Regression Analyses of the Philippine Birth Weight Distribution

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Low birth weight has both short-term and long-term effects. It can lead to complications among infants causing neonatal deaths. Several literatures also suggested relationships between low birth weight and delayed mental and physical development. These negative effects are further magnified in developing countries, one of which is the Philippines. In this paper, birth weight is analysed through logistic, ordinary least squares, and quantile regression techniques using a sample from the 2008 National Demographic and Health Survey. Quantile regression results offer a more dynamic picture of how these correlates affect the conditional distribution of birth weight. The estimates of the marginal effects of several demographical and maternal health correlates of birth weight suggest that socially and economically impoverished mothers are more likely to have low birth weight babies. These results would recommend a focus on improving maternal health care through proper education.

Keywords: *birth weight, quantile regression, logistic regression, ordinary least squares*

1. Introduction

A particular target in the Millennium Development Goals (MDG) is to reduce child mortality by two-thirds between 1990 and 2015. One key indicator of this goal is a decreased infant mortality rate, which for the Philippines would entail a decline from 57.0 per 1,000 live births (1990) to 19.0 per 1,000 live births (2015). Though figures from 2008 (24.9 per 1,000 live births) suggested a high pace of progress, it is still probable that the Philippines will not be able to achieve its target by 2015 (NSO, 2012).

Most literatures (Lewit et al., 1995; Lavado et al. 2010; Reolalas and Novilla, 2010) have found strong associations between infant mortality and low birth weight (LBW). Although LBW is not a direct cause, the complications due to it (e.g. inability to maintain body temperature) account for 13.8% and 15.3% of infant deaths in the Philippines for the years 2006 and 2007, respectively. Also, these complications currently rank as the third leading cause of infant deaths both locally and globally (Reolalas and Novilla, 2010).

The United Nations Children's Fund (UNICEF) defined LBW babies as newborns weighing less than 2,500 grams with the measurement taken within the first hour of life. Globally, 15.50% of total live births in 2008 are of LBW classification. In the Philippines, 21.20% of live births in 2008 are classified as LBW babies which is the largest for the past 23 years. Currently, the country ranks as the 14th (out of 225 countries) with the highest incidence of LBW cases (WHO, 2012).

The primary determinants of birth weight are gestation period and prenatal growth rate, while secondary factors consist of genetics and maternal behavior during pregnancy. External influences can be classified as environmental and socioeconomic factors such as educational attainment and wealth status. Many literatures and discussions on birth weight focus on prenatal care and micronutrient supplementation of the mother during her pregnancy. The Department of Health (DOH) defined *prenatal care* as the use of health care during pregnancy, which includes screening for health conditions, providing therapeutic interventions, and educating women about safe child birth. Prenatal care quality is considered as an essential indicator for maternal and infant health status. Lavado et al. (2010) has found that 96.16% of mothers had prenatal care but only 49.51% can be considered as 'good quality care.' For the past 10 years, micronutrient supplementation during pregnancy had also earned great amount of interest in research in relation to birth weight. While there are several micronutrients (e.g. Zinc, Vitamin A, Calcium, Iodine) being associated with positive outcomes, the most important are Iron and Folic Acid. Both micronutrients are commonly found in many iron supplements because of constant concern about high prevalence of maternal iron deficiency (Allen and Gillespie, 2001).

Aside from significant associations with infant mortality, LBW also has other negative effects particularly on physical and mental development of children. Barker (1997) has found that reduced fetal growth is strongly associated with many chronic conditions (e.g. cardiovascular disease, diabetes, obesity) in later life. Now known as the *Barker's Hypothesis*, it states that "conditions in the maternal womb have a programming effect (*fetal programming*) on fetal physiology." For instance, when a fetus is deprived of adequate nutrient supply in the womb, it will develop a *thrifty phenotype* causing smaller body size and lowered metabolic rate to name a few. In another study, LBW children are more likely to delay entry into school or attend special classes suggesting a direct link between birth weight and intelligence quotient (Corman and Chaikind, 1998). In the light of socioeconomic concerns, LBW babies result in higher economic costs for society such as higher health care costs and lower labor market payoffs. Even worse, socioeconomic inequality causes great disparity between LBW outcomes (Lewit et al., 1995).

For these reasons, there is a need to better understand the determinants of birth weight, both demographical and behavioral, as well as the extent of their impact. While several studies focused either only on LBW outcomes through logistic regression or on general marginal effects of several determinants through ordinary least squares regression, it would be better to study how these factors affect different conditional birth weight distributions. Abrevaya (2001) has focused on the above rationale which made use of quantile regression as its primary statistical technique. The aforementioned study has served as the motivation for this research to be done in the local setting. There are two objectives in this study: (1) on a medical aspect, to provide a better understanding of the impact of various maternal characteristics and pregnancy behaviour on the distribution of birth weight, and (2) on a statistical aspect, to introduce quantile regression as a technique in analysing data requiring assessment of marginal effects of the covariates on the different conditional quantile distributions.

2. Methodology

2.1 Data

The data used in this study was the 2008 Philippine Birth Recode from the National Demographic and Health Survey. Data management and preparation were aided by medical literatures and by an expert obstetrician-gynecologist.

The 2008 Philippine Birth Recode is classified as a standard survey with recode value DHS V. It originally consisted of 28,518 observations with a set of 1,031 variables from which the researchers obtained 14 variables that are essential to the study. Table 1 shows the variables (determinants of birth weight) and their descriptions. These variables contain information on maternal characteristics (age of mother at birth of child, type of place of residence, region of residence, educational attainment, wealth index, total children ever born, and preceding birth interval), maternal behavior during pregnancy (smoking status, pregnancy complications, prenatal care measures, and iron supplementation), and birth outcome (birth weight in grams and gender of child).

From the full data set, only 3,327 cases were taken for the study using the following inclusion criteria: (1) birth weight entry is nonmissing and valid (i.e. at least 500 grams), (2) child is born alive from a single birth outcome, and (3) information on prenatal measures is existent. Observations which do not satisfy any of the stated conditions were dropped.

There were four missing observations for the variable IRON which were accounted through logistic prediction from the other observations. COMPLI, which is a dichotomous variable, determines the occurrence of any of the three major pregnancy complications: hemorrhage, hypertension, and infection. For the 75 observations with missing COMPLI entries, classification is done through evaluation of the reported symptoms experienced by the mother.

2.2 Analysis

Regression models fitted on the data were logistic, ordinary least squares, and quantile models. For the quantile regression models, five quantiles were considered: τ = 0.05, 0.20, 0.50, 0.80 and 0.95 Full models were fitted for all quantile models while stepwise selection was applied for the logistic model. For ordinary least squares, both full and stepwise models were fitted. Diagnostics, goodness-of-fit, and accuracy tests were done afterwards. All statistical procedures and inferences were done at a significance level α of 0.05 using Stata/SE 10.

3. Theoretical Framework

3.1 Logistic regression

Logistic regression is a special case of Generalized Linear Models (GLM). Often called *logit models,* it is a linear model for the *logit* transformation of a binomial parameter by the *logit* function log $\frac{\pi}{1-\pi}$ of π. For a binary response variable y and a vector of explanatory variable x, let $\pi(x)$ be equal to P (y = 1|X = x) = 1 – P(y = 0 | X = x). The logistic regression model is given by

$$\pi(x)=\frac{\exp\left(\beta_0+\sum\beta_i x_i\right)}{1+\exp\left(\beta_0+\sum\beta_i x_i\right)}. \quad (1)$$

Equivalently, the log odds (*logit*), has the linear relationship

$$\text{logit}[\pi(x)]=\log\frac{\pi(x)}{1-\pi(x)}=\beta_0+\sum\beta_i x_i. \quad (2)$$

The parameter β_i determines the rate of increase or decrease of the curve. When $\beta_i > 0$, $\pi(x_i)$ increases as x_i increases and when $\beta_i < 0$, $\pi(x_i)$ decreases as x_i increases. When $\beta_i = 0$, y is independent of x_i (Agresti, 2007).

A general method of estimation of β is the maximum likelihood estimation. For any pair (x_i , y_i), its contribution to the likelihood function can be expressed as

$$\pi(x_i)^{y_i}\left[1-\pi(x_i)\right]^{1-y_i}. \quad (3)$$

By assuming independence of the observations, the likelihood function is obtained as the product of the terms given in (3) as follows

$$L(\beta)=\Pi_{i=1}^{n}\pi(x_i)^{y_i}\left[1-\pi(x_i)\right]^{1-y_i}. \quad (4)$$

Hence, its log likelihood function is defined as

$$\ln\left[L(\beta)\right] = \sum\left\{\ln\left[\pi(x_i)^{y_i}\right] + \ln\left[\left(1-\pi(x_i)\right)^{1-y_i}\right]\right\}. \tag{5}$$

Maximizing (5) with respect to β results to the normal equations

$$\sum\left[y_i - \pi\left(x_i\right)\right] = 0. \tag{6}$$

and

$$\sum x_i\left[y_i - \pi\left(x_i\right)\right] = 0. \tag{7}$$

Since both equations (6) and (7) are nonlinear in β_0 and β_i's, it requires special iterative methods (Hosmer and Lemeshow, 2000).

An important interpretation of the logistic regression model uses the *odds* and the *odds ratio*. In the case of a simple logistic model, it can be shown that the odds are an exponential function of the lone predictor, that is,

$$\frac{\pi\left(x\right)}{1-\pi\left(x\right)} = \exp\left(\beta_0 + \beta_1 x_1\right) = e^{\beta_0}\left(e^{\beta_1}\right)^x. \tag{8}$$

Equation (8) provides an interpretation for β_1: The odds increase multiplicatively by e^{β_1} for every one unit increase in x. In other words, the odds at level $x + 1$ equal the odds at x multiplied by e^{β_1}. For the case when X is binary, e^{β_1} is the odds ratio for $X = 1$ against $X = 0$ (Agresti, 2002).

3.2 Ordinary least squares regression

Another special case of GLM is the ordinary least squares regression. It is the simplest of all linear regression models for which the response variable Y is written as a linear combination of a set of independent variables x and a random error term ε .

One of the objectives of linear regression analysis is to estimate the parameter vector β and the variance σ_ε^2 of the ε_i's from the data matrix X of size n x p and the associated vector of random observations y of size n x 1. In order to do this, certain assumptions must be made about the model. One assumption is that the values of the matrix X are fixed in repeated sampling and that the only random component in the model is ε_i. Another assumption is that $\varepsilon_i \overset{iid}{\sim} N\left(0,\sigma_\varepsilon^2\right)$. The final assumption is that the rank of the matrix X must be equal to the number of parameters being estimated, therefore requiring that the column vectors form a linearly independent set. This is an important assumption since the matrix X^TX must be invertible in order for the parameters to be estimable.

The model based upon least squares estimation is

$$\hat{y} = \widehat{E[Y]} = X\hat{\beta} \tag{9}$$

where $\hat{\beta}$ is the least-squares estimator of β, which is a vector of size $(p + 1)$ x 1, given by

$$\hat{\beta} = \left(X^T X\right)^{-1} X^T y \tag{10}$$

The vector of residuals, denoted by e, is the difference between y and $\hat{y}$. The vector of parameter estimates $\hat{\beta}$ minimizes the error sum of squares (SSE) $\sum \varepsilon_i^2$, also written as $\varepsilon^T \varepsilon = (y - X\beta)^T (y - X\beta)$. Minimizing $\varepsilon^T \varepsilon$ with respect to $\hat{\beta}$ results into the normal equation

$$X^T X\hat{\beta} = X^T y, \tag{11}$$

which yields equation (10).

The variance-covariance matrix of $\hat{\beta}$ is given by

$$Var\left[\hat{\beta} \mid X\right] = \sigma_\varepsilon^2 \left(X^T X\right)^{-1}. \tag{12}$$

The scalar term σ_ε^2 is estimated by

$$s^2 = \frac{1}{n-p}\left(e^T e\right). \tag{13}$$

where $e = y - X\hat{\beta}$ is the vector n x 1 of residuals.

One desirable characteristic of the OLS regression is that under the condition of spherical errors, the Gauss-Markov Theorem states that $\hat{\beta}$ is the best linear unbiased estimator (BLUE) for β (Dunteman, 1984).

3.3 Quantile regression

Quantile (linear) regression is a regression analysis which specifies the linear dependence of the conditional quantiles of a response variable Y on a set of covariates χ and a random error component ε. First introduced by Koenker and Bassett (1978), it is a generalization of the median regression.

For a specified quantile τ, the model can be expressed as

$$Q_y(\tau \mid X) = X\beta_\tau + \varepsilon \tag{14}$$

with the assumption that

$$Q_\varepsilon(\tau \mid X) = 0 . \tag{15}$$

Unlike the OLS regression, the random component ε need not be homoskedastic, thus, allowing the marginal effects of covariates to vary across different quantiles. For the special case that ε is homoskedastic for a particular τ, then the marginal effects of X is the same with the effects obtained from the OLS regression (Koenker, 2005).

Several literatures have found quantile regression estimates as robust, insensitive to outliers, and revealing of various modes of the distribution (Koenker and Bassett, 1978, Buchinsky, 1998, Koenker, 2005). Thus, it is ideal for cases when the conditional distribution of y given X exhibits the following characteristics: (1) thick tails, (2) asymmetry, and (3) nonunimodal.

For a given quantile τ, a method for estimating β_τ is given by

$$\widehat{\beta_{\tau}} = \underset{\beta \in \mathbb{R}^k}{\arg\min} \sum \left[\rho_\tau \left(y_i - X\beta \right) \right], \tag{16}$$

where $\rho_\tau(u)$ is the loss function given by

$$\rho_\tau(u) = u\left[\tau - I(u < 0)\right]. \tag{17}$$

The minimization problem in (16) can be reformulated as a linear programming problem as

$$\underset{\beta^+,\beta^-,u^+,u^- \in \mathbb{R}^{2k} \times \mathbb{R}_+^{2n}}{\min} \left\{ \tau 1_n^T u^+ + (1-\tau) 1_n^T u^- \mid X\left(\beta^+ - \beta^-\right) + u^+ - u^- = Y \right\}, \tag{18}$$

where $\beta_j^+ = \max\left(\beta_j, 0\right) u_j^+ = \max\left(u_j, 0\right)$

$$\beta_j^- = \min\left(\beta_j, 0\right) u_j^- = \min\left(u_j, 0\right)$$

Simplex method or advance interior point algorithms can be applied to solve the linear programming problem in (18) (Portnoy and Koenker, 1997).

Under some regularity conditions, the asymptotic variance-covariance matrix of $\widehat{\beta_\tau}$ is given by

$$Var\left[\widehat{\beta_\tau} \mid X\right] = \frac{\tau(1-\tau)}{n} D^{-1} \Omega_x D, \tag{19}$$

where $D=E[f_y\ (X\beta)XX^T]$ and $\Omega_x=E[X^TX]$.

However, direct estimation of (19) is not always satisfactory. One approach for estimating this conditional variance is the design matrix bootstrap estimator (Buchinsky, 1998).

It can be shown that $\widehat{\beta_\tau}$ exhibits several equivariance properties, such as shift equivariance, scale equivariance, equivariance to monotone transformations, and equivariance to reparametrization of design (Koenker and Bassett, 1978).

The Machado and Santos-Silva (MSS) Test for Heteroskedasticity can be used to test the null hypothesis that the parameter vector τ^{th} quantile model β_t is equivalent to the parameter vector of the ordinary least squares model β_{ols} (Machado and Santos-Silva, 2000). If R^2 is the coefficient of determination of the auxiliary regression on ρ_τ ($Y_i - X_i\ \beta_\tau$) with test variables $\widehat{Q_{Y_1}(\tau \mid X_1)}$ and $\widehat{Q^2_{Y_1}(\tau \mid X_1)}$, then under the null hypothesis, the test statistic

$$nR^2 \xrightarrow{d} \chi^2_{(2)}. \tag{20}$$

To test for equality of parameter vectors across different quantiles, the Wald Test for General Linear Hypotheses (Koenker and Bassett, 1978) can be used. Let $\varsigma = \left[\beta^T_{\tau_1}, \ldots, \beta^T_{\tau_m}\right]^T$ and R be a matrix of contrasts with rank q, then the null hypothesis $R\varsigma = r$ has the test statistic

$$T_n = n\left(R\hat{\varsigma} - r\right)^T \left[RV_n^{-1}R^T\right]\left(R\hat{\varsigma} - r\right) \xrightarrow{d} \chi^2_{(q)}, \tag{21}$$

where V_n is the $m(p+1) \times m(p+1)$ matrix with (i,j)th block

$$V_n\left(\tau_i, \tau_j\right) = \left[\tau_i \wedge \tau_j - \tau_i \tau_j\right] H_n\left(\tau_i\right)^{-1} J_n\left(\tau_i, \tau_j\right) H_n\left(\tau_i\right)^{-1}. \tag{22}$$

4. Result and Discussion

4.1 Descriptive statistics

The summary statistics of the determinants of birth weight considered in the study are given in Table 1. The means of the uncategorized AGE and PARITY are 28.38 years (SE = 0.1133) and 2.89 (SE = 0.0353), respectively. For the subsample of mothers who reported their child as not first born, the mean preceding birth interval is 46.51 months (SE = 0.6869). On the other hand, for the subsample of mothers who had at least one prenatal care, the mean number of visits is around 6 or 7 visits during pregnancy (SE = 0.0622).

Table 2 shows the summary statistics of birth weight (BIRTHWT). A graphical representation of the birth weight distribution is shown in Figure 1. It can be seen that the empirical birth weight distribution is bimodal with modes at around 2,700 grams and 3,200 grams. A difference of 160 grams is observed between the mean and the median, suggesting that the distribution of birth weight is skewed to the left ($\hat{\gamma}_3$ = -0.37). Furthermore, the distribution has heavier lower tail, suggesting a high occurrence of lower birth weights.

Table 1. Summary Statistics of the Determinants of Birth Weight

Variable Name	Description	Proportion (SE)	Variable Name	Description	Proportion (SE)
Maternal Characteristics			Pregnancy Behavior		
AGE	Age of Mother at Birth of Child 0 – 14 to 19 years old 1 – 20 to 34 years old 2 – 35 to 49 years old	7.66% (0.0050) 73.17% (0.0083) 19.17% (0.0073)	SMOKE	Smoking Status 0 – Non Smoker 1 – Smoker	95.19% (0.0040) 4.81% (0.0040)
PLACE	Type of Place of Residence 0 – Rural 1 – Urban	43.42% (0.0090) 56.58% (0.0090)	VISIT	Prenatal Visits for Pregnancy No Visit Less than 4 Visits At Least 4 Visits	2.07% (0.0026) 12.69% (0.0060) 85.24% (0.0064)
REGION	Region of Residence 0 – NCR 1 – North Luzon 2 – South Luzon 3 – Visayas 4 – Mindanao	17.94% (0.0080) 18.72% (0.0071) 22.17% (0.0081) 18.94% (0.0070) 22.23% (0.0070)	PRE NATAL	Prenatal Care Attendant 0 – None 1 – Doctor 2 – Nurse or Midwife 3 – Others	2.07% (0.0026) 47.67%(0.0093) 48.73% (0.0093) 1.53% (0.0021)
EDUC	Educational Attainment 0 – Primary/None 1 – Secondary 2 – Higher	17.25% (0.0068) 49.32% (0.0093) 33.43% (0.0088)	COMPLI	Pregnancy Complications 0 – No 1 – Yes	27.18% (0.0082) 72.82% (0.0082)
WEALTH	Wealth Index 0 – Poor 1 – Middle 2 – Rich	36.61% (0.0086) 21.45% (0.0077) 41.94% (0.0093)	IRON	Iron Supplementation 0 – No 1 – Yes	11.68% (0.0057) 88.32% (0.0057)
EDUC	Educational Attainment 0 – Primary/None 1 – Secondary 2 – Higher	17.25% (0.0068) 49.32% (0.0093) 33.43% (0.0088)	COMPLI	Pregnancy Complications 0 – No 1 – Yes	27.18% (0.0082) 72.82% (0.0082)
PARITY	Total Children ever Born Single Child Multi-Para (2-4) Grand Multi-Para (5 or more)	31.39% (0.0086) 52.64% (0.0093) 15.97% (0.0065)			
BIRTHINT	Preceding Birth Interval (Months) First Born At Most 3 Years Greater than 3 Years	31.39% (0.0086) 52.64% (0.0093) 15.97% (0.0065)			
			Birth Outcome		
			GEN-DER	Gender of Child 0 – Female 1 – Male	47.31% (0.0093) 52.69% (0.0093)

Table 2. Detailed Summary of Birth Weight

Birth Weight (BIRTHWT) in grams	
Mean	3,157.17
Standard Error	11.26
Minimum	725
Maximum	6,758
5th Percentile	1,587
20th Percentile	2,585
50th Percentile (Median)	2,993
80th Percentile	3,583
95th Percentile	4,082
Proportion of LBW	19.11%
95% Confidence Interval	(16.72%, 21.50%)

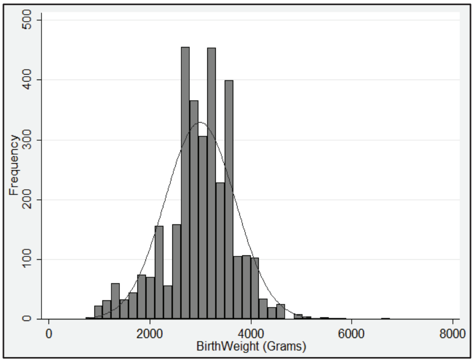

Figure 1.Birth Weight (grams) Histogram

4.2 Fitted logistic regression model

Table 3 shows the estimates of the fitted logistic regression model obtained using stepwise procedure. Note that only the reduced model is presented since only an overview of significant covariates is desired. Among these variables, only AGE appears to be a risk factor for LBW, particularly giving birth between ages 35 and 49. Supposing equal status for all other variables involved, the odds of a mother aged 35 to 49 years old giving birth to an LBW baby are almost 1.5 times the odds of a mother aged 20 to 34 giving the same birth outcome. However, the model suggests no significant risk associated with giving birth at an earlier age (i.e. 14 to 19 years old). In terms of region of residence, mothers from North Luzon are significantly at lesser risk of delivering an LBW baby as compared to mothers from the National Capital Region (NCR). However, for other regions specified above, the odds are likely to be the same and insignificant.

In view of socioeconomic characteristics, it is interesting to note that the odds of having an LBW baby by mothers attaining at least a secondary education is almost 20% lower than the odds of having the same outcome by mothers who at most finished a primary education. The socioeconomic disparity is further magnified by wealth classification as the odds of having an LBW infant decrease significantly by almost 30% and 35% as the mother obtains higher wealth status. Moreover, for both variables EDUC and WEALTH, there is a significant decreasing trend in the odds of obtaining LBW babies as the mother classifies herself 'further' from the assigned baseline levels.

Table 3. Logistic Regression Estimates

Variable	**Coefficient (β)**	**Odds Ratio (θ)**	**Standard Error**	***p-value***
AGE (0 = 20 to 34 years old)				
1 = 14 to 19 years old	0.0801	1.0834	0.1710	0.612
2 = 35 to 49 years old	0.3858	1.4708*	0.1765	0.001
REGION (0 = NCR)				
1 = North Luzon	-0.3665	0.6932*	0.1226	0.038
2 = South Luzon	0.1103	1.1166	0.1784	0.490
3 = Visayas	-0.0125	0.9876	0.1730	0.943
4 = Mindanao	-0.0386	0.9621	0.1623	0.819
EDUC (0 = Primary/None)				
1 = Secondary	-0.2413	0.7856	0.1292	0.142
2 = Tertiary	-0.2433	0.7841*	0.0975	0.050
WEALTH (0 = Poor)				
1 = Middle	-0.3353	0.7151*	0.1000	0.016
2 = Rich	-0.3930	0.6751*	0.0867	0.002
BIRTHINT (0 = First Born)				
1 = At Most 3 Years	-0.3967	0.6725*	0.0797	0.001
2 = Greater than 3 Years	-0.6964	0.4984*	0.0710	0.000
VISIT	-0.0246	0.9757*	0.0122	0.049
GENDER (0 = Female)				
1 = Male	-0.1873	0.8292*	0.0751	0.039
constant	-0.4410	0.6434*	0.1405	0.043

**Significant at 5% significance level*

A birth interval of at most three years reduces the risk of having LBW babies by almost one-third but a reduction of more than half is expected for longer birth intervals. BIRTHINT also exhibits a significant decreasing trend in the odds of having an LBW infant as the interval between births gets longer. For the number of prenatal visits, the odds of obtaining an LBW outcome change by a multiplicative factor of 97.57% for each visit. Finally, female infants are more likely to be classified as LBW than male infants by a ratio of 0.8292. This result is, however, typical in a medical perspective.

Testing for model significance, its Wald $\chi^2_{(14)}$ statistic value of 78.19 suggests significance of the fitted model (p≈0.0001). From the same model, the concordance index (i.e. area under the ROC (Receiver Operating Characteristic) curve) is 0.6136. Given any randomly selected pair of infants, one of which is LBW while the other is not, there is a 61.36% chance of correctly determining the true birth weight classification of these infants on the basis of the variables included in the model.

The cut-off of 0.195 for predicting an LBW outcome was determined by taking the probability associated with the intersection of the sensitivity and specificity plots as shown in Figure 2. This was done to obtain a balance between both statistics due to their medical and economic implications. The resulting predictive power is 58.52%, which means that the model does not actually do much better than doing random prediction (with a 50% chance of being correct). Other measures of predictive accuracy are given in Table 4.

Table 4. Birth Weight Confusion Matrix

	True Classification		
Predicted Classification + - Total	D 366 276 642	~D 1.104 1.581 2,685	Total 1.470 1.857 3,327
Classified + if predicted Pr (D) >= 0.195			
True D defined as low birth weight babies			
Sensitivity	Pr (+ | D)		57.01%
Specificity	Pr (- | ~D)		58.88%
Positive predictive value	Pr (D | +)		24.90%
Negative predictive value	Pr (~D | -)		85.14%
False + rate for true ~D	Pr (+ | ~D)		41.12%
False – rate for true D	Pr (- | D)		42.99%
False + rate for classified +	Pr (~D | +)		75.10%
False – rate for classified -	Pr (D | -)		14.86%
Hit Ratio			58.52%

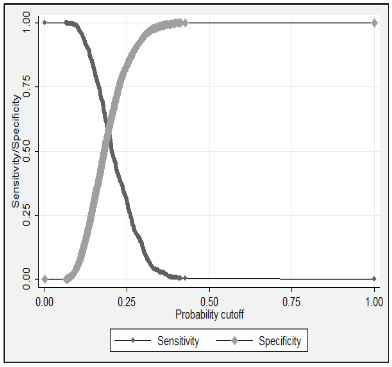

Figure 2.Specificity and Sensitivity Plots

4.3 Fitted ordinary least squares and quantile regression models

Table 5 shows the estimation results for the full models of both quantile regression and ordinary least squares (OLS) regression.

Age of mother at birth of child

AGE enters the model as a quadratic effect with a downward concavity, which indicates the occurrence of optimal ages for giving birth. The effects at various quantiles are shown in Figure 3. At the lower quantiles ($\tau = 0.05, 0.20$), the mother's age effect tends to be more concave. It increases up to ages 26 or 27 (which are considered as the optimal ages) with magnitudes of about 780 grams and 840 grams for 5% and 20% quantiles, respectively. However, less concavity is observed for $\tau = 0.50$ and $\tau = 0.80$, with optimal ages of 18 to 20 years. The magnitudes of the effect are 105 grams and 150 grams for the respective quantiles. For the same quantiles, negative effects of AGE can be observed at ages 34 and 38 years, respectively. At the highest quantile ($\tau = 0.95$), there is an immediate decline in the effect of AGE reaching optimality at the earliest age considered in the study (14 years old) with a negative magnitude of about 50 grams.

In the OLS model, mother's age effect reaches optimality at around ages 22 to 24 (with magnitudes of around 290 grams) and negative effect starts at age

Table 5.Quantile regression and OLS regression estimates (full models)

	Quantile Regression					OLS
	5%	20%	50%	80%	95%	
AGE	57.10 (52.12)	63.89* (29.46)	12.73 (15.28)	15.87 (22.05)	-1.73 (31.11)	26.12 (17.57)
AGESQ	-1.04 (0.87)	-1.21* (0.49)	-0.38 (0.26)	-0.42 (0.35)	-0.13 (0.51)	-0.5855 (0.30)
PLACE	-190.69 (104.88)	-15.07 (38.48)	4.97 (27.80)	-9.06 (35.16)	-12.52 (51.03)	-8.84 (26.72)
REGION1	117.15 (196.62)	138.23* (55.11)	138.46* (42.22)	96.73 (70.35)	-0.85 (88.04)	146.13* (39.66)
REGION2	-502.77* (198.28)	-4.83 (72.37)	90.58* (43.54)	-38.01 (60.08)	-196.35* (86.86)	-37.62 (41.04)
REGION3	-272.57 (228.73)	38.19 (62.46)	27.32 (50.12)	-64.72 (68.42)	-143.06 (85.20)	-20.26 (46.07)
REGION4	-275.36 (184.08)	35.33 (69.85)	101.61* (46.44)	32.36 (64.31)	59.72 (90.76)	41.38 (43.50)
EDUC1	47.99 (105.20)	205.10* (67.80)	115.75* (44.14)	62.13 (54.63)	-25.64 (66.55)	90.72* (35.95)
EDUC2	25.90 (142.75)	170.05* (74.50)	62.67 (51.35)	58.60 (62.90)	-58.77 (73.22)	76.27 (42.35)
WEALTH1	31.64 (140.76)	128.26* (61.18)	33.52 (36.62)	21.95 (45.57)	-61.08 (64.44)	59.08 (32.50)
WEALTH2	129.37 (145.46)	116.95* (56.80)	-0.54 (37.89)	-64.26 (45.04)	-142.09* (66.75)	26.00 (37.71)
PARITY	16.76 (32.37)	21.96 (15.75)	35.00* (11.58)	45.79* (13.74)	57.63* (26.25)	37.59* (9.75)
BIRTHINT1	149.32 (130.83)	74.11 (62.92)	76.24 (42.29)	63.48 (56.57)	-71.42 (74.28)	62.51 (37.66)
BIRTHINT2	82.71 (145.96)	200.80* (59.16)	176.86* (40.09)	122.53* (52.98)	48.48 (91.00)	152.26* (38.23)
SMOKE	45.57 (235.24)	26.40 (90.14)	-32.04 (43.24)	-120.21 (82.26)	26.00 (131.16)	-44.52 (55.18)
VISIT	5.26 (15.06)	12.20* (4.27)	12.38* (4.74)	8.82* (4.48)	0.30 (7.03)	9.54* (3.83)
PRENATAL1	-1.38 (219.13)	-168.64 (102.42)	83.57 (63.21)	21.52 (114.29)	177.13 (166.98)	8.58 (67.12)
PRENATAL2	-49.72 (203.52)	-182.45 (102.37)	30.98 (62.16)	3.72 (110.40)	54.11 (162.55)	-30.05 (64.81)
COMPLI	-22.71 (90.89)	1.20 (50.80)	-46.64 (32.82)	-66.54 (38.22)	-57.42 (52.13)	-29.36 (30.17)
IRON	186.68 (111.97)	69.35 (64.16)	43.19 (37.18)	27.60 (48.46)	51.46 (70.43)	33.33 (41.99)
GENDER	69.08 (87.39)	60.84 (45.08)	69.05* (24.93)	64.31 (34.34)	51.13 (45.34)	78.94* (22.24)
constant	829.45 (764.10)	1328.52* (445.11)	2461.58* (215.51)	3130.26* (338.72)	4051.06* (436.02)	2353.02* (256.66)

**Significant at 5% significance level*
( ) Standard errors enclosed in parentheses

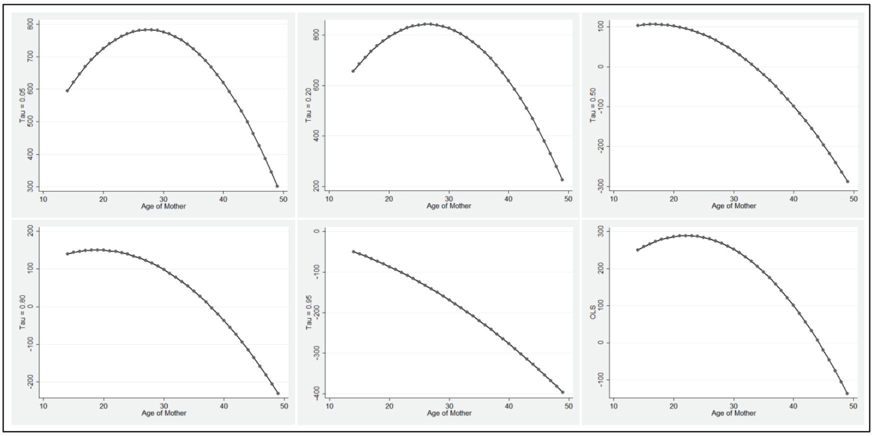

Figure 3. Quadratic Effects of AGE

45. Collectively, it can be seen that for the lower quantiles, OLS tends to provide smaller estimates of the quadratic effects of AGE but the opposite is observed for the other quantiles.

Type of place of residence

The differential in birth weights between mothers living in urban and rural areas is 191 grams at the 5% quantile which is quite large compared to the disparities at other quantiles ranging from 5 grams to 15 grams only. Also, PLACE generally has negative effects at several quantiles, with the largest magnitude at $\tau = 0.05$ which suggests that holding all other variables constant, the 5% quantile of birth weight for a baby born to a mother living in urban area is 191 grams below the 5% quantile of birth weight for a baby born to a mother living in rural area. For the same quantile, OLS tends to provide a smaller estimate of the magnitude of the effects of variable PLACE.

Region of residence

The estimates of the various region categorical variables are differences in birth weights from infants whose mothers are from the National Capital Region (NCR).The disparity between birth weights of infants born to a mother from NCR and North Luzon (REGION1) is large and positive across the different quantiles ranging from 95 to 140 grams except at the 95% quantile where the differential is negatively small. OLS regression tends to provide a larger estimate of the magnitude of these effects across quantiles.

For the differential in birth weights between mothers in the NCR and South Luzon (REGION2), there is a very large negative effect of almost half a kilogram at the 5% quantile. There is also a large effect in birth weight at both 50% and 95% quantiles with 91 grams and 196 grams, respectively. Also, OLS tends to provide a smaller estimate of the magnitude of the effects of variable REGION2 at different quantiles except at the 20% quantile.

The differentials in birth weights between mothers in the NCR and Visayas region (REGION3) are larger in the extreme quantiles (5% and 95%) and tend to go smaller towards the intermediate quantiles (20%, 50%, 80%). Also, the OLS tends to provide a smaller estimate of the magnitude of the effects of REGION3 at the different quantiles.

For mothers in Mindanao region (REGION4), their differentials in birth weight from mothers in NCR are large at the 5% and 50% quantiles which are also much larger than estimates from the OLS regression. Furthermore, only at 5% quantile does REGION4 have a negative effect on birth weight.

Educational attainment

For the education categorical variables (EDUC1 and EDUC2), the estimates are the differences in birth weights from infants whose mothers had at most a primary education. The differentials in birth weights between mothers who attended at most a primary level education and secondary education is highest at the 20% quantile with a magnitude of about 205 grams. The disparity in birth weight is also considerably large at the median with a magnitude of almost 116 grams. For mothers who had at least a tertiary educational attainment, the birth weight differential is also highest at the 20% quantile with a magnitude of about 170 grams. These magnitudes tend to be larger than the estimates provided by OLS regression.

Wealth index

The estimates of the wealth categorical variables are differences in birth weights from infants whose mothers belong to the poor class. The largest disparity between mothers who are in the lower class and the middle class (WEALTH1) is at the 20% quantile with a magnitude of 128 grams. This magnitude tends to be larger than the estimate from OLS regression. Meanwhile, the disparity between birth weights of infants born to poor mothers and infants born to rich mothers (WEALTH2) is large at different quantiles except at the median where it is very small. These large differentials tend to be larger than the estimate from OLS regression. Also, the magnitudes of the effects of being rich tend to increase towards the extreme quantiles of the distribution. Lastly, there is a positive effect of being rich at the lower quantiles but negative effect at the upper quantiles.

Total children ever born

Among all the other variables, only PARITY increases monotonically when moving from the lower quantiles to the higher quantiles. The magnitudes are all positive ranging from 15 to 60 grams. The OLS estimate tends to have a larger magnitude for the effect of variable PARITY as compared to quantile regression estimates at $\tau=0.05$, $\tau=0.20$, and $\tau=0.50$. However, the opposite is observed when compared to quantile regression estimates at $\tau=0.80$ and $\tau=0.95$.

Preceding birth interval (Months)

The estimates of the birth interval categorical variables are differences in birth weights from infants who were first born. The disparity between birth weights of first born babies and infants preceded by at most 3 years (BIRTHINT1) ranges from 60 grams to 80 grams except at the 5% quantile where the differential is almost 150 grams. Furthermore, the magnitudes across quantilestend to be larger than the estimate provided by OLS. For the differentials in birth weights between first born babies and infants who were preceded by more than 3 years (BIRTHINT2), the effects are positive in all the different quantiles. The largest difference is at the 20% quantile with a magnitude of 200 grams. The disparities are also considerably large at the 50% and 80% quantiles. These magnitudes tend to be larger than the estimate provided by OLS regression.

Smoking status and prenatal visits for pregnancy

For mothers who are nonsmokers, the differential in birth weights against mothers who are smokers is large at the 80% quantile with a negative magnitude of about 120 grams. For other quantiles, the differentials are not that large ranging from 25 to 45 grams only.

The effects at the different quantiles of prenatal visits during pregnancy are all positive ranging from 5 to 12 grams except at $\tau = 0.95$ where the magnitude is very small. These positive magnitudes indicate higher birth weight outcomes for every prenatal visitation made during pregnancy.

Prenatal care

The estimates of prenatal care attendant categorical variables are differences from mothers whose prenatal care attendants are traditional *hilots*, traditional health care workers, or none at all. The differentials in birth weights as compared to mothers whose prenatal care attendants are doctors (PRENATAL1) and nurse or midwife (PRENATAL2) are positive at higher quantiles of the birth weight distribution. The OLS estimates of the magnitude of the effects of the two variables tend to be smaller than those obtained at the different quantiles except at $\tau = 0.05$ and $\tau = 0.80$ for PRENATAL1 and PRENATAL2, respectively.

Pregnancy complications, iron supplementation, and gender of child

The differentials of birth weights between mothers with no pregnancy complications and with pregnancy complications are generally negative indicating lower birth weights for infants whose mothers had complications during pregnancy. The magnitude of the effects ranges from 20 to 70 grams except at the 20% quantile where the magnitude is very small.

For infants whose mothers had not taken up iron supplementation during pregnancy, the differential of their birth weights against those whose mothers had iron supplementation is highest at $\tau = 0.05$ with a magnitude of about 187 grams. Also, iron supplementation has a positive effect on birth weight distribution at the different quantiles.

The differentials in birth weights of female infants and male infants range from 50 to 70 grams. Note also that the effects at the different quantiles are all positive which suggest higher birth weights among male infants. Moreover, OLS regression tends to provide larger estimates of the magnitude of these effects at the different quantiles.

From the aforementioned discussion of the marginal effects of the covariates, the first half can be grouped as the maternal characteristics of mothers. The latter half, starting from PARITY, can be grouped as variables of public health concern except GENDER. However, it should be noted that the interpretation of several covariates' causal effects may be somewhat controversial, especially across quantiles. This may be due to several unobservable factors exogenous to the study. For instance, both indicator variables for prenatal care attendants indicate negative effects at the lower quantiles suggesting that intervention by medical professionals may "decrease" birth weight. In this case, it is suspected that there is the self-selection of mothers to only seek medical help only because of the presence of pregnancy abnormalities.

At a significance level of $\tau = 0.05$, the significant variables from the OLS regression model are as follows: REGION, EDUC, PARITY, BIRTHINT, VISIT, and GENDER. The same set of covariates is obtained for the median regression model ($\tau = 0.50$). At the 5% quantile, the only significant variable is REGION. At the 20% quantile, the significant variables are AGE, REGION, EDUC, WEALTH, BIRTHINT, and VISIT. At the higher quantiles ($\tau = 0.80, 0.95$), the set of significant variables consists of PARITY, BIRTHINT, and VISIT for $\tau = 0.80$, and REGION, WEALTH, and PARITY for $\tau = 0.95$.

Figure 4 shows the marginal effects of different covariates across various quantiles. The first picture gives the values of intercepts with centered covariates for the various conditional quantile models as well as for the conditional mean model. It is interpreted as the estimated birth weight of a girl, who is first-born to a 28-year old poor mother with at most a primary education, did not smoke nor suffer from any complication during pregnancy, but received no prenatal care nor iron supplementation. Note that the 20% quantile of the distribution for this group is below the threshold of the conventional definition of LBW baby.

For several variables, the 95% confidence intervals for some quantiles seem not to overlap with their respective OLS intervals. This may suggest a significant difference between the parameter vectors β_τ and β_{OLS}. To formally test this, the MSS test for heteroskedasticity was used. It resulted to the rejection of the null hypothesis for quantiles 0.05, 0.20, and 0.95, with the same $p \approx 0.000$. This indicates that for the said quantiles, their parameter vector is significantly different from that of the OLS regression.

To test for equality of β_τ across different quantiles, a pairwise procedure was conducted using the Wald Test. The results suggest that the parameter vector of the 20th quantile is significantly different from that of all other quantiles considered

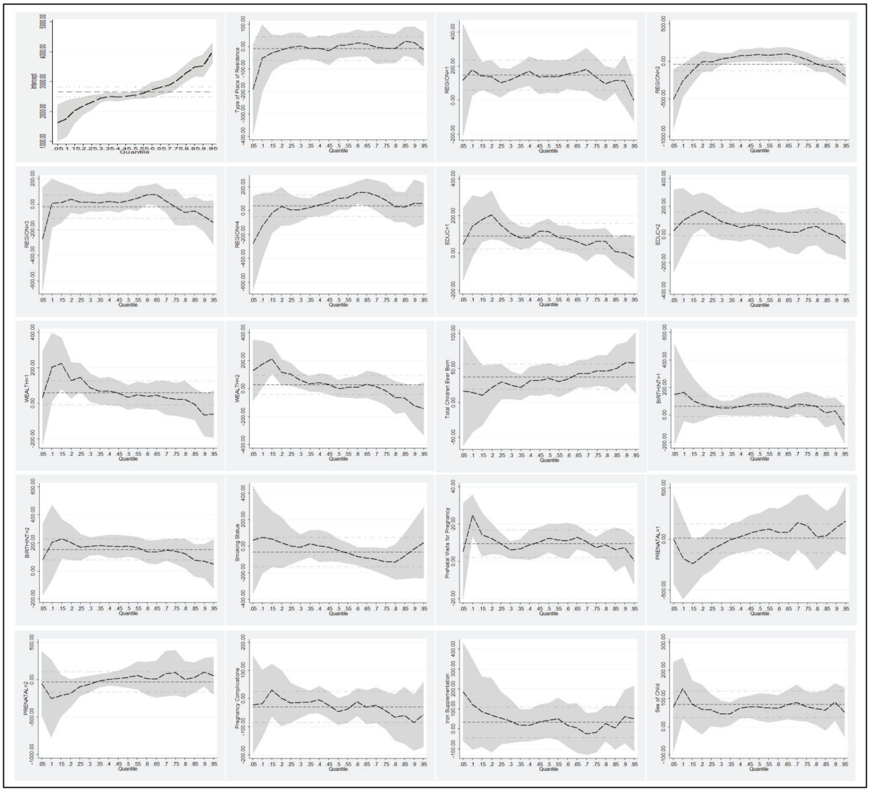

Figure 4. Marginal Effects of Different Covariates Across Various Quantiles

with $p<0.05$. Also, both the parameter vectors of the 5th and 95th quantiles are significantly different from that of the median. Moreover, the test suggested equality of the parameter vectors for the median and the 80th quantile which is consistent from the MSS test. From those quantiles for which their corresponding β_τ are unequal, the variables which caused their differences pertained to the following characteristics of the mother: age of mother at birth of child, region of residence, educational attainment, wealth index, and prenatal care attendant.

Reduced models

Table 6 shows the parameter estimates for the reduced ordinary least squares model obtained using stepwise procedure. Estimates of the coefficients for each quantile model regressed on the same set of predictors are also shown. Interpretations of these coefficients, albeit changes in magnitudes, are still the same as interpreted earlier from the full ordinary least squares and quantile regression models except for variables REGION1 and BIRTHINT2. That is, for the reduced models, the coefficients of REGION1 now give the differences in birth weights of infants born to mothers coming from North Luzon as against

Table 6. Quantile Regression and OLS Regression Estimates (reduced models)

	Quantile Regression					OLS
	5%	20%	50%	80%	95%	
AGE	77.66 (43.18)	*65.67** (30.82)	*21.36** (15.11)	18.53 (20.78)	-8.96 (38.15)	*35.43** (14.56)
AGESQ	-1.35 (0.74)	*-1.23** (0.52)	*-0.51** (0.25)	-0.42 (0.32)	0.02 (0.64)	*-0.73** (0.24)
REGION1	*452.98** (94.54)	*147.23** (44.18)	*94.87** (27.07)	*99.83** (38.51)	70.28 (57.58)	*176.31** (31.60)
EDUC1	1.49 (116.93)	*229.39** (70.88)	*134.98** (37.27)	91.50 (49.64)	-23.87 (59.04)	*108.52** (33.66)
EDUC2	117.32 (123.36)	*226.33** (70.24)	*97.96** (43.71)	53.86 (59.12)	-41.22 (66.65)	*104.92** (38.22)
PARITY	36.45 (27.55)	22.32 (13.95)	*38.53** (7.99)	*49.24** (12.60)	*43.30** (19.02)	*41.58** (8.20)
BIRTHINT2	25.55 (104.90)	*167.20** (40.95)	*130.09** (29.20)	57.17 (34.50)	89.54 (52.71)	*109.93** (27.89)
VISIT	24.66 (13.02)	*9.98** (3.81)	*11.41** (4.60)	3.07 (3.85)	-2.95 (6.60)	*9.67** (3.49)
GENDER	92.84 (88.24)	*78.75** (33.66)	*67.53** (26.73)	52.71 (30.34)	61.73 (48.46)	*78.45** (23.86)
constant	166.61 (579.29)	*1274.22** (456.38)	*2460.74** (210.18)	*3072.54** (314.28)	*4109.83** (559.51)	*2204.47** (210.81)

**Significant at 5% significance level*
( ) *Standard errors enclosed in parentheses*

those who are not from the same region. For BIRTHINT2, the coefficients are the differentials in birth weights of babies preceded by more than three years as against those who were not.

The median regression has a full set of significant predictors as well as the 20^{th} quantile model except for PARITY. For other quantile models, very few of these variables were found to be significantly related to birth weight. The reduced models derived from the stepwise procedure on ordinary least squares, however, do not give information with regards to the significance of other predictors on different quantile models. For instance, WEALTH1 and WEALTH2 were found to be significant in the full 20^{th} quantile model but were not accounted for in the reduced models.

Diagnostic checking

Both the full and reduced ordinary least squares models were found to be significant with $p<0.0001$. However, the full model did poorly in explaining the variation among the values of birth weights with an adjusted of 3.39%. The reduced model did better with an adjusted of 11.67%. The models were also found to violate the assumptions of normality (Shapiro-Wilk's Test $p \approx 0.0001$ for both models) and homoskedasticity (Bartlett's Test $p \approx 0.0476$ for the full model and $p \approx 0.0391$ for the reduced model). Multicollinearity existed on the full model but the same was not found for the reduced model. Both, however, did not violate the assumption of stochastic independence (Durbin-Watson Test min $(p_-, p_+) \approx 0.0759$ for the full model and min $(p_-, p_+) \approx 0.1091$ for the reduced model). Several potential influential points were also inherent in the data (Cook's D > 0.0012) which have strongly affected the parameter estimates for both ordinary least squares models. However, these points were not removed since they were found not to influence quantile regression estimates. Nevertheless, these issues were not addressed since the fitted OLS models only served as comparisons for the fitted quantile regression models, which were the main focus of the study.

5. Conclusion

Quantile regression provided an interesting picture of the marginal effects of the covariates considered in the birth weight distribution. It shows fluctuation of effects of some variables across different conditional quantiles of the response variable which cannot be observed from a conditional mean model. For instance, a particular predictor may not be significant in an OLS model but it actually is at lower quantiles. Though quantile regression involves more rigorous computations, it still offers a model with fewer assumptions, thus, making it more flexible. In comparison with a logistic regression model, it allows a quantitative assessment of the marginal effects of the predictors at any distribution of the response variable rather than a likelihood association of the predictors to a certain characteristic of the response variable. However, it should be considered that in interpreting results obtained from quantile regression, proper care should be administered. That is, similar to any other regression models, coefficients should not be interpreted as causal effects due to the existence of several unobserved factors.

From the set of all variables considered in the study, several exhibited significant relationships with birth weight in all the fitted regression models: logistic, ordinary least squares, and quantile regressions. Majority of these variables are of maternal characteristics (e.g. region of residence, educational attainment, total number of children ever born, and preceding birth interval in months). From the constructed models, similar information can be extracted from logistic, conditional mean, and conditional median models. However, the same cannot be said in considering other conditional quantiles. That is, there are instances when variables behave differently across these quantiles. Specifically at the lower quantiles which represents the low birth weight infants, it is evident that socially and economically impoverished mothers are marginalized in terms of birth weight outcomes. Furthermore, most of them were also underprivileged in areas concerning maternal health. Thus, it is recommended that policymakers should give focus on improving both the accessibility and quality of prenatal health care for mothers, especially among those who are marginalized. One way of doing this is through proper education, both on the side of mothers and public health workers.

6. Recommendation

For further studies, the following directions may be considered: (1) Include other relevant variables which are not considered in the study such as mother's weight gain during pregnancy and other nutritional intakes. Possible interaction effects among covariates of birth weight may also be taken into consideration. Moreover, exploration of other model selection procedures (aside from stepwise selection) may help in understanding the relationships between variables considered. (2) Use a data set with larger sample size, especially at the extreme quantiles to allow stability of results. It is highly encouraged to use panel data to possibly control for some exogenous maternal characteristics (i.e. genetics, pregnancy history, etc.). (3) Do parallel studies for both the 2003 and the upcoming 2013 Philippine Birth Recode from NDHS to compare results and look at the effectiveness of certain government policies regarding the improvement of maternal health through time. (4) Explore other statistical information from the results obtained from quantile regression which are currently being studied in a wide variety of literature. This information may pertain not only to the true distribution of birth weight (e.g. scale shift and skewness shift) but also to the relationships among its covariates (e.g. R-squared).

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