

Bagging Based Heteroscedasticityadjusted Ridge Regression For District Level Poverty Modeling in West Nusa Tenggara Province

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ABSTRACT

This study develops an applied bagging-based heteroscedasticity-adjusted ridge (HAR) regression framework for district-level poverty modeling in West Nusa Tenggara Province, Indonesia. The response is the percentage of people living below the poverty line, while the predictors represent life expectancy, expected years of schooling, mean years of schooling, adjusted expenditure per capita, and the open unemployment rate. Because a verified district-year microdataset was not supplied, the empirical section is explicitly presented as a reproducible illustration using 50 synthetic observations for the ten regencies and cities during 2020-2024, calibrated to plausible ranges reported in recent official publications. The predictor correlations range from 0.957 to 0.979 for the four human-development variables, with variance inflation factors between 17.47 and 44.26. The Breusch-Pagan statistic is 14.619 ($p = 0.012$), indicating heteroscedastic residuals. Leave-one-out cross-validation shows that the bagged HAR-HK estimator achieves the smallest predicted residual sum of squares ($PRESS = 213.307$), compared with 218.997 for HAR-HK and 231.562 for ordinary least squares. The bagged estimator therefore reduces $PRESS$ by 2.60% relative to its HAR counterpart and by 7.88% relative to OLS. The results illustrate how bootstrap aggregation can stabilize ridge-parameter selection when regional development indicators are strongly collinear and residual variance is unequal. The numerical findings are methodological illustrations and must be re-estimated using quality-controlled BPS data before policy use.

Keywords: bagging; heteroscedasticity; multicollinearity; ridge regression; poverty; West Nusa Tenggara

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1. INTRODUCTION

Poverty reduction remains a central development priority in West Nusa Tenggara (NTB), a province consisting of ten regencies and cities distributed across Lombok and Sumbawa. Recent official publications document persistent differences in poverty, education, health, employment, and household purchasing power across these administrative areas [1]–[3]. National evidence also shows that economic security depends not only on movement above a single poverty line, but on households' resilience to shocks and access to human-development opportunities [4].

The regional setting of NTB is heterogeneous. Population concentration, urbanization, agricultural dependence, tourism, mining, and inter-island accessibility vary substantially, so a single development indicator cannot represent the complete poverty mechanism. Mobility and welfare research in NTB further emphasizes that demographic distribution and economic opportunity are spatially uneven [5]. These conditions make district-level statistical modeling relevant for development planning and the targeting priorities emphasized in Indonesia's recent national planning framework [6].

A common empirical strategy is multiple linear regression with poverty as the response and health, education, expenditure, and labor-market measures as predictors. However, these predictors often move

together because they reflect a shared development process. Strong multicollinearity inflates coefficient variance, while unequal regional variability creates heteroscedastic errors. Their joint presence can make ordinary least squares (OLS) coefficients unstable and predictive comparisons unreliable. Recent methodological work proposes heteroscedasticity-adjusted ridge estimators and bootstrap aggregation to address these two problems simultaneously [7]–[11].

Recent ridge-regression research has also examined large collections of shrinkage parameters, bootstrap selection, jackknife stabilization, non-normal errors, generalized ridge formulations, and adaptive estimation under heteroscedasticity [12]–[21]. The central idea is to accept a controlled amount of bias in exchange for a potentially substantial reduction in variance and prediction error. This trade-off is particularly appropriate for regional datasets, where the number of administrative units is limited and development indicators are highly correlated.

This study reformulates the bagging-based HAR framework for district-level poverty modeling in NTB. The objectives are to: (1) present the OLS, ridge, HAR, and bagging equations in editable form; (2) provide a transparent sequence for diagnosing multicollinearity and heteroscedasticity; (3) compare estimators using leave-one-out cross-validation; and (4) demonstrate coefficient stabilization using an explicitly labeled illustrative NTB panel. The analysis is methodological; the synthetic values are not official district statistics.

2. LITERATURE REVIEW AND STATISTICAL FRAMEWORK

2.1 Regional Poverty and Development Indicators in NTB

Provincial statistical publications provide annual district-level indicators on poverty, health, education, purchasing power, employment, and regional economic structure [1], [22]–[25]. Welfare reporting also shows that monetary poverty is closely related to education, labor conditions, housing, and access to basic services [26]. Human-development research treats health, knowledge, and living standards as complementary dimensions rather than isolated outcomes [3], [27]. Accordingly, the predictors selected in this study represent mutually reinforcing dimensions of regional welfare.

The close conceptual relationship among these dimensions creates an econometric difficulty. Mean years of schooling, expected years of schooling, life expectancy, and expenditure per capita typically rise together. Although this joint movement is substantively meaningful, it can make individual OLS slopes sensitive to small changes in the sample. Recent development research therefore increasingly combines substantive regional knowledge with regularization, hierarchical structures, and cross-validation [28]–[30].

2.2 Linear Regression, Ridge Shrinkage, and Multicollinearity

For n district-year observations and p predictors, the multiple linear regression model is

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \quad E(\boldsymbol{\varepsilon}) = \mathbf{0}, \quad \text{Var}(\boldsymbol{\varepsilon}) = \sigma^2 \mathbf{I}_n. \quad (1)$$

The OLS estimator is

$$\hat{\boldsymbol{\beta}}_{\text{OLS}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}. \quad (2)$$

When the columns of $\mathbf{X}$ are nearly linearly dependent, the inverse of $\mathbf{X}^T \mathbf{X}$ becomes unstable. Ridge regression adds a positive constant k to the diagonal, yielding

$$\hat{\boldsymbol{\beta}}_R(k) = (\mathbf{X}^T \mathbf{X} + k \mathbf{I}_p)^{-1} \mathbf{X}^T \mathbf{y}, \quad k > 0. \quad (3)$$

Let $\mathbf{Q}$ contain the eigenvectors of $\mathbf{X}^T \mathbf{X}$. The orthogonal representation and OLS estimator are

$$\mathbf{Q}^T \mathbf{X}^T \mathbf{X} \mathbf{Q} = \boldsymbol{\Lambda} = \text{diag}(\lambda_1, \dots, \lambda_p) \quad (4)$$

$$\mathbf{Z} = \mathbf{X} \mathbf{Q}, \quad \boldsymbol{\alpha} = \mathbf{Q}^T \boldsymbol{\beta}, \quad \hat{\boldsymbol{\alpha}}_{\text{OLS}} = \boldsymbol{\Lambda}^{-1} \mathbf{Z}^T \mathbf{y}. \quad (5)$$

Small eigenvalues inflate the total mean squared error of OLS, summarized by

$$\text{MSE}(\hat{\boldsymbol{\alpha}}_{\text{OLS}}) = \hat{\sigma}_{\text{OLS}}^2 \sum_{t=1}^p \lambda_t^{-1} \quad (6)$$

2.3 Heteroscedasticity-Adjusted Ridge Estimators

Following the recent HAR formulation, the OLS error variance is increased by a residual-based scaling factor to reflect unequal error dispersion [7], [8]. The scaling factor and adjusted variance are

$$\tau = \left\{ \frac{p \text{abs}(e_{\max})}{\text{abs}(e_{\min})} \right\}^{1/2} \quad (7)$$

$$\hat{\sigma}_{\text{HA}}^2 = \tau \hat{\sigma}_{\text{OLS}}^2 \quad (8)$$

Four HAR ridge parameters are considered. They are the heteroscedasticity-adjusted versions of the HK, LW, HSL, and KMS rules:

$$\hat{k}_{\text{HAR-HK}} = \frac{\hat{\sigma}_{\text{HA}}^2}{\hat{\sigma}_{\max}^2} \quad (9)$$

$$\hat{k}_{\text{HAR-LW}} = \frac{p \hat{\sigma}_{\text{HA}}^2}{\sum_{t=1}^p \lambda_t \hat{\sigma}_t^2} \quad (10)$$

$$\hat{k}_{\text{HAR-HSL}} = \frac{\hat{\sigma}_{\text{HA}}^2 \sum_{t=1}^p (\lambda_t \hat{\sigma}_t^2)^2}{(\sum_{t=1}^p \lambda_t \hat{\sigma}_t^2)^2} \quad (11)$$

$$\hat{k}_{\text{HAR-KMS}} = \frac{\lambda_{\max}}{\sum_{t=1}^p (\hat{\sigma}_t^2)^{1/2}} \left(\frac{\hat{\sigma}_{\text{HA}}^2}{\hat{\sigma}_{\max}^2} \right) \quad (12)$$

2.4 Bootstrap Aggregation of the Ridge Parameter

Bagging draws B bootstrap samples from the original data, estimates the ridge parameter in every sample, and aggregates the estimates. The general bagged ridge parameter is

$$k_{\text{bag}} = \frac{1}{B} \sum_{b=1}^B \hat{k}(D_b) \quad (13)$$

Applied to the four HAR rules, the proposed parameters are

$$k_{\text{HAR-HK,bag}} = \frac{1}{B} \sum_{b=1}^B \hat{k}_{\text{HAR-HK},b} \quad (14)$$

$$k_{\text{HAR-LW,bag}} = \frac{1}{B} \sum_{b=1}^B \hat{k}_{\text{HAR-LW},b} \quad (15)$$

$$k_{\text{HAR-HSL,bag}} = \frac{1}{B} \sum_{b=1}^B \hat{k}_{\text{HAR-HSL},b} \quad (16)$$

$$k_{\text{HAR-KMS,bag}} = \frac{1}{B} \sum_{b=1}^B \hat{k}_{\text{HAR-KMS},b} \quad (17)$$

Bagging primarily targets variance reduction. Its bias, variance, and mean squared error can be summarized by

$$\text{Bias}(k_{\text{bag}}) = E(k_{\text{bag}}) - k \quad (18)$$

$$\text{Var}(k_{\text{bag}}) = \frac{v}{B} + \frac{B-1}{B} c \quad (19)$$

$$\text{MSE}(k_{\text{bag}}) = \text{Var}(k_{\text{bag}}) + \text{Bias}(k_{\text{bag}})^2 \quad (20)$$

In Equation (19), $v = \text{Var}(k_b)$ and $c = \text{Cov}(k_b, k_c)$ for two distinct bootstrap samples b and c.

3. RESEARCH METHODS

3.1 Study Area and Data Design

The target area is West Nusa Tenggara Province, covering West Lombok, Central Lombok, East Lombok, Sumbawa, Dompu, Bima Regency, West Sumbawa, North Lombok, Mataram City, and Bima City. A production analysis should compile district-year observations from BPS publications or official statistical tables and preserve publication year, revision status, units, and metadata.

Because the uploaded source article did not contain an NTB socioeconomic dataset, this manuscript uses a reproducible synthetic panel of 50 observations for 2020-2024. The values were generated within plausible regional ranges and were designed to reproduce the statistical challenges of interest: strong correlation among human-development predictors and heteroscedastic residual variance. Table 1 summarizes the design.

Table 1. Study design for the illustrative NTB poverty case

Component	Specification
Target area	Ten regencies and cities of West Nusa Tenggara Province
Illustrative period	2020-2024
Sample size	50 district-year observations
Response	Percentage of population below the poverty line
Predictors	Life expectancy, expected schooling, mean schooling, adjusted expenditure, unemployment
Estimators	OLS; HAR-HK, HAR-LW, HAR-HSL, HAR-KMS; and four bagged versions
Validation	Leave-one-out cross-validation (LOOCV)
Status	Reproducible simulation; not official BPS district estimates

3.2 Variable Definition and Preprocessing

The variables, measurement units, expected directions, and preprocessing steps are presented in Table 2. Continuous predictors are standardized before ridge estimation so that the penalty is applied on a comparable scale.

Table 2. Variables used in the NTB poverty-regression illustration

Symbol	Variable	Unit	Expected relation / treatment
Y	Poverty rate	%	Response variable
X ₁	Life expectancy	years	Negative; standardize
X ₂	Expected years of schooling	years	Negative; standardize
X ₃	Mean years of schooling	years	Negative; standardize
X ₄	Adjusted expenditure per capita	million rupiah/year	Negative; standardize
X ₅	Open unemployment rate	%	Positive; standardize

3.3 Diagnostic and Performance Measures

Multicollinearity is assessed using the variance inflation factor and the eigenvalue condition number:

$$VIF_j = \frac{1}{1 - R_j^2} \quad (21)$$

$$CN = \frac{\lambda_{\max}}{\lambda_{\min}} \quad (22)$$

Heteroscedasticity is assessed using the Breusch-Pagan test and a residual-versus-fitted plot. Predictive performance is evaluated by leave-one-out PRESS, where each observation is predicted by a model estimated without that observation:

$$\text{PRESS} = \sum_{i=1}^n (y_i - \hat{y}_{(-i)})^2. \quad (23)$$

The predictive gain of a bagged estimator over its nonbagged HAR counterpart is calculated as

$$G(\%) = 100 \left(\frac{P_0 - P_B}{P_0} \right) \quad (24)$$

Here, P_0 denotes the PRESS of the nonbagged baseline estimator and P^B denotes the PRESS of its bagged counterpart.

3.4 Step-by-Step Statistical Analysis

- Step 1. Data acquisition and provenance. Compile district-year poverty and development indicators from BPS or another documented official source; record definitions, units, and revisions.
- Step 2. Data quality control. Check duplicates, missing values, inconsistent district names, changes in indicator methodology, and implausible values.
- Step 3. Descriptive exploration. Summarize each variable by year and district, inspect distributions, and calculate the predictor correlation matrix.
- Step 4. Standardization. Center and scale the predictors using training-sample statistics. Apply the same transformation to validation observations.
- Step 5. OLS diagnostics. Estimate OLS, compute VIF and condition number, inspect residuals, and perform the Breusch-Pagan test.
- Step 6. HAR estimation. Calculate the residual scaling factor, adjusted error variance, four HAR ridge parameters, and the corresponding ridge coefficients.
- Step 7. Bagging. Draw $B = 500$ bootstrap samples for the final fit, estimate each HAR parameter in every bag, and average the ridge parameters.
- Step 8. Cross-validation. Re-estimate every method in each LOOCV training set and accumulate squared prediction errors.
- Step 9. Model comparison. Rank estimators by PRESS and RMSE, examine coefficient shrinkage, and check whether bagging improves the corresponding HAR estimator.
- Step 10. Reporting. Present uncertainty, data provenance, limitations, and the distinction between predictive association and causal interpretation.

The complete analytical sequence is summarized in Figure 1.

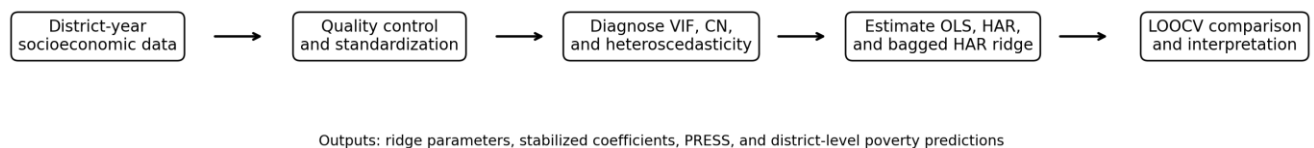


Figure 1. Reproducible workflow for bagging-based HAR ridge analysis of district-level poverty in NTB.

4. RESULTS AND DISCUSSION

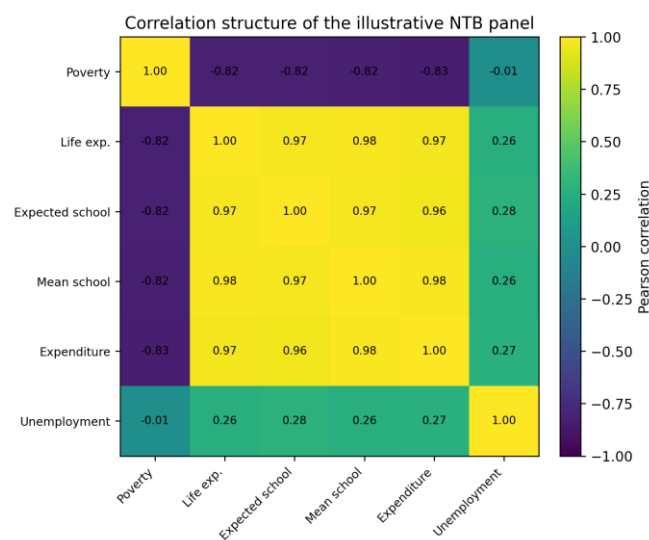
4.1 Descriptive Characteristics and Correlation Structure

Table 3 provides descriptive statistics for the 50 illustrative district-year observations. The values are intended to resemble plausible ranges rather than reproduce official district estimates.

Table 3. Descriptive statistics of the illustrative NTB panel

Variable	Mean	Std. dev.	Minimum	Maximum
Poverty rate (%)	14.41	3.82	7.29	26.00
Life expectancy (years)	68.98	1.42	66.28	71.59
Expected schooling (years)	12.86	0.66	11.46	14.03
Mean schooling (years)	8.48	1.12	6.06	10.41
Expenditure (million rupiah)	12.16	1.74	8.32	15.32
Unemployment rate (%)	2.47	0.39	1.58	3.30

The correlation structure is visualized in Figure 2. Life expectancy, expected schooling, mean schooling, and expenditure are correlated between 0.957 and 0.979. Each of these variables also has a strong negative bivariate relationship with poverty, while unemployment is less closely aligned with the common human-development dimension.

**Figure 2.** Correlation matrix for poverty and the five predictors in the illustrative NTB panel.

4.2 Regression Diagnostics

The diagnostic statistics are summarized in Table 4. Four predictors have VIF values substantially above 10, confirming severe multicollinearity. The condition number of the standardized design matrix is 15.43. The Breusch-Pagan test rejects homoscedasticity at the 5% level (BP = 14.619; $p = 0.012$).

Table 4. Multicollinearity and heteroscedasticity diagnostics

Diagnostic	Value
LifeExpectancy	29.78
ExpectedSchooling	23.48
MeanSchooling	44.26
Expenditure	23.06
Unemployment	1.09
Condition number	15.43
Breusch-Pagan statistic	14.619
Breusch-Pagan p-value	0.012

Figure 3 complements the formal test. The residual spread changes across fitted poverty values, indicating that the constant-variance assumption is not appropriate for the illustrative data.

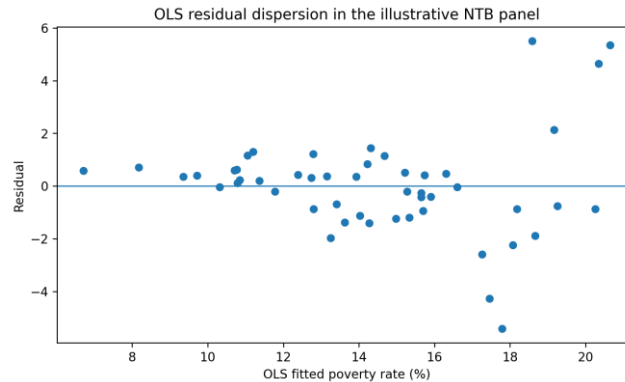


Figure 3. OLS residual dispersion for the illustrative NTB poverty model.

4.3 Ridge Parameters and Predictive Performance

The estimated ridge parameters and LOOCV performance measures are presented in Table 5. The HAR-KMS rules produce very large penalties and consequently over-shrink the model in this illustration. HAR-HK* yields the smallest PRESS and RMSE.

Table 5. Ridge parameters and leave-one-out predictive performance

Estimator	Ridge k	PRESS	LOOCV RMSE
OLS	0.000	231.562	2.152
HAR-HK	16.419	218.997	2.093
HAR-LW	0.418	222.732	2.111
HAR-HSL	15.040	218.991	2.093
HAR-KMS	1971.397	640.212	3.578
HAR-HK*	8.341	213.307	2.065
HAR-LW*	0.434	222.729	2.111
HAR-HSL*	15.953	216.848	2.083
HAR-KMS*	1017.135	589.057	3.432

Compared with OLS, HAR-HK* reduces PRESS from 231.562 to 213.307, an improvement of 7.88%. Relative to its direct nonbagged counterpart, HAR-HK, the reduction is 2.60%. The improvement is modest but consistent with the variance-stabilization purpose of bagging. Figure 4 shows the complete model ranking.

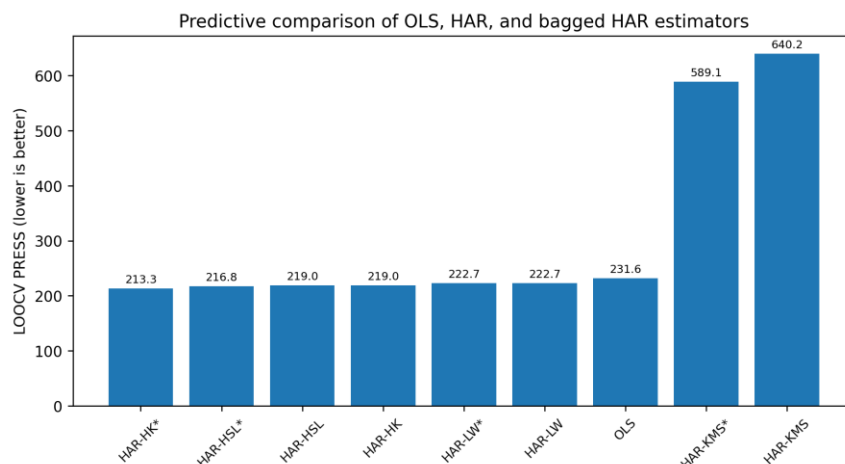


Figure 4. LOOCV PRESS comparison for OLS, HAR, and bagging-based HAR estimators.

4.4 Coefficient Stabilization and Regional Interpretation

Table 6 compares OLS, HAR-HK, and the best-performing HAR-HK* coefficients on the original measurement scales. Under severe multicollinearity, individual slopes should not be interpreted as isolated causal effects. The comparison instead shows how shrinkage redistributes the combined contribution of highly correlated education, health, and expenditure indicators.

Table 6. Selected regression coefficients on the original scales

Estimator	Life exp.	Expected school	Mean school	Expenditure	Unemployment
OLS	0.234	-2.023	-0.063	-1.378	2.375
HAR-HK	-0.480	-1.162	-0.672	-0.523	1.571
HAR-HK*	-0.449	-1.230	-0.680	-0.607	1.882

The negative direction of the human-development block and the positive direction of unemployment are consistent with the data-generating structure. However, coefficient magnitudes vary because the first four predictors contain overlapping information. The bagged ridge solution is therefore better interpreted as a stabilized predictive model than as a set of independent structural parameters.

The average illustrative poverty rates by district are summarized in Table 7. North Lombok and Bima Regency have the highest generated averages, whereas West Sumbawa, Bima City, and Mataram City have lower averages. These rankings are part of the simulation design and are not official poverty estimates.

Table 7. District-level averages in the illustrative NTB panel

Region	Poverty (%)	Mean schooling	Expenditure	Unemployment
North Lombok	20.39	6.49	9.37	2.23
Bima Regency	19.33	7.44	10.40	2.49
Central Lombok	15.40	7.81	11.38	2.51
Sumbawa	14.20	8.64	12.17	2.17
East Lombok	14.08	7.92	11.28	2.30
West Lombok	13.87	8.88	12.67	2.67
Dompu	13.84	8.16	11.64	2.41
Mataram City	11.72	9.91	14.56	3.07
Bima City	11.54	9.49	13.86	2.78
West Sumbawa	9.71	10.01	14.24	2.08

Figure 5 compares observed values with LOOCV predictions from HAR-HK*. The points generally follow the 45-degree reference line, although larger errors remain for several high-variance observations. This pattern reinforces the need to report predictive uncertainty and to avoid deterministic policy conclusions from a small regional panel.

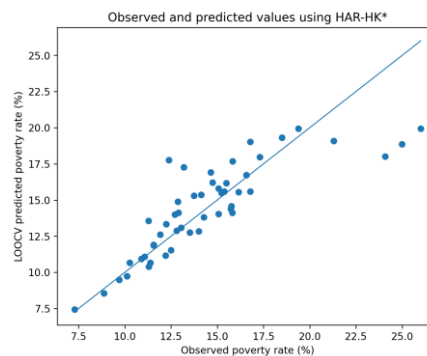


Figure 5. Observed and LOOCV-predicted poverty rates using the bagged HAR-HK estimator.

4.5 Statistical and Practical Implications

The analysis demonstrates three practical points. First, closely related development indicators can be retained as a policy-relevant block without allowing near-collinearity to dominate estimation. Second, the HAR adjustment recognizes that residual variability differs across regional development profiles. Third, bagging reduces sensitivity of the ridge parameter to a single small sample. These properties are useful when planners need stable district-level prediction rather than fragile interpretation of individual OLS slopes.

For an empirical NTB study, the most important extensions are replacement of the synthetic panel with official BPS data, sensitivity analysis across time windows, blocked validation by year, robust comparison with generalized least squares and elastic net, and explicit treatment of district and year dependence. Spatial or hierarchical models may also be necessary when neighboring districts share unobserved characteristics [29], [30].

4.6 Limitations

The principal limitation is that the numerical analysis is illustrative. It demonstrates the method, equations, workflow, and journal presentation, but it does not estimate official poverty relationships in NTB. The panel also treats district-year observations as independent, whereas real data may contain serial and spatial dependence. Finally, the residual scaling factor and the ridge-parameter rules are heuristic; their predictive value must be compared through cross-validation rather than assumed in advance.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

This article adapts bagging-based heteroscedasticity-adjusted ridge regression to district-level poverty modeling in West Nusa Tenggara Province. The framework combines OLS diagnostics, residual variance adjustment, four ridge-parameter rules, bootstrap aggregation, and leave-one-out predictive comparison. All principal formulas are provided as editable Word equations.

In the reproducible illustrative panel, the human-development predictors exhibit severe multicollinearity and the OLS residuals are heteroscedastic. HAR-HK* produces the lowest PRESS, improving predictive performance relative to both OLS and the corresponding nonbagged HAR-HK estimator. The result supports the use of bagged shrinkage when regional samples are small, predictors overlap strongly, and error variance is unequal. The numerical values must not be treated as official NTB statistics.

5.2 Recommendations

Future work should compile at least five to ten years of verified BPS district-level data, document changes in poverty and human-development definitions, and use year-blocked or district-blocked validation. The bagging-based HAR estimators should be compared with elastic net, generalized least squares, Bayesian shrinkage, and spatial hierarchical models. Policy interpretation should emphasize prediction intervals and joint development dimensions rather than causal claims from individual collinear coefficients.

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ETHICAL STATEMENT

This methodological study uses no human participants, personal data, or animal subjects. The district-year values are synthetic and were generated solely to demonstrate the statistical workflow.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Conceptualization, methodology, simulation, statistical analysis, visualization, writing, review, and editing: to be completed according to the final author roles.

DATA AND CODE AVAILABILITY

The illustrative panel and analysis outputs were generated with a fixed random seed and are reproducible. Before submission as an empirical regional study, the synthetic data should be replaced with properly documented official observations.

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