Synthetic and composite estimators for small area estimation under Lahiri – Midzuno sampling scheme

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ON SYNTHETIC AND COMPOSITE ESTIMATORS FOR SMALL AREA ESTIMATION UNDER LAHIRI – MIDZUNO SAMPLING SCHEME

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ABSTRACT

This paper studies performance of synthetic ratio estimator and composite estimator, which is a weighted sum of direct and synthetic ratio estimators, under Lahiri – Midzuno (L-M) sampling scheme. Both the estimators under L-M scheme are unbiased and consistent if the assumption of synthetic estimator is satisfied. Further, this paper compares performance of the estimators empirically under L-M and SRSWOR schemes for estimating crop acreage for small domains. The study suggests that both the estimators under L-M scheme perform better than, under SRSWOR scheme, as having smaller absolute relative biases and relative standard errors.

Key words: Composite estimators, Synthetic ratio estimators, Small domains, Lahiri – Midzuno sampling design, SICURE model.

1. INTRODUCTION

Gonzalez and Wakesberg (1973) and Schaible, Brock, Casady and Schnack (1977) compare errors of synthetic and direct estimators for standard Metropolitan Statistical Areas and Counties of U.S.A. The authors of both the papers conclude that when in small domains sample sizes are relatively small the synthetic estimator out performs the simple direct; whereas, when sample sizes are large the direct outperforms the synthetic. These results suggest that a weighted sum of these two estimators, known as composite estimator, can provide an alternative to choosing one over the other. Tikkiwal, B.D. and Tikkiwal G.C. (1998) and Tikkiwal G.C. and Ghiya (2004) define a generalized class of composite estimators for small domains using auxiliary variable, under simple random sampling and stratified random sampling schemes. Further, the authors compare the relative performance of the estimators belonging to the generalized class with the corresponding direct and synthetic estimators. The study suggest the use of composite estimator, combining direct and synthetic ratio estimators, as it has smaller relative bias and standard error.

In this paper we study the performance of synthetic ratio and composite estimators belonging to the generalized class of composite estimators for small domains, under Lahiri – Midzuno scheme of sampling. The study suggest that the estimators under Lahiri – Midzuno scheme of sampling perform better than, under SRSWOR scheme as having smaller absolute relative biases and relative standard errors.

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2. NOTATIONS

Suppose that a finite population U = (1, ... , i, ... , N) is divided into 'A' non overlapping small domains U_a of size N_a (a = 1, ... , A) for which estimates are required. We denote the characteristic under study by 'y'. We further assume that the auxiliary information is available and denote this by 'x'. A random sample s of size n is selected through Lahri-Midzuno sampling scheme (1951, 52) from population U such that n_a units in the sample's' comes from small domain U_a (a = 1, ..., A).

Consequently,

$$\sum_{a=1}^{A} N_a = N \quad and \quad \sum_{a=1}^{A} n_a = n$$

We denote the various population and sample means for characteristics Z = X, Y by

$\overline{Z}$ = mean of the population based on N observations.

$\overline{Z}_a$ = population mean of domain 'a' based on N_a observations.

$\overline{z}$ = mean of the sample 's' based on n observations.

$\overline{z}_a$ = sample mean of domain 'a' based on n_a observations.

Also, the various mean squares and coefficient of variations of the population 'U' for characteristics Z are denoted by

$$S_z^2 = \frac{1}{N-1} \sum_{i=1}^{N} \left(Z_i - \overline{Z}\right)^2, \qquad C_z = \frac{S_z}{\overline{Z}}$$

The coefficient of covariance between X and Y is denoted by

$$C_{xy} = \frac{S_{xy}}{\overline{X}\,\overline{Y}}$$

where,

$$S_{xy} = \frac{1}{N-1} \sum_{i=1}^{N} \left(y_i - \overline{Y}\right)\left(x_i - \overline{X}\right)$$

The corresponding various mean squares and coefficient of variations of small domains U_a are denoted by

$$S_{z_a}^2 = \frac{1}{N_a - 1} \sum_{i=1}^{N_a} \left(z_{a_i} - \overline{Z}_a \right)^2, \; C_{z_a} = \frac{S_{z_a}}{\overline{Z}_a} \quad \text{and } C_{x_a y_a} = \frac{S_{x_a y_a}}{\overline{X}_a \overline{Y}_a}$$

where,

$$S_{x_a y_a} = \frac{1}{N_a - 1} \sum_{i=1}^{N_a} \left(y_{a_i} - \overline{Y}_a \right) \left(x_{a_i} - \overline{X}_a \right)$$

and z_{ai} (a = 1, ... , A and i = 1, ... , N_a) denote the i-th observation of the small domain 'a' for the characteristic Z = X, Y.

3. SYNTHETIC RATIO ESTIMATOR

We consider here synthetic ratio estimator of population mean $\overline{Y}_a$, based on auxiliary information 'x' under Lahiri-Midzuno sampling scheme, as described in previous section. The synthetic ratio estimator of population mean $\overline{Y}_a$ of small area 'a' is defined as follows :

$$\overline{y}_{syn,a} = \frac{\overline{y}}{\overline{x}} \overline{X}_a \qquad \text{... (3.1)}$$

This estimator may be heavily biased unless the following assumption is satisfied

$$\left(\overline{Y}_a / \overline{X}_a \right) = \left(\overline{Y} / \overline{X} \right) \qquad \text{... (3.2)}$$

3.1 Bias and Mean Square Error

Under Lahiri-Midzuno sampling design

$$E\left(\overline{y}_{syn,a} \right) = E\left(\frac{\overline{y}}{\overline{x}} \overline{X}_a \right)$$

$$= \frac{\overline{X}_a}{\overline{X}} E\left(\frac{\overline{y}}{\overline{x}} \overline{X} \right)$$

$$= \frac{\overline{X}_a}{\overline{X}} \overline{Y} \qquad \text{... (3.3)}$$

Therefore, design bias of $\bar{y}_{syn,a}$ is

$$B\left(\bar{y}_{syn,a}\right)=\left(\frac{\bar{Y}}{\bar{X}}\bar{X}_a-\bar{Y}_a\right)=B_1\text{ (say)} \qquad \text{... (3.4)}$$

The mean square error of $\bar{y}_{syn,a}$ is given by

$$\text{MSE}\left(\bar{y}_{syn,a}\right)=\frac{\bar{X}_a^2}{\bar{X}^2}V\left(\frac{\bar{y}}{\bar{x}}\bar{X}\right)+B_1^{\ 2}$$

$$=\frac{\bar{X}_a^2}{\bar{X}}\left[\frac{1}{\binom{N}{n}}\sum_c\left(\frac{\bar{y}^2}{\bar{x}}\right)_c-\bar{Y}^2\right]+B_1^{\ 2} \qquad \text{....(3.5)}$$

where, $\sum_c$ stands for summation over all possible samples.

<u>Remark 3.1</u> The above expressions of MSE $\left(\bar{y}_{syn,a}\right)$ is not in analytical form.

<u>Remark 3.2</u> If the synthetic assumption given in Eq. (3.2) satisfies then the $B_1=B\left(\bar{y}_{syn,a}\right)=0$ and hence consistent estimator of MSE $\left(\bar{y}_{syn,a}\right)$ is given by

$$\text{mse}\left(\bar{y}_{syn,a}\right)=\frac{\bar{X}_a^{\ 2}}{\bar{X}^2}\,v\left(\bar{y}_R\right)$$

$$=\frac{\bar{X}_a^{\ 2}}{\bar{X}^2}\left[\bar{y}_R^2-\frac{\bar{X}}{\bar{x}}\left\{\bar{y}^{\ 2}-\left(\frac{1}{n}-\frac{1}{N}\right)s_y^2\right\}\right] \qquad \text{... (3.6)}$$

where, $\bar{y}_R=\frac{\bar{y}}{\bar{x}}\bar{X}$

3.2 Comparison under SRSWOR

The Bias and Mean square error of synthetic ratio estimator under SRSWOR scheme is given by Tikkiwal & Ghiya (2000), while discussing the properties of generalized class of synthetic estimator, as under

$$B_2 = B(\bar{y}_{syn,a}) = \frac{\bar{Y}}{\bar{X}}\bar{X}_a\left[1+\frac{N-n}{Nn}(C_x^2 - C_{xy})\right] - \bar{Y}_a \qquad \ldots (3.7)$$

and

$$MSE(\bar{y}_{syn,a}) = \left(\frac{\bar{Y}}{\bar{X}}\bar{X}_a\right)^2\left[1+\frac{N-n}{Nn}(3C_x^2 + C_y^2 - 4C_{xy})\right] - 2\bar{Y}_a\left(\frac{\bar{Y}}{\bar{X}}\bar{X}_a\right)\left[1+\frac{N-n}{Nn}(C_x^2 - C_{xy})\right] + \bar{Y}_a^2 \qquad \ldots (3.8)$$

Comparing the expression of biases B_1 and B_2 of $\bar{y}_{syn,a}$ under L-M design & SRSWOR schemes, we get from Eqs. (3.4) and (3.7)

$$B_2 - B_1 = \frac{N-n}{Nn}\frac{\bar{Y}}{\bar{X}}\bar{X}_a(C_x^2 - C_{xy}) \qquad \ldots (3.9)$$

So, $B_2 \geq B_1$ *if*

$$C_x^2 - C_{xy} \geq 0 \Rightarrow \rho\frac{C_y}{C_x} \leq 1$$

<u>Remark 3.3</u> If the synthetic assumption given in Eq. (3.2) satisfies then the expression of bias B_2 given in Eq. (3.7) reduces to

$$B_2 = \frac{N-n}{Nn}(C_x^2 - C_{xy}) \qquad \ldots (3.10)$$

That is, $B_2 \neq 0$ even if synthetic assumption is satisfied. Whereas under this condition $B_1 = 0$.

Remark 3.4 If the synthetic assumption is satisfied than the expressions of MSE $\left(\bar{y}_{syn,a}\right)$ given in Eq. (3.5) and Eq. (3.8) reduces to

$$M_1 = MSE\left(\bar{y}_{syn,a}\right) = \frac{\bar{X}_a^2}{\bar{X}}\left[\frac{1}{\binom{N}{n}}\sum_c\left(\frac{\bar{y}^2}{\bar{x}}\right)_c - \bar{Y}^2\right] \quad ...(3.11)$$

and

$$M_2 = MSE\left(\bar{y}_{syn,a}\right) = \frac{N-n}{Nn}\left(C_x^2 + C_y^2 - 2\,C_{xy}\right) \quad ...(3.12)$$

As the expression M_1 under L-M design is still not in analytical form, therefore, a theoretical comparison of expressions M_1 and M_2 is not possible.

4. COMPOSITE ESTIMATOR

We consider in this section a composite estimator $\left(\bar{y}_{c,a}\right)$ which is a combination of direct ratio $\left(\bar{y}_{d,a}\right)$ and synthetic ratio $\left(\bar{y}_{syn,a}\right)$ estimators, under L-M design.

That is,

$$\bar{y}_{c,a} = w_a\,\bar{y}_{d,a} + \left(1 - w_a\right)\bar{y}_{syn,a} \quad ...(4.1)$$

Where $\bar{y}_{d,a} = \frac{\bar{y}_a}{\bar{x}_a}\bar{X}_a$ and w_a is suitably chosen constant.

As $\bar{y}_{d,a} = \frac{\bar{y}_a}{\bar{x}_a}\bar{X}_a$ is an unbiased estimator of $\bar{Y}_a$ under L-M design and B ($\bar{y}_{syn,a}$) = B_1, as given in Eq. (3.4),

$$E(\bar{y}_{c,a}) = w_a\,\bar{Y}_a + (1 - w_a)\frac{\bar{Y}}{\bar{X}}\bar{X}_a$$

and

$$B(\bar{y}_{c,a}) = (1-w_a)(\frac{\bar{Y}}{\bar{X}}\bar{X}_a - \bar{Y}_a) \;=\; B_1^1 \quad (say) \tag{4.2}$$

Remark 4.1 If the synthetic assumption given in Eq. (3.2) satisfies then $B_1^1 = 0$.

Remark 4.2 The bias of $\bar{y}_{c,a}$ can be express as

$$B(\bar{y}_{c,a}) = w_a B(\bar{y}_{d,a}) + (1-w_a) + B(\bar{y}_{syn,a})$$

under SRSWOR scheme

$$B(\bar{y}_{d,a}) = \left(\frac{1}{n_a} - \frac{1}{N_a}\right)\bar{Y}_a\,(C_{x_a}^2 - C_{x_a y_a})$$

and

$$B(\bar{y}_{syn,a}) = B_2$$

We note under SRSWOR, the $B(\bar{y}_{c,a}) \neq 0$ even if the synthetic assumption given in (3.2) is satisfied, unlike the case under L-M scheme.

Remark 4.3 Under L-M scheme, the mean square even of $\bar{y}_{c,a}$ is not in analytical form, therefore, a theoretical comparison of expressions of MSE ($\bar{y}_{c,a}$) under SRSWOR and L-M schemes is not possible.

4.1 Estimation of Weights

The optimum values $w_a^{'}$ of w_a may be obtained by minimizing the mean square error of $\bar{y}_{c,a}$ with respect to w_a and it is given by

$$w_a^{'} = \frac{MSE(\bar{y}_{syn,a}) - E(\bar{y}_{d,a} - \bar{Y}_a)(\bar{y}_{syn,a} - \bar{Y}_a)}{MSE(\bar{y}_{d,a}) + MSE(\bar{y}_{syn,a}) - 2E(\bar{y}_{d,a} - \bar{Y}_a)(\bar{y}_{syn,a} - \bar{Y}_a)}$$

Under the assumption that $E(\bar{y}_{d,a} - \bar{Y}_a)(\bar{y}_{syn,a} - \bar{Y}_a)$ is small relative to $MSE(\bar{y}_{syn,a})$, the w_a reduced to

$$w_a^* = \frac{MSE(\bar{y}_{syn,a})}{MSE(\bar{y}_{d,a}) + MSE(\bar{y}_{syn,a})} \qquad ...(4.3)$$

Here $\bar{y}_{d,a}$ is an unbiased estimator and the unbiased estimator of MSE ($\bar{y}_{d,a}$) = V($\bar{y}_{d,a}$) is given by

$$v\,(\bar{y}_{d,a}) = \bar{y}_{d,a}^2 - \frac{\bar{X}_a}{\bar{x}_a}\left\{\bar{y}_a^{\,2} - \left(\frac{1}{n_a} - \frac{1}{N_a}\right)s_{y_a}^2\right\} \qquad ...(4.4)$$

Since $\bar{y}_{syn,a}$ is not an unbiased estimator, therefore, an unbiased estimator of MSE($\bar{y}_{syn,a}$) under the assumption that Cov($\bar{y}_{d,a}$, $\bar{y}_{syn,a}$) = 0, is given by [cf. Rao (2003), Eq. 4.2.12)]

$$mse(\bar{y}_{syn,a}) = (\bar{y}_{syn,a} - \bar{y}_{d,a})^2 - v(\bar{y}_{d,a}) \qquad ....(4.5)$$

To estimate w_a^*, we substitute estimates of mean square error terms by their corresponding estimates given in Eq. (4.4) and Eq. (4.5) and get

$$\hat{w}_a^* = \frac{mse(\bar{y}_{syn,a})}{(\bar{y}_{syn,a} - \bar{y}_{d,a})^2} \qquad ...(4.6)$$

But this estimator of w_a^* can be very unstable. Schaible (1978) proposes an average weighting scheme based on several variables or "similar" areas or both, to overcome this difficulty. In our empirical study presented in next section, we take average of $\hat{w}_a^*$ over "similar" areas.

5. Crop Acreage Estimation for Small Domains — A Simulation Study

In this section we compare the relative performance of $\bar{y}_{syn,a}$ and $\bar{y}_{c,a}$ under L-M and SRSWOR sampling schemes, through a simulation study, as the mean square errors of $\bar{y}_{d,a}$ and $\bar{y}_{syn,a}$ are not in analytical form. This we do by taking up the state of Rajasthan, one of the states in India, for our case study.

5.1 Existing methodology for estimation

In order to improve timelines and quality of crop acreage statistics, a scheme known as Timely Reporting Scheme (TRS) has been in vogue since early seventies in most of the States of India. The TRS has the objective of providing quick and reliable estimates of crop acreage statistics and there-by production of the principle crops during each agricultural season. Under the scheme the Patwari (Village Accountant) is required to collect acreage statistics on a priority basis in a 20 percent sample of villages, selected by stratified linear systematic sampling design taking Tehsil (a sub-division of the District) as a stratum. These statistics are further used to provide state level estimates using direct estimators viz. Unbiased (based on sample mean) and ratio estimators.

The performance of both the estimators in the State of Rajasthan, like in other states, is satisfactory at state level, as the sampling error is within 5 percent. However, the sampling error of both the estimators increases considerably, when they are used for estimating acreage statistics of various principle crops even at district level, what to speak of levels lower than a district. For example, the sampling error of direct ratio estimator for Kharif crops (the crop sown in June-July and harvested in October- November every year) of Jodhpur district (of Rajasthan State) for the agricultural season 1991-92 varies approximately between 6 to 68 percent. Therefore, there is need to use indirect estimators at district and lower levels for decentralized planning and other purposes like crop insurance.

5.2 Details of the simulation study

For the collection of revenue and other administrative purposes, the State of Rajasthan, like most of the other states of India, is divided into a number of districts.

Further, each district is divided into a number of Tehsils and each Tehsil is also divided into a number of Inspector Land Revenue Circles (ILRCs). Each ILRC consists of a number of villages. For the present study, we take ILRCs as small areas.

In the simulation study, we undertake the problem of crop acreage estimation for all Inspector Land Revenue Circles (ILRCs) of Jodhpur Tehsil of Rajasthan. They are seven in number and these ILRCs contain respectively 29, 44, 32, 30, 33, 40 and 44 villages. These ILRCs are small domains from the TRS point of view. The crop under consideration is Bajra (Indian corn or millet) for the agriculture season 1993-94. The bajra crop acreage for agriculture season 1992-93 is taken as the auxiliary characteristic x.

We consider the following estimators of population total T_a of small domain 'a' for a = 1,2,..., 7

Synthetic ratio estimator $t_{1,a} = N_a \left(\frac{\bar{y}}{\bar{\bar{x}}} \right) \bar{X}_a$

and

Composite estimator $t_{2,a} = N_a \ \bar{y}_{c,a}$

To assess the relative performance of the estimators under two different sampling schemes viz. L-M and SRSWOR, their Absolute Relative Bias (ARB) and Simulated relative standard error (Srse) are calculated for each ILRC as follows :

$$ARB(t_{k,a}) = \frac{\left| \frac{1}{500} \sum_{s=1}^{500} t_{k,a}^{s} - T_a \right|}{T_a} x100 \qquad (5.2.1)$$

and

$$Srse(t_{k,a}) = \frac{\sqrt{SMSE(t_{k,a})}}{T_a} x100 \qquad (5.2.2)$$

where

$$SMSE(t_{k,a}) = \frac{1}{500} \sum_{s=1}^{500} (t_{k,a}^{s} - T_a)^2 \qquad (5.2.3)$$

for k = 1, 2 and a = 1, ..., 7

5.3 Results

We present the results of ARB (in %) synthetic ratio estimator $\left(\bar{y}_{syn,a}\right)$ in Table 5.3.2 and of composite estimator $\left(\bar{y}_{c,a}\right)$ in Table 5.3.3 . The Srse (in %) of composite estimator are presented in Table 5.3.4 and Table 5.3.5. The total number of villages in Jodhpur Tehsil are 252. We take n = 25, 50, 63 and 76 i.e. samples, approximately, of 10%, 20%, 25% and 30% villages. It may be noted that a sample of 20% villages are presently adopted in TRS. Before simulation , we first examined the validity of synthetic assumption given in Eq. (3.1) . The results of these are presented in Table 5.3.1 . From this we note that the assumption closely meets for ILRCs (3), (5) and (7) . Where as, the assumption deviate moderately for ILRC (4) , and deviate considerably for ILRCs (1) and (2). In case of composite estimators, we estimate the weight using Eq. (4.6) for each small area but for estimating total of small areas of ILRCs (3), (5) and (7) we take average of $\hat{w}_a^*$ over these areas, being "similar".

We observe from Table 5.3.2 to Table 5.3.5 (specially for n=50 i.e. a sample of 20% villages that is being selected under TRS scheme) that both the estimators perform well in ILRCs (3) , (5) and (7) under both the sampling designs, where synthetic assumption closely satisfied . But the composite estimator $\hat{Y}_{c,a}$ performs better than the synthetic ratio estimator. The ARB of both the estimators under consideration is much smaller in case of L-M design than in case of SRSWOR. Also the Srse of both the estimators reduces under L-M design and is about 5% . Here we suggest that when the synthetic assumption is not valid one should look for other types of estimators such as those obtained through the SICURE MODEL [B.D.Tikkiwal (1993)] or presented in Ghosh and Rao (1994).

TABLE 5.3.1

Absolute Differences (Relative) under Synthetic Assumption of Synthetic Ratio Estimator for Various ILRCs.

ILRC	$\overline{Y}_a / \overline{X}_a$	$\overline{Y} / \overline{X}$	$\left(\left\|\overline{Y}_a / \overline{X}_a - \overline{Y} / \overline{X}\right\| / \overline{Y}_a / \overline{X}_a\right) X100$
(1)	.7303	.8675	18.17
(2)	.7402	.8675	17.19
(3)	.8663	.8675	0.13
(4)	.9416	.8675	7.86
(5)	.8595	.8675	0.91
(6)	.9666	.8675	10.25
(7)	.8815	.8675	1.58

TABLE 5.3.2

Absolute Relative Biases (in %) of Synthetic Ratio Estimator under L-M and SRSWOR Designs for different sample sizes.

ILRC	For n = 25		For n = 50		For n = 63		For n = 76	
	LM	SRSWOR	LM	SRSWOR	LM	SRSWOR	LM	SRSWOR
(1)	17.06	18.01	15.88	17.90	14.01	17.68	13.65	18.02
(2)	18.79	19.65	9.01	19.5	8.94	19.32	7.05	19.66
(3)	0.59	0.62	0.016	0.72	0.011	0.895	0.008	0.61
(4)	1.06	8.57	1.28	8.66	1.13	8.81	1.11	8.55
(5)	0.132	0.156	0.021	0.55	0.014	0.11	0.012	0.17
(6)	8.34	10.94	7.79	11.03	5.83	11.18	5.14	10.93
(7)	0.96	1.12	0.34	1.02	0.26	0.85	0.22	1.13

TABLE 5.3.3

Absolute Relative Biases (in %) of Composite Estimator under L-M and SRSWOR Designs for different sample sizes.

ILRC	For n = 25		For n = 50		For n = 63		For n = 76	
	LM	SRSWOR	LM	SRSWOR	LM	SRSWOR	LM	SRSWOR
(1)	9.68	10.72	8.10	8.40	7.65	8.01	4.63	5.18
(2)	11.53	12.6	8.76	10.02	5.43	7.60	5.15	6.42
(3)	0.36	1.98	0.009	0.50	0.006	0.53	.008	0.28
(4)	6.97	7.57	1.19	6.30	2.19	5.20	2.08	4.73
(5)	0.105	0.01	0.019	0.38	0.008	0.29	0.007	0.41
(6)	7.14	7.60	3.45	4.60	4.19	4.60	3.01	3.51
(7)	0.83	1.53	0.24	1.20	0.18	1.01	0.17	1.40

TABLE 5.3.4

Simulated Relative Standard Error (Srse in %) of Synthetic Ratio Estimator under L-M and SRSWOR Designs for different sample sizes.

ILRC	For n = 25		For n = 50		For n = 63		For n = 76	
	LM	SRSWOR	LM	SRSWOR	LM	SRSWOR	LM	SRSWOR
(1)	19.87	20.15	18.34	19.11	17.67	18.07	19.78	18.67
(2)	21.34	22.34	19.39	20.67	19.81	20.01	18.54	19.98
(3)	7.15	7.67	5.01	5.71	5.03	5.15	5.51	5.01
(4)	10.13	11.08	9.87	10.10	9.81	10.01	8.31	9.87
(5)	7.65	8.14	5.14	5.91	5.01	5.05	4.98	5.01
(6)	16.01	15.13	11.13	12.14	12.15	13.14	11.98	13.06
(7)	6.85	7.97	5.36	5.85	4.98	5.18	5.11	5.08

TABLE 5.3.5

Simulated Relative Standard Error (Srse in %) of Composite Estimator under L-M and SRSWOR Designs for different sample sizes.

ILRC	For n = 25		For n = 50		For n = 63		For n = 76	
	LM	SRSWOR	LM	SRSWOR	LM	SRSWOR	LM	SRSWOR
(1)	17.65	18.93	13.67	16.48	14.65	15.83	15.01	16.71
(2)	14.98	15.61	11.81	13.48	12.74	13.01	11.82	14.63
(3)	6.08	6.81	4.34	4.78	4.11	4.54	4.08	4.89
(4)	11.98	12.34	9.16	10.15	8.84	9.71	8.01	8.76
(5)	6.34	6.98	4.73	5.01	4.25	4.98	4.13	4.31
(6)	9.24	9.89	7.63	8.13	8.01	7.63	6.79	7.01
(7)	7.11	7.63	5.14	5.44	4.91	5.31	4.16	5.28

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