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LONGITUDINAL DATA ANALYSIS BY NONPARAMETRIC BI-RESPONSE SPLINE TRUNCATED REGRESSION MODEL

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Abstract: This study aims to construct a growth model for toddlers based on longitudinal data using a nonparametric bivariate response truncated spline regression approach. The data used consisted of routine toddler weighing records from the Integrated Health Post in Bontosunggu Village, South Bontonompo Sub-District, Gowa Regency, encompassing age, body weight, and height of toddlers from January to December 2021. The analysis was conducted by developing two regression models for each response variable, namely body weight and height, using four knot points (12, 24, 36, and 48 months), and parameter estimation was carried out using the Ordinary Least Squares (OLS) method. The analysis results indicate that the growth of toddlers' weight and height does not follow a linear pattern with age but rather displays a change in growth rate at specific age points. This model provides a more realistic and flexible depiction of growth and can serve as a useful tool for monitoring the nutritional and health status of early childhood populations.

Keywords: bivariate response; longitudinal data; nonparametric regression; truncated spline; toddler growth.

2020 AMS Subject Classification: 62P10.

1. INTRODUCTION

Statistics have rapidly developed in the era of globalization. This development is characterized by the wider application of statistical methods in various fields, both for data exploration and data-

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based decision making. Regression analysis is a statistical technique used to identify the relationship between a predictor variable and a response variable [1]. In regression analysis, there are three main approaches: parametric, nonparametric, and semiparametric. A parametric method was used when the shape of the regression curve was completely defined, whereas a nonparametric method was selected when the curve's form is either unknown or varies across sections. In contrast, a semiparametric approach is employed when part of the curve's structure is known and the remaining portion is not specified [2]. Semiparametric and nonparametric regression approaches are complementary, where semiparametric regression is used when the shape of the regression curve is partially known, whereas nonparametric regression is used when the shape of the curve is completely unknown and no prior information about the data pattern is available.

Nonparametric regression is one of the approaches used to determine the relationship pattern between response variables and predictor variables, whose regression curve is not known, and there is no complete past information about the form of data patterns [3]. Nonparametric regression offers flexibility in determining the shape of the regression curve independently, without being affected by the subjectivity of the researcher [4]. To identify complex data patterns in nonparametric regression, a flexible estimator that is adaptive to unknown data structures is required [5]. Estimators that are often used because they have such flexibility are spline, kernel, and Fourier estimators.

Estimators in nonparametric regression models, including spline, are important for estimating the regression curves. A spline regression model was used to estimate the regression curve. Spline is a polynomial piece that has the properties of being formed at knot points [6]. Spline functions are more specialized, provide more flexibility than general polynomial functions, have a simple statistical interpretation, and have excellent visual presentation [7], [8]. One specialized form of the spline is the truncated spline, where the spline function is constructed by adding a component of the truncated function at each knot point. This function is zero before the knots and follows a polynomial after passing through the knots, thus providing additional flexibility locally in certain parts of the data [9]. Nonparametric regression using a truncated spline estimator is well-suited for managing irregular data patterns, as it offers local flexibility by employing functions that are zero before the knots and take on a polynomial form afterward.

A nonparametric regression method that can cope with irregular data patterns uses a nonparametric regression with a truncated spline estimator. Truncated spline nonparametric regression can model data on changing patterns at certain sub-intervals [10], [11]. Truncated splines are flexible because they are assisted by knot points to follow the movement of the data patterns [12]. Various truncated spline estimators have been developed to increase flexibility in nonparametric modelling [13-16]. The truncated spline method in the regression modelling analysis obtained an accuracy rate of 87,5%. Achieving this level of accuracy indicates that the model can accurately represent the data pattern [17]. This finding strengthens the validity of using a truncated spline as an alternative approach in regression analysis, particularly for data that do not follow a simple linear pattern.

Non-simple linear patterns occur in nonparametric regressions. However, when the data involves two correlated responses, conventional nonparametric regression cannot effectively model them [18]. One form of data that often displays this type of problem is longitudinal biresponse data, which records two response variables repeatedly over a period of time in the same subject [19]. These data exhibit correlations over time and between responses, thus requiring statistical methods that can handle both simultaneously [20]. Classical nonparametric regression is unable to handle complex dependencies, so flexible models such as biresponse nonparametric regression are needed for longitudinal data [21]. Thus, it is important to develop a nonparametric regression model that can handle the multiple correlation structure in longitudinal biresponse data, to obtain more precise estimates and fully reflect the complex relationship patterns in the data.

One example of longitudinal data is the under-five weighing data, which are routinely collected every month. Toddlerhood is an important and vulnerable early stage of human development and is characterized by high sensitivity to growth disorders. This stage is also known as the golden age, when the basics of sensory abilities, thinking, speaking and intensive intellectual mental growth and the beginning of moral growth are formed [22]. Given the importance of toddlerhood as a critical period for child growth and development, monitoring nutritional status is very important. Weighing data for children under five years of age was one of the main indicators used in this monitoring.

Based on the background explanation above, this study aimed to determine the parameters of a bi-response nonparametric regression model on longitudinal data using a spline truncated approach. In addition, this study also aims to obtain a growth model for under-five children based on a birresponse nonparametric regression framework using a truncated spline function, so that it can describe growth patterns more flexibly and accurately over time.

2. PRELIMINARIES

This study utilized secondary data on age (in months), weight (in kilograms), and height (in centimeters) of toddlers, obtained from the weighing results recorded by the Integrated Health Post in Bonto Sunggu Village, South Bontonompo Sub-district, Gowa Regency, South Sulawesi Province, covering the period from January to December 2021.

This study used two variable categories: predictors and responses. The predictor variables consist of one variable, toddler age (in months), denoted by x. Meanwhile, the response variables are bi-response, which consists of two variables at once, namely toddler weight (in kilograms), which is denoted by $y^{(1)}$ and height (in centimeters) denoted by $y^{(2)}$. Both variables were observed simultaneously on the age of the toddler to form a comprehensive growth model.

The bivariate nonparametric truncated spline regression model was applied. The objective of this study is to determine the form of the truncated spline estimator and the form of the toddler growth models based on bivariate response nonparametric regression with a truncated spline on longitudinal data.

The steps for modeling the toddler growth using bivariate nonparametric regression with a truncated spline estimator are as follows:

1. Construct descriptive statistics and scatter plots for the toddler growth data to explore the relationships and pattern forms between the response and predictor.
2. Estimate the spline model using several knot point configurations.
3. Apply nonparametric truncated spline regression to the longitudinal toddler weight and height data.
4. Estimate the bivariate nonparametric regression model using the truncated spline estimator on longitudinal data.
5. Modeling the equation using knot points.
6. Interpret the final model and conclude.

3. MAIN RESULTS

A total of 109 respondents were identified, with each subject observed or measured 12 times, resulting in a dataset comprising 1308 entries. A summary of the general characteristics of the data is presented in the following table:

Table 1. Statistic Descriptive

	Variable Definition	Min.	1st Qu	Median	Mean	3rd Qu	Max.
x	Age	1.00	17.00	30.00	30.32	44.00	59.00
$y^{(1)}$	Wight	4.00	9.30	11.50	11.29	13.30	17.10
$y^{(2)}$	Height	57.00	76.70	86.15	85.45	94.62	108.60

According to Table 1, the youngest age in the data was 1 month, and the oldest age was 59 months. The first quartile (1st Qu) showed that 25% of the participants were under 17 months of age. The median in the data was 30 months, meaning that half of the samples were less than or equal to 30 months old, and the other half were over 30 months old. The mean or average age was 30.32 months, which was almost the same as the median. The third quartile (3rd Qu) showed that 75% of the participants were under 44 months of age. The lowest recorded weight was 4 kg, and the highest was 17.10 kg. The first quartile showed that 25% of the participants weighted 9.30 kg. Median and midpoint weight were 11.5 kg. The average body weight was 11.29 kg, which was almost the same as the median body weight, indicating a balanced distribution. The third quartile showed that 75% of the participants had a weight below 13.30 kg. The lowest height was 57 cm, and the highest was 108.60 cm. The first quartile showed that 25% of the participants had a height below 76.70 cm. The median height is 86.15 cm. The average height of the patients was 85.45 cm, slightly lower than the median, which shows a slight skewness in the data, meaning that there is an impurity in the data. The third quartile showed that 75% of the participants had a height below 94.62 cm.

In a regression analysis, a scatterplot is required to determine the form of the relationship pattern between the predictor and the response variables. The scatterplot is shown in the following figure.

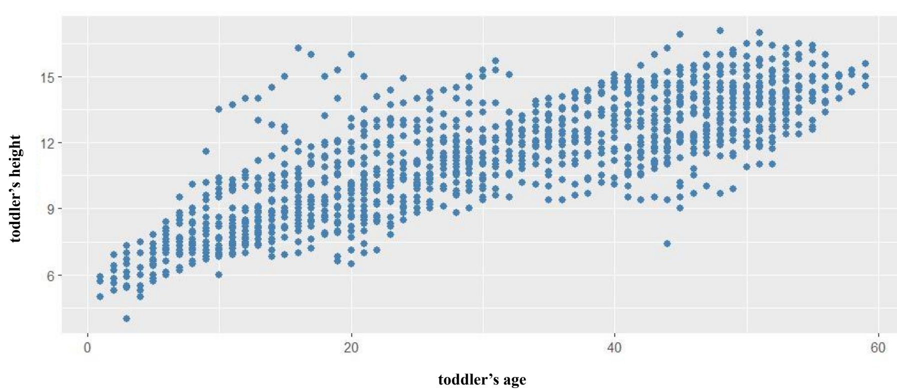

Figure 1. Scatterplot Toddler's Body Weight Data

Based on Figure 1, the weight and age of toddlers have a positive relationship pattern, whereas as age increases, the weight of toddlers also tends to increase, although not linearly. However, there is quite a large variation or spread of data in the middle age, around 20-40 months. This may be caused by individual differences such as genetics, health conditions, and other factors that influence toddlers' weight.

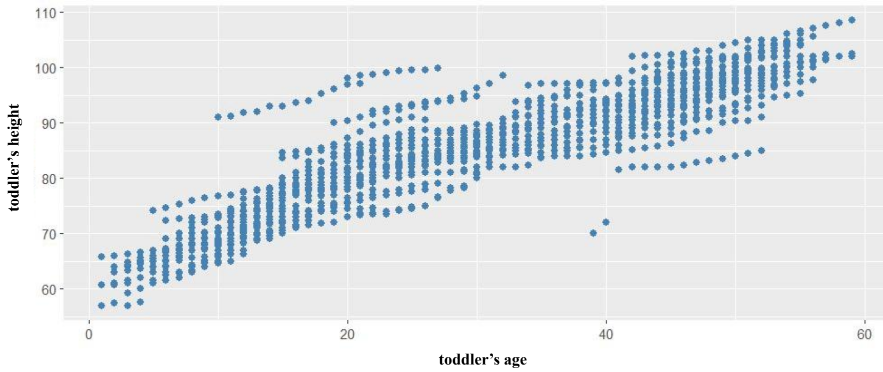

Figure 2. Scatterplot Toddler's Body Height Data

Figure 2 also illustrates that as toddlers grow older, their height increases. Although Figures 1 and 2 display a pattern resembling a parametric form, this study employed a non-parametric regression approach to better capture the variations in the growth patterns of toddlers' weight and height in relation to age.

The estimation technique applied in this study is the Ordinary Least Squares (OLS) method. To obtain the parameter estimates for the regression model using OLS, the process involves minimizing the sum of the squared errors, as described below:

$$\vec{e}^T\vec{e} = \left(\vec{y} - \boldsymbol{X}\vec{\beta}\right)^T\left(\vec{y} - \boldsymbol{X}\vec{\beta}\right)$$

$$\vec{e}^T\vec{e} = \vec{y}^T\vec{y} - \boldsymbol{X}\vec{\beta}\vec{y}^T - \boldsymbol{X}^T\vec{\beta}^T\vec{y} + \boldsymbol{X}^T\vec{\beta}^T\boldsymbol{X}\vec{\beta}$$

$$\vec{e}^T\vec{e} = \vec{y}^T\vec{y} - 2\boldsymbol{X}^T\vec{\beta}^T\vec{y} + \boldsymbol{X}^T\vec{\beta}^T\boldsymbol{X}\vec{\beta} \tag{1}$$

Then Equation (1) is derived against $\vec{\beta}$:

$$\frac{\partial(\vec{e}^T\vec{e})}{\partial\vec{\beta}} = \frac{\partial\left(\vec{y}^T\vec{y} - 2\boldsymbol{X}^T\vec{\beta}^T\vec{y} + \boldsymbol{X}^T\vec{\beta}^T\boldsymbol{X}\vec{\beta}\right)}{\partial\vec{\beta}}$$

$$= -2\boldsymbol{X}^T\vec{y} + 2\boldsymbol{X}^T\boldsymbol{X}\hat{\vec{\beta}}$$

Next, it is equal to zero

$$-2\boldsymbol{X}^T\vec{y} + 2\boldsymbol{X}^T\boldsymbol{X}\hat{\vec{\beta}} = \boldsymbol{0} \tag{2}$$

$$-\boldsymbol{X}^T\vec{y} + \boldsymbol{X}^T\boldsymbol{X}\hat{\vec{\beta}} = \boldsymbol{0}$$

$$\boldsymbol{X}^T\boldsymbol{X}\hat{\vec{\beta}} = \boldsymbol{X}^T\vec{y}$$

From Equation (2), the estimator is obtained $\vec{\beta}$, that:

$$\hat{\vec{\beta}} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\vec{y} \quad (3)$$

The truncated spline bi-response nonparametric regression model involving two response variables can be expressed as follow:

$$y_{it}^{(1)} = \beta_0 + \beta_1 x_{it}^1 + \beta_2 x_{it}^2 + \cdots + \beta_u x_{it}^u + \beta_{(u+1)}(x_{it} - k_1)_+^u + \cdots + \beta_{(u+p)}\left(x_{nm} - k_p\right)_+^u + e_{it}$$

$$y_{it}^{(2)} = \beta_0 + \beta_1 x_{it}^1 + \beta_2 x_{it}^2 + \cdots + \beta_u x_{it}^u + \beta_{(u+1)}(x_{it} - k_1)_+^u + \cdots + \beta_{(u+p)}\left(x_{nm} - k_p\right)_+^u + e_{it}$$

After making a general model of birespon spline nonparametric regression, a model was made with a birespon spline nonparametric regression approach involving four knot points to observe changes in the pattern of age and weight in months 12, 24, 36, and 48. The aim was to detect changes in patterns that occur at each age interval in the growth category [23]. The GCV values obtained using the four knot points are presented in the table below.

Table 2. GCV Value of Nonparametric Regression

Response	Orde	GCV Value	Knot Point			
			$\boldsymbol{k_1}$	$\boldsymbol{k_2}$	$\boldsymbol{k_3}$	$\boldsymbol{k_4}$
$\boldsymbol{y^{(1)}}$	1	2.18	12	24	36	48
$\boldsymbol{y^{(2)}}$	1	20.01	12	24	36	48

Model of nonparametric regression bi-response spline for variables $y^{(1)}$ and $y^{(2)}$ based on Table 2, namely order 1 using four knot points. The minimum GCV values obtained are 2.18 and 20.01 with knot points 12, 24, 36, 48, meaning the data is divided into five segments. These knot points indicate changes in the growth rate of toddlers' weight at these ages. Before the age of 12 months, the growth pattern may not be linear or the growth rate may decrease.

Table 3 presents the estimated parameter values of the nonparametric bi-response spline regression model.

Table 3. Parameter Estimates from the Bi-response Spline Nonparametric Regression

Response	Predictor	Parameter	Estimation parameter
$\boldsymbol{y}^{(1)}$	Intercept	β_0	5.47
		β_1	0.28
		β_2	-0.11
		β_3	-0.06
		β_4	-0.01
		β_5	0.04
$\boldsymbol{y}^{(2)}$	Intercept	β_0	59.18
		β_1	1.13
		β_2	-0.15
		β_3	-0.61
		β_4	0.23
		β_5	0.18

The truncated birespon spline nonparametric regression model for the toddler weight variable ($y^{(1)}$), as shown in Table 3, is presented below:

$$\hat{y}_{it}^{(1)} = 5{,}47 + 0{,}28x_{it}^{1} - 0{,}11(x_{it} - 12)_{+}^{1} - 0{,}06(x_{it} - 24)_{+}^{1} - 0{,}01(x_{it} - 36)_{+}^{1} + 0{,}04(x_{it} - 48)_{+}^{1}$$

The optimal truncated spline bi-response nonparametric regression model for toddler weight variables demonstrated a flexible association between age (months) and body weight (kilograms). Based on this model, at the beginning of life or 0 months of age, the toddler's weight is estimated to be approximately 5.47 kg. The most rapid weight growth occurs at the age of 0-12 months, with an average increase of 0.28 kg per month. However, after 12 months, the growth rate gradually decreased. The first decrease occurred after 12 months of age, amounting to 0.11 kg/month, followed by an additional decrease of 0.06 kg per month after 24 months of age, and 0.01 kg per month after 36 months of age. Interestingly, after 48 months of age, there was a slight rebound in the growth rate to 0.04 kg per month.

This pattern shows that toddlers' weight growth occurs rapidly in the first year of life, then slows down gradually until the age of four years, and increases slightly thereafter. This model provides an overview of the growth rate through a truncated spline approach, which allows changes in the direction or rate of growth at certain age points (knots). Overall, this model reflects a reasonable and realistic weight growth pattern for toddlers, and can be used as a basis for longitudinal growth and development monitoring.

Figure 3 shows the relationship between age (in months) and body weight (in kilograms) in toddlers. In general, there appears to be a positive relationship between the two variables, whereas as children age, their weight tends to increase. This is reflected in the pattern of data points that form an upward trend and the red line shows the average weight gain over time. This growth pattern is not linear because weight gain appears faster at the age of 0-12 months, and then growth slows down gradually thereafter. In addition, there is a large variation in body weight in each age group, indicating that children of the same age can have different body weights, influenced by various factors such as genetics, nutrition, and health conditions. Several points that deviate significantly from the general pattern are also visible, which may be outliers or data from children with special conditions. Overall, this graph illustrates that age is an important factor influencing a child's weight growth, although it is not the only one. By using truncated splines, this model can describe changes in growth dynamics more accurately than ordinary linear models and is very suitable for longitudinal data where children's growth is observed periodically over a certain period.

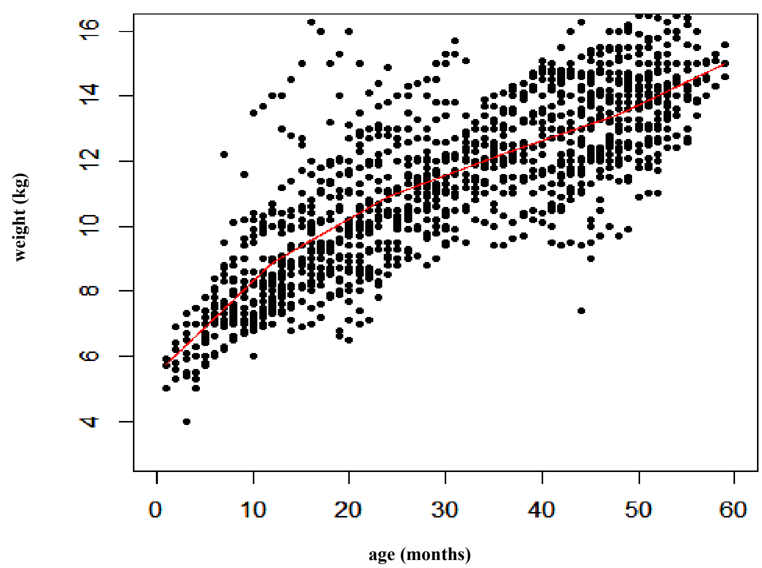

Figure 3. Data Plot of the Effect of Age on Body Weight

The truncated birespon spline nonparametric regression model for the toddler height variable ($y^{(2)}$), as indicated in Table 3, is presented below:

$$\hat{y}_{it}^{(2)} = 59{,}18 + 1{,}13x_{it}^1 - 0{,}15(x_{it} - 12)_+^1 - 0{,}61(x_{it} - 24)_+^1 + 0{,}23(x_{it} - 36)_+^1 + 0{,}18(x_{it} - 48)_+^1$$

This truncated spline bi-response nonparametric regression model shows the relationship between toddler age (in months) and body height (in centimeters) with a flexible approach using knot points at the ages of 12, 24, 36, and 48 months. Based on this model, the initial height of a toddler at the age of 0 months age was estimated to be 59.18 cm. At the age of 0-12 months, height increases rapidly at a growth rate of 1.13 cm per month. However, after 12 months of age, the growth rate begins to decrease by 0.15 cm/month, and decreases more sharply after 24 months of age with an additional decrease of 0.61 cm/month. Interestingly, after the age of 36 months, the growth rate increased again by 0.23 cm/month, and increased again by 0.18 cm/month after the age of 48 months.

Overall, this model shows that toddler height growth is not constant, but experiences acceleration and deceleration at certain age points. In the first year, growth is very rapid, but slows down significantly after two years of age, before experiencing a slight acceleration again closer to four to five years of age. This pattern is in accordance with children's biological growth, which is generally rapid at the beginning of life, stable in the middle of toddlerhood, and then increases again towards the pre-school period. This truncated spline model is very useful in capturing complex patterns of growth changes in longitudinal data, as well as in helping to monitor toddlers' physical development more accurately.

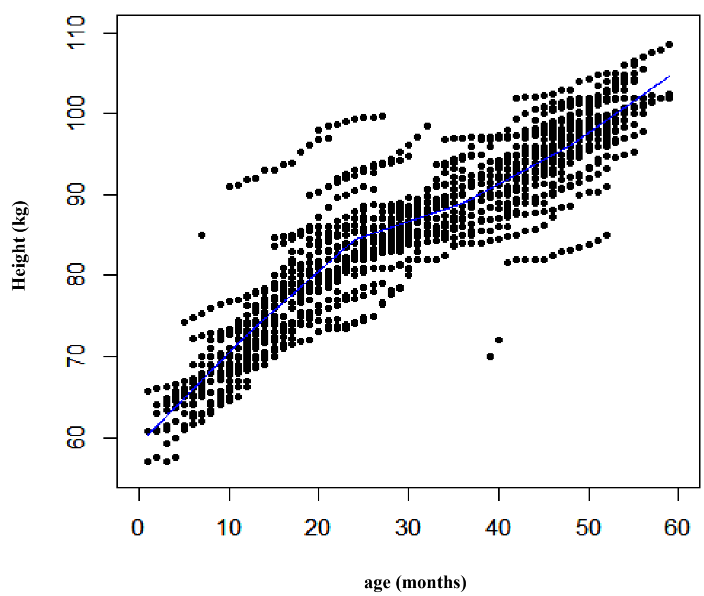

Figure 4. Data Plot of the Effect of Age on Height

The graph in Figure 4 illustrates the relationship between toddlers' age and height, based on longitudinal data analyzed using nonparametric regression with the truncated spline method. From the results of the graph, in general, there was a pattern of growth in height that increased as the age of the toddler increased. At the age of 0 to approximately 20 months, the rate of growth in height appears quite sharp, reflecting the rapid growth phase in early life. After 20 months of age, growth continued but at a slower and more stable rate until 60 months of age.

The blue line in the graph is the curve resulting from spline regression estimation, which shows the general trend of toddler height growth in a smooth manner without assuming a particular functional form. This curve shows flexibility in capturing non-linear growth dynamics. The distribution of black dots representing individual data shows that there is a variation in height at the same age, and this variation tends to increase with age. This may indicate that the older the toddler, the more diverse the growth patterns that occur between individuals.

Overall, this graph provides a visual depiction and strong statistical analysis of toddler height growth patterns, and can be used as a reference for monitoring child development and detecting possible growth disorders if the height is far outside the general pattern shown by the curve.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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