*	0.4348	
t_{4Re2}^*	0.4557	t_{4Pe2}^*	0.2435	
t_{4Re3}^*	1.1721	t_{4Pe3}^*	0.3466	
t_{4Re4}^*	0.2290	t_{4Pe4}^*	0.1524	
t_{4Re5}^*	0.8855	t_{4Pe5}^*	0.3142	
t_{4Re6}^*	0.3927	t_{4Pe6}^*	0.3130	
t_{4Re7}^*	1.6236	t_{4Pe7}^*	0.3867	
t_{4Re8}^*	0.6653	t_{4Pe8}^*	0.2830	
t_{4Re9}^*	0.1933	t_{4Pe9}^*	0.1364	
t_{4Re10}^*	0.3949	t_{4Pe10}^*	0.2286	
t_{4Re11}^*	0.2081	t_{4Pe11}^*	0.1597	
t_{4Re12}^*	1.4280	t_{4Pe12}^*	0.3706	
t_{4Re13}^*	0.2642	t_{4Pe13}^*	0.1793	

Thus, we recommend that the proposed class of estimators t^* is the best in terms of having least *MSE* among all the estimators discussed here. Finally, the results of this simulation study provides an evidence that the proposed class of estimators t^* should be used when the study as well as auxiliary variables are linearly related in presence of non-response.

6 Conclusion

In this article, a class of estimators is proposed. The expressions of bias and *MSE/VAR* are derived under simple random sampling without replacement when non response occurs both on study and auxiliary variables. Proposed estimators are compared with other existing estimators by different authors and usual unbiased estimator. Theoretically, it is shown that the members of the proposed class of estimators are more efficient than already existing estimators.

Simulation study is conducted to show the performance of the proposed class of estimators under the assumption that the relationship between *Y* and *X* is linear with drift 3 and slope 1.5 and the auxiliary information on variable *X* has been generated from *N*(0.5, 0.3) population. The results are shown in tables (9-12) which indicate that the proposed class of estimators is performing more efficiently than the usual unbiased estimator and the existing estimators. Finally we recommend for precise estimation of population mean of the study variable in presence of non-response under double sampling, the use of proposed family of estimators are recommended.

Appendix

Table A1: Some members of the class of estimators t^*

Ratio type estimator $(\alpha, g, \delta) = (1, 1, 0)$	Product type estimator $(\alpha, g, \delta) = (1, -1, 0)$	a	b
$t_{R1}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x}}{\bar{x}^*} \right) + \omega_2 \bar{y}^*$	$t_{P1}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x}}{\bar{x}^*} \right) + \omega_2 \bar{y}^*$	1	0
$t_{R2}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + C_x}{\bar{x} + C_x} \right) + \omega_2 \bar{y}^*$	$t_{P2}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + C_x}{\bar{x} + C_x} \right) + \omega_2 \bar{y}^*$	1	C_x
$t_{R3}^* = \omega_1 \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + C_x}{\beta_2(x)\bar{x} + C_x} \right) + \omega_2 \bar{y}^*$	$t_{P3}^* = \omega_1 \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + C_x}{\beta_2(x)\bar{x} + C_x} \right) + \omega_2 \bar{y}^*$	$\beta_2(x)$	C_x
$t_{R4}^* = \omega_1 \bar{y}^* \left(\frac{C_x \bar{x} + \beta_2(x)}{C_x \bar{x} + \beta_2(x)} \right) + \omega_2 \bar{y}^*$	$t_{P4}^* = \omega_1 \bar{y}^* \left(\frac{C_x \bar{x} + \beta_2(x)}{C_x \bar{x} + \beta_2(x)} \right) + \omega_2 \bar{y}^*$	C_x	$\beta_2(x)$
$t_{R5}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + S_x}{\bar{x} + S_x} \right) + \omega_2 \bar{y}^*$	$t_{P5}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + S_x}{\bar{x} + S_x} \right) + \omega_2 \bar{y}^*$	1	S_x
$t_{R6}^* = \omega_1 \bar{y}^* \left(\frac{\beta_1(x)\bar{x} + S_x}{\beta_1(x)\bar{x} + S_x} \right) + \omega_2 \bar{y}^*$	$t_{P6}^* = \omega_1 \bar{y}^* \left(\frac{\beta_1(x)\bar{x} + S_x}{\beta_1(x)\bar{x} + S_x} \right) + \omega_2 \bar{y}^*$	$\beta_1(x)$	S_x
$t_{R7}^* = \omega_1 \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + S_x}{\beta_2(x)\bar{x} + S_x} \right) + \omega_2 \bar{y}^*$	$t_{P7}^* = \omega_1 \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + S_x}{\beta_2(x)\bar{x} + S_x} \right) + \omega_2 \bar{y}^*$	$\beta_2(x)$	S_x
$t_{R8}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + \rho}{\bar{x} + \rho} \right) + \omega_2 \bar{y}^*$	$t_{P8}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + \rho}{\bar{x} + \rho} \right) + \omega_2 \bar{y}^*$	1	ρ
$t_{R9}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + \beta_2(x)}{\bar{x} + \beta_2(x)} \right) + \omega_2 \bar{y}^*$	$t_{P9}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + \beta_2(x)}{\bar{x} + \beta_2(x)} \right) + \omega_2 \bar{y}^*$	1	$\beta_2(x)$
$t_{R10}^* = \omega_1 \bar{y}^* \left(\frac{C_x \bar{x} + \rho}{C_x \bar{x} + \rho} \right) + \omega_2 \bar{y}^*$	$t_{P10}^* = \omega_1 \bar{y}^* \left(\frac{C_x \bar{x} + \rho}{C_x \bar{x} + \rho} \right) + \omega_2 \bar{y}^*$	C_x	ρ
$t_{R11}^* = \omega_1 \bar{y}^* \left(\frac{\rho \bar{x} + C_x}{\rho \bar{x} + C_x} \right) + \omega_2 \bar{y}^*$	$t_{P11}^* = \omega_1 \bar{y}^* \left(\frac{\rho \bar{x} + C_x}{\rho \bar{x} + C_x} \right) + \omega_2 \bar{y}^*$	ρ	C_x
$t_{R12}^* = \omega_1 \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + \rho}{\beta_2(x)\bar{x} + \rho} \right) + \omega_2 \bar{y}^*$	$t_{P12}^* = \omega_1 \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + \rho}{\beta_2(x)\bar{x} + \rho} \right) + \omega_2 \bar{y}^*$	$\beta_2(x)$	ρ
$t_{R13}^* = \omega_1 \bar{y}^* \left(\frac{\rho \bar{x} + \beta_2(x)}{\rho \bar{x} + \beta_2(x)} \right) + \omega_2 \bar{y}^*$	$t_{P13}^* = \omega_1 \bar{y}^* \left(\frac{\rho \bar{x} + \beta_2(x)}{\rho \bar{x} + \beta_2(x)} \right) + \omega_2 \bar{y}^*$	ρ	$\beta_2(x)$

Table A2: Some members of the class of estimators t^*

Ratio type exponential estimator $(g, \delta) = (0, 1)$	Product type exponential estimator $(g, \delta) = (0, -1)$	a	b
$t_{Re1}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x}}{\bar{x}^*} \right) + \omega_2 \bar{y}^* \exp \left(\frac{\bar{x} - \bar{x}^*}{\bar{x} + \bar{x}^*} \right)$	$t_{Pe1}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left(\frac{\bar{x} - \bar{x}^*}{\bar{x} + \bar{x}^*} \right)$	1	0
$t_{Re2}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\bar{x} - \bar{x}^*}{(\bar{x} + \bar{x}^*) + 2C_x} \right\}$	$t_{Pe2}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\bar{x} - \bar{x}^*}{(\bar{x} + \bar{x}^*) + 2C_x} \right\}$	1	C_x
$t_{Re3}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\beta_2(x)(\bar{x} - \bar{x}^*)}{\beta_2(x)(\bar{x} + \bar{x}^*) + 2C_x} \right\}$	$t_{Pe3}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\beta_2(x)(\bar{x} - \bar{x}^*)}{\beta_2(x)(\bar{x} + \bar{x}^*) + 2C_x} \right\}$	$\beta_2(x)$	C_x
$t_{Re4}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{C_x(\bar{x} - \bar{x}^*)}{C_x(\bar{x} + \bar{x}^*) + 2\beta_2(x)} \right\}$	$t_{Pe4}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{C_x(\bar{x} - \bar{x}^*)}{C_x(\bar{x} + \bar{x}^*) + 2\beta_2(x)} \right\}$	C_x	$\beta_2(x)$
$t_{Re5}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{(\bar{x} - \bar{x}^*)}{(\bar{x} + \bar{x}^*) + 2S_x} \right\}$	$t_{Pe5}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{(\bar{x} - \bar{x}^*)}{(\bar{x} + \bar{x}^*) + 2S_x} \right\}$	1	S_x
$t_{Re6}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\beta_1(x)(\bar{x} - \bar{x}^*)}{\beta_1(x)(\bar{x} + \bar{x}^*) + 2S_x} \right\}$	$t_{Pe6}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\beta_1(x)(\bar{x} - \bar{x}^*)}{\beta_1(x)(\bar{x} + \bar{x}^*) + 2S_x} \right\}$	$\beta_1(x)$	S_x
$t_{Re7}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\beta_2(x)(\bar{x} - \bar{x}^*)}{\beta_2(x)(\bar{x} + \bar{x}^*) + 2S_x} \right\}$	$t_{Pe7}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\beta_2(x)(\bar{x} - \bar{x}^*)}{\beta_2(x)(\bar{x} + \bar{x}^*) + 2S_x} \right\}$	$\beta_2(x)$	S_x
$t_{Re8}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{(\bar{x} - \bar{x}^*)}{(\bar{x} + \bar{x}^*) + 2\rho} \right\}$	$t_{Pe8}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{(\bar{x} - \bar{x}^*)}{(\bar{x} + \bar{x}^*) + 2\rho} \right\}$	1	ρ
$t_{Re9}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{(\bar{x} - \bar{x}^*)}{(\bar{x} + \bar{x}^*) + 2\beta_2(x)} \right\}$	$t_{Pe9}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{(\bar{x} - \bar{x}^*)}{(\bar{x} + \bar{x}^*) + 2\beta_2(x)} \right\}$	1	$\beta_2(x)$
$t_{Re10}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{C_x(\bar{x} - \bar{x}^*)}{C_x(\bar{x} + \bar{x}^*) + 2\rho} \right\}$	$t_{Pe10}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{C_x(\bar{x} - \bar{x}^*)}{C_x(\bar{x} + \bar{x}^*) + 2\rho} \right\}$	C_x	ρ
$t_{Re11}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\rho(\bar{x} - \bar{x}^*)}{\rho(\bar{x} + \bar{x}^*) + 2C_x} \right\}$	$t_{Pe11}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\rho(\bar{x} - \bar{x}^*)}{\rho(\bar{x} + \bar{x}^*) + 2C_x} \right\}$	ρ	C_x
$t_{Re12}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\beta_2(x)(\bar{x} - \bar{x}^*)}{\beta_2(x)(\bar{x} + \bar{x}^*) + 2\rho} \right\}$	$t_{Pe12}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\beta_2(x)(\bar{x} - \bar{x}^*)}{\beta_2(x)(\bar{x} + \bar{x}^*) + 2\rho} \right\}$	$\beta_2(x)$	ρ
$t_{Re13}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\rho(\bar{x} - \bar{x}^*)}{\rho(\bar{x} + \bar{x}^*) + 2\beta_2(x)} \right\}$	$t_{Pe13}^* = \omega_1 \bar{y}^* + \omega_2 \bar{y}^* \exp \left\{ \frac{\rho(\bar{x} - \bar{x}^*)}{\rho(\bar{x} + \bar{x}^*) + 2\beta_2(x)} \right\}$	ρ	$\beta_2(x)$

Table A5: Some members of the class of estimators t_1^*

Ratio-type estimators $(\alpha, g) = (1, 1)$	Product-type estimators $(\alpha, g) = (1, -1)$	a	b
$t_{1R1}^* = \bar{y}^* \left(\frac{\bar{x}}{\bar{x}} \right)$	$t_{1P1}^* = \bar{y}^* \left(\frac{\bar{x}}{\bar{x}} \right)$	1	0
$t_{1R2}^* = \bar{y}^* \left(\frac{\bar{x} + C_x}{\bar{x} + C_x} \right)$ Singh and Kumar (2009)	$t_{1P2}^* = \bar{y}^* \left(\frac{\bar{x} + C_x}{\bar{x} + C_x} \right)$	1	C_x
$t_{1R3}^* = \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + C_x}{\beta_2(x)\bar{x} + C_x} \right)$	$t_{1P3}^* = \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + C_x}{\beta_2(x)\bar{x} + C_x} \right)$	$\beta_2(x)$	C_x
$t_{1R4}^* = \bar{y}^* \left(\frac{C_x\bar{x} + \beta_2(x)}{C_x\bar{x} + \beta_2(x)} \right)$	$t_{1P4}^* = \bar{y}^* \left(\frac{C_x\bar{x} + \beta_2(x)}{C_x\bar{x} + \beta_2(x)} \right)$	C_x	$\beta_2(x)$
$t_{1R5}^* = \bar{y}^* \left(\frac{\bar{x} + S_x}{\bar{x} + S_x} \right)$	$t_{1P5}^* = \bar{y}^* \left(\frac{\bar{x} + S_x}{\bar{x} + S_x} \right)$	1	S_x
$t_{1R6}^* = \bar{y}^* \left(\frac{\beta_1(x)\bar{x} + S_x}{\beta_1(x)\bar{x} + S_x} \right)$	$t_{1P6}^* = \bar{y}^* \left(\frac{\beta_1(x)\bar{x} + S_x}{\beta_1(x)\bar{x} + S_x} \right)$	$\beta_1(x)$	C_x
$t_{1R7}^* = \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + S_x}{\beta_2(x)\bar{x} + S_x} \right)$	$t_{1P7}^* = \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + S_x}{\beta_2(x)\bar{x} + S_x} \right)$	$\beta_2(x)$	S_x
$t_{1R8}^* = \bar{y}^* \left(\frac{\bar{x} + \rho}{\bar{x} + \rho} \right)$	$t_{1P8}^* = \bar{y}^* \left(\frac{\bar{x} + \rho}{\bar{x} + \rho} \right)$	1	ρ
$t_{1R9}^* = \bar{y}^* \left(\frac{\bar{x} + \beta_2(x)}{\bar{x} + \beta_2(x)} \right)$	$t_{1P9}^* = \bar{y}^* \left(\frac{\bar{x} + \beta_2(x)}{\bar{x} + \beta_2(x)} \right)$	1	$\beta_2(x)$
$t_{1R10}^* = \bar{y}^* \left(\frac{C_x\bar{x} + \rho}{C_x\bar{x} + \rho} \right)$	$t_{1P10}^* = \bar{y}^* \left(\frac{C_x\bar{x} + \rho}{C_x\bar{x} + \rho} \right)$	C_x	ρ
$t_{1R11}^* = \bar{y}^* \left(\frac{\rho\bar{x} + C_x}{\rho\bar{x} + C_x} \right)$	$t_{1P11}^* = \bar{y}^* \left(\frac{\rho\bar{x} + C_x}{\rho\bar{x} + C_x} \right)$	ρ	C_x
$t_{1R12}^* = \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + \rho}{\beta_2(x)\bar{x} + \rho} \right)$	$t_{1P12}^* = \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + \rho}{\beta_2(x)\bar{x} + \rho} \right)$	$\beta_2(x)$	ρ
$t_{1R13}^* = \bar{y}^* \left(\frac{\rho\bar{x} + \beta_2(x)}{\rho\bar{x} + \beta_2(x)} \right)$	$t_{1P13}^* = \bar{y}^* \left(\frac{\rho\bar{x} + \beta_2(x)}{\rho\bar{x} + \beta_2(x)} \right)$	ρ	$\beta_2(x)$

Table A6: Some members of the class of estimators t_2^*

Ratio-type estimators $(\alpha, g) = (1, 1)$	Product-type estimators $(\alpha, g) = (1, -1)$	a	b
$t_{2R1}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x}}{\bar{x}} \right)$	$t_{2P1}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x}}{\bar{x}} \right)$	1	0
$t_{2R2}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + C_x}{\bar{x} + C_x} \right)$	$t_{2P2}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + C_x}{\bar{x} + C_x} \right)$	1	C_x
$t_{2R3}^* = \omega_1 \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + C_x}{\beta_2(x)\bar{x} + C_x} \right)$	$t_{2P3}^* = \omega_1 \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + C_x}{\beta_2(x)\bar{x} + C_x} \right)$	$\beta_2(x)$	C_x
$t_{2R4}^* = \omega_1 \bar{y}^* \left(\frac{C_x\bar{x} + \beta_2(x)}{C_x\bar{x} + \beta_2(x)} \right)$	$t_{2P4}^* = \omega_1 \bar{y}^* \left(\frac{C_x\bar{x} + \beta_2(x)}{C_x\bar{x} + \beta_2(x)} \right)$	C_x	$\beta_2(x)$
$t_{2R5}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + S_x}{\bar{x} + S_x} \right)$	$t_{2P5}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + S_x}{\bar{x} + S_x} \right)$	1	S_x
$t_{2R6}^* = \omega_1 \bar{y}^* \left(\frac{\beta_1(x)\bar{x} + S_x}{\beta_1(x)\bar{x} + S_x} \right)$	$t_{2P6}^* = \omega_1 \bar{y}^* \left(\frac{\beta_1(x)\bar{x} + S_x}{\beta_1(x)\bar{x} + S_x} \right)$	$\beta_1(x)$	C_x
$t_{2R7}^* = \omega_1 \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + S_x}{\beta_2(x)\bar{x} + S_x} \right)$	$t_{2P7}^* = \omega_1 \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + S_x}{\beta_2(x)\bar{x} + S_x} \right)$	$\beta_2(x)$	S_x
$t_{2R8}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + \rho}{\bar{x} + \rho} \right)$	$t_{2P8}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + \rho}{\bar{x} + \rho} \right)$	1	ρ
$t_{2R9}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + \beta_2(x)}{\bar{x} + \beta_2(x)} \right)$	$t_{2P9}^* = \omega_1 \bar{y}^* \left(\frac{\bar{x} + \beta_2(x)}{\bar{x} + \beta_2(x)} \right)$	1	$\beta_2(x)$
$t_{2R10}^* = \omega_1 \bar{y}^* \left(\frac{C_x\bar{x} + \rho}{C_x\bar{x} + \rho} \right)$	$t_{2P10}^* = \omega_1 \bar{y}^* \left(\frac{C_x\bar{x} + \rho}{C_x\bar{x} + \rho} \right)$	C_x	ρ
$t_{2R11}^* = \omega_1 \bar{y}^* \left(\frac{\rho\bar{x} + C_x}{\rho\bar{x} + C_x} \right)$	$t_{2P11}^* = \omega_1 \bar{y}^* \left(\frac{\rho\bar{x} + C_x}{\rho\bar{x} + C_x} \right)$	ρ	C_x
$t_{2R12}^* = \omega_1 \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + \rho}{\beta_2(x)\bar{x} + \rho} \right)$	$t_{2P12}^* = \omega_1 \bar{y}^* \left(\frac{\beta_2(x)\bar{x} + \rho}{\beta_2(x)\bar{x} + \rho} \right)$	$\beta_2(x)$	ρ
$t_{2R13}^* = \omega_1 \bar{y}^* \left(\frac{\rho\bar{x} + \beta_2(x)}{\rho\bar{x} + \beta_2(x)} \right)$	$t_{2P13}^* = \omega_1 \bar{y}^* \left(\frac{\rho\bar{x} + \beta_2(x)}{\rho\bar{x} + \beta_2(x)} \right)$	ρ	$\beta_2(x)$

Table A7: Some members of the class of estimators t_3^*

Ratio-type estimators $\delta = 1$	Product-type estimators $\delta = -1$	a	b
$t_{3Re1}^* = \bar{y}^* \exp\left(\frac{\bar{y} - \bar{y}^*}{\bar{x} + \bar{x}^*}\right)$ Singh et. al (2010)	$t_{3Pe1}^* = \bar{y}^* \exp\left(\frac{\bar{y}^* - \bar{y}}{\bar{x}^* + \bar{x}}\right)$ Singh et. al (2010)	1	0
$t_{3Re2}^* = \bar{y}^* \exp\left\{\frac{\bar{y} - \bar{y}^*}{(\bar{x} + \bar{x}^*) + 2C_x}\right\}$	$t_{3Pe2}^* = \bar{y}^* \exp\left\{\frac{\bar{y}^* - \bar{y}}{(\bar{x}^* + \bar{x}) + 2C_x}\right\}$	1	C_x
$t_{3Re3}^* = \bar{y}^* \exp\left\{\frac{\beta_2(x)(\bar{y} - \bar{y}^*)}{\beta_2(x)(\bar{x} + \bar{x}^*) + 2C_x}\right\}$	$t_{3Pe3}^* = \bar{y}^* \exp\left\{\frac{\beta_2(x)(\bar{y}^* - \bar{y})}{\beta_2(x)(\bar{x}^* + \bar{x}) + 2C_x}\right\}$	$\beta_2(x)$	C_x
$t_{3Re4}^* = \bar{y}^* \exp\left\{\frac{C_x(\bar{y} - \bar{y}^*)}{C_x(\bar{x} + \bar{x}^*) + 2\beta_2(x)}\right\}$	$t_{3Pe4}^* = \bar{y}^* \exp\left\{\frac{C_x(\bar{y}^* - \bar{y})}{C_x(\bar{x}^* + \bar{x}) + 2\beta_2(x)}\right\}$	C_x	$\beta_2(x)$
$t_{3Re5}^* = \bar{y}^* \exp\left\{\frac{(\bar{y} - \bar{y}^*)}{(\bar{x} + \bar{x}^*) + 2S_x}\right\}$	$t_{3Pe5}^* = \bar{y}^* \exp\left\{\frac{(\bar{y}^* - \bar{y})}{(\bar{x}^* + \bar{x}) + 2S_x}\right\}$	1	S_x
$t_{3Re6}^* = \bar{y}^* \exp\left\{\frac{\beta_1(x)(\bar{y} - \bar{y}^*)}{\beta_1(x)(\bar{x} + \bar{x}^*) + 2S_x}\right\}$	$t_{3Pe6}^* = \bar{y}^* \exp\left\{\frac{\beta_1(x)(\bar{y}^* - \bar{y})}{\beta_1(x)(\bar{x}^* + \bar{x}) + 2S_x}\right\}$	$\beta_1(x)$	C_x
$t_{3Re7}^* = \bar{y}^* \exp\left\{\frac{\beta_2(x)(\bar{y} - \bar{y}^*)}{\beta_2(x)(\bar{x} + \bar{x}^*) + 2S_x}\right\}$	$t_{3Pe7}^* = \bar{y}^* \exp\left\{\frac{\beta_2(x)(\bar{y}^* - \bar{y})}{\beta_2(x)(\bar{x}^* + \bar{x}) + 2S_x}\right\}$	$\beta_2(x)$	S_x
$t_{3Re8}^* = \bar{y}^* \exp\left\{\frac{(\bar{y} - \bar{y}^*)}{(\bar{x} + \bar{x}^*) + 2\rho}\right\}$	$t_{3Pe8}^* = \bar{y}^* \exp\left\{\frac{(\bar{y}^* - \bar{y})}{(\bar{x}^* + \bar{x}) + 2\rho}\right\}$	1	ρ
$t_{3Re9}^* = \bar{y}^* \exp\left\{\frac{(\bar{y} - \bar{y}^*)}{(\bar{x} + \bar{x}^*) + 2\beta_2(x)}\right\}$	$t_{3Pe9}^* = \bar{y}^* \exp\left\{\frac{(\bar{y}^* - \bar{y})}{(\bar{x}^* + \bar{x}) + 2\beta_2(x)}\right\}$	1	$\beta_2(x)$
$t_{3Re10}^* = \bar{y}^* \exp\left\{\frac{C_x(\bar{y} - \bar{y}^*)}{C_x(\bar{x} + \bar{x}^*) + 2\rho}\right\}$	$t_{3Pe10}^* = \bar{y}^* \exp\left\{\frac{C_x(\bar{y}^* - \bar{y})}{C_x(\bar{x}^* + \bar{x}) + 2\rho}\right\}$	C_x	ρ
$t_{3Re11}^* = \bar{y}^* \exp\left\{\frac{\rho(\bar{y} - \bar{y}^*)}{\rho(\bar{x} + \bar{x}^*) + 2C_x}\right\}$	$t_{3Pe11}^* = \bar{y}^* \exp\left\{\frac{\rho(\bar{y}^* - \bar{y})}{\rho(\bar{x}^* + \bar{x}) + 2C_x}\right\}$	ρ	C_x
$t_{3Re12}^* = \bar{y}^* \exp\left\{\frac{\beta_2(x)(\bar{y} - \bar{y}^*)}{\beta_2(x)(\bar{x} + \bar{x}^*) + 2\rho}\right\}$	$t_{3Pe12}^* = \bar{y}^* \exp\left\{\frac{\beta_2(x)(\bar{y}^* - \bar{y})}{\beta_2(x)(\bar{x}^* + \bar{x}) + 2\rho}\right\}$	$\beta_2(x)$	ρ
$t_{3Re13}^* = \bar{y}^* \exp\left\{\frac{\rho(\bar{y} - \bar{y}^*)}{\rho(\bar{x} + \bar{x}^*) + 2\beta_2(x)}\right\}$	$t_{3Pe13}^* = \bar{y}^* \exp\left\{\frac{\rho(\bar{y}^* - \bar{y})}{\rho(\bar{x}^* + \bar{x}) + 2\beta_2(x)}\right\}$	ρ	$\beta_2(x)$

Table A8: Some members of the class of estimators t_4^*

Ratio type exponential estimator $\delta = 1$	Product type exponential estimator $\delta = -1$	a	b
$t_{4Re1}^* = \omega_2 \bar{y}^* \exp\left(\frac{\bar{y} - \bar{y}^*}{\bar{x} + \bar{x}^*}\right)$	$t_{4Pe1}^* = \omega_2 \bar{y}^* \exp\left(\frac{\bar{y}^* - \bar{y}}{\bar{x}^* + \bar{x}}\right)$	1	0
$t_{4Re2}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\bar{y} - \bar{y}^*}{(\bar{x} + \bar{x}^*) + 2C_x}\right\}$	$t_{4Pe2}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\bar{y}^* - \bar{y}}{(\bar{x}^* + \bar{x}) + 2C_x}\right\}$	1	C_x
$t_{4Re3}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\beta_2(x)(\bar{y} - \bar{y}^*)}{\beta_2(x)(\bar{x} + \bar{x}^*) + 2C_x}\right\}$	$t_{4Pe3}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\beta_2(x)(\bar{y}^* - \bar{y})}{\beta_2(x)(\bar{x}^* + \bar{x}) + 2C_x}\right\}$	$\beta_2(x)$	C_x
$t_{4Re4}^* = \omega_2 \bar{y}^* \exp\left\{\frac{C_x(\bar{y} - \bar{y}^*)}{C_x(\bar{x} + \bar{x}^*) + 2\beta_2(x)}\right\}$	$t_{4Pe4}^* = \omega_2 \bar{y}^* \exp\left\{\frac{C_x(\bar{y}^* - \bar{y})}{C_x(\bar{x}^* + \bar{x}) + 2\beta_2(x)}\right\}$	C_x	$\beta_2(x)$
$t_{4Re5}^* = \omega_2 \bar{y}^* \exp\left\{\frac{(\bar{y} - \bar{y}^*)}{(\bar{x} + \bar{x}^*) + 2S_x}\right\}$	$t_{4Pe5}^* = \omega_2 \bar{y}^* \exp\left\{\frac{(\bar{y}^* - \bar{y})}{(\bar{x}^* + \bar{x}) + 2S_x}\right\}$	1	S_x
$t_{4Re6}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\beta_1(x)(\bar{y} - \bar{y}^*)}{\beta_1(x)(\bar{x} + \bar{x}^*) + 2S_x}\right\}$	$t_{4Pe6}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\beta_1(x)(\bar{y}^* - \bar{y})}{\beta_1(x)(\bar{x}^* + \bar{x}) + 2S_x}\right\}$	$\beta_1(x)$	S_x
$t_{4Re7}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\beta_2(x)(\bar{y} - \bar{y}^*)}{\beta_2(x)(\bar{x} + \bar{x}^*) + 2S_x}\right\}$	$t_{4Pe7}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\beta_2(x)(\bar{y}^* - \bar{y})}{\beta_2(x)(\bar{x}^* + \bar{x}) + 2S_x}\right\}$	$\beta_2(x)$	S_x
$t_{4Re8}^* = \omega_2 \bar{y}^* \exp\left\{\frac{(\bar{y} - \bar{y}^*)}{(\bar{x} + \bar{x}^*) + 2\rho}\right\}$	$t_{4Pe8}^* = \omega_2 \bar{y}^* \exp\left\{\frac{(\bar{y}^* - \bar{y})}{(\bar{x}^* + \bar{x}) + 2\rho}\right\}$	1	ρ
$t_{4Re9}^* = \omega_2 \bar{y}^* \exp\left\{\frac{(\bar{y} - \bar{y}^*)}{(\bar{x} + \bar{x}^*) + 2\beta_2(x)}\right\}$	$t_{4Pe9}^* = \omega_2 \bar{y}^* \exp\left\{\frac{(\bar{y}^* - \bar{y})}{(\bar{x}^* + \bar{x}) + 2\beta_2(x)}\right\}$	1	$\beta_2(x)$
$t_{4Re10}^* = \omega_2 \bar{y}^* \exp\left\{\frac{C_x(\bar{y} - \bar{y}^*)}{C_x(\bar{x} + \bar{x}^*) + 2\rho}\right\}$	$t_{4Pe10}^* = \omega_2 \bar{y}^* \exp\left\{\frac{C_x(\bar{y}^* - \bar{y})}{C_x(\bar{x}^* + \bar{x}) + 2\rho}\right\}$	C_x	ρ
$t_{4Re11}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\rho(\bar{y} - \bar{y}^*)}{\rho(\bar{x} + \bar{x}^*) + 2C_x}\right\}$	$t_{4Pe11}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\rho(\bar{y}^* - \bar{y})}{\rho(\bar{x}^* + \bar{x}) + 2C_x}\right\}$	ρ	C_x
$t_{4Re12}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\beta_2(x)(\bar{y} - \bar{y}^*)}{\beta_2(x)(\bar{x} + \bar{x}^*) + 2\rho}\right\}$	$t_{4Pe12}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\beta_2(x)(\bar{y}^* - \bar{y})}{\beta_2(x)(\bar{x}^* + \bar{x}) + 2\rho}\right\}$	$\beta_2(x)$	ρ
$t_{4Re13}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\rho(\bar{y} - \bar{y}^*)}{\rho(\bar{x} + \bar{x}^*) + 2\beta_2(x)}\right\}$	$t_{4Pe13}^* = \omega_2 \bar{y}^* \exp\left\{\frac{\rho(\bar{y}^* - \bar{y})}{\rho(\bar{x}^* + \bar{x}) + 2\beta_2(x)}\right\}$	ρ	$\beta_2(x)$

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