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Beyond Gender: Socio-Economic and Regional Determinants of Household Poverty in West Nusa Tenggara, Indonesia

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ABSTRACT

Household poverty reflects differences in socioeconomic conditions and place, and female-headed households are often discussed in relation to possible economic vulnerability. However, empirical evidence does not yield a uniform conclusion regarding household head gender and poverty. This study examines household poverty in West Nusa Tenggara by considering household head gender together with education, employment status, household size, and region. The analysis uses March 2025 National Socio-Economic Survey (SUSENAS) data for 5,990 households and combines binary logistic regression with Average Marginal Effects to estimate poverty probability and the associated differences. Household head gender is not statistically significant, with an estimated 0.41 percentage-point difference in poverty probability between female- and male-headed households. Larger household size is positively associated with poverty, whereas education and formal employment are negatively associated. Households in regencies also have a higher estimated poverty probability than those in cities. Overall, the results indicate that household poverty in West Nusa Tenggara is more closely related to socioeconomic and regional characteristics than to household head gender considered separately. The findings underscore the relevance of education and vocational training, access to stable work, household-sensitive social protection, and attention to regional disparities in economic opportunities and public services.

INTRODUCTION

Households in West Nusa Tenggara differ in their demographic and socioeconomic circumstances, including the gender of the household head. Information from Badan Pusat Statistik Indonesia (BPS Indonesia) shows that women headed 18.45 percent of households in NTB at the end of 2025, or roughly one household in five. Household headship entails responsibility for family decisions as well as for meeting economic needs and maintaining members' welfare. In practice, women who serve as the main providers may need to balance household expenditures and family needs while also facing constraints in obtaining income. This raises the question of whether female-headed households have a different exposure to poverty from male-headed households.

Possible vulnerability among female-headed households needs to be considered within the broader concept of poverty. Sen (1999), through the Capability Approach, describes poverty in terms of deprivation in the capabilities needed to attain a life people have reason to value. Poverty, therefore, concerns more than inadequate income; it can also involve restricted opportunities in education, employment, and economic activity. From a gender perspective, the feminization of poverty introduced by Pearce (1978) draws attention to barriers that may limit women's access to productive resources and economic opportunities. This framework provides a reason to consider whether female-headed households face greater poverty risks. In Indonesia, Ekaputri et al. (2025) reported an association between female headship and household poverty using SUSENAS data. The evidence is nevertheless mixed. Appleton (1996) reported that female-headed households were not necessarily worse off, whereas Zhang et al. (2025) found no statistically significant overall difference in poverty vulnerability between female- and male-headed households. These contrasting findings suggest that household head gender on its own may not adequately account for poverty status.

The poverty relationship may also reflect differences in household socioeconomic conditions. Household size influences the amount of consumption needs to be met and the way available resources are distributed. Meenakshi & Ray (2002) linked household size and family composition with poverty, while noting that the relationship depends on composition and economies of scale. Education can strengthen economic capacity through gains in knowledge, productivity, and access to employment (Becker, (1964). Empirical evidence also indicates that Ekaputri et al. (2025) found that education is associated with household poverty status in Indonesia, while Panyi et al. (2025) reported that the education–poverty relationship varies across locations and periods. Employment is another key household resource because earnings from work help finance daily needs; Ekaputri et al. (2025) likewise identified employment characteristics as relevant to poverty status. Consequently, female- and male-headed households may differ in poverty outcomes partly because their education, employment, and household composition also differ.

The observed relationship between household head gender and poverty may therefore depend on the socioeconomic characteristics that accompany household headship. Ichwara et al. (2023) reported higher poverty among female-headed households in the setting they examined, but the difference was also connected with education, employment, household size, and residence. The findings of Appleton (1996) and Zhang et al. (2025), which found no significant overall gap, further suggest substantial variation within female-headed households. Their socioeconomic circumstances are not uniform: some households may have stronger access to education and employment, whereas others may face tighter resource constraints. For this reason, female headship should be examined together with the other characteristics that describe household economic conditions.

The household's geographic setting may also affect the opportunities available to its members. In West Nusa Tenggara, households in regencies and cities operate in environments that differ in socioeconomic conditions, service availability, infrastructure, and economic

activity. Such differences may influence access to employment, education, and other resources. Ichwara et al. (2023) included residence as a household characteristic in poverty analysis. The Circular and Cumulative Causation perspective of Myrdal (1957) further describes how development processes can accumulate and create different opportunities across regions. Here, the Region variable distinguishes households in regencies from those in cities within NTB. Including this factor allows the analysis to consider poverty in relation to both household circumstances and the regional setting in which those households live.

Overall, the available evidence does not provide a single conclusion about the association between female headship and poverty in West Nusa Tenggara. Some studies report greater vulnerability among female-headed households, whereas others find that the difference is no longer statistically evident after household characteristics are considered. This variation is relevant because households differ in educational attainment, employment, size, and residence. The present study consequently uses household head gender as the principal explanatory variable and evaluates it alongside socioeconomic and regional factors. The analysis examines whether poverty probability differs by household head gender and assesses how education, employment status, household size, and place of residence are associated with household poverty in West Nusa Tenggara.

METHODS

This study investigates household characteristics associated with poverty probability in West Nusa Tenggara, focusing on household head gender. Poverty status is the dependent variable and is divided into poor and non-poor households. The classification is based on household per capita expenditure relative to the poverty line: households whose per capita expenditure is below the line are categorized as poor, whereas those at or above the threshold are categorized as non-poor. The binary nature of this outcome makes binary logistic regression appropriate for the analysis. The variable structure and poverty-status definition follow the research design used for the article template.

The empirical analysis uses secondary data from the March 2025 National Socio-Economic Survey (SUSENAS) conducted by Badan Pusat Statistik (BPS). Households sampled in West Nusa Tenggara constitute the unit of analysis. SUSENAS was used because it contains information on household head characteristics, household size, education, employment, socioeconomic conditions, and expenditure that is required to determine poverty status. In accordance with the research design, the final analytical sample contains 5,990 households.

The explanatory specification centers on household head gender, with education, employment status, household size, and place of residence included as control variables. The selected predictors are intended to capture socioeconomic and household characteristics that may be associated with poverty probability. This choice is consistent with earlier household-poverty studies that apply binary logistic regression, including Sihombing et al. (2024), Acharya et al. (2022), Saputri (2021), and Norhidayati et al. (2023).

Household poverty status is modeled as the dependent variable, household head gender as the main explanatory variable, and education, employment status, household size, and residence as controls. Gender is coded 0 for male and 1 for female. Education is represented by the household head's highest educational attainment. Employment status is coded 0 for informal and 1 for formal employment. Household size records the number of household members on a ratio scale, while residence is coded 0 for city and 1 for regency. These coding decisions follow the operationalization established in the research design.

The definitions and measurement procedures for the research variables are summarized in Table 1.

Table 1. Operational Definitions of Research Variables

Variable	Variable code	Operational definition	Measurement	Scale
Poverty status (Y)	Poverty	Poverty status determined by comparing household per capita expenditure with the poverty line	1 = Poor; 0 = Non-poor	Dummy
Household head gender (X_1)	Female	Gender of the household head	0 = Male; 1 = Female	Dummy
Household head education (X_2)	Education	Total schooling years completed by the household head	Completed years of schooling	Ratio
Household head employment status (X_3)	Work	Employment form of the household head's main job	0 = Informal; 1 = Formal	Dummy
Household size (X_4)	HouseholdSize	Count of household members	Household size (persons)	Ratio
Place of residence (X_5)	Region	Administrative category of the household's place of residence	0 = City; 1 = Regency	Dummy

Source: Processed from the March 2025 SUSENAS microdata.

Because poverty status takes only two values, poor and non-poor, the study estimates a binary logistic regression model. The model relates the probability of one outcome category to a set of explanatory variables. Similar applications in household poverty research include Sihombing et al. (2024) in Bengkulu Province, Acharya et al. (2022) in Nepal, Saputri (2021) in Indonesia, and Charles et al. (2023) in studies of multidimensional poverty. The selected

specification is therefore consistent with the binary outcome used in this study and with prior empirical applications.

The binary logistic regression specification estimated in the study is written as follows.

$$\ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 Female_i + \beta_2 Education_i + \beta_3 Work_i + \beta_4 HouseholdSize_i + \beta_5 Region_i + \varepsilon_i$$

where:

- P_i= probability that household i is classified as poor;
- β_0= constant;
- $\beta_1 - \beta_5$= coefficient associated with the explanatory variables;
- Female = household head gender;
- Education = completed years of schooling of the household head;
- Work = employment status of the household head;
- HouseholdSize = number of household members;
- Region = household residence category;
- ε_i= error term.

Descriptive statistics are used first to summarize the composition of the analytical sample. Frequencies and percentages describe categorical measures, while numerical variables are summarized through their mean, standard deviation, minimum, and maximum. The resulting summaries establish the initial distribution of poverty status and household characteristics before multivariable estimation.

Binary logistic regression is subsequently estimated in Stata version 17. It is appropriate because the dependent variable separates households into poor and non-poor groups, while the explanatory variables include both numerical and categorical measures. The specification therefore allows the probability of poverty to be related simultaneously to household head gender, education, employment status, household size, and residence. Previous household-poverty applications using binary logistic regression include Sihombing et al. (2024), Acharya et al. (2022), Saputri (2021), Charles et al. (2023), and Ekaputri et al. (2025). In particular, Ekaputri et al. (2025) used SUSENAS data to estimate the probability of household poverty.

The model places household head gender at the center of the analysis, while education, employment status, household size, and place of residence serve as controls. Numerical values are retained for education and household size; gender, employment status, and residence are represented by dummy variables. Combining demographic and socioeconomic characteristics in this way permits the gender–poverty relationship to be examined in the context of other household conditions.

Joint significance of the explanatory variables is assessed with the Likelihood Ratio Test (LRT). This procedure compares the estimated model with a restricted baseline that contains only the constant and tests whether the added predictors provide a statistically meaningful

improvement. Its use for joint testing in binary logistic regression is also reported by Gultom & Atira (2025).

The Wald Test is applied to the coefficients one at a time. It evaluates whether each coefficient is statistically different from zero conditional on the other variables in the model, thereby identifying predictors with statistically significant associations with poverty probability. Similar partial-significance testing is reported by Gultom & Atira (2025) and Ekaputri et al. (2025).

Average Marginal Effects (AME) are calculated to translate the model estimates into changes in predicted poverty probability. Since logistic coefficients are expressed on the logit scale, their numerical values do not directly show probability differences. AME provides a probability-scale interpretation that makes the size of the estimated associations easier to communicate. Related use of marginal effects in poverty analysis is reported by Ekaputri et al. (2025) and Ichwara et al. (2023).

Model fit is examined with the Hosmer–Lemeshow Goodness-of-Fit Test after the AME results are interpreted. The procedure assesses how closely the probabilities predicted by the model correspond to the outcomes observed in the sample. The Hosmer–Lemeshow test is commonly used for logistic-regression fit assessment, although its behavior should be considered in relation to sample size and model characteristics (Surjanovic & Loughin, 2024).

McFadden Pseudo R^2 is included as a supplementary fit statistic. It reflects the change in the likelihood-based fit of the model relative to a baseline specification without explanatory variables. Unlike the R^2 in linear regression, it should not be interpreted as the share of variation in the dependent variable explained by the model. Its use with binary outcomes is reported by Pamela et al. (2020), while Widyangga et al. (2025) discusses the measure specifically as an evaluation statistic for binary logistic regression.

The model's discriminatory performance is assessed using the Receiver Operating Characteristic (ROC) curve together with the Area Under the Curve (AUC). ROC evaluates classification across alternative probability thresholds by comparing true-positive and false-positive rates, whereas AUC summarizes the model's classification performance over the full range of thresholds. Ramos et al. (2017) describe ROC as an evaluation approach for binary logistic regression and AUC as a summary indicator of classification performance.

All statistical processing was carried out in Stata version 17. The analysis covers descriptive statistics, binary logistic regression, the Likelihood Ratio Test, the Wald Test, Average Marginal Effects, and the Hosmer–Lemeshow, McFadden Pseudo R^2, and ROC/AUC evaluations. Interpretation focuses on coefficient signs, statistical significance, and AME values to describe the direction and magnitude of the relationships between the explanatory variables and household poverty probability.

RESULTS AND DISCUSSION

The analytical dataset comprises 5,990 households. Non-poor households account for 5,581 observations (93.17 percent), while 409 households (6.83 percent) are classified as poor. Men

are the household heads in 5,157 observations (86.09 percent), compared with 833 female-headed households (13.91 percent). Household heads completed an average of 8.58 years of schooling, with a range of 0–21 years, and the mean household size is 3.41 members, ranging from 1 to 11. Formal employment represents 51.35 percent of household heads and informal employment 48.65 percent. Most households in the sample reside in cities (83.07 percent), while 16.93 percent reside in regencies.

Table 2. Household Characteristics in the Research Sample

Variable	**Category**	**Frequency (N)**	**Percentage (%)**
Poverty status	Non-poor (0)	5.581	93,17
	Poor (1)	409	6,83
Household head gender	Male (0)	5.157	86,09
	Female (1)	833	13,91
Household head education	Low (0–6 years)	2.531	42,25
	Medium (7–12 years)	2.696	45,01
	High (≥13 years)	763	12,74
Household head employment status	Informal (0)	2.914	48,65
	Formal (1)	3.076	51,35
Household size	Small (1–3 persons)	3.120	52,09
	Medium (4–5 persons)	2.572	42,94
	Large (≥6 persons)	298	4,97
Place of residence	City (0)	4.976	83,07
	Regency (1)	1.014	16,93
Total	**Entire sample**	**5.990**	**100,00**

Source: Processed from the March 2025 SUSENAS microdata.

Table 3. Summary Statistics for Continuous Variables

Variable	N	Mean	Std. Dev.	Minimum	Maksimum
Household head education (years)	5.990	8,58	4,8323	0	21
Household size (persons)	5.990	3,41	1,3290	1	11

Source: Processed from the March 2025 SUSENAS microdata.

Table 2 shows a markedly larger number of non-poor than poor households. The sample also contains variation in household head gender, educational attainment, employment status, household size, and residence. According to Table 3, household heads have an average of 8.58 years of schooling and households contain an average of 3.41 members. These descriptive patterns provide the context for the multivariable estimates that follow.

The estimated binary logistic model is jointly significant (LR $\chi^2 = 295.51$; $p < 0.001$). Compared with the constant-only specification, the model that includes household head gender, education, employment status, household size, and region contains significantly more information about poverty status. The Wald results show statistically significant individual associations for household size, education, employment status, and region, whereas household head gender is not statistically significant.

Table 4. Binary Logistic Estimates and Average Marginal Effects

Variable	Coefficient	AME	p-value
Household size	0,6201	0,0368	<0,001
Household head education	−0,0736	−0,0044	<0,001
Household head gender (female = 1)	0,0684	0,0041	0,727
Employment status (formal = 1)	−0,3940	−0,0233	0,001
Region (regency = 1)	0,3233	0,0209	0,021

The estimates in Table 4 show a positive and statistically significant association between household size and poverty status (coefficient = 0.6201; AME = 0.0368; p<0.001). Holding the other variables constant, an additional household member is associated with an estimated 3.68 percentage-point increase in poverty probability. The size of this marginal effect indicates that household size is an important correlate of poverty in the NTB sample. One explanation is that household expansion raises expenditures for food, schooling, health care, and other necessities.

When household growth is not accompanied by a comparable increase in income or the number of earners, the resources available to each member may become more limited.

The evidence from earlier studies provides context for this association. Ekaputri et al. (2025) reported that larger family size was associated with a greater likelihood of household poverty in Indonesia. A positive relationship between family size, dependency ratio, and poverty vulnerability was also reported by Zhang et al. (2025). Meenakshi & Ray (2002) emphasized that household-size effects depend on family composition and economies of scale. In contrast, Munyanyi & Churchill (2022) noted that larger households can contain both greater dependency burdens and additional members who may contribute resources. For the NTB sample, the observed positive association suggests that the additional needs generated by household size exceed the potential resource contribution of added members.

The schooling level of the household head is negatively and significantly associated with poverty status (coefficient = −0.0736; AME = −0.0044; $p < 0.001$). With other characteristics held constant, one additional year of schooling is associated with an estimated 0.44 percentage-point reduction in poverty probability. The persistence of this association after controls are included is consistent with Human Capital Theory Becker (1964), which treats education as an investment capable of raising productivity and earning potential. The Capability Approach further emphasizes that education can expand people's ability to make informed choices, obtain information, and use economic opportunities. At the household level, these capabilities may support job search, livelihood selection, and resource management.

The broader literature also reports a negative education–poverty relationship in several settings. Ekaputri et al. (2025) identified education as a significant correlate of poverty status in Indonesia. Zhang et al. (2025) found lower poverty vulnerability among households with more educated heads, while Panyi et al. (2025) reported that the relationship can differ across space and time. Evidence from Bagnoli & Bertoméu-Sánchez (2022) likewise suggests that the education–energy poverty relationship may change when regional and year effects are considered. Thus, the role of education is context dependent; in the present NTB model, its negative association remains after the other characteristics are taken into account.

Household head gender is the principal variable of interest, but its estimated association with poverty status is not statistically significant. The coefficient is 0.0684, the AME is 0.0041, and $p=0.727$. The model estimates a 0.41 percentage-point higher poverty probability for female-headed households than for male-headed households, but the difference is not statistically significant. Once the socioeconomic and regional variables are considered jointly, the results do not provide sufficient evidence of an independent gender difference in poverty probability. This finding does not contradict the possibility of gender-related economic constraints; rather, it indicates that household head gender alone does not statistically distinguish poverty status in the present specification. Appleton (1996) reported that female-headed households in Uganda were not generally worse off in welfare terms and highlighted heterogeneity by marital status. Zhang et al. (2025) similarly found no significant aggregate

difference in poverty vulnerability, although de jure and de facto female-headed households followed different patterns.

Evidence of a gender-related poverty gap has nevertheless been reported elsewhere. Ekaputri et al. (2025) found a higher poverty risk among female-headed households, while Ichwara et al. (2023) reported higher poverty incidence among female-headed households in Kenya. At the same time, Ichwara et al. (2023) showed that education, employment, and other household characteristics were also related to the observed differences. The non-significant gender estimate in NTB is therefore consistent with the view that poverty differences cannot be explained adequately by household head gender without considering the broader socioeconomic context.

The category of female-headed households is itself heterogeneous. Differences may occur in schooling, employment, household structure, access to resources, and livelihood strategies. Because the gender measure records only the sex of the household head while these other characteristics enter the model separately, some variation initially associated with gender may be represented through the socioeconomic controls. The non-significant estimate should consequently not be interpreted as proof that gender-related barriers do not exist; it indicates only that female headship is not associated with a sufficiently precise statistical difference in poverty probability under this model specification.

The employment status of the household head has a negative and statistically significant association with poverty status. The coefficient of −0.3940 and AME of −0.0233 ($p = 0.001$) imply that households with formally employed heads have an estimated poverty probability 2.33 percentage points lower than households whose heads work informally, after the other characteristics are held constant. This difference may reflect variation in employment conditions and economic security. Formal employment generally involves more structured work arrangements, greater access to social protection, and relatively stable income. Even so, employment formality alone does not describe household welfare completely because wages, working hours, productivity, the number of earners, and income stability are not directly measured.

Prior findings provide supporting context for the employment result. Ekaputri et al. (2025) links working status and employment sector with poverty status in Indonesia. Khoiruddin et al., (2025) reports an association between labor informality and multidimensional child poverty and a lower poverty risk under formal employment. Dunga & Mwandama (2025) likewise finds a greater likelihood of poverty among households with informal employment, while Mwankusye et al. (2025) relates limited access to formal jobs to poverty vulnerability among female-headed households. Although the studies differ in setting and poverty measurement, they point to employment formality as a relevant household economic characteristic. Because the present study uses only the formal–informal distinction, the −2.33 percentage-point difference should be read as an association rather than causal evidence that formal employment by itself removes poverty.

Regional context is also associated with household poverty after employment characteristics are considered. The place-of-residence indicator is positive and statistically significant. With a coefficient of 0.3233, AME of 0.0209, and p = 0.021, households in regencies have an estimated poverty probability 2.09 percentage points higher than households in cities, conditional on the other variables. Romadhon et al. (2022) reports that Indonesian household poverty is related to regional as well as household factors, with differences across 514 regencies. At the household level, Saputri (2021) includes residence in its poverty analysis, while Sudaryanto et al. (2023) links changes in rural regional conditions with household income and poverty incidence. The result therefore highlights the relevance of spatial context, although mechanisms such as employment access, infrastructure, transport, public services, and economic opportunities are not estimated directly here.

Interpretation of the regional coefficient depends on the construction of the Region variable. In this study, Region separates administrative regencies from cities rather than applying an urban–rural classification. Consequently, the coefficient should not be compared directly with poverty statistics based on urban versus rural categories. A household situated administratively in a regency is not necessarily equivalent to a household classified as rural. Under other regional definitions, Romadhon et al. (2022) shows variation across administrative areas, whereas Sudaryanto et al. (2023) focuses on changes in rural areas related to income and poverty. The way geography is defined can therefore affect how regional poverty patterns are observed.

The distribution of the sample between the two regional categories also matters. Cities contain 83.07 percent of the observations, compared with 16.93 percent in regencies. The 2.09 percentage-point difference consequently represents an average conditional association within this sample and should not be mechanically generalized to every household in a regency. More detailed regional classifications or spatial indicators, such as road access, service facilities, and regional economic characteristics, could be examined in future work. The regional result should also be interpreted alongside the model-evaluation statistics.

Table 5. Model Evaluation Summary

Indicator	Result	Interpretation
Likelihood Ratio Test	LR $\chi^2(5)=295,51$; $p<0,001$	Full specification is statistically significant relative to the baseline
Wald Test	Household size $p<0.001$; Education $p<0.001$; Gender $p=0.727$; Employment $p=0.001$; Region $p=0.021$	Household size, education, employment, and region are significant; gender is not

Indicator	Result	Interpretation
McFadden Pseudo R^2	0,0990	Supplementary fit indicator; not interpreted as the share of variation explained in linear R^2
Hosmer–Lemeshow	$\chi^2(8)=22,62$; p=0,0039	Fit is not optimal under this goodness-of-fit criterion
AUC	0,7516	Reasonable discrimination across probability thresholds
Classification at a 0.5 cut-off	Correctly classified 93,06%; sensitivity 1,22%; specificity 99,78%	Overall accuracy is influenced by the larger non-poor group; sensitivity for poor households remains low

The Likelihood Ratio Test produces LR chi-square = 295.51 with $p < 0.001$. This indicates that the model containing all explanatory variables provides statistically more information than the baseline specification and that the predictors are jointly associated with poverty status.

The Hosmer–Lemeshow statistic is $\chi^2 = 22.62$ with $p = 0.0039$. Under this goodness-of-fit criterion, the model does not match the observed outcomes closely enough across all probability groups. The result should therefore be reported as evidence of imperfect fit, while the model remains useful for examining associations between household characteristics and poverty status.

The AUC of 0.7516 indicates that the model can distinguish poor from non-poor households with a reasonable level of discrimination across probability thresholds. At the 0.5 cut-off, 93.06 percent of observations are correctly classified, but sensitivity is only 1.22 percent and specificity is 99.78 percent. Because non-poor households make up 93.17 percent of the sample, the high overall classification rate is driven largely by correct classification of that majority group. Overall accuracy should therefore be considered together with sensitivity when assessing identification of poor households.

After socioeconomic and regional characteristics are included, the estimated gender difference remains small. The gender AME is 0.41 percentage points and is not statistically significant, indicating no statistically significant difference in poverty probability by household head gender in this specification. Education, employment status, household size, and region have clearer statistical associations with poverty status. The results therefore place greater empirical emphasis on socioeconomic and regional circumstances than on household head gender considered alone.

CONCLUSION AND RECOMMENDATIONS

Using the March 2025 SUSENAS, the study evaluates poverty status among 5,990 households in West Nusa Tenggara while accounting for household head gender and selected

socioeconomic and regional characteristics. The overall binary logistic model is statistically significant. The AME estimates show that one additional household member is associated with a 3.68 percentage-point increase in poverty probability, whereas one additional year of household head schooling is associated with a 0.44 percentage-point decrease. Formal employment is associated with a 2.33 percentage-point lower poverty probability, while residence in a regency is associated with a 2.09 percentage-point higher probability than residence in a city.

Household head gender does not have a statistically significant association with poverty status in the estimated model. After education, employment, household size, and region are controlled for, the analysis does not provide sufficient statistical evidence of a difference in poverty probability between female- and male-headed households. This result should not be taken to mean that gender-related barriers are absent; it indicates that household head gender is not sufficient on its own to identify variation in poverty probability within the present specification.

The findings support several policy considerations. Expanding access to education and vocational training may strengthen household opportunities for stable employment. Social protection can also consider differences in household size and educational attainment when identifying needs. At the regional level, policy formulation may account for variation in economic opportunities and access to services across locations. Combining household-level characteristics with regional context can complement measures that address gender-related concerns.

The study is subject to several limitations. The cross-sectional design identifies statistical associations rather than causal effects. The gender measure records the sex of the household head but does not distinguish marital status, de jure and de facto female headship, or differences in asset and income access. Employment is classified only as formal or informal, so aspects of job quality are not captured. The regional indicator separates regencies and cities but does not describe finer geographic variation within NTB. Future research could incorporate more detailed regional measures, additional employment and asset indicators, and analyses of heterogeneity across household groups.

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