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Animal Science Faculty of Andalas University
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Determinants of Birth Weight At Various Quantiles in West Sumatera

Ferra Yanuar

Department of Mathematics, Faculty of Mathematics and Natural Sciences,
Andalas University, Kampus Limau Manis, 25163, Padang – Indonesia
Corresponding Author: ferrayanuar@yahoo.co.id

Abstract

Covariates could affect the responses differently at various points of the response distribution. Many covariates might have higher impact on conditional mean of the response than on conditional 10th percentile, for example. These effect can be analyzed directly by using quantile regression. This paper aims to implement the use of quantile regression to identify the determinants of birth weight at various quantiles. A cross-sectional study was conducted in March to June 2016 by distributing the questionnaires to mother who gave birth at any selected hospital in West Sumatera. This research proves that determinants of birth weight at low quantile are education level, problems during pregnancy and prenatal care. Meanwhile parity, pregnancy spacing, problems during pregnancy and gender are associated with higher birth weights. All proposed model could be accepted based on goodness of fit test.

Keywords: quantile regression, cross-sectional study, birth weight.

1. Introduction

Birth weight has served as leading indicator of infant health, with low birth weight infants classified as those weighing less than 2500 grams at birth. Obsevable measures of mother weight gain, education level, problems while pregnant, age, parity, prenatal care, mother weight gain, hemoglobin (Hb) and spacing pregnancies (Abrevaya & Dahl, 2008; Burgette & Reiter, 2012) were assummed had strong associations with birth weight. For instance, according to a report by Burgette & Reiter (2012), mothers who had problems during pregnancy would have babies with birth weight less than 2500 grams.

Many researches have examined that the low birth weight will cause many problems. Abrevaya in his article wrote that the infant mortality rate increases at lower birth weights. The direct medical costs for babies with low birth weight are quite high as well. The babies with low birth weight have the long term effects on their cognitive development, educational outcomes and labor market outcomes. The babies would have development problems in cognition, attention and neuromotor functioning that persist until adolescence. The babies with low birth weight are more likely to attend special class, delay entry into kindergarden or repeat a grade in school. Those babies are also more likely to have inferior labor-market outcomes, being more likely to be unemployed and earn lower wages.

Although it has received less attention in the economics literature, high birthweight outcomes can also represent adverse outcomes.

For instance, babies weighing more than 4000 grams, classified as high birthweight (HBW) and especially those weighing more than 4500 grams, classified as very high birthweight (VHBW) are more likely to require cesarean-section births, have higher infant mortality rates, and develop health problems later in their life (Hulman *et al*., 2015).

A difficulty in evaluating initiatives aimed at improving birth outcomes is to accurately estimate the causal effects of prenatal activities on these birth outcomes. Unobserved heterogeneity among childbearing women makes it difficult to isolate causal effects of various determinants of birth outcomes. Whether or not a mother's age affect the infant weight, for instance, is likely to be correlated with unobserved characteristics of the mother. To deal with this difficulty, various studies have used an instrumental-variable approach to estimate the effects of prenatal care on birth outcomes.

Another approach has been to utilize panel data (i.e., several births for each mother) to identify these effects from changes in prenatal behavior or maternal characteristics between pregnancies (Wei & Carroll (2008). One concern with the panel-data identification strategy is the presence of "feedback effects," specifically that prenatal care and mother's habbits in later pregnancies may be correlated with birth outcomes in earlier pregnancies. Wei *et al.*(2015) provides an explicit estimation strategy to deal with such feedback effects (using data on at least three births per mother). Since the costs associated with birthweight have been found to exist primarily at the low end of the birthweight distribution (with costs increasing significantly at the very low end), any studies have estimated the effects of birth inputs on the fraction of births below various intervals. This present study conside a quantile regression approach to estimate the effects of birth inputs on birthweight. Quantile approach provides a method for determining how birth inputs affect birthweight at different parts of the distribution (Wang *et al*., 2009). The birth inputs involved in this study are 8 indicators consists of continuous and categorical types, they are education level, problems while pregnant, age, parity, prenatal care, mother weight gain, hemoglobin (Hb) and spacing pregnancies (Abrevaya & Dahl, 2008; Burgette & Reiter, 2012; Feng & Zhu, 2016).

There are any advantages using quantiles regression then analysis of variance or classical regression. Any reasons why we better use quantile regression are :

- Analysis of variance (ANOVA) and regression provide information only about the conditional mean.
- More knowledge about the distribution of the statistic may be important.
- The distribution of , the dependent variable, conditional on covariate X, may have thick tails.
- The conditional distribution of Y may be asymmetric.
- The conditional distribution of Y may not be unimodal.
- Neither regression nor ANOVA (analysis of variance) will give the robust results, especially if the outlier exist inside the data.

2. Material and Methods

In this present study, we used primary data collected by distributing the questionnaires to mother who just have baby, live, single and stay in West Sumatera. The questionnaires were distributed from March to July 2016. There are 93 respondents with complete information that involved in this study.

The response variable is birth weight, recorded in kilograms. Meanwhile the birth inputs are assummed affeced by eight indicators consists of continuous and categorical types. There are education level, problems while pregnant, age, parity, prenatal care, mother weight gain, hemoglobin (Hb) and spacing pregnancies. The following Table 1 presents the summary statistics of Birthweight data.

Table 1. Descriptive of Birth Weight Data

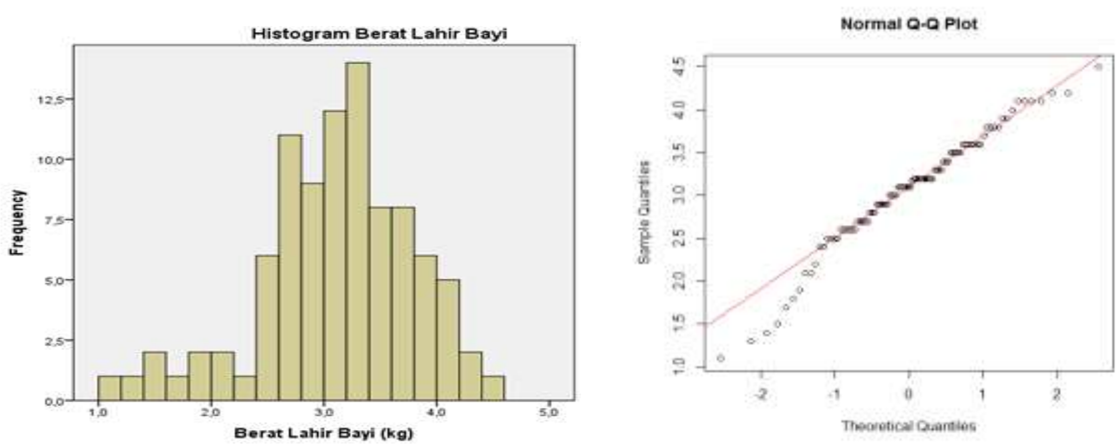
Mean		3,063
Median		3,100
Mode		3,2
Skewness		-0,592
Kurtosis		0,578
Minimum		1,1
Maximum		4,5
	25	2,700
Percentiles	50	3,100
	75	3,500

Based on the description in Table 1 we are informed that the mean of birthweigth data is 3,063. The highest value of the data is 4,5 and the lowest value is 1,1. We also see that the distribution of the data is skewed to the left since its skewness is - 0.592, as presented in Figure 1.(a).

For construction of Birthweight model, this present study apply the quantile regression approch, since we purpose to identify the Birthweigth model for any quantiles (low quantile, middle quantile and high quantile). The following is the general explanation regard quantile procedure used in this research.

As described by Davino *et al*. (2014), quantile is defined as the value that corresponds to a specified proportion of a sample or population. Thus, we may defined τ th quantile as the value which divide the data into two parts, the τ fraction of the data below it and 1-τ fraction of the data above it, and $0<\tau<1$. Median is a very commonly used quantile, which is aqual to a proportion of 0.5 is the ordered data. Regression analysis is used to quantify the relationship between a responce variable and one or several of free covariates (Yanuar, 2014).

Quantiles regression is a statistical method used to estimate models for conditional quantile functions. Unlike the classical linear regression methods that are based on minimizing sums of squared residuals and to estimate models for conditional mean functions, quantile regression methods are based on minimizing absolute residuals, and intended to estimate conditional median functions and a full range of other conditional quantile functions. Quantile regression also provides a more complete graph of the conditional distribution of variable ot interest Y given $X = x$.



(a) (b)

Figure 1.(a) Histogram of Birthweight data.
(b) Empirical quantile plot and Normal plot of Birthweight data.

For a random sample $\{y_1, \ldots, y_n\}$, the classical linear regression can be estimated by the well-known method, which minimizes the sum of squared residuals:

$$\min \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (1)$$

For the special case of estimation the conditional median of function, we can define the solution as problem to minimization a sum of absolute residuals, where there are the same numbers of observations above and below the median, which can be calculated by:

$$\min \sum_{i=1}^{n} |y_i - \hat{y}_i| \qquad (2)$$

Analogous to the concept of median, Davino *et al* (2014) proposed a complete and different method for estimation of an unknown value, say a, for any τ in the interval (0,1), which may be defined as any solution to the minimization problem of the equation:

$$\min_{a\in\Re} \left\{ \sum_{i=1}^{n} \tau \, |y_i - a| + \sum_{i=1}^{n} (1-\tau) \, |y_i - a| \right\}$$

$$0 < \tau < 1 \qquad (3)$$

Consider a classical linear regression model $y_i = \boldsymbol{x}_i' \boldsymbol{\beta} + e_i$, we defined a linear model for the τ-th quantile as:

$$y_i = \boldsymbol{x}_i' \boldsymbol{\beta}_\tau + e_i \qquad i = 1, \ldots, n \qquad (4)$$

In estimating models for conditional quantile function, we minimize a sum of asymmetrically weighted absolute residuals. This will contribute to different weights to positive and negative residuals. The general τ-th sample quantile, which is the analogue to equation (3) can be formulated as:

$$\hat{\beta}(\tau) = \min_{\beta\in\Re} \left\{ \sum_{i=1}^{n} \tau \, |y_i - \boldsymbol{x}_i' \boldsymbol{\beta}_\tau| + \sum_{i=1}^{n} (1-\tau) \, |y_i - \boldsymbol{x}_i' \boldsymbol{\beta}_\tau| \right\}$$

And equivalently written as:

$$\hat{\beta}(\tau) = \min_{\beta\in\Re} \sum_{i=1}^{n} \rho_\tau \left(y_i - \boldsymbol{x}_i' \boldsymbol{\beta}_\tau \right)$$

$$0 < \tau < 1 \qquad (5)$$

Several software packages can be used to implement the quantile regression method, such as S-plus, R-program and Stata. In this research, R software was used to analyze data of the Birthweight.

3. Result And Discussion

In this analysis, quantile regression approach is used to examine the relationships between the Birthweight and some potential explanatory variables. Table 2 provides a summary of describe the explanatory variables which are found to have a significant relationships with Birthweight for various conditional quantile function, particularly for τ equals 0.10, 0.25, 0.50, 0.75 and 0.90. In the last column are the estimated of ordinary least square approach and its corresponding standard errors in the brackets.

Table 2 informs us that mother with middle or high education level tent to have havier baby than mother with low education level. Mother with more parities tent to have havier baby than less parities. Mother with longer space of pregnancies tent to have baby. The heavier of mother's weight gain the heavier of birthweight of her baby. The higher of mother's hemoglobin, the heavier of her baby's birthweight. Thus this study found that significant variables which effect the baby's birthweight are education level, parity, spacing pregnancies, mother's weight gain and mother's hemoglobin.

Table 3 presents the goodness of fit for all model, indicated by *PseudoR*^{2} value. Based on the result of this study, it proved that all model at any selected quantiles are acceptable since all *PseudoR*^{2} values more than 0.7 (Feng *et al.*, 2011; He & Zhu, 2011). The best model is at middle quantile (*PseudoR*^{2} equals 0.910).

Table 2. Coefficient Estimated for Birth Weight Model Using Quantile Regression (QR) and OLS

Indicator Variable	Estimate of QR (Standard Error)					Estimate of OLS (Standard Error)
	τ = 0.10	τ = 0.25	τ = 0.50	τ = 0.75	τ = 0.90	
β_2 (Middle)	0.700 (0.224)**	0.501 (0.243)**	0.378 (0.173)**	0.421 (0.262)	0.203 (0.228)	0.364 (0.174)**
β_3 (High)	0.662 (0.345)**	0.433 (0.258)*	0.378 (0.184)**	0.613 (0.279)**	0.149 (0.243)	0.420 (0.178)**
β_4 (Parity)	0.331 (0.137)**	0.235 (0.102)**	0.106 (0.073)	0.216 (0.111)**	0.279 (0.096)**	0.242 (0.073)**
β_5 (Spacing pregnancies)	-0.089 (0.057)	-0.070 (0.042)*	0.014 (0.030)	-0.039 (0.046)	-0.074 (0.040)	-0.052 (0.030)*
β_6 (Weight gain)	0.038 (0.025)	0.023 (0.019)	0.033 (0.013)**	0.006 (0.020)	0.015 (0.017)	0.021 (0.013)
β_9 (Hb)	0.108 (0.099)	0.130 (0.074)*	0.097 (0.052)*	0.062 (0.080)	0.126 (0.069)*	0.077 (0.053)

* Significant at 10% level
**Significant at 5% level

Table 3. *PseudoR*^{2} for Selected Quantile for Low Birth weight Cases

Quantiles	*PseudoR*^{2}
0.10	0.736
0.25	0.877
0.50	0.910
0.75	0.909
0.90	0.856

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