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Analysis of Factors Affecting Weight of Child at Birth in Pakistan: Multiple Imputation of Missing Data

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Abstract

The problem of missing data arises very often in studies based on secondary data. Similar problem was encountered while identifying the potential risk factors of Low Birth Weight infants in Pakistan. Low Birth Weight (LBW) is an important indicator of newborn's health status at the time of birth and during infancy. LBW is also identified as one of the significant risk factor of mortality during neonatal period. It would be useful for health sector to identify the significant risk factors associated with LBW infants for a particular community. Data of LBW infants was obtained from Pakistan Demographic and Health Survey (2006-07). It was found that data contained 76.8% missing observations for various potential risk factors. Missing values cause reduction in sample size leading to reduction in statistical power. Multiple Imputation is used to deal with the problem of missing values which is a powerful and flexible technique and is relatively easy to implement for handling missing data. To handle the problem, Multiple Imputation was used before fitting the Ordinal Regression model. It is a powerful and flexible technique and is relatively easy to implement for dealing with missing data. After Multiple Imputation of missing data, an Ordinal Regression model was fitted to determine the associated risk factors of LBW for infants. The analysis revealed that place of residence of the mother, wealth index, gender of the child, number of antenatal visits and multiple births have significant effect on birth weight of child in Pakistan.

Keywords

Low Birth Weight, Multiple Imputations, Ordinal regression

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1. Introduction

The problem of missing data arises frequently in studies involving secondary data. In the current study 76.8% data is missing for available potential risk factors. Missing values cause reduction in the sample size resulting in reduction in the statistical power which may lead to biased results. So handling of missing data by using appropriate methods is necessary. Generally three categories are used to specify the nature of missing data i.e. Missing Completely At Random (MCAR), Missing At Random (MAR) and Not Missing At Random (NMAR).

Handling of missing data is possible. Wayman (2003) suggested different methods for dealing with missing data which include ad-hoc deletion method, list wise deletion, mean substitution, pair wise deletion, Maximum Likelihood method, Single Imputation method and Multiple Imputation method. The Multiple Imputation is considered better than the other methods as other methods produced biased results (Wayman, 2003). Acock (2005) also showed that Multiple Imputation technique works better than other methods for large samples. Scheffer (2002) stated that Multiple Imputation performs well in case of more than 25% missing data.

LBW is an indicator of infant’s survival chances. It also reveals the health status of mothers. The physical and socio demographic status of a mother is portrayed by LBW. (Viengsakhone et al., 2010). Babies born with weight less than 2.5 kg are considered as “Low Birth Weight (LBW)”. Every year, twenty million babies are born with LBW, 50% of all perinatal deaths are related to LBW and 90% of these are born in developing countries. (Matin et al., 2008). LBW is also related with physical problems occurring in later life of child. It is one of the vital reasons of mortality and morbidity (Negi et al., 2006). As compared to normal babies, LBW babies were 40 times more likely to die during neonatal period (Metgud et al., 2012).

There are various risk factors (socio economic, medical) associated with the LBW (Singh et al., 2009). Multiple pregnancies are found to be associated with LBW. The infant’s death rate is 5 times higher in multiple pregnancies than single pregnancy (Almond et al., 2002). Poor maternal health is a potential risk factor of LBW. Low socioeconomic status resulting in poor nutrition and less prenatal care is related with LBW (Vahdaninia et al., 2008, Viengsakhone et al., 2010). The birth weight of newborns is also significantly affected by the age of mother and the number of antenatal visits made by her. When compared to those who had one antenatal visit, the risk of delivering LBW baby was lesser for mothers who had made at least five antenatal visits (Negi et al., 2006). Negi et al. (2006) also concluded that women who were more than 35 or less than 20 years of age had higher risk of delivering low weight infants as compared to women who were 20 to 34 years old. Physical activities carried out during pregnancy are associated with risk of abortion and premature delivery (Muthayya, 2009). Maternal education was found to be significantly associated with LBW babies (Viengsakhone et al., 2010). Educated mothers visit doctors for routine checkups and have good eating habits during their pregnancy. Inter-Pregnancy interval is also a risk factor associated with LBW. According to Bhatti et al. (2010) women with closely spaced births were at higher risk of delivering LBW babies. Babies born to mothers residing in the rural areas had increased risk of being LBW as compared to those who had born to their urban counter-part (Dickute et al., 2004). According to Viengsakhone et al. (2010) birth order is also one of reliable indicator of birth weight. Births of first order were found to have high risk of falling in LBW category (Viengsakhone et al., 2010). Gender of a child is another potential risk factor of LBW. Hirve et al. (1994) showed that the proportion of low weight is higher among female births as compared to male counter-parts.

In this study, socio-economic and demographic factors for LBW in Pakistan are identified after imputing the missing observations through Multiple Imputations.

2. Methodology

Data is taken from the Pakistan Demographic and Health Survey (PDHS) 2006-07 which is the second survey in the country, conducted as part of the world wide Demographic and Health Survey (DHS) project.

2.1 Sample: In DHS respondents are ever married women aged 15-49. To avoid recall bias the sample used in our study is restricted to only those births that occurred during five years preceding the survey and comprised of 39049 births. In Pakistan, a large number of births occur at home and it is difficult to obtain exact weight of these babies. Hence in DHS, subjective assessment is obtained from mothers about birth weight as: very small, smaller than average, average, larger than average and very large. This assessment (size of child at birth) is used as proxy for birth weight. In our sample these categories are merged for simplification in analysis. The dependent variable is re-categorized into three categories as:

Variable	Categories and Code Number	Missing Value Code	Scale

Size of Child at Birth	1: Very Small 2: Smaller Than Average 3: Average Or Larger 8: Don't Know	9	Ordinal

In our study, children of first two categories i.e very small and smaller than average are considered as Low Birth Weight infants.

2.2 Statistical analysis: Bivariate Analysis: To study the relationship between birth weight (very small, smaller than average, average or large) and various socio-economic and demographic factors Chi-Square statistics for testing association is used after verifying the assumptions for these tests.

2.3 Missing observation: Multiple Imputation method is used to handle missing data. Rubin (1976) first developed this method to handle missing data in survey. In Multiple Imputation process, missing values are predicted by using the values available in other variables. These values are called imputed values and are used as the substitute of the missing values after declaring that data as "imputed data set". In current study overall 76.8% data are missing. Multiple Imputation is carried in three steps, which are illustrated as following:

- Imputations are generated using appropriate imputation model.
- Analysis or estimation can be carried out after imputing missing observation.
- The results for M (number of imputation) imputation are combined into one Multiple Imputation result.

It is necessary to check the pattern of missing data. When data is monotone multiple variables are imputed without iteration by using univariate conditional models. Such imputations are not possible when data are non-monotone in which case imputation requires iteration. There are two methods to handle non-monotone pattern i.e. multivariate normal and Imputation Chained Equations (ICE) methods.

After diagnostic checking the next step is to run imputation model. In STATA "M" denotes number of imputation. Rubin (1987) suggested number of imputation (M=5) to get reliable results. Number of imputation can be increased to 20 for Table and valid results. Kenward and Carpenter (2007) and Horton and Lipsitz (2001) suggested that number of imputations may be raised to 50 for this purpose.

Multivariate analysis, Bivariate analysis just shows association between dependent and each of the independent variables. Nature and direction of effect is also very important which can be determined by using multivariate analysis. In this regard, multivariate analysis is carried out by fitting Ordinal Regression model to identify the significant risk factors of size of child at birth.

3. Analysis and results

Percentage of various categories of size of child at the time of birth can be observed from Figure 1. Majority of infants born in Pakistan falls in the category of average or higher birth weight. A substantial number also exist for those infants whose birth size was very small or smaller than average.

In current study birth weight for 29,978 cases out of total sample of 39049 births is missing leaving only 9,071 values as valid. It means that 76.8% data is missing and hence, 23.8% data is valid. Since percentage of missing data is high, it is better to handle missing data before modeling the birth weight with potential risk factors.

3.1 Handling of missing data problem: Table 2 shows percentage of observations missing for different factors. Large numbers of observations are observed to be missing for three variables i.e. number of antenatal visits, prenatal visit to doctor and size of child at birth. To handle missing values it is decided to impute the missing observation using Multiple Imputation technique. Before imputation it is necessary to verify the related assumptions.

3.1.1 Testing randomness of missing observations: To test randomness, the means of (two groups) missing and non-missing can be compared by using separate variance t test for variables containing more than 1% missing values. Results of this test are presented in Table 3 where column contain the two non-categorical variables (preceding birth interval and antenatal visits for pregnancy) and rows have variables (preceding birth interval, antenatal visits for pregnancy, size of child at birth and prenatal visits to doctor). The grouping is done whether variable is missing or present. It is observed from Table 3 that p-value for all variables is less than .05 so null hypothesis of missing completely at random is rejected and concluded that data are not missing completely at random.

The little's MCAR test is also computed (Table 4) to test randomness of missing observation. The null hypothesis can be illustrated as the data are missing completely at random at the significant level .05. The p-value is less than .05 resulting in rejection of null hypothesis. Results for above methods shows that data is not missing completely at random so deletion method is not recommended and Multiple Imputation can be used to impute missing observations.

3.1.2 Testing pattern of missing observations: Results of testing the pattern of missing observations are presented in Table 5. Zero value shows missing and one indicate the complete observation. In current analysis missing observations appear for different types of variables which include binary (prenatal visit to doctor, work status of women and husbands), count (antenatal visits for pregnancy), ordinal (size of child at birth) and continuous (preceding birth interval).

Since the pattern of missing observation is non-monotone so the Sequential Imputation using Chain Equation is used. STATA 12.0 is used to apply Sequential Imputations using Chain Equation for imputing the missing observations. To generate missing data no. of imputation used are 5, 10, 20. After Multiple Imputation of missing data the Bivariate and Multivariate analyses are carried out and the result are presented in the next section.

3.2 Bivariate analysis: Relationship between weight of babies and its expected determinants/ factors is investigated through bivariate analysis. Categories of the factors involved in the study are given in Table 1. A result obtained from Chi-Square tests is reported in Table 6. The result in Table 6 show that region, place of residence, education of women, education of husband, gender of child, wealth index, work status of husband, work status of women, multiple pregnancies, birth order, age of women at 1st birth and number of antenatal visits are significantly associated with size of child at birth at 5% level of significance.

3.3 Multivariate analysis: Since dependent variable is ordinal so ordinal regression model is fitted. Logit link is used because it is better than others in three aspects i.e. interpretation is easy, its analysis is easy for retrospective sampled data and mathematical formulation of the model is simpler. Application of Ordinal Regression model requires certain diagnostics which are given as following:

3.3.1 Assumptions of Ordinal Regression model: Following are the assumptions which must be satisfied before the fitting of proposed regression model.

- ***Assumption of parallel lines:*** Assumption of parallel lines is very important for application of Ordinal Regression model. Results in Table 7 show that the regression lines are parallel for each level of the dependent variable. The β coefficients of the independent variable for each ordinal level of the dependent variable are same.

- ***Detection of influential observations:*** Influential observations may change the direction and magnitude of regression coefficients and can also affect their significance so these observations must be identified, if exist in the data should be tackled accordingly. Cook's D is used here to identify the influential observations and found that no observation exceed the cut off criterion i.e. greater than one.

The results obtained from Ordinal Regression model (with imputation) after fulfilling the assumptions are summarized in Table 8. Differences among model coefficients and their significance for three choices of number of imputation (M=5, 10, 20) is negligible.

Only minor differences are observed in the magnitude of coefficients while no change is observed in their direction and significance on the response variable (Size of child at birth/birth weight). So in Table 9 results for M=20 are reported in detail.

It is evident from Table 9 that significance and direction of education of women, prenatal visits to doctors, work status of women, multiple pregnancies, birth order, preceding birth interval and age of women at first birth on weight of child remains same in both models i.e. with imputation and without imputation (deletion method or complete case analysis). However direction/trend of two factors i.e. education of husband and current age of mother is reversed. In model without imputation increase in the level of both factors has contributed negatively towards size of child while after imputation it resulted in positive impact. Significance of some factors also changed e.g. Place of residence, wealth index, gender of child, number of antenatal visits showed insignificant effect on weight of child but after imputation their effect becomes significant. Work status of husband played a significant role on birth weight/size of child at birth in model without imputation while in model with imputation its impact turned into insignificant.

4. Discussion

The discussion on all significant factors in the Ordinal Regression model for M=20 is presented in this section.

- ***Place of residence:*** The current study shows that children born to women residing in urban areas were more likely to have Low Birth Weight (very small or smaller than average) as compared to those born to women living in rural areas. However, some other studies has reported an opposite results. Vahdaninia et al. (2008) found that the women living in deprived areas and having low socioeconomic status had greater chance to give birth to low weight babies. Another study by Dickute et al. (2004) showed that women who belonged to rural areas were uneducated and had low income so they were less likely to give birth to normal weight babies.
- ***Wealth index:*** Wealth index is positively associated with weight of child at birth. It is observed from Table 9 that children born to women who belonged to higher category of wealth index had more chances of being in the higher category of birth weight as compared to those born to mothers belonging to poorest wealth index. A study carried out by Muula et al. (2011) also showed similar results.
- ***Gender of child:*** Gender of child is found to be significantly associated with weight of child at birth. Table 8 shows that female babies are more likely to be of less than average size at birth as compared to male babies. Hirve et al. (1994) and Joshi (2003) also reported that rate of Low Birth Weight was higher among female children than that among male children.
- ***Antenatal visits:*** Number of antennal visits is significantly positively associated with weight of child at birth. Result show that women with more number of antenatal visits during pregnancy had greater chance of delivering babies, falling into the higher categories of birth weight. Memon at al. (2005) found that less number of antenatal visits during pregnancy were significantly associated with infants of low weight in Sindh.
- ***Multiple pregnancies:*** Twins births results in increased risk of infant mortality which along with other factors is attributed mainly to Low Birth Weight (Aziz et al., 2011). Our study also showed that multiple births are less likely to be in the higher category of birth weight.

5. Conclusion

Low Birth Weight is a reliable indicator of public health. Chances of morbidity and mortality both are higher for babies having Low Birth Weight. In our sample, place of residence, wealth index. gender of child, number of antenatal visits and multiple births have significantly affected birth weight of babies in Pakistan.

Results reveal that rural residence of mother, wealth index and number of antenatal visits have significant positive impact on birth weight of a child. Furthermore risk of Low Birth Weight is higher for female children and for those born as an outcome of multiple pregnancy.

Finally it is concluded that the rate of Low Birth Weight can be reduced in Pakistan by providing improved and free antenatal health facilities to pregnant women belonging to poor class. There is a need to launch public health awareness programs to create awareness among women and their guardians for regular antenatal checkups during pregnancies.

Table 1: Description of covariates and predictors for size of child at birth

No.	Variables	Categories and Code Number	Missing Value Code	Scale
1	Region	1:Punjab 2:Sindh 3:KPK 4:Baluchistan	-	Nominal
2	Place of Residence	1:Rural 2:Urban	-	Nominal
3	Education of Women	0:No Education 1:Primary 2:Secondary 3:Higher	9	Ordinal
4	Wealth Index	1:Poorest 2:Poorer 3:Middle 4:Richer 5:Richest		Ordinal
5	Age of Women at 1st Birth	None		Scale
6	Education of Husband	0:No Education 1:Primary 2:Secondary 3:Higher 8: Do Not Know	9	Ordinal

7	Birth Order Number	None	-	Scale
8	Gender of Child	1:Male 2:Female		Nominal
9	Preceding Birth Interval	None		Scale
10	Prenatal Visits to Doctor	0:No 1:Yes	9	Nominal
11	Antenatal Visits for Pregnancy	0: No Antennal Visits 98: Don't Know	99	
12	Current Age of Mothers	1: Less Than 20 2: 20-34 3: Greater Than Or Equal To 30		Ordinal
13	Work Status of Husband	0: Unemployed 1: Employed 98: Don't Know	99	Nominal
14	Work Status of Women	0: Not Working 1: Working 98: Don't Know	99	Nominal
15	Multiple Pregnencies	0:No 1:Yes		Nominal

Table 2: General pattern of missing data

Factors	N	Mean	Std. Deviation	Missing	
				Count	Percent
Preceding Birth Interval	30193	28.85	17.373	8856	22.7
Antenatal Visits	5636	2.58	3.250	33413	85.6
Education of Father	38921			128	.3
Prenatal Visits to Doctor	5699			33350	85.4
Size of Child at Birth	9071			29978	76.8
Work Status of husband	39044			5	.0
Work Status of Women	39032			17	.0

Table 3: Separate Variance t- test

		Preceding Birth Interval	Antenatal Vistis
Preceding Birth interval	t		-.6.6 (0.000)
	Mean(present)	28.85	2.44
	Mean(missing)	.	3.25
Antenatal Visits	t	23.9 (0.000)	
	Mean(present)	35.36	2.58
	Mean(missing)	27.67	.

Prenatal Vistits to Doctor	t	24.2 (0.000)	.
	Mean(present)	35.44	
	Mean(missing)	27.64	
Size of Child at Birth	t	22.4 (0.000)	1.8
	Mean(present)	33.16	2.58
	Mean(missing)	27.52	1.36

Table 4: Little's MCAR test for randomness

Little's MCAR: chi-square	832.138
DF	2
Sig.	.000

Table 5: Patterns of missing value

Missing-Value Patterns
(1 means complete)

Percent	Pattern 1	2	3	4	5	6	7
12%	1	1	1	1	1	1	1
59	1	1	1	1	0	0	0
18	1	1	1	0	0	0	0
6	1	1	1	1	1	0	0
2	1	1	1	0	1	1	1
2	1	1	1	0	1	0	0
<1	1	1	0	1	0	0	0
<1	1	1	1	1	1	1	0
<1	1	1	0	0	0	0	0
<1	1	1	0	1	1	1	1
<1	1	1	1	0	1	1	0
<1	1	1	0	1	1	0	0
<1	1	1	1	1	0	1	1
<1	1	0	1	1	0	0	0
<1	1	1	0	0	1	1	1
<1	1	0	1	1	1	0	0
<1	1	0	1	1	1	1	1
<1	0	1	1	0	0	0	0
<1	0	1	1	1	1	1	1
<1	1	0	1	0	0	0	0
<1	1	1	0	0	1	0	0
<1	1	1	1	0	0	1	1
<1	0	1	1	1	1	0	0
<1	1	0	1	0	1	0	0
<1	1	0	1	0	1	1	1
<1	1	1	0	1	1	1	0
<1	1	1	1	0	0	1	0

Table 6: Bivariate analysis of size of child at birth versus factors

No.	Factors	Chi-Square	P-Value
1	Region	117.022	.000
2	Place of Residence	15.067	.033
3	Education of Women	68.103	.000

4	Education of Husband	28.756	.017
5	Gender of Child	11.997	.009
6	Prenatal: Doctor	8.546	.053
7	Mother Age	10.483	.144
8	Wealth Index	71.899	.000
9	Work Status of Husband	17.736	.006
10	Work Status of Women	21.503	.002
11	Multiple Pregnancies	44.957	.000
12	Birth Order	27.361	.004
13	Preceding Birth Interval	7.280	.073
14	Age of Women at 1st Birth	16.478	.029
15	Number of Antenatal Visits	11.198	.023

Table 7: Test of parallel lines

df1	df2	Wald F	Sig.
22.000	452.000	1.534	.058

Table 8: Ordinal Regression model for three different number of imputation

	M=5	**M=10**	**M=20**
Factors	**Coeff.**	**Coeff.**	**Coeff.**
Place of Residence=Rural	.1779335*	.179884*	.1792528*
Education of Women			
Primary	.0677504	.0604514	.0465206
Secondary	.1555262	.1481434	.1464709
Higher	.2089423	.1752971	.2074477
Wealth Index			
Poorer	.0938085	.1105028*	.1152102*
Middle	.1686023*	.1886733*	.1960974*
Richer	.2847832*	.2987633*	.3010898*
Richest	.3779211*	.3987018*	.3994175*
Education of Husband			
Primary	.0674409	.0509253	.0736544
Secondary	.0372568	.0233344	.0270143
Higher	.0184303	.0050257	.004205
Gender of Child=Female	-.1228954*	-.1230617*	-.13153588*
Prenatal Visits to Doctor=Yes	-.1822257	-.1400425	-.1548477
Antenatal Visits	.0548919	.0551666*	.0550121*
Current Age of Mother			
20-34	.2250042	.2077516	.2032726
> 35	.2774509	.2857179	.2752385
Work Status of Husband			
Employed	.0449041	.0530791	.0537481
Work Status of Women			

Working	-.0329526	-.0318055	-.0306113
Multiple Pregnancies	-.7992921*	-.8604687*	-.8526838*
Birth Order	.0007211	.0008638	.0005722
Preceding Birth Interval	.0009438	.0008115	.0007783
Age of Women at 1st Birth	.0041988	.0032204	.0035101
Constant			
Very Small	-1.33181	-1.350452	-1.353512
Smaller than Average	-.0501745	-.0477953	-.0510635

Table 9: Ordinal Regression model for size of child at birth in Pakistan (PDHS, 2006-07)

Factors	**Without imputation**	**With imputation**					
	Coeff.	**Coefficient**	**Std.Err**	**T**	**p>t**	**95% Conf. Interval**	
Place of Residence=Rural	.1359959	.1792528 *	.0625756	2.86	0.006	.0534431	.3050625
Education of Women							
Primary	.0285575	.0465206	.0612486	0.76	0.450	-.075256	.1682977
Secondary	.1830624	.1464709	.0871854	1.68	0.098	-.027745	.3206871
Higher	.2901383	.2074477	.1382817	1.50	0.138	-.067975	.4828713
Wealth Index							
Poorer	.1747432	.1152102 *	.0533534	2.16	0.033	.0094421	.2209782
Middle	.2115621	.1960974 *	.0648624	3.02	0.004	.0666504	.3255444
Richer	.2497357	.3010898 *	.0764694	3.94	0.000	.1481125	.4540671
Richest	.5013334*	.3994175 *	.1079322	3.70	0.001	.182428	.6164069
Education of Husband							
Primary	-.0198887	.0736544	.0828828	0.89	0.380	-.094575	.2418842
Secondary	-.045996	.0270143	.0599595	0.45	0.654	-.093204	.1472329
Higher	-.0145365	.004205	.0740216	0.06	0.955	-.143173	.1515831
Gender of Child=Female	-.1216621	-.1315358*	.0482664	-2.7	0.009	-.228832	-.034239
Prenatal Visits to Doctor=Yes	-.0737755	-.1548477	.0786063	-1.9	0.057	-.314790	.0050954
Number of Antenatal Visits	.0293669	.0550121*	.0160045	3.44	0.001	.022594	.0874301
Current Age of Mother							
20-34	-.1390436	.2032726	.1479848	1.37	0.170	-.087697	.4942426
>35	-.2658609	.2752385	.1750642	1.57	0.118	-.070689	.6211662
Work Status of Husband							
Employed	.3844*	.0537481	.0885597	0.61	0.545	-.121896	.229393
Work Status of							

Women							
Working	-.1472138	-.0306113	.038403	-0.8	0.427	-.106754	.045532
Multiple Pregnancies	-.9877174*	-.8526838*	.1566903	-5.4	0.000	-1.16630	-.5390649
Birth Order	.0149935	.0005722	.012207	0.05	0.963	-.024086	.0252312
Preceding Birth Interval	.0013485	.0007783	.0014883	0.52	0.604	-.002227	.0037843
Age of Women at 1st Birth	.0314015	.0035101	.0049264	0.71	0.478	-.006250	.0132711
Very Small	-.8683905	-1.353512	.2033706	-6.6	.000	-1.75442	-.9525994
Smaller than Average	.4366242	-.0510635	.2008944	-0.2	.800	-.446935	.3448088

*significance level at 5%

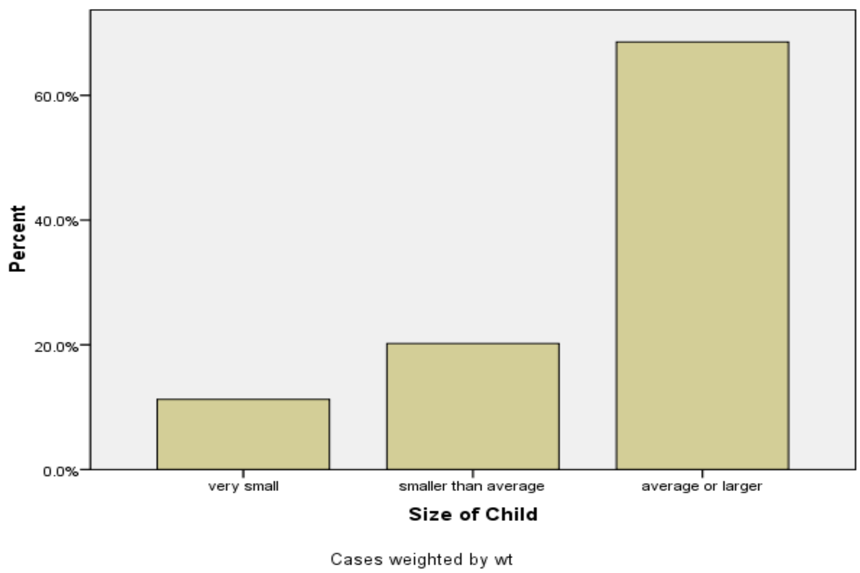

Figure 1: Frequency of various categories of size of child at birth

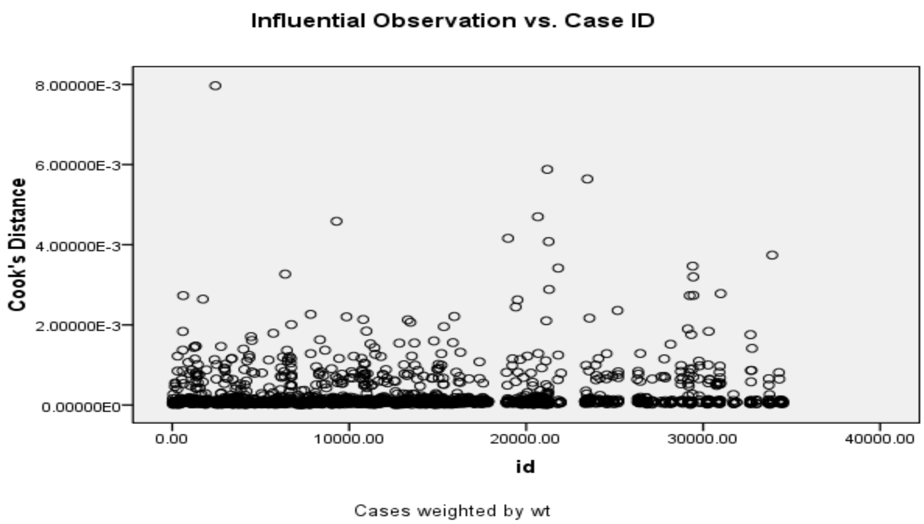

Figure 2: Influential observation vs. case ID

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