# Comparison between ratio estimation using sampling with and without replacement via the MSE criterion

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#### Overview

- Sampling Methods
- Other Methods of Ratio Estimate
- Simulations
- Results

## Sampling Methods

- Simple Random Sampling With Replacement(SRSWR)
- Simple Random Sampling Without Replacement(SRSWOR)
- Simple Random Sampling With Replacement Based Only on distinct Units(SRSWR(D))

# Sampling Methods - SRSWR I

Sample data:  $y_1, ..., y_n$ 

Auxiliary sample data:  $x_1, ..., x_n$ 

We estimate  $\bar{Y}$  by  $\bar{y}_n$  and  $\bar{X}$  by  $\bar{x}_n$  where  $\bar{y}_n = \frac{1}{n} \sum_{i=1}^n y_i$  and

$$\bar{x}_n = \frac{1}{n} \sum_{i=1}^n x_i.$$

Hence,

$$E(\bar{y}_n) = \bar{Y}, \ V(\bar{y}_n) = (\frac{N+n-1}{Nn} - \frac{1}{N})S_Y^2 = (\frac{N-1}{Nn})S_Y^2$$

$$E(\bar{x}_n) = \bar{X}, \ V(\bar{x}_n) = (\frac{N+n-1}{Nn} - \frac{1}{N})S_X^2 = (\frac{N-1}{Nn})S_X^2,$$

## Sampling Methods - SRSWR II

where

$$S_Y^2 = \frac{1}{N-1} \sum_{i=1}^{N} (Y_i - \bar{Y})^2$$

$$S_X^2 = \frac{1}{N-1} \sum_{i=1}^N (X_i - \bar{X})^2$$

Thus 
$$R = rac{ar{y}}{X}$$
 may be estimated by  $\hat{r} = rac{ar{y}_n}{ar{x}_n}$ 

## Sampling Methods - SRSWOR I

Sample data:  $y_1, ..., y_n$ 

Auxiliary sample data:  $x_1, ..., x_n$ 

Hence,

$$E(\bar{y}_n) = \bar{Y}, \ V(\bar{y}_n) = (\frac{N-n}{Nn})S_Y^2$$

$$E(\bar{x}_n) = \bar{X}, \ V(\bar{x}_n) = (\frac{N-n}{Nn})S_X^2,$$

## Sampling Methods - SRSWOR II

Thus, 
$$R=rac{ar{Y}}{ar{X}}$$
 can be estimated by  $\hat{r}=rac{ar{y}_{a}}{ar{x}_{a}}$ 

Hence, approximation of MSE for  $\hat{r}$  would be:

$$MSE(\hat{r}) \simeq R^2(\frac{N-n}{N-1})\frac{(S_X^2 - 2S_{XY} + S_Y^2)}{n},$$

where

$$S_{XY} = \frac{1}{N-1} \sum_{i=1}^{N} (X_i - \bar{X})(Y_i - \bar{Y})$$

# Sampling Methods - SRSWR(D) I

Sample data:  $y_1, ..., y_n$ 

Auxiliary sample data:  $x_1, ..., x_n$ 

From these samples, duplicate sample units are deleted. Sample of distinct responses would be  $y_1^*, ..., y_{\nu_1}^*$  and corresponding auxiliary sample would be  $x_1^*, ..., x_{\nu_2}^*$ . Then,

$$\bar{y}_{v_1} = \frac{1}{v_1} \sum_{i=1}^{v_1} y_i^*$$
, where  $y_1^* \neq y_2^* \neq ... \neq y_{v_1}^*$ 

and

$$\bar{x}_{v_2} = \frac{1}{v_2} \sum_{i=1}^{v_2} x_i^*$$
, where  $x_1^* \neq x_2^* \neq ... \neq x_{v_2}^*$ .

Note that  $v_1 \leq n$ , and  $v_2 \leq n$ , and  $v_1$  and  $v_2$  are integer-valued random variables.

# Sampling Methods - SRSWR(D) II

$$E(\bar{y}_{v_1}) = \bar{Y}, \ V(\bar{y}_{v_1}) = (E(\frac{1}{v_1} - \frac{1}{N}))S_Y^2$$

and

$$E(\bar{x}_{v_2}) = \bar{X}, \ V(\bar{x}_{v_2}) = (E(\frac{1}{v_2} - \frac{1}{N}))S_X^2,$$

where

$$E(\frac{1}{v_1}) = E(\frac{1}{v_2}) = \frac{1}{N^n} \sum_{i=1}^{N} i^{(n-1)}$$

Thus,  $R = \frac{\bar{Y}}{\bar{X}}$  can be estimated by  $\hat{r}(v_1, v_2) = \frac{\bar{y}_{v_1}}{\bar{x}_{v_2}}$ .

Hence, the MSE of  $\hat{r}(v_1, v_2)$  is approximated by:

$$E(\hat{r}(v_1,v_2)-R)^2 \simeq V(\bar{y}_{v_1}) + \frac{V(\bar{x}_{v_2})}{R} + (\frac{\bar{X}}{R})^2 V(\bar{y}_{v_1}) V(\bar{x}_{v_2})$$

# Sampling Methods - SRSWR(D) III

For ease of presentation, set

$$\delta \bar{y}_{v_1} = \frac{\bar{y}_{v_1} - \bar{Y}}{\bar{Y}},$$

and

$$\delta \bar{x}_{v_2} = \frac{\bar{x}_{v_2} - \bar{X}}{\bar{X}}$$

$$ar{y}_{\hat{r}(v_1,v_2)} = ar{X} rac{ar{y}_{v_1}}{ar{x}_{v_2}}$$

# Sampling Methods - SRSWR(D) IV

Then,

$$\begin{split} (\bar{y}_{\hat{r}(v_1,v_2)} - \bar{Y})^2 & \simeq \bar{Y}^2 [(\delta \bar{y}_{v_1} - \delta \bar{x}_{v_2}) + (\delta \bar{x}_{v_2})^2 (\delta \bar{y}_{v_1} - \delta \bar{x}_{v_2})^2] \\ &= \bar{Y}^2 [(\delta \bar{y}_{v_1})^2 + (\delta \bar{x}_{v_2})^2 + (\delta \bar{y}_{v_1})^2 (\delta \bar{x}_{v_2})^2] \end{split}$$

Hence,

$$(\hat{r}(v_1, v_2) - R)^2 \simeq (\delta \bar{y}_{v_1})^2 + (\delta \bar{x}_{v_2})^2 + (\delta \bar{y}_{v_1})^2 (\delta \bar{x}_{v_2})^2$$

Taking expectations we get that

$$E((\hat{r}(v_1, v_2) - R)^2) \simeq (E(\frac{1}{v}) - \frac{1}{N})(\frac{S_Y^2}{\bar{Y}^2} + \frac{S_X^2}{\bar{X}^2} + \frac{S_Y^2 S_X^2}{\bar{Y}^2 \bar{X}^2})$$

## Other Ratio Estimate Methods - Quenouille Estimate

Quenouille's ratio estimator (Jack-knife):

$$t_Q = 2\hat{r} - \frac{1}{2}(\hat{r_1} + \hat{r_2})$$

where  $\hat{r} = \frac{\bar{y}}{\bar{x}}$  or  $\hat{r}(v_1.v_2) = \frac{\bar{y}_{v_1}}{\bar{x}_{v_2}}$ , and  $\hat{r}_1$  and  $\hat{r}_2$  would be ratios from two random halves of sample data.

Note that we can instead define

 $\hat{r}_{-i} = \hat{r}$  based on all y's except  $y_i$  and all x's except  $x_i$ .

and define

$$t_Q = n\hat{r} - \frac{1}{n} \sum_{i=1}^n \hat{r}_{-i}$$

## Other Ratio Estimate Methods - Chakrabarty Estimate

Chakrabarty's ratio estimators:

$$\begin{split} \bar{y}_{c1} &= (1-W)\bar{y} + W\bar{y}_{\hat{r}} = (1-W)\bar{y} + W\frac{\bar{y}}{\bar{x}}\bar{X} = \bar{y}((1-W) + W\frac{\bar{X}}{\bar{x}})\\ \bar{y}_{c2} &= (1-W)\bar{y} + Wt_Q\bar{X} = (1-W)\bar{y} + W[2r - \frac{1}{2}(r_1 + r_2)]\bar{X} \end{split}$$
 where  $0 \leq W \leq 1$  and  $\hat{r}_{c1} = \frac{\bar{y}_{c1}}{\bar{x}_{c1}}$  and  $\hat{r}_{c2} = \frac{\bar{y}_{c2}}{\bar{x}_{c2}}$ .

#### Simulation I

- Generate data of population size N from each of the following distributions:
  - Normal(X) population
  - 2 LogNormal(Y) population
  - Gamma(Z) population
- Select a pair of the above populations
- Oraw SRSWR of size n from a selected populations.
- Delete duplicates from this SRSWR to get SRSWR(D), and calculate ratio estimate of any two of the above 3 populations using these SRSWR(D).
- **5** Sample size changes:  $n \rightarrow v_1$  and  $v_2$ .

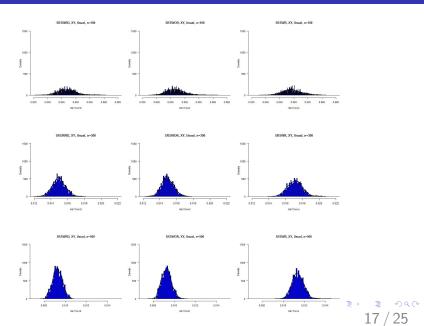
#### Simulation II

- Select SRSWR of size  $v_1$  and  $v_2$  and a SRSWOR of size  $v_1$  and  $v_2$ .
- Repeat the above steps, a number of replications(reps).
- **3** Calculate the MSE,  $s_j^2 = \frac{1}{reps-1} \sum_{i=1}^{reps} (\hat{r}_i \bar{r})^2$ , where  $\bar{r} = \frac{1}{reps} \sum_{i=1}^{reps} \hat{r}_i$ , where j is repitition number j.
- Repeat the above process for the remaining two other pair choices.

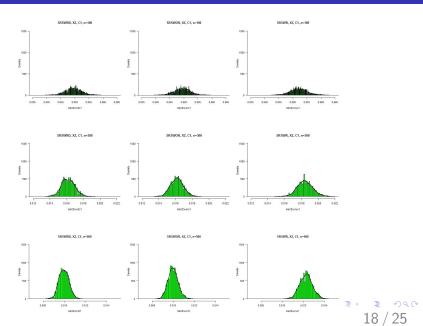
#### Result

N = 2000, n = 100, 300, 500				
Pop R	XY	XZ	YZ	
Usual	•			(1)
Quenouille			0	(4)
C(1)		•		(2)
C(2)		•		(3)

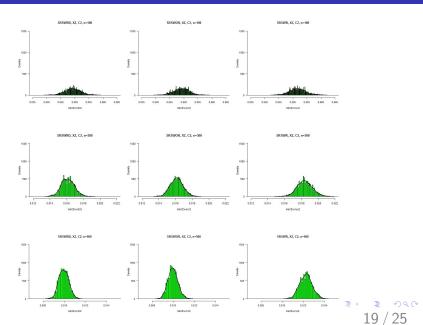
# Result - (1)



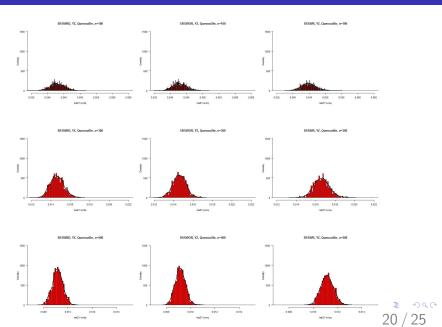
# Result - (2)



# Result - (3)



# Result - (4)



#### Conclusion

- •SRSWR(D) is outstanding method that deserves further investigation.
- •SRSWOR sometimes is better and most of the time is second.
- Thus a good competitor to SRSWR(D).
- •SRSWR falls third uniformly.

#### References I

- Asok, C., A Note on the comparison between simple mean and mean based on distinct units in sampling with replacement,

  The American Statistician 34 3 (1980) 158.
- Basu, D., On sampling with and without replacement, Sankhya: The Indian Journal of Statistics, **20** 3 (1958), 287-294.
- Cochran, W. G., Sampling techniques 3<sup>rd</sup> ed., New York, NY: Wiley and Sons, 1977

#### References II

- Chaudhuri, A., Stenger H., Survey sampling: Theory and methods., 2<sup>nd</sup> ed., New York, NY: Chapman and Hoff, 2005
- Fuller, W.A., Sampling statistics., New York, NY: Wiley and Sons, 2009
- Korwar, R. M. and Serfling, R. J., On averaging over distinct units in sampling with replacement, *The Annals of Mathematical Statistics*, **41** 6 (1970), 2132-2134.
- Mussa, A. S., A new bias-reducing modification of the finite population ratio estimator and a comparison among proposed alternatives, *Journal of Official Statistics*, **15** 1 (1999), 25-38.

#### References III

- Pathak, P. K., On the evaluation of moments of distinct units in a sample, *Sankhya: The Indian Journal of Statistics*, **23** 4 (1961) 415-420.
- Raj, D., Khamis, S. H., Some remarks on sampling with replacement, *Ann. Math. Statist.*, **29** 2 (1958) 550-557.
- Sukhatme, P. V., Sukhatme, B. V., Sampling theory of surveys applications., Ames, IA: Iowa State University Press, 198

## THANK YOU