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Evaluating Double Resampling Through Simulation and Application in Semiparametric Truncated Spline for Waste Economic Value

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ABSTRACT

This study developed a double resampling procedure as a method for estimating standard error in truncated spline semiparametric path modeling, given that standard error cannot be obtained analytically. Primary data were collected from 100 respondents through a Likert scale questionnaire and analyzed using a path structure involving Facility and Infrastructure Quality (X_1) and Waste Bank Participation (X_2) have a significantly positive effect on 3R-Based Waste Management Practices (Y_1) and the Waste Economic Value (Y_2). The modeling process involved selecting knots, estimating spline functions, and evaluating double resampling performance through simulation studies. The results showed that X_1 and X_2 had a significant positive effect on Y_1 and Y_2, while the relationship between Y_1 and Y_2 was negative before and after the 21% threshold. The simulation study shows that the Jackknife-Bootstrap method produces lower standard errors and bias, while the Bootstrap-Jackknife method is more stable at very small sample size. These findings confirm the effectiveness of double resampling.

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1. INTRODUCTION

Semiparametric path analysis is a combination of two approaches, namely parametric and nonparametric approaches [1]. The model structure, which contains nonparametric components, makes it impossible to calculate standard errors using conventional methods. Therefore, resampling techniques are used to form empirical distributions of estimators, allowing for the standard errors to be obtained in a data-driven manner. The resampled standard error values are then used as the basis for calculating test statistics in path coefficient testing. Thus, the use of resampling methods is necessary to produce reliable standard error estimates.

The general form of the semiparametric path analysis model used in this study can be written as Equation (1) and Equation (2).

$$Y_{1i} = \beta_{10} + \beta_{11}X_{1i} + \beta_{12}X_{2i} + f(X_{ki}) + \varepsilon_{1i}; i = 1,2, \dots, n \tag{1}$$

$$Y_{2i} = \beta_{20} + \beta_{21}X_{1i} + \beta_{22}X_{2i} + f(X_{ki}) + f(Y_{1i}) + \varepsilon_{2i}; i = 1,2, \dots, n \tag{2}$$

In the initial modeling stage, the assumption of linearity between variables was tested using the Ramsey RESET test. Significant test results indicate that a linear model is inadequate for use, so a nonparametric truncated spline approach is used. In Equation (1) and Equation (2), the functions $f(X_{ki})$ and $f(Y_{1i})$ are functions constructured using truncated splines, where the shape of the curve is determined by the position of the knot, making its selection an important element. This study determines the optimal knot points based on the smallest Generalized Cross Validation (GCV) value, so that the nonlinear structure of the model can be formed adaptively according to the data pattern.

In various studies, single resampling methods have proven to be practical, but they are not always optimal for semiparametric models because they are less capable of capturing structural variations between parametric and nonparametric components. This limitation often results in biased standard errors. Through a double resampling approach, such as stratified resampling, this problem can be corrected because the second stage provides high level bias correction, stabilizes estimator variance, and is more resistant to the influence of extreme observations or local nonlinearity [2], [3]. This aspect forms the basis of the novelty of this research, namely, the systematic application and evaluation of double resampling in truncated spline based semiparametric path analysis.

In the context of utilizing the economic value of waste, semiparametric path analysis is highly relevant because the relationships between variables in waste management systems do not always follow linear patterns. Improvements in facilities and infrastructure are not always accompanied by proportionally increased economic benefits. At a certain point, a saturation effect or change in community behavior may occur after passing a certain threshold [4], which indicates the existence of a partial nonparametric relationship that cannot be assumed a priori. By combining parametric and nonparametric relationships, semiparametric path analysis is able to capture these dynamics more accurately [5]. This study focuses on the influence of environmental quality, infrastructure, and the use of waste banks on the economic value of waste, mediated by the 3R principle, given the high economic potential of efficient waste management.

This study was designed to fill a methodological gap that has rarely been systematically addressed in the literature, namely, the performance evaluation of double resampling methods in truncated spline semiparametric path analysis. Using a semi-data-driven simulation design that reflects realistic nonlinear patterns, this study explicitly compares bootstrap-jackknife and jackknife-bootstrap with single resampling methods. An important contribution of this study is identifying the conditions under which double resampling provides more stable variance estimates, thereby offering practical recommendations for researchers working with nonlinear structural models [6]. The novelty of this research also lies in presenting theoretical evidence regarding the stability and bias correction of double resampling, not just empirical evidence, thereby strengthening the justification for the methods used.

In addition, the development of double resampling-based semiparametric path analysis in hypothesis testing is still very limited. Razak [7] showed that double Bootstrap in SEM analysis produces lower standard errors, Mean Squared Error (MSE), and root MSE, as well as narrower confidence intervals compared to single Bootstrap. The consistency of these advantages reinforces that resampling, especially double resampling, which has the ability to overcome violations of normality assumptions and reduce estimator bias, is highly relevant for use in complex semiparametric models [8]. This is a novelty of this study, which combines truncated spline semiparametric path analysis with double resampling to produce more reliable inferences on nonlinear relationship structures. Thus, the purpose of this study is to evaluate the performance of double resampling in estimating standard errors in semiparametric path analysis, compare it with the single resampling method, and apply it to data on the economic value of waste utilization to provide more reliable inference recommendations.

2. RESEARCH METHOD

The following sections will describe the research design, data sources and variables, data collection techniques, semiparametric path analysis, optimal knot point selection, resampling methods, and simulation studies.

2.1 Research Design

This study has been designed using a quantitative approach utilizing latent variables measured through a Likert scale questionnaire instrument. Latent variable values were calculated by averaging the scores of all indicators in each construct, so that each variable was represented by a single composite value that met the measurement characteristics of the Likert scale. The research stages included testing the assumption of linearity, estimating the parameters of the semiparametric model, designing and conducting a simulation study, and testing hypotheses based on the results of evaluating the performance of the resampling methods.

2.2 Data Source and Variables

The data used in this study are primary data and simulation data. Primary data were obtained through a survey using a Likert scale questionnaire. The population in this study included the people of Batu City. The research sample consisted of residents living in Batu District, with a total sample size determined by quota sampling of 100 people.

The proposed research model is presented in Figure 1. Several variables were used, including two exogenous variables, Facility and Infrastructure Quality (X_1) and Waste Bank Participation (X_2), each with three indicators. Furthermore, there is one mediating variable, namely 3R-Based Waste Management Practices (Y_1), which is measured by four indicators. Then there is a pure endogenous variable, namely, Waste Economic Value (Y_2), which is measured by three indicators.

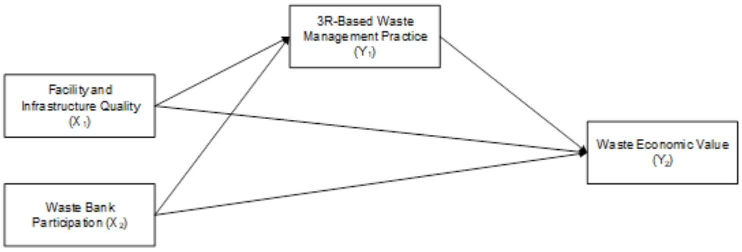


Figure 1. Research Model

2.3 Data Collections

The data collection process was conducted through self-administered questionnaires and guided interviews with enumerators to ensure the completeness of responses and consistency in filling out the questionnaires. This approach was chosen to obtain accurate and representative information about community behavior and the dynamics of waste management in Batu District.

2.4 Selection of Optimal Knot Points

The nonparametric spline model is an analytical approach that utilizes nonparametric methods, where estimation is performed using the least squares method with knot points determined optimally based on the smallest Generalized Cross Validation (GCV) value [9]. GCV is used as a tool for internal model evaluation, including determining the number and position of knot points in each model. The advantages of the GCV method lie in its asymptotic optimality, efficiency, simplicity in calculation, and lack of requirement for variance information. The best spline function is obtained from optimal knot points; thus, the selection of knot points not only determines the quality of the spline but also considers the simplicity of the model. The GCV value can be calculated using the Equation (3).

$$GCV(\mathbf{K}) = \frac{MSE(\mathbf{K})}{[n^{-1}trace(\mathbf{I} - \mathbf{A}[\mathbf{K}])]^2} \tag{3}$$

Where $MSE(\mathbf{K}) = n^{-1}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ and $\mathbf{K}$ is the knot point with matrix $\mathbf{A}[\mathbf{K}]$ obtained from Equation (4).

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_n \end{bmatrix} = \begin{bmatrix} 1 & X_1 & X_1^2 & \cdots & X_1^p & (X_1 - K_1)_+^p & \cdots & (X_1 - K_r)_+^p \\ 1 & X_2 & X_2^2 & \cdots & X_2^p & (X_2 - K_1)_+^p & \cdots & (X_2 - K_r)_+^p \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_n & X_n^2 & \cdots & X_n^p & (X_n - K_1)_+^p & \cdots & (X_n - K_r)_+^p \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \\ \delta_1 \\ \vdots \\ \delta_r \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \tag{4}$$

or can be written in Equation (5) and Equation (6).

$$\boldsymbol{y}_{n\times1} = \mathbf{X}[K_1, K_2, \dots, K_r]_{n\times(1+p+r)}\boldsymbol{\beta}_{(1+p+r)\times1} + \boldsymbol{\varepsilon}_{n\times1} \tag{5}$$

$$\widehat{\boldsymbol{\beta}}_{(1+p+r)\times1} = \left(\mathbf{X}[\mathbf{K}]'_{(1+\mathrm{p}+\mathrm{r})\times\mathrm{n}}\mathbf{X}[\mathbf{K}]_{\mathrm{n}\times(1+\mathrm{p}+\mathrm{r})}\right)^{-1}\mathbf{X}[\mathbf{K}]'_{(1+\mathrm{p}+\mathrm{r})\times\mathrm{n}}\,\boldsymbol{y}_{n\times1} \tag{6}$$

where

$$\mathbf{X}[\mathbf{K}] = \mathbf{X}[K_1, K_2, \dots, K_r] = \begin{bmatrix} 1 & X_1 & X_1^2 & \cdots & X_1^p & (X_1 - K_1)_+^p & \cdots & (X_1 - K_r)_+^p \\ 1 & X_2 & X_2^2 & \cdots & X_2^p & (X_2 - K_1)_+^p & \cdots & (X_2 - K_r)_+^p \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_n & X_n^2 & \cdots & X_n^p & (X_n - K_1)_+^p & \cdots & (X_n - K_r)_+^p \end{bmatrix} \tag{7}$$

The estimated spline knot k regression curve is obtained Equation (8).

$$\hat{\boldsymbol{f}}(X_i)_{n\times 1} = \mathbf{X}[\mathbf{K}]_{n\times(1+p+r)}\hat{\boldsymbol{\beta}}_{(1+p+r)\times 1} = \mathbf{X}[\mathbf{K}](\mathbf{X}[\mathbf{K}]'\mathbf{X}[\mathbf{K}])^{-1}\mathbf{X}[\mathbf{K}]'\boldsymbol{y} \tag{8}$$

So that the function of the knot point is as in Equation (9).

$$\hat{\boldsymbol{f}}(X_i) = \boldsymbol{A}[\mathbf{K}]\boldsymbol{y} \tag{9}$$

where $\mathbf{A}[\mathbf{K}] = \mathbf{X}[\mathbf{K}](\mathbf{X}[\mathbf{K}]'\mathbf{X}[\mathbf{K}])^{-1}\mathbf{X}[\mathbf{K}]'$.

2.5 Semiparametric Path Analysis

Semiparametric path analysis integrates the structure of parametric path modeling with the flexibility of nonparametric regression. In this framework, part of the regression function is specified in a known parametric form, while another part is modeled nonparametrically to capture unknown or nonlinear relationships. As noted in [10], semiparametric regression allows the analyst to combine interpretability with functional flexibility, while [11] and [12] emphasize that such models are particularly suitable when theoretical relationships are only partially understood. In general, the semiparametric path model with a single intervening variable can be expressed as shown in Equation (10) and Equation (11).

$$Y_{1i} = X\beta + f(X_{ki}) + \varepsilon_{1i}; i = 1,2, \dots, n \tag{10}$$

$$Y_{2i} = X\beta + f(X_{ki}) + f(Y_{1i}) + \varepsilon_{2i}; i = 1,2, \dots, n \tag{11}$$

where

Y_{1i}, Y_{2i}	: Endogenous variables for the i-th observation
$X\beta$	: Parametric component
$f(X_{ki}), f(Y_{1i})$	: Nonparametric components
X_{ki}	: k-th exogenous variable of the i-th observation in the nonparametric component
$\varepsilon_{1i}, \varepsilon_{2i}$	: Error terms

2.6 Bootstrap-Jackknife

The bootstrap–jackknife procedure applies bootstrap sampling at the outer level and jackknife resampling within each bootstrap replicate. The bootstrap stage generates replicated datasets that approximate the sampling distribution of the original data, while the subsequent jackknife stage reduces bias and stabilizes variance estimates. This combination is useful when flexible distributional resampling is required but additional bias correction is necessary [13], [14] . The procedure is summarized as follows:

(1) Outer layer in Equation (12): Generate B bootstrap samples (delete-5% and resample with replacement):

$$\mathrm{xy}_b^* = \{(x_i^*, y_i^*)\}_{i=1}^n, b = 1,2, \dots, B \tag{12}$$

(2) Inner layer in Equation (13): For each xy_b^*, draw J jackknife subsamples by deleting 5% without replacement:

$$\mathrm{xy}_{b,j}^{**}, j = 1,2, \dots, J \tag{13}$$

(3) Estimate the parameter for each inner resample and average in Equation (14):

$$\hat{\theta}_{b,j}^{**} = f_{spline}\left(\mathbf{xy}_{\mathrm{b},j}^{**}\right), \quad \bar{\theta}_b^* = \frac{1}{J}\sum_{j=1}^{J}\hat{\theta}_{b,j}^{**} \tag{14}$$

(4) Estimate the bias and standard error across the outer loop in Equation (15):

$$Bias_{\text{BJ}} = \bar{\theta}^{**} - \hat{\theta}, \quad SE_{\text{BJ}} = \sqrt{\frac{1}{B-1}\sum_{b=1}^{B}(\bar{\theta}_b^{*} - \bar{\theta}^{**})^2} \tag{15}$$

Where $\bar{\theta}^{**} = \frac{1}{B}\sum_{b=1}^{B}\bar{\theta}_b^{*}$

2.7 Jackknife-Bootstrap

The Jackknife-Bootstrap resampling procedure is a combination of two resampling methods. In the first stage, Jackknife resampling is performed to obtain Jackknife data sets, and then Bootstrap resampling is performed on each of these data sets. This sequence is advantageous when outlier sensitivity must be minimized while retaining flexibility for distributional approximation [15], [16]. The steps are:

(1) Outer layer: Generate J jackknife samples by deleting 5% without replacement in Equation (16):

$$\text{xy}_j^{*} = \{(x_i^{*}, y_i^{*})\}_{i=1}^{n}, j = 1,2,\dots,J \tag{16}$$

(2) Inner layer: For each xy_j^{*}, draw B bootstrap subsamples (delete-5% and resample with replacement) in Equation (17):

$$\text{xy}_{j,b}^{**}, b = 1,2,\dots,B \tag{17}$$

(3) Estimate the parameter for each inner resample and average in Equation (18):

$$\hat{\theta}_{j,b}^{**} = f_{spline}\left(\text{xy}_{\text{j,b}}^{**}\right), \quad \bar{\theta}_j^{*} = \frac{1}{B}\sum_{b=1}^{B}\hat{\theta}_{j,b}^{**} \tag{18}$$

(4) Estimate the bias and standard error across the outer loop in Equation (19):

$$Bias_{\text{JB}} = \bar{\theta}^{**} - \hat{\theta}, \quad SE_{\text{JB}} = \sqrt{\frac{1}{J-1}\sum_{j=1}^{J}\left(\bar{\theta}_j^{*} - \bar{\theta}^{**}\right)^2} \tag{19}$$

Where $\bar{\theta}^{**} = \frac{1}{J}\sum_{j=1}^{J}\bar{\theta}_j^{*}$

2.8 Simulation Study

This simulation study was conducted to assess the performance of various single and double resampling methods in estimating standard errors for varying sample sizes and levels of error variance. Three main conditions were used: sample size, error variance (EV), and resampling type, with assessments based on three performance measures, namely the average SE as an indicator of accuracy, the average bias as a measure of deviation from the actual parameter and the SE ratio to assess the consistency of the estimation. All combinations of conditions were repeated 100 times so that the results obtained were more representative.

The main steps of the simulation study are outlined as follows. The simulation was conducted on three sample sizes: small, medium, and large $(n = 25, 100, 1000)$ following the path structure in Figure 1 and the model equations in Equation (3) and Equation (4). The initial path coefficients and MSE values were obtained from secondary data, which then became the basis for data generation. The exogenous variables were maintained according to their observed values so that the data patterns remained realistic; while the errors were generated from a multivariate normal distribution with three levels of variance $(0.5 \times \text{MSE}, 1.0 \times \text{MSE}, \text{and } 2.0 \times \text{MSE})$ to reflect different noise conditions. Based on the path coefficients, exogenous variables, and generated errors, the intervening and endogenous variables are calculated according to the model structure. Each dataset is then analyzed using four resampling schemes: Single Bootstrap, Single Jackknife, Jackknife-Bootstrap, and Bootstrap-Jackknife, each run 500 times with a 5% deletion rate. For each simulation condition, three main metrics were calculated, namely average standard error, average bias, and SE ratio, then all results were averaged to compare the performance of the methods across different sample sizes and levels of error variance.

3. RESULT AND ANALYSIS

This chapter presents the results of analysis and interpretation of the application of a semiparametric path analysis model based on truncated splines to data on the economic value of waste. The following sections will describe the linearity assumption, simulation study results, semiparametric path analysis using double resampling, and a discussion of the research results.

3.1 Linearity Assumptions

The linearity assumption was evaluated using the Ramsey Regression Equation Specification Error Test (RESET). The results of the linearity assessment are presented in Table 1.

Table 1. Results of the Ramsey RESET Linearity Test

Variable Relationship	p-value		Interpretation
	Linear	Quadratic	
Facility and Infrastructure Quality ($\mathbf{X_1}$) to 3R-Based Waste Management Practices ($\mathbf{Y_1}$)	0.192	-	Linear
Waste Bank Participation ($\mathbf{X_2}$) to 3R-Based Waste Management Practices ($\mathbf{Y_1}$)	0.236	-	Linear
Facility and Infrastructure Quality ($\mathbf{X_1}$) to Waste Economic Value ($\mathbf{Y_2}$)	0.398	-	Linear
Waste Bank Participation ($\mathbf{X_2}$) to Waste Economic Value ($\mathbf{Y_2}$)	0.141	-	Linear
3R-Based Waste Management Practices ($\mathbf{Y_1}$) to Waste Economic Value ($\mathbf{Y_2}$)	<0.001	0.022	Non Linear and Non Quadratic

Based on Table 1, the Ramsey RESET test shows that four relationships have p-values greater than 0.05, indicating that they follow a linear functional form. These cover the paths from Facility and Infrastructure Quality (X_1) to 3R-Based Waste Management Practices (Y_1) and Waste Economic Value (Y_2), as well as from Waste Bank Participation (X_2) to Y_1 and Y_2. Meanwhile, the path from 3R-Based Waste Management Practices (Y_1) to Waste Economic Value (Y_2) shows a p-value < 0,05 in both linear and quadratic Ramsey RESET tests, leading to rejection of H_0. This means that the relationship between these variables is neither linear nor quadratic and is assumed to be nonparametric. Furthermore, a modified Ramsey RESET test can be performed to determine the best nonparametric relationship form. Accordingly, a modified Ramsey RESET test is applied to identify the most appropriate nonlinear structure, and the results are presented in Table 2.

Table 2. Results of the Ramsey RESET Modification

Variable Relationship	Ramsey RESET Modifications	p-value	Interpretation
3R-Based Waste Management Practices ($\mathbf{Y_1}$) to Waste Economic Value ($\mathbf{Y_2}$)	RRTL1K	<0.0001	Ramsey RESET Truncated Spline Linear 1 Knot
	RRTL2K	0.0004	
	RRTL3K	0.0014	
	RRTQ1K	0.0030	
	RRTQ2K	0.0123	
	RRTQ3K	0.0358	

Where
RRTL1K : Ramsey RESET Truncated Spline Linear 1 Knot
RRTL2K : Ramsey RESET Truncated Spline Linear 2 Knot
RRTL3K : Ramsey RESET Truncated Spline Linear 3 Knot
RRTQ1K : Ramsey RESET Truncated Spline Quadratic 1 Knot
RRTQ2K : Ramsey RESET Truncated Spline Quadratic 2 Knot
RRTQ3K : Ramsey RESET Truncated Spline Quadratic 3 Knot

Based on Table 2, it can be seen that a smaller p-value indicates that the model will be more identifiable. The results of the Ramsey RESET modification test show that the relationship between the variables 3R-Based Waste Management Practices (Y_1) and Waste Economic Value (Y_2) is a truncated spline of order one with 1 knot point. This shows that there is a parametric and nonparametric relationship between the variables. Thus, in this study, a semiparametric truncated spline analysis of order one with 1 knot point was used.

3.2 Simulation Study Outcomes

The simulation study was conducted by generating simulation data designed based on various sample size variations, error variance levels, and resampling methods used. The equations used to generate the simulation data are presented in Equation (20) and Equation (21), which serve as the foundation for all subsequent resampling analyses.

$$\hat{f}_{1i} = 1.652 + 0.305X_{1i} + 0.174X_{2i} \tag{20}$$

$$\hat{f}_{2i} = 5.441 + 0.566X_{1i} + 0.252X_{2i} - 1.823Y_{1i} + 1.786(Y_{1i} - 2.549)_+ \tag{21}$$

Where

$$(Y_{1i} - 2.549)_+ = \begin{cases} (Y_{1i} - 2.549) & ; Y_{1i} \geq 2.549 \\ 0 & ; Y_{1i} < 2.549 \end{cases}$$

After generating the data, the performance of resampling methods was evaluated in terms of mean bias, mean standard error, and SE ratio across varying sample sizes ($n = 25, 100, 1000$) and different levels of error variance ($0.5 \times$MSE, $1.0 \times$ MSE, $2.0 \times$MSE), where the MSE value is obtained based on the results of empirical data analysis, which is 0.022. The simulation results for the combination of all three conditions: sample size, error variance (EV), and resampling method, are summarized in Table 3.

Table 3. Performance of Resampling Method with Varying Sample Size and Different Levels of Error Variance

Sample Size	Error Variance	Resampling Method	Average SE	Average Bias	Ratio SE
$n = 25$	$EV = 0.5 \times MSE$	SB	0.0826	0.0657	3.1334
		SJ	0.0871	0.0684	3.6097
		BJ	0.0264	0.0428	1.7989
		JB	0.0250	0.0408	1.2210
	$EV = 1.0 \times MSE$	SB	0.0864	0.1332	3.3794
		SJ	0.0812	0.1308	3.5414
		BJ	0.0242	0.0842	1.8958
		JB	0.0271	0.0749	1.1256
	$EV = 2.0 \times MSE$	SB	0.0843	0.2755	3.6507
		SJ	0.0854	0.2692	3.6038
		BJ	0.0274	0.1739	1.9247
		JB	0.0262	0.1487	1.0981
$n = 100$	$EV = 0.5 \times MSE$	SB	0.0541	0.0667	3.4086
		SJ	0.0542	0.0661	3.3313
		BJ	0.0154	0.0412	1.7505
		JB	0.0169	0.0447	1.1523
	$EV = 1.0 \times MSE$	SB	0.0532	0.1361	3.3143
		SJ	0.0523	0.1338	3.6184
		BJ	0.0141	0.0835	1.9782
		JB	0.0146	0.0736	1.0914
	$EV = 2.0 \times MSE$	SB	0.0512	0.2749	3.4488
		SJ	0.0566	0.2646	3.1640
		BJ	0.0163	0.1648	1.9244
		JB	0.0149	0.1543	1.1656
$n = 1000$	$EV = 0.5 \times MSE$	SB	0.0355	0.0663	3.4911
		SJ	0.0361	0.0668	3.3520
		BJ	0.0087	0.0420	1.8534
		JB	0.0103	0.0393	1.2003
	$EV = 1.0 \times MSE$	SB	0.0359	0.1321	3.2728
		SJ	0.0332	0.1335	3.6609
		BJ	0.0077	0.0901	1.9359
		JB	0.0104	0.0711	1.0580
	$EV = 2.0 \times MSE$	SB	0.0339	0.2622	3.6674
		SJ	0.0344	0.2733	3.3735
		BJ	0.0104	0.1834	1.9096
		JB	0.0104	0.1643	1.0520

Based on Table 3, the simulation study results show differences in estimation characteristics between four resampling methods, including Single Bootstrap (SB), Single Jackknife (SJ), Bootstrap-Jackknife (BJ), and Jackknife-Bootstrap (JB), at various sample sizes and error variance levels. In general, the results obtained show that the double resampling methods, namely BJ and JB, produce smaller mean standard errors and lower mean biases compared to the two single resampling methods. This indicates that the double resampling stage is able to provide more stable estimates in the truncated spline semiparametric path model.

Overall, the simulation results show that the Jackknife–Bootstrap (JB) method produces the lowest mean SE and bias values in most combinations of sample size and error variance, thus providing more stable standard error estimates in the semiparametric truncated spline model. However, these findings are not absolute. In some scenarios, particularly with very small sample sizes or when the error variance is at a moderate level, the Bootstrap–Jackknife (BJ) method actually produces a smaller mean SE value than JB. This indicates that BJ tends to provide advantages, especially when the first Bootstrap stage is able to capture the model's variability pattern well, allowing the Jackknife correction in the next stage to provide more accurate estimates.

Thus, the choice between JB and BJ depends on the characteristics of the data, where JB is more suitable for data with medium to large sample sizes or when the error variance is relatively high due to its ability to reduce estimation variability. Meanwhile, BJ can be considered for small sample sizes or in conditions where data variability is relatively low, with the Bootstrap in the first stage being able to map relationship patterns quite well before correction by Jackknife in the second stage. Both methods offer their own advantages, and the simulation results in this study provide practical guidelines regarding the conditions that support the optimal performance of each approach.

3.3 Semiparametric Path Analysis Using Double Resampling

Based on the modified Ramsey RESET test results in Table 2, It can be seen that the relationship between the 3R-Based Waste Management Practices (Y_1) and Waste Economic Value (Y_2) is a truncated spline with 1 knot point. The estimation of the truncated spline semiparametric path function was performed after obtaining the optimal knot point. The optimal knot point is obtained based on the smallest GCV value. The determination of the optimal knot point for a nonparametric relationship with 1 knot point can be visualized as shown in Figure 2 and presented in Table 4.

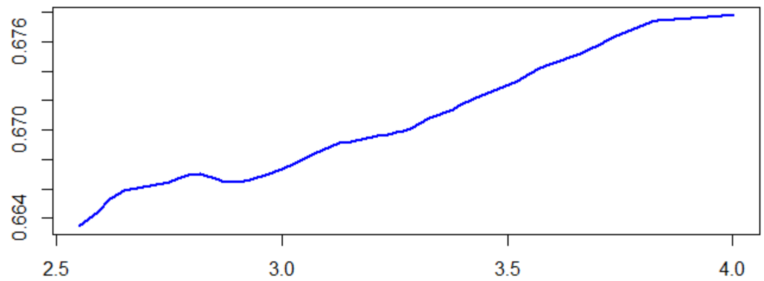


Figure 2. Plot of the Generalized Cross Validation (GCV)

Table 4. Selection of the Optimal Knot Point

Variable Relationship	Knot Point	GCV
3R-Based Waste Management Practices (Y_1) to Waste Economic Value (Y_2)	2.549	0.663
	2.592	0.664
	2.619	0.665
	2.622	0.665
	2.649	0.666
	2.748	0.666
	2.775	0.667
	2.790	0.667
	2.817	0.667
	2.859	0.667
	⋮	⋮
	4.002	0.678

Based on Figure 2 and Table 4, It can be seen that the optimal knot point with the smallest GCV value is at 2.549. Next, a semiparametric path function estimation was performed using the WLS method. The results of the truncated spline semiparametric path function estimation with 1 knot point are shown in Equation (22) and Equation (23).

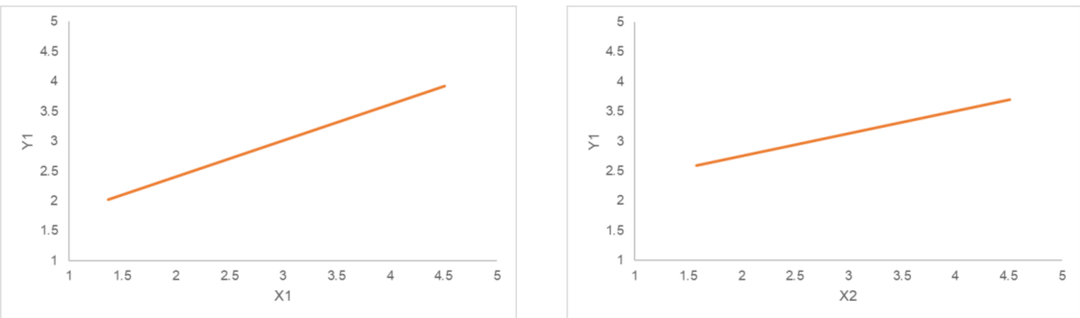
Hypothesis testing was performed using double resampling Jackknife-Bootstrap (JB), which contributes to calculating standard errors more accurately for use in hypothesis testing. The simulation results show that this combination approach is capable of producing lower standard error (SE) and bias estimates compared to single resampling or other double resampling methods, thus providing better stability and accuracy of estimates. The results of direct, indirect, and total effect hypothesis tests are presented in Table 5.

Table 5. Results of Direct, Indirect, and Total Effect Hypothesis Testing

Direct Effect					
Variable Relationship	**Estimation**	**SE**	**CR**	**p-value**	**Interpretation**
Facility and Infrastructure Quality (X_1) to 3R-Based Waste Management Practices (Y_1)	0.305	0.019	15.982	< 0.0001	Significant
Waste Bank Participation (X_2) to 3R-Based Waste Management Practices (Y_1)	0.274	0.022	8.094	< 0.0001	Significant
Facility and Infrastructure Quality (X_1) to Waste Economic Value (Y_2)	0.566	0.025	22.531	< 0.0001	Significant
Waste Bank Participation (X_2) to Waste Economic Value (Y_2)	0.252	0.027	9.288	< 0.0001	Significant
3R-Based Waste Management Practices (Y_1) to Waste Economic Value (Y_2)	-1.823	0.114	-16.015	< 0.0001	Significant
	-0.037	0.032	-1.117	< 0.0001	Significant
Indirect Effect					
Variable Relationship	**Estimation**	**SE**	**CR**	**p-value**	**Interpretation**
Facility and Infrastructure Quality (X_1) to Waste Economic Value (Y_2) through 3R-Based Waste Management Practices (Y_1)	-0.556	0.049	-11.329	< 0.0001	Significant
	-0.011	0.010	-1.106	< 0.0001	Significant
Waste Bank Participation (X_2) to Waste Economic Value (Y_2) through 3R-Based Waste Management Practices (Y_1)	-0.499	0.042	-7.669	< 0.0001	Significant
	-0.010	0.006	-1.041	< 0.0001	Significant
Total Effect					
Variable Relationship	**Estimation**	**SE**	**CR**	**p-value**	**Interpretation**
Facility and Infrastructure Quality (X_1) to Waste Economic Value (Y_2)	0.010	0.050	0.123	< 0.0001	Significant
	0.555	0.021	26.004	< 0.0001	Significant
Waste Bank Participation (X_2) to Waste Economic Value (Y_2)	-0.248	0.043	-1.668	< 0.0001	Significant
	0.242	0.024	10.281	< 0.0001	Significant

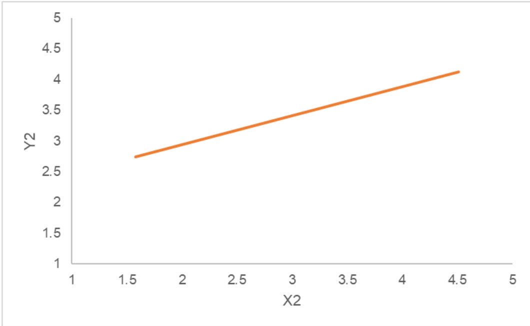
Based on Table 5, all relationship between exogenous and endogenous variables show a significant direct effect, as seen from p-values less than 0.05, thus rejecting the null hypothesis (H_0). Similar results were also found for indirect and total effects, with p-values remaining below 0.05. Thus, it can be concluded that the Facility and Infrastructure Quality (X_1) and the Waste Bank Participation (X_2) have significant effect, both directly and indirectly on the Waste Economic Value (Y_2).

Overall, the results of the direct effect test show that the relationship between exogenous variables and endogenous variables has a significant effect. This means that exogenous variables can contribute to changes in endogenous variables. The direct effect relationship between exogenous variables and endogenous variables can be visualized as shown in Figure 3.

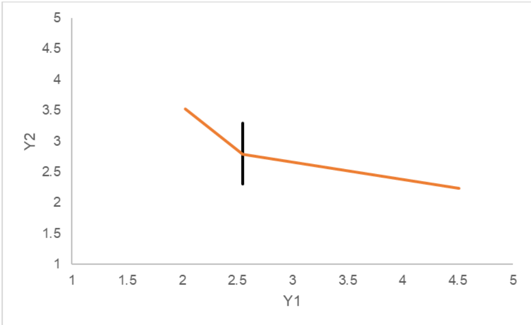


(a) (b)

(c)



(d)



(e)

Figure 3. Plot of the Relationship between Exogenous and Endogenous Variables

(a) Linear plot of the relationship between Facility and Infrastructure Quality (X_1) to 3R-Based Waste Management Practices (Y_1)
(b) Linear plot of the relationship between Waste Bank Participation (X_2) to 3R-Based Waste Management Practices (Y_1)
(c) Linear plot of the relationship between Facility and Infrastructure Quality (X_1) to Waste Economic Value (Y_2)
(d) Linear plot of the relationship between Waste Bank Participation (X_2) to Waste Economic Value (Y_2)
(e) Truncated spline plot of order 1 with 1 knot point on the relationship between 3R-Based Waste Management Practices (Y_1) to Waste Economic Value (Y_2)

Based on Table 5 and Figure 3, the estimation results show that the Facility and Infrastructure Quality (X_1) has a significant positive effect on 3R-Based Waste Management Practices (Y_1) with a coefficient of 0.305 and a p-value < 0.05. This result is shown in Figure 3 (a), which illustrates the direction and strength of the positive relationship between X_1 and Y_1, indicating that improvements in facilities and infrastructure directly increase the effectiveness of 3R-based waste management. Furthermore, the Waste Bank Participation (X_2) also has a significant positive effect on Y_1 with a coefficient of 0.274 and a p-value < 0.05. This is shown in Figure 3 (b), which illustrates that active community participation in waste banks can encourage the effectiveness of 3R-based waste management.

Facility and Infrastructure Quality (X_1) also shows a significant positive effect on the Utilization of the Waste Economic Value (Y_2) with a coefficient of 0.566 and a p-value < 0.05, as shown in Figure 3 (c). This indicates that the availability of adequate facilities and infrastructure plays an important role in increasing the economic value of waste. The Waste Bank Participation (X_2) also has a significant positive effect on Waste Economic Value (Y_2) with a coefficient of 0.252 and a p-value < 0.05, as shown in Figure 3 (d), confirming the contribution of community participation to increasing the economic value of waste management.

Further analysis shows that the relationship between 3R-Based Waste Management Practices (Y_1) and Waste Economic Value (Y_2) is nonlinear and divided into two regimes. The first regime applies when $Y_{1i} <$ 2.549, with the Equation (21).

$$\hat{f}_{2i} = 5{,}441 - 1{,}823Y_{1i} \tag{21}$$

The second regime applies when $Y_{1i} \geq 2.549$, which can be written in Equation (22).

$$\hat{f}_{2i} = 0{,}888 - 0{,}037Y_{1i} \tag{22}$$

The coefficient of -1.823 in the first regime shows that at low levels of 3R-based waste management, an increase in such activities can reduce economic value, because operational costs or recycling process inefficiencies are still higher than the economic benefits. In the second regime, the coefficient of -0.037 indicates that when 3R-based management is relatively high, the negative effect on economic value becomes very weak. This indicates that the waste management system has reached a more stable stage and is approaching equilibrium, as shown in Figure 3 (e).

The total coefficient of determination, which serves as an indicator of model validity in the first-order truncated spline semiparametric path analysis with one knot, is presented in Table 6.

Table 6. Coefficients of Determination

Endogenous Variable	**Coefficients of Determination** $\left(R^2_{k,adj}\right)$	**Total Coefficients of Determination**$\left(R^2_{T,adj}\right)$
3R-Based Waste Management Practices (Y_1)	0.283	0.627
Waste Economic Value (Y_2)	0.450	

Based on Table 6, Overall, both models can explain 62.70% of the diversity information from the Waste Economic Value (Y_2), while the remaining 37.30% is explained by other variables outside the model. Referring to the criteria for interpreting the coefficient of determination, the total coefficient of determination obtained can be categorized as quite good, as it has a value in the range of 0.50 to 0.75 [17]. Therefore, it can be stated that the model obtained is quite good in describing the diversity of the endogenous variable of Waste Economic Value (Y_2).

3.4 Discussion

Simulation studies show that with small sample sizes ($n = 25$), single resampling methods such as SB and SJ tend to produce higher SE and bias compared to double resampling methods, especially when error variance increases, consistent with findings that Bootstrap and Jackknife have limitations in small samples that can be overcome with a double approach [18]. When the sample size increased to n = 100, the performance of all methods improves, but the JB and BJ methods continue to show smaller SE and bias, and in large samples ($n = 1000$), the JB method produces the most stable estimates, consistent with the results of Kumar [19]. An increase in error variance increases the SE and bias in the SB and SJ methods, while the JB and BJ methods are more stable to these changes, as explained by Sroka [20]. In general, JB provides the lowest SE and bias, although under some conditions of very small samples or medium error variance, BJ can produce a smaller SE, indicating that the order of resampling combinations needs to be adjusted to the characteristics of the data [21].

The results of hypothesis testing show that the effectiveness of 3R-based waste management is significantly influenced by the quality of infrastructure and the use of waste banks. Infrastructure has been proven to be a key factor, as demonstrated by the readiness of TPS3R, which influenced the success of the program in Semarang [22], increased efficiency at TPS3R Bungo Lintas [23], and capacity constraints at TPS3R Saling Asih, Bandung [24]. The use of waste banks also has a positive impact through increased community participation, environmental education, and the strengthening of circular behavior, as reported in various participatory studies [25], [26], [27].

The quality of infrastructure not only improves the effectiveness of 3R, but also the economic value of waste through direct and indirect relationships. Nonlinear analysis shows a 3R effectiveness threshold of 21%; below this threshold, infrastructure is not yet able to generate optimal economic benefits, but once this threshold is exceeded, the contribution of infrastructure increases, as supported by international studies [28] and Indonesia's 2024-2029 circular economy policy direction [29].

The use of waste banks shows two regimes of influence with the same critical point, where in the early stages the contribution is low or negative [30], but becomes positive when 3R effectiveness increases. The 3R management variable also shows two patterns, namely a negative impact in the early stages due to high operational costs, low implementation quality, and limited community participation [31], [32], while in the advanced regime (>21%) its influence weakens to near zero, in line with literature emphasizing the need for a more comprehensive 3R approach [33].

Although the relationships between variables appear strong, the generalization of findings is limited by the characteristics of the sample, which focuses on specific areas and uses a non-probabilistic approach. Social and institutional factors, levels of urbanization, and variations in infrastructure capacity in other regions have the potential to produce different dynamics. In additions, the use of perception data can lead to reporting bias, so the results must be interpreted with caution, and cross-regional validation is recommended for future research.

4. CONCLUSION

This study shows that the double resampling method produces more stable and consistent standard error estimates than single resampling in truncated spline semiparametric path analysis. In simulations, the JB method provides the lowest average SE, 0.0262 at $n = 25$ (high EV) and decreasing to 0.0087 at $n = 1000$ (low EV), as well as less bias compared to SB and SJ. However, this study has limitations such as a limited sample size $(n = 100)$, a cross-sectional design, and narrow geographical coverage. The computational complexity of the double resampling method also needs to be considered. Nevertheless, fo studies requiring high accuracy, double resampling is still recommended. In the context of the economic value of waste, the model shows that infrastructure contributes 0.305 to the effectiveness of 3R and has an indirect effect of -0.556 before threshold 21% and -0.011 after threshold 21%. While waste banks have a direct effect of 0.274. These findings can form the basis for more evidence-based operational and policy decisions.

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