

Estimation of Missing Data Using Convoluted Weighted Method in Nigeria Household Survey

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To cite this article:

Faweya Olanrewaju, Amahia Godwin Nwanzu, Adeniran Adefemi Tajudeen. Estimation of Missing Data Using Convoluted Weighted Method in Nigeria Household Survey. *Science Journal of Applied Mathematics and Statistics*. Vol. 5, No. 2, 2017, pp. 70-77.

doi: 10.11648/j.sjams.20170502.12

Received: October 4, 2016; Accepted: October 12, 2016; Published: March 10, 2017

Abstract: The analysis of survey data becomes difficult in the presence of missing data. By the use of Least Squares and Stein Rule method, estimator for the parameters of interest can be obtained. In this study, proposed convoluted Weighted Least Squares and Stein Rule method is compared with some existing techniques where the data is considered missing completely at random (MCAR). The results show that other techniques are occasionally useful in estimating most of the parameter, but proposed (LSSR) technique perform better regardless of the percentage of the missing data under MCAR assumption.

Keywords: Missing Data, MCAR, Stein Rule, Least Squares, Convoluted Weighted Method

1. Introduction

Missing data problem is an inherent feature of all surveys and one of the greatest threats compromising the precision of most surveys estimate during design and analysis. It can impair the quality of survey statistics by threatening the ability to draw valid inference from the sample to the target population of the survey. The problem of missing data occurs when some or all of the responses are not collected for a sampled element or when some responses are deleted because they failed to satisfy edit constraints. It is common practice to distinguish between unit (or total) non response, when none of the survey responses are available for a sampled element and item non response, when some but not all of the responses are available. Total non response arises because of refusals, inability to participate, not at home, units closed, away on vacation, unit vacant or demolished and untraced units. Item non response arises because of item refusals, “don’t know” omissions and answers deleted in editing.

Over the years, attempts with varying degrees of success have been made in the literature to solve problem of missing data. The success of a particular technique is dependent on

the complexity of the problem and no technique is robust for all purposes of estimation but techniques are used indiscriminately.

This paper presents a robust technique of handling missingness and compare how well this technique performs with some existing ones in terms of what happens to mean, variance, correlation coefficient, skewness, and kurtosis under MCAR with different amount of missing data concerning Nigeria household survey.

2. Missing Data Mechanisms

2.1. Missing Completely at Random (MCAR)

The distribution of missing value R is assumed to be independent of both the target variable Y and auxiliary variable X . Thus

$$P(R/Y, X) = P(R) \quad (1)$$

2.2. Missing at Random (MAR)

In general, MAR occur when there is no direct relation between the target variable Y and response behavior R and the same time there is a relation between the auxiliary

variable and the response behavior R.

This is expressed as:

$$P(R/Y, X) = (R/Y^0, X) \quad (2)$$

2.3. Missing Not at Random (MNAR)

Missing data Mechanism where values are assumed to be related to the unobserved dependent variable vector Y_t^m , in addition to the remaining observed values is called Missing not at Random (MNAR). This is expressed as:

$$P(R/Y, X) = p(R/Y^m, Y^0, X) \quad (3)$$

3. Methodology: Techniques for Handling Missing Values

3.1. Least Square (Yates) Procedure

Yates (1933) proposed a technique that first estimating the parameters of the model with the help of the complete observations alone and obtaining the predicted values for the missing observations, when linearity and unbiasedness criteria of estimates are of interest [18]. The predicted value of the study variable is given as:

$$\hat{y}_{LS}^* = x_* b_c \quad (4)$$

where

$$b_c = (x_c' x_c)^{-1} x_c' y_{obs} \quad (5)$$

x_* denote the k explanatory variable corresponding to the unobserved responses y_{mis}

The variance of Least Squares (Yates) procedure is computed as follows:

$$\text{Var}(\hat{y}_{LS}) = \hat{\sigma}_{LS}^2 = \frac{1}{T-K} \left\{ \sum_{t=1}^{t_c} (y_t - \hat{y}_{LS}^*)^2 + \sum_{t=t_c+1}^T (\hat{y}_{LS}^* - \right.$$

$$\left. \hat{y}_{LS}^*)^2 \right\} \quad \text{Var}(\hat{y}_{LS}) = \hat{\sigma}_{LS}^2 = \frac{\sum_{t=1}^{t_c} (y_t - \hat{y}_{LS}^*)^2}{(T-K)} \quad (6)$$

Which makes use of t_c observations but has T-K instead of t_c -k degrees of freedom, and \hat{y}_{LS}^* in the expression from (4)

3.2. Stein-Rule Strategy

This other method called Stein-Rule was proposed by James and Stein (1961), providing the following predictions:

$$\hat{y}_{SR}^* = \left(1 - \frac{KR_C}{t_c - k + 2} b_c' x_c' x_c b_c\right) x_* b_c \quad (7)$$

where: $\hat{y}_c = x_c b_c$ and $R_c = (y_c - x_c b_c)'(y_c - x_c b_c)$ is the residual sum of square and k is a positive non stochastic scalar. [18]

The variance of the Stein-Rule procedure is given as:

$$\text{Var}(\hat{y}_{SR}^*) = \sigma_{stein}^2 = \frac{\sum_{t=1}^{t_c} (y_t - \hat{y}_{SR}^*)^2}{(T-K)} \quad (8)$$

where: \hat{y}_{SR}^* is the expression from (7)

3.3. Proposed Convolved Weighted Method

If $\hat{Y}_1^* = \phi_1(x)$ and $\hat{Y}_2^* = \phi_2(x)$ are two different functions (models) in estimating the missing values of the study variables.

Let us define our target model as:

$$\hat{Y} = \alpha_1 \phi_1(x) + \alpha_2 \phi_2(x) \quad (9)$$

Which is a linear combination of two existing models.

Where $\alpha_1 + \alpha_2 = 1$ and α_1 is a non stochastic scalar between 0 and 1; see [18]. The value of α_1 may reflect the weight been given to the prediction of first model value in relation to the prediction of second model values.

This implies that, $\alpha_2 = 1 - \alpha_1$

Also let $P = \hat{Y}^2 = [\alpha_1 \phi_1(x) + \alpha_2 \phi_2(x)]^2$ be a quadratic combination of the models, we have

$$P = \hat{Y}_*^2 = \alpha_1^2 (\phi_1(x))^2 + \alpha_2^2 (\phi_2(x))^2 + 2\alpha_1 \alpha_2 \phi_1(x) \phi_2(x) \quad (10)$$

$$\text{If } \hat{Y}_1^* = \hat{Y}_{LS}^* = x_* b_c \quad (11)$$

$$\hat{Y}_2^* = \hat{Y}_{SR}^* = \left(1 - \frac{KR_C}{(t_c - k + 2) b_c' x_c' x_c b_c}\right) x_* b_c \quad (12)$$

where:

$b_c = (x_c' x_c)^{-1} x_c' y_{obs}$ (Least Squares Method).

$R_c = (y_c - x_c b_c)'(y_c - x_c b_c)$ (Stein Rule Model).

$\alpha_2 = 1 - \alpha_1$

t_c = Number of observed cases

k = Number of explanatory variables (which is a positive non stochastic scalar)

Then,

$$P = \alpha_1^2 [x_* b_c]^2 + \alpha_2^2 \left[1 - \frac{KR_C}{(t_c - k + 2) b_c' x_c' x_c b_c}\right]^2 x_* b_c^2 + (2\alpha_1 - 2\alpha_1^2) [x_* b_c] \left[1 - \frac{KR_C}{(t_c - k + 2) b_c' x_c' x_c b_c}\right] x_* b_c$$

$$p = \alpha_1^2 [x_* b_c]^2 + (1 - 2\alpha_1 + \alpha_1^2) \left[1 - \frac{KR_C}{(t_c - k + 2) b_c' x_c' x_c b_c}\right]^2 x_* b_c^2 + \alpha_1 2\alpha_1^2 [x_* b_c] \left[1 - \frac{KR_C}{(t_c - k + 2) b_c' x_c' x_c b_c}\right] x_* b_c \quad (13)$$

Taking the partial derivative of the expression (13) above with respect to parameter α_1 , we have

$$\frac{dp}{d\alpha_1} = 2\alpha_1 [x_* b_c]^2 - 2[(1 - w)x_* b_c]^2 + 2\alpha_1 [(1 - w)x_* b_c]^2 + 2[x_* b_c] ((1w)x_* b_c) - 4\alpha_1 [x_* b_c] [(1 - w)x_* b_c] \quad (14)$$

where:

$$W = \frac{KR_C}{(t_c - k + 2) b_c' x_c' x_c b_c}$$

At turning point $\frac{d_p}{d\alpha_1} = 0$, therefore, setting (14) to zero, we have

$$2\alpha_1[x_*b_c]^2 + 2\alpha_1[(1-w)x_*b_c]^2 - 4\alpha_1[x_*b_c][(1-w)x_*b_c] -$$

$$2[(1-w)x_*b_c]^2 + 2(x_*b_c)((1-w)x_*b_c) = 0 \quad (15)$$

Therefore, Solving for α_1 in (15), we have

$$\alpha_1 = \frac{((1-w)x_*b_c)^2 - (x_*b_c)((1-w)x_*b_c)}{[x_*b_c]^2 + ((1-w)x_*b_c)^2 - 2[x_*b_c][(1-w)x_*b_c]}$$

$$\text{Hence, } \hat{\alpha}_1 = \frac{\left(1 - \frac{KR_C}{(t_c - k + 2)b_c^1 x_c^1 x_c b_c}\right)(x_*b_c)^2 - (x_*b_c)\left(1 - \frac{KR_C}{(t_c - k + 2)b_c^1 x_c^1 x_c b_c}\right)(x_*b_c)}{[x_*b_c]^2 + \left(1 - \frac{KR_C}{(t_c - k + 2)b_c^1 x_c^1 x_c b_c}\right)(x_*b_c)^2 - 2[x_*b_c]\left(1 - \frac{KR_C}{(t_c - k + 2)b_c^1 x_c^1 x_c b_c}\right)(x_*b_c)}$$

$$\hat{\alpha}_1 = \frac{\left(1 - \frac{KR_C}{(t_c - k - 2)b_c^1 x_c^1 x_c b_c}\right)(x_*b_c)^2 - \left(1 - \frac{KR_C}{(t_c - k - 2)b_c^1 x_c^1 x_c b_c}\right)(x_*b_c)^2}{\left[\left(1 - \frac{KR_C}{(t_c - k - 2)b_c^1 x_c^1 x_c b_c}\right)x_*b_c - x_*b_c\right]^2} \quad (16)$$

The predicted values of the study variable using the proposed model is given as:

$$\hat{y}_{LSSR}^* = \hat{\alpha}_1 \hat{y}_{LS}^* + \hat{\alpha}_2 \hat{y}_{SR}^* \quad (17)$$

where:

$\hat{y}_{LS}^*, \hat{y}_{SR}^*$ is as shown in (4), (7) respectively and

$\hat{\alpha}_2 = 1 - \hat{\alpha}_1$

t_c = Indicates the number of observed cases

K = Number of explanatory variables (which is a positive non stochastic scalar)

Thus, the proposed weighted convoluted model is:

$$\hat{Y}_{LSSR}^* = \hat{\alpha}_1 \hat{Y}_{LS}^* + (1 - \hat{\alpha}_1) \hat{Y}_{SR}^* \quad (18)$$

4. Efficiency Comparison

If the data are complete, then $S^2 = \frac{\sum_{t=1}^T (y_t - \hat{y}_t)^2}{T-K}$ is the corresponding estimator of variance (σ^2). If $T-t_c$ cases are incomplete, that is, observation y_{mis} are missing in the model, then the variance σ^2 can be estimated using the complete case estimator as:

$$\hat{\sigma}_c^2 = \frac{\sum_{t=1}^{t_c} (y_t - \hat{y}_t)^2}{t_c - K} \quad (19)$$

4.1. Using Least Square Method

If the missing data are imputed using Least Square (Yates) method, then we have the estimator

$$\hat{\sigma}_{LS}^2 = \frac{1}{(T-K)} \left\{ \sum_{t=1}^{t_c} (y_t - \hat{y}_{LS})^2 + \sum_{t=1}^T (y_{LS} - \hat{y}_{LS})^2 \right\} \quad (20)$$

$$= \frac{\sum_{t=1}^{t_c} (y_t - \hat{y}_{LS})^2}{T-K}$$

$$= \frac{\sum_{t=1}^{t_c} (y_t - x_* b_c)^2}{T-K} \quad (21)$$

which makes use of t_c observations but has $T-K$ instead of t_c-k degrees of freedom. As

$$\hat{\sigma}_{LS}^2 = \hat{\sigma}_c^2 \frac{t_c - k}{T - K} < \hat{\sigma}_c^2 \quad (22)$$

4.2. Using Stein Rule Method

If the missing data are imputed using Stein Rule approach, then we have the estimate

$$\hat{\sigma}_{SR}^2 = \frac{\sum_{t=1}^{t_c} (y_t - (1 - \frac{KR_C}{t_c - k + 2})x_* b_c)^2}{T-K} \quad (23)$$

4.3. Efficiency Comparison: Least Squares Versus Stein Rule Techniques

The following three possible conditions will hold iff $x_* b_c > 0$:

(i) when $\frac{KR_C}{t_c - k + 2} > 0$, then $\hat{\sigma}_{SR}^2 > \hat{\sigma}_{LS}^2$ Hence, Least Squares technique will be more efficient

(ii) when $\frac{KR_C}{t_c - k + 2} = 0$, then $\hat{\sigma}_{SR}^2 = \hat{\sigma}_{LS}^2$ Hence, both techniques perform at the same level.

(iv) when $\frac{KR_C}{t_c - k + 2} < 0$, $\hat{\sigma}_{SR}^2 < \hat{\sigma}_{LS}^2$ Hence, Stein Rule method will be more efficient.

4.4. Efficiency Comparison: Proposed Technique Versus Least Squares and Stein Rules Techniques

If the missing data are imputed using the proposed weighted least square stein rule (LSSR) method, then we have the estimator

$$\hat{\sigma}_{LSSR}^2 = \frac{\sum_{t=1}^{t_c} \{y_t - [\hat{\alpha}_1 x_* b_c + (1 - \hat{\alpha}_1) \left(1 - \frac{KR_C}{t_c - k + 2} \frac{x_* b_c}{x_c^1 x_c b_c}\right) x_* b_c]\}^2}{T-K} \quad (24)$$

Comparison of variance Estimates from Least Square, Stein Rule and Proposed Technique.

(i) When $\hat{\alpha}_1 \rightarrow 1$, then $\sigma_{LSSR}^2(\text{Proposed}) \rightarrow \sigma_{LS}^2(\text{Least Square})$

(ii) When $\hat{\alpha}_1 \rightarrow 0$, then $\sigma_{LSSR}^2(\text{Proposed}) \rightarrow \sigma_{SR}^2(\text{Stein Rule})$

5. Performance Criteria for the Techniques

The criteria comprises of the following:

(i) Descriptive and analytic statistics obtained under

MCAR with different percentage of missing data.

(ii) Bias of the parameter estimate from each technique such as;

$$\begin{aligned} \text{BIAS}_{\text{SR}}(\hat{\mu}) &= \hat{\mu}_{\text{SR}} - \mu \\ \text{BIAS}_{\text{LS}}(\hat{\mu}) &= \hat{\mu}_{\text{LS}} - \mu \\ \text{BIAS}_{\text{LSSR}}(\hat{\mu}) &= \hat{\mu}_{\text{LSSR}} - \mu \end{aligned}$$

where $\hat{\mu}_{\text{SR}}$ = Estimated mean at i% of data missing using stein Rule method. i = 5%, 12%, 23% and 44%. μ = Actual mean value when data is complete.

(iii) The Root Mean Square Error for each technique as:

$$\text{RMSE}_{\text{SR(SteinRule)}} = [\text{Bias}_{\text{SR(Stein Rule)}}^2 + \text{Var}_{\text{SR(Stein Rule)}}]^{1/2}$$

$$\text{RMSE}_{\text{LS(LeastSquare)}} = [\text{Bias}_{\text{LS(Least Square)}}^2 + \text{Var}_{\text{LS(Least Square)}}]^{1/2}$$

$$\text{RMSE}_{\text{LSSR (proposed)}} = [\text{Bias}_{\text{LSSR(proposed)}}^2 + \text{Var}_{\text{LSSR(proposed)}}]^{1/2}$$

The technique with minimum (RMSE) is adjudged the best.

6. Numerical Illustration for the Proposed Technique

A simple random sample of $n = 100$ households was selected from the records of survey data on “household income” from Akure North Local Government, Iju/Ita-Ogbolu in Ondo state, Nigeria to evaluate the performance of the proposed model with some existing techniques of handling missing data under MCAR using different percentage of missing data.

Three demographic variables; Y (income N’000), Age (X_2) and year of schooling (X_1) were considered. The Y variable was generated as a combination of explanatory variables with added random components. Then, differing amounts were deleted at random causing MCAR data which had 0, 5, 12, 23 and 44% missing data.

7. Results and Discussion

Table 1. Performance of Some Missing Data Techniques for Parameter Estimates when Differing Amount of Data are Missing Under MCAR Assumption of Missingness.

ESTIMATED PARAMETERS	PERCENTAGE OF MISSINGNESS	MISSING DATA TECHNIQUES				
		MI (Mean Imputation)	LS (Least Square)	SR (Stein Rule)	LSSR (Proposed)	LW (List Wise)
MEAN (\bar{y})	0%	13.814	13.814	13.814	13.814	13.814
	5%	13.6198	13.79885	13.804	13.80323	13.68989
	12%	13.6044	13.8055	13.41354	13.80565	13.68787
	23%	14.1119	13.79732	13.79741	13.8074	14.30282
	44%	13.7306	13.80303	13.87161	13.74924	14.11842
CORRELATION (ρ)	0%	0.946	0.946	0.946	0.946	0.946
	5%	0.881	0.967	0.967	0.967	0.978
	12%	0.686	0.966	0.793	0.966	0.978
	23%	0.596	0.981	0.981	0.98	0.976
	44%	0.488	0.518	0.886	0.961	0.994
VARIANCE ($\hat{\sigma}^2$)	0%	46.577	46.577	46.577	46.577	46.577
	5%	45.94065	46.63859	46.67568	46.67109	48.14344
	12%	38.10063	47.8907	41.78268	47.88495	42.64912
	23%	35.14046	48.80046	48.80107	48.84908	44.57015
	44%	28.59472	49.14666	48.6712	48.83988	48.94685
SKEWNESS (S_k)	0%	0.217	0.217	0.217	0.217	0.217
	5%	0.291648	0.222904	0.221543	0.221757	0.258074
	12%	0.190889	0.248072	0.124799	0.248259	0.144436
	23%	0.169918	0.227823	0.227841	0.223639	0.071633
	44%	0.194166	0.259757	0.243059	0.282537	-0.00069
KURTOSIS (K)	0%	2.616	2.616	2.616	2.616	2.616
	5%	2.704214	2.611784	2.608406	2.608843	2.580429
	12%	2.793288	2.653841	2.567728	2.653645	2.496646
	23%	3.089743	2.608665	2.608734	2.602258	2.45105
	44%	3.995174	2.626688	2.660419	2.681545	2.387055
COEFFICIENT OF VARIATION (CV)	0%	49.62	49.62	49.62	49.62	49.62
	5%	49.76544	49.4914	49.4926	49.49294	50.68371
	12%	45.37187	50.12722	48.18977	50.12365	47.71109
	23%	42.00667	50.63109	50.63107	50.61933	46.67672
	44%	38.94515	50.78933	50.29317	50.82865	49.55372



Figure 1. Graph of mean for MCAR imputed data by Amount of data missing.

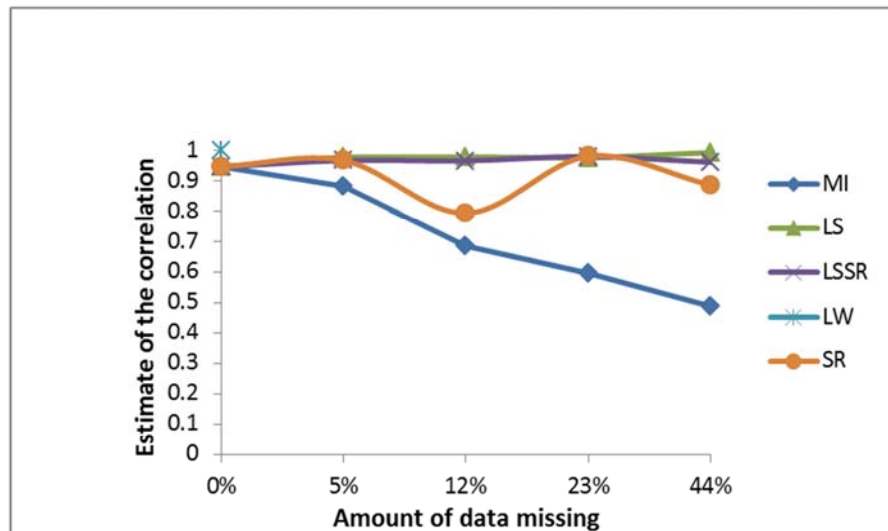


Figure 2. Graph of correlation for MCAR imputed data by Amount of data missing.

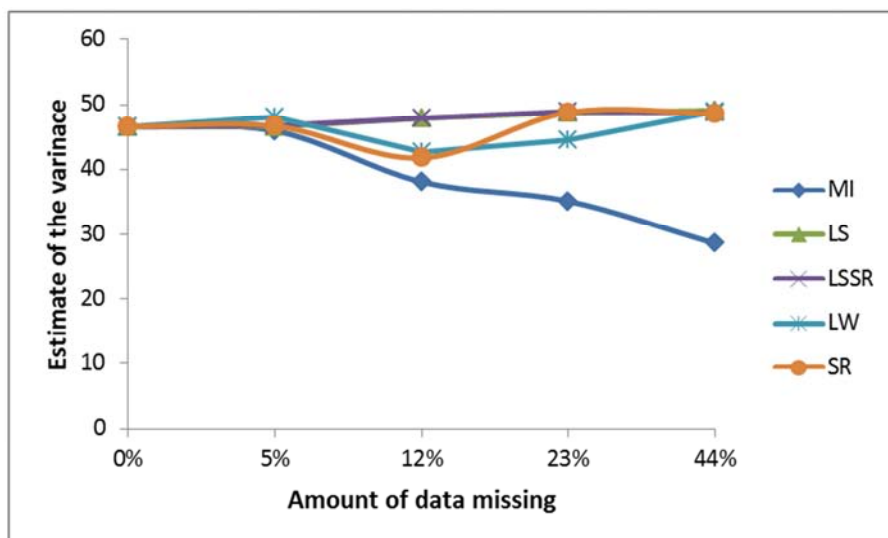


Figure 3. Graph of variance for MCAR imputed data by Amount of data missing.



Figure 4. Graph of skewness for MCAR imputed data by Amount of data missing.

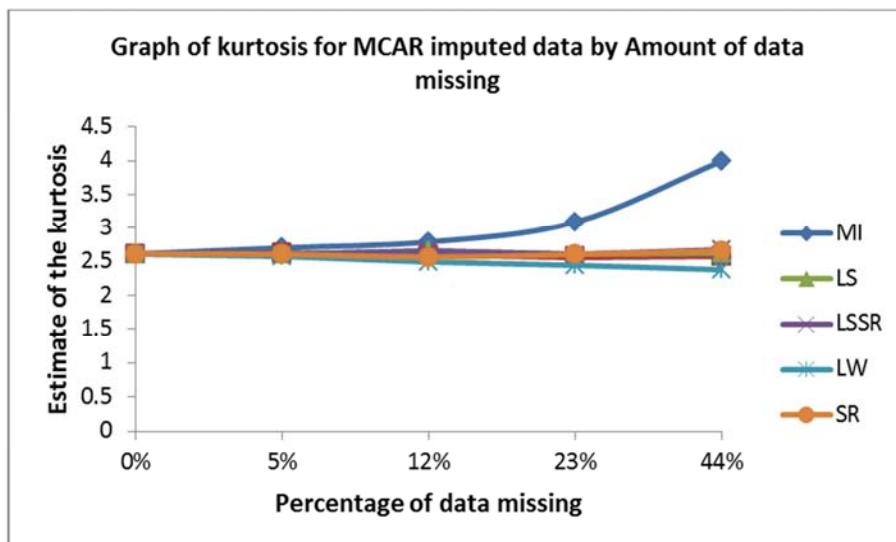


Figure 5. Graph of kurtosis for MCAR imputed data by Amount of data missing.



Figure 6. Graph of coefficient of variation for MCAR imputed data by Amount of data missing.

Table 2. Performance of Missing Techniques for Parameter Estimates Under Missing Completely at Random (MCAR).

Average Parameter Estimate (with RMSE in Parenthesis)					
PARAMETER	MI (Mean Imputation)	LS (Least Square)	SR (Stein Rule)	LSSR (Proposed)	LW (List Wise)
mean = 13.814	13.767 (0.237)	13.801 (0.004)	13.722 (0.208)	13.791 (0.028)	13.950 (0.310)
VAR = 46.577	36.944 (7.194)	48.119 (1.120)	46.483 (3.281)	48.061 (1.031)	46.077 (2.974)
STDEV = 6.8247	6.056 (0.593)	6.936 (0.081)	6.815 (0.244)	6.932 (0.075)	6.785 (0.220)
SKEW = 0.217	0.212 (0.054)	0.240 (0.017)	0.204 (0.054)	0.244 (0.028)	0.118 (0.110)
KURT = 2.616	3.146 (0.590)	2.625 (0.021)	2.611 (0.038)	2.637 (0.038)	2.479 (0.081)
COV = 49.62	44.022 (4.642)	50.260 (0.585)	49.652 (1.085)	50.266 (0.594)	48.656 (1.801)
COR = 0.946	0.663 (0.167)	0.858 (0.227)	0.907 (0.087)	0.969 (0.008)	0.982 (0.008)

**Figure 7.** Graph of Root Mean Square Error of some missing data techniques under MCAR missingness assumption.**Table 3.** Summary of the Result from the Figure 1-6 of Performance of some Missing Data Techniques under MCAR as Percentage of Missing Value Increases.

Estimated parameter	MI (Mean Imputation)	LS (Least Square)	SR (Stein Rule)	LSSR (Proposed)	LW (List Wise)
Mean	High percentage discrepancy in the true value	Approximately constant (within target value)	Approximately constant (within target value)	Approximately constant (within target value)	High percentage discrepancy in the true value
Correlation	High percentage discrepancy in the true value	Approximately constant (within target value)	Some percentage discrepancy of true value	Approximately constant (within target value)	High percentage discrepancy in the true value
Variance	High percentage discrepancy in the true value	Approximately constant (within target value)	High percentage discrepancy in the true value	Approximately constant (within target value)	Little percentage of discrepancy
Skewness	High percentage discrepancy in the true value	Approximately constant (within target value)	High percentage discrepancy in the true value	Approximately constant (within target value)	High percentage discrepancy in the true value
Kurtosis	High percentage discrepancy in the true value	Approximately constant (within target value)	Approximately constant (within target value)	Approximately constant (within target value)	High percentage discrepancy in the true value
CV	High percentage discrepancy in the true value	Approximately constant (within target value)	Approximately constant (within target value)	Approximately constant (within target value)	Little percentage of discrepancy

Remark: Although, other techniques are occasionally useful in estimating most of the true parameter, proposed (LSSR) technique perform better regardless of the percentage of the missing data under MCAR assumption considered the results from the criteria for selection. However, for mean imputation (MI) and list wise (LW), there is higher percentage of discrepancy in the true values of most of the parameters. Hence, the proposed technique preserve most of the parameters structure within the data. That is there is almost no change in the mean, variance, skewness, kurtosis, coefficient of variation and correlation coefficient under MCAR assumption using the proposed model of imputation.

8. Conclusion

Although other procedures are occasionally useful, proposed (LSSR) technique performed better regardless of the percentage of the existing data under MCAR nature of missingness.

Considered the result from the criteria for selection, the proposed model reduces the variability around the true parameter value without discarding the linearity and unbiasedness criteria.

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