

Who Are the Poor in Rural and Coastal Sumatra? A Monetary and Multidimensional Inquiry

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Abstract

Coastal and rural communities face not only limited income but also marginalization in their access to education, healthcare services, and infrastructure. The reality on the ground highlights an economic paradox: many households financially sit above the poverty line yet remain multidimensionally poor due to severe constraints in accessing these basic services. This study aims to analyze the determinants of poverty in rural and coastal areas using a microdata approach, which provides a more in-depth analysis of the characteristics of poor individuals and households. Utilizing secondary microdata at the individual and household levels sourced from the Central Bureau of Statistics (BPS), this study blends two datasets: the 2024 National Socio-Economic Survey (SUSENAS) and the 2024 Village Potential (PODES). The unit of analysis is households with poor residents aged 15 years and older residing in the coastal rural areas of Sumatra. To analyze the influence of socioeconomic characteristics on multidimensional poverty, this study employs the Alkire-Foster method and multinomial logistic regression. The findings reveal that social, economic, demographic, and infrastructural variables significantly determine household poverty levels on the Sumatran coast. Notably, education increases the likelihood of households escaping poverty while mitigating its impact across both monetary and multidimensional spectrums. Additionally, access to credit and health insurance provides substantial socio-economic capital that enhances household well-being. Access to technology also emerges as a key driver, highlighting the pivotal role of digitalization in uplifting the economy of low-income households. Based on these insights, poverty alleviation policies in Sumatra's coastal areas must shift focus toward improving community education and skills—particularly for the younger generation and farmers—rather than merely providing financial assistance.

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1. Introduction

Over the past decade, poverty has remained a central concern of public policy and economic research because of its complexity and its many dimensions. Poverty is no longer understood solely through monetary indicators such as income or consumption (Gamboa et al., 2020; Kwadzo, 2015; Salecker et al., 2020; Salam & Suwandana, 2024). A multidimensional perspective recognises that individuals and households may simultaneously experience several forms of deprivation that lower their quality of life, including in health, education, and living conditions (Agyeman-Boaten, 2024; Rizal et al., 2024; Salam et al., 2022). Capturing both the monetary and the non-monetary faces of poverty is therefore essential for designing effective interventions.

In Indonesia, both monetary and multidimensional poverty remain pressing problems, and they are spatially concentrated. The Central Statistics Agency (BPS, 2024) reported that the number of poor people in March 2024 was 25.22 million, or 9.03 percent of the population, down 0.33 percentage points from March 2023. The disparity between urban and rural areas is striking: the rural poverty rate was 11.79 percent in March 2024, considerably higher than the urban rate of 7.09 percent, although both declined relative to March 2023 (12.22 percent and 7.29 percent, respectively). These figures confirm that rural poverty continues to be a structural challenge that monetary measures alone may understate.

Rural and coastal areas warrant particular attention because deprivation there is often deeper and more multidimensional than in urban settings. Rural labour markets tend to be less robust than urban ones, generating fewer employment opportunities and wider income gaps (T. Li et al., 2020). In the Philippines, reducing rural poverty has proved difficult in the absence of targeted policies for smallholders (Andriesse, 2018), while in Ethiopia, sustained public investment in agriculture has been crucial for tackling rural poverty (Meseret Chanie et al., 2018). Coastal communities face additional vulnerabilities: a household may report an income above the poverty line yet still live in a dwelling with an earthen floor and limited access to clean water and sanitation, conditions that directly affect the health of its members. Such households are not captured by monetary measures but are clearly deprived in multidimensional terms.

Sumatra provides a relevant context for this inquiry. Its long coastline supports a large population of fishing and rural households whose livelihoods are exposed to natural-disaster risk and to thin markets for credit, technology, and public services. Several of its provinces report rural poverty rates above the national average, yet micro-level evidence on the determinants of poverty in coastal Sumatra remains scarce. Studying this region therefore

offers insight into how household characteristics and village-level conditions jointly shape poverty in a setting that is both economically marginal and environmentally exposed.

Previous research has been dominated by studies that link the socio-economic characteristics of workers to a poverty status defined only in monetary terms, even though poverty is inherently multidimensional. Studies by Adeleye et al. (2020) and Haitao (2015) found that economic growth is significantly and negatively correlated with poverty, although growth must be inclusive to reduce poverty effectively (Marrero & Servén, 2022). Other work emphasises that improving educational attainment expands employment opportunities and thereby reduces poverty (Feriyanto et al., 2020; Ratri & Sholeh, 2019). However, most of these studies rely on individual-level SUSENAS variables and rarely incorporate regional or village-level conditions, so the contextual determinants of coastal poverty remain underexplored.

The main contribution of this study is to combine SUSENAS household microdata with PODES contextual variables in order to identify the determinants of monetary poverty, multidimensional poverty, and combined poverty among rural-coastal households in Sumatra. Unlike earlier studies that treat poverty as a single monetary outcome, this study estimates a multinomial model in which households can be monetarily poor, multidimensionally poor, both, or non-poor, allowing the determinants of each category to be compared directly. To our knowledge, few studies have examined multidimensionally poor coastal workers in Indonesia using a merged household-and-village dataset, which is the gap this study addresses.

Accordingly, the objectives of this study are: (1) to describe the incidence of monetary, multidimensional, and combined poverty across the coastal provinces of Sumatra; and (2) to estimate the household and village-level determinants associated with each poverty category, so as to inform region-specific poverty-reduction policy.

2. Literature Review

2.1 Monetary and Multidimensional Poverty

Poverty is a condition in which people lack sufficient resources to meet basic living needs (Wolff, 2020). Absolute poverty focuses on meeting basic needs and is typically measured using income, consumption, or other monetary metrics, whereas relative poverty emphasises exclusion and inequality relative to the wider population (Shen, 2022). Monetary poverty thus refers to an income or consumption shortfall below a defined poverty line. Multidimensional poverty, by contrast, captures a broader set of deprivations affecting

individuals across several dimensions, including education, health, and living standards (Y. Li et al., 2022). Poverty, inequality, and growth are closely interrelated, and the conflicting findings of the cross-country literature underline that these relationships are context-dependent (Kakwani & Son, 2022).

Because monetary and multidimensional measures capture different deprivations, they do not always coincide: a household may be income-poor but not multidimensionally poor, or vice versa. Garcia-Diaz and Prudencio (2016) show that monetary indicators often dominate the poverty discourse and overshadow other critical dimensions, while Alkire and Seth (2015) find that, in India, monetary poverty can fall even as multidimensional gaps persist. A comprehensive strategy that addresses both the monetary and non-monetary dimensions is therefore needed to achieve meaningful poverty reduction (Salam et al., 2022). The Multidimensional Poverty Index (MPI) developed by Alkire and Foster has been widely adopted to capture these interactions (Alkire & Santos, 2010; J. Wang et al., 2023).

2.2 Household Characteristics and Poverty

A substantial literature links household and individual characteristics to poverty status. Education is consistently identified as a fundamental determinant: higher educational attainment is associated with better health outcomes, higher incomes, and improved living standards, and it serves both as an indicator of poverty and as a catalyst for escaping it (Ogutu & Qaim, 2018; Wei et al., 2021). Age and generation matter as well, with older household heads typically facing higher risks of multidimensional poverty owing to declining productivity and weaker labour-market participation (Q. Wang et al., 2023; Septa et al., 2024). Gender, marital status, and household size shape the distribution of resources within the household; larger families often face a heavier financial burden, particularly where resources are constrained (Heitzmann & Pennerstorfer, 2024; Stewart et al., 2025). Employment status and the sector of work are also decisive: unstable or low-quality work raises poverty risk (Brülle et al., 2019; Damaske et al., 2017; Hick & Lanau, 2018), an issue that is especially relevant for households dependent on the volatile fisheries sector.

2.3 Infrastructure, Financial Access, and Coastal Poverty

Beyond household traits, the surrounding infrastructure and access to services strongly influence poverty in rural-coastal settings. Health insurance can help break the poverty trap by improving access to health services and cushioning households against health-related financial shocks (Atake, 2018; Liao et al., 2022; M. Zhang & Wu, 2024). Financial inclusion, through access to credit and proximity to banks, enables households to manage risk, smooth



consumption, and accumulate assets (Dawood et al., 2019; Zia & Prasetyo, 2018). Access to information and communication technology widens households' reach to information, public services, and markets, and is increasingly viewed as a lever for reducing deprivation. Physical connectivity is equally important: investment in rural roads can raise agricultural productivity, lower transport costs, and improve market access, thereby reducing poverty (Asher & Novosad, 2018). Finally, coastal communities face elevated exposure to natural disasters, which damage assets and infrastructure and tend to deepen and perpetuate poverty (Hallegatte et al., 2020; Kyne & Kyei, 2024; Padli et al., 2019).

2.4 Research Gap and Hypothesis Development

Taken together, the literature establishes that poverty is shaped jointly by household characteristics and contextual conditions, yet most micro-level studies in Indonesia define poverty in monetary terms only and seldom integrate village-level variables. This study addresses that gap by merging SUSENAS household microdata with PODES village data to model monetary, multidimensional, and combined poverty simultaneously

3. Research Method

3.1 Data and Study Area

This study uses secondary household microdata from the 2024 National Socio-Economic Survey (SUSENAS) conducted by the Central Statistics Agency (BPS), merged with village-level data from the 2024 Village Potential Survey (PODES). SUSENAS provides individual and household characteristics together with consumption data used to determine monetary poverty status, while PODES supplies contextual village variables such as road conditions, distance to health facilities and banks, access to information technology, and the intensity of natural disasters. The two sources are linked at the village level: each household in SUSENAS is matched to its village identifier in PODES, so that household-level outcomes can be analysed alongside the conditions of the village in which the household resides. The data are cross-sectional.

The study area comprises the six provinces of Sumatra with a coastline: Aceh, North Sumatra, West Sumatra, Riau, Jambi, and Bengkulu. Within these provinces, the analysis is restricted to households classified as rural and located in coastal sub-districts, in line with the study's focus on rural-coastal livelihoods. The unit of analysis is the household with at least one member aged 15 years and over. After merging and cleaning, the final sample comprises 75,047 households. Where relevant, descriptive estimates of poverty incidence apply the SUSENAS household sampling weights to remain representative of the target population;



the regression estimates report robust standard errors clustered at the village level to account for the multistage sampling design and the village-level nature of the PODES variables.

3.2 Measuring Multidimensional Poverty

Multidimensional poverty is measured using the Alkire-Foster (AF) method (Alkire & Foster, 2011; Salam & Suwandana, 2024), adapting the indicators of each dimension to the available data. The procedure comprises five steps: (1) defining the dimensions of poverty (health/nutrition, education, and standard of living); (2) selecting indicators within each dimension; (3) setting the deprivation cut-off for each indicator; (4) assigning weights to each indicator; and (5) computing the weighted deprivation score for each household. The household deprivation score is defined as:

$$C_i = \sum \omega_j I_{ij} \dots\dots\dots(1)$$

Where C_i is the weighted deprivation score of household i , ω_j is the weight of indicator j , and I_{ij} equals 1 if household i is deprived in indicator j and 0 otherwise. The weights of all indicators sum to one, and each of the three dimensions carries an equal weight of 1/3. Following the AF approach, a household is classified as multidimensionally poor if its deprivation score exceeds the cut-off of 0.33 (33.33 percent) (Alkire & Foster, 2011). The dimensions, indicators, deprivation cut-offs, and weights are presented in Table 1; the weights within each dimension sum to 1/3.

Table 1. Dimensions, Indicators, Deprivation Cut-offs, and Weights of the Multidimensional Poverty Measure

Dimension (weight)	Indicator	Deprived if...	Weight
Nutrition (1/3)	Calorie intake	Household calorie consumption is less than 70% of the recommended nutritional adequacy rate (AKG 2013)	1/6
	Protein intake	Household protein consumption is less than 80% of the recommended nutritional adequacy rate (AKG 2013)	1/6
Education (1/3)	Educational attainment	No household member has completed nine years of education (minimum junior secondary school)	1/6
	School attendance	There is a school-age child (7–15 years) who is not attending school	1/6

Dimension (weight)	Indicator	Deprived if...	Weight
Standard living (1/3)	Improved drinking water	No access to improved drinking water	1/18
	Improved sanitation	No access to improved sanitation	1/18
	Electricity	Does not use electricity as the main source of lighting	1/18
	Flooring material	Dwelling uses an earth or sand floor	1/18
	Cooking fuel	Uses wood or charcoal as the main cooking fuel	1/18
	Asset ownership	Owns no car or motorcycle, or owns no more than one of the following assets: motorcycle, bicycle, boat, cable television, air conditioner, water heater, gas cylinder of 12 kg or more, refrigerator/freezer, or telephone	1/18

Source: Alkire & Foster (2011), modified by the authors (2024). Note: the weights within each dimension sum to 1/3, and the weights across all ten indicators sum to 1.

3.3 Empirical Model

Households are classified into four mutually exclusive categories. A household is monetarily poor if its per-capita consumption falls below the official BPS poverty line; multidimensionally poor if its AF deprivation score exceeds 0.33; combined poor if it is both monetarily and multidimensionally poor; and non-poor otherwise. Because the dependent variable is a nominal categorical outcome, the determinants are estimated using multinomial logistic regression. Combined poverty (monetary and multidimensional) is used as the base outcome, so that the coefficients for each of the other three categories are interpreted relative to the combined-poor group.

The explanatory variables comprise individual characteristics (education, age, gender, generation), household characteristics (marital status, employment status, household size, working hours, and sector of work), social variables (health-insurance use and credit access), and village-level topographic variables (road access, distance to the health centre, access to information technology, distance to a bank, and disaster intensity). The three category-specific log-odds equations, relative to the combined-poor base outcome, are:



$$\ln(\pi_{\text{Monetary}}/\pi_{\text{Combined}}) = \beta_0 + \Sigma\beta_1 \text{Ind_Charac} + \Sigma\beta_2 \text{HH_Charac} + \Sigma\beta_3 \text{Topography} + \varepsilon \quad (2)$$

$$\ln(\pi_{\text{Multidim}}/\pi_{\text{Combined}}) = \beta_0 + \Sigma\beta_1 \text{Ind_Charac} + \Sigma\beta_2 \text{HH_Charac} + \Sigma\beta_3 \text{Topography} + \varepsilon \quad (3)$$

$$\ln(\pi_{\text{Non-poor}}/\pi_{\text{Combined}}) = \beta_0 + \Sigma\beta_1 \text{Ind_Charac} + \Sigma\beta_2 \text{HH_Charac} + \Sigma\beta_3 \text{Topography} + \varepsilon \quad (4)$$

To ease interpretation, marginal effects on the probability of each outcome are computed, holding the other variables constant. The operational definitions and expected signs of all variables are summarised in Table 2.

Table 2. Operational Definition of Variables

Variable	Definition / Measurement	Expected sign
Education (Edu)	Years of schooling completed by the household head	-
Age (Age)	Age of the household head, in years	+
Gender (Gender)	1 = male head, 0 = female head	±
Generation (Gen X/Y/Z)	Generational cohort of the head (reference: older cohorts)	±
Marital status (Married)	1 = married, 0 = otherwise	-
Household size (HHSIZE)	Number of household members	+
Employment status (Work)	1 = head is employed, 0 = otherwise	-
Sector (Agr)	1 = works in the agriculture/fisheries sector, 0 = otherwise	+
Working hours (Hours)	Main weekly working hours of the head	-
Health insurance (ASKES)	1 = household holds health insurance (BPJS/Jamkesda/private), 0 = otherwise	-
Credit ownership (Credit)	1 = household accesses bank/non-bank credit, 0 = otherwise	-
Village road (Rural_RD)	Condition/length of the main village road (gravel/stone/earth/wood)	+
Distance to health centre (DIST_HC)	Distance from the village to the nearest health centre (km)	+
Technology access (Tech)	Village access to information and communication technology (internet/mobile)	-
Distance to bank (DIST_Bank)	Distance from the village to the nearest bank (km)	+
Disaster intensity (DIS_Intensity)	Frequency/intensity of natural disasters affecting the village	+

Source: Authors (2025). Expected signs refer to the probability of each poverty category relative to the non-poor outcome and are indicative.

4. Results and Discussion

4.1 The Incidence of Poverty in Coastal Sumatra

This study first describes household poverty in the rural-coastal areas of six Sumatran provinces: Aceh, North Sumatra, West Sumatra, Riau, Jambi, and Bengkulu. Households are grouped into four categories: monetary poor, multidimensional poor, combined poor (both monetary and multidimensional), and non-poor. The distribution by province is shown in Table 3.

Table 3. Classification of Poverty Status by Province (2024)

Province	Monetary poor	Multidim. poor	Combined poor	Non-poor				
	Freq	%	Freq	%	Freq	%	Freq	%
Aceh	1,562	9.44	519	3.14	62	0.37	14,404	87.05
North Sumatra	1,182	5.74	2,191	10.64	433	2.10	16,778	81.51
West Sumatra	481	4.07	1,570	13.28	163	1.38	9,605	81.27
Riau	290	3.03	791	8.27	101	1.06	8,379	87.64
Jambi	301	3.31	1,182	12.98	94	1.03	7,529	82.68
Bengkulu	574	7.73	891	11.99	172	2.31	5,793	77.97
Total	4,390	5.85	7,144	9.52	1,025	1.37	62,488	83.27

Source: SUSENAS 2024, authors' calculation. Percentages are row shares within each province.

Table 3 shows that, in 2024, 16.73 percent of rural-coastal households in the six provinces were poor in at least one sense, while 83.27 percent were non-poor. Monetary poverty affected 5.85 percent of households, multidimensional poverty 9.52 percent, and combined poverty 1.37 percent. A key pattern emerges: multidimensional poverty is markedly more prevalent than monetary poverty in rural-coastal Sumatra. This indicates that many households are not income-poor yet still experience deprivation in nutrition, education, or living standards, so that relying on monetary measures alone would substantially understate the extent of deprivation in these communities.

Aceh records the highest monetary poverty rate (9.44 percent), followed by Bengkulu (7.73 percent), while Riau has the lowest (3.03 percent). For multidimensional poverty, West Sumatra is highest (13.28 percent), with Jambi (12.98 percent), Bengkulu (11.99 percent), and North Sumatra (10.64 percent) also above the regional average, whereas Aceh is lowest (3.14 percent). The contrast between Aceh's high monetary but low multidimensional poverty, and West Sumatra's opposite pattern, underscores that the two measures capture different aspects of deprivation. Combined poverty is highest in Bengkulu (2.31 percent) and North Sumatra (2.10 percent) and lowest in Aceh (0.37 percent).

4.2 Determinants of Poverty: Multinomial Logit Estimates

The determinants of poverty status are estimated using a multinomial logit model with combined poverty as the base outcome. The coefficients, standard errors, and odds ratios for the monetary-poor, multidimensional-poor, and non-poor categories (each relative to combined poverty) are reported in Table 4.

Table 4. Multinomial Logistic Regression Results (base outcome: combined poverty)

Variable	β	Std. Error	Exp(β)
Monetary Poverty			
Constant	-13.18*	(7.373)	0.000
Education (Edu)	0.211***	(0.011)	1.235
Age	-0.032***	(0.007)	0.968
Gender	0.108	(0.088)	1.114
Generation X	-0.047	(0.153)	0.954
Millennial (Gen Y)	-0.794***	(0.232)	0.452
Generation Z	-1.503**	(0.711)	0.222
Married	-0.202	(0.136)	0.817
Household size (HHSIZE)	0.266***	(0.023)	1.305
Employment status (Work)	-0.095	(0.133)	0.909
Sector (Agr)	-0.329***	(0.098)	0.720
Working hours (Hours)	0.003	(0.003)	1.003
Health insurance (ASKES)	2.531***	(0.084)	12.566
Credit ownership (Credit)	1.044***	(0.208)	2.841
Village road (Rural_RD)	0.004***	(0.001)	1.004
Distance to health centre (DIST_HC)	0.008	(0.009)	1.008

Variable	β	Std. Error	Exp(β)
Technology access (Tech) ^a	12.73*	(7.345)	—
Distance to bank (DIST_Bank)	-0.017***	(0.005)	0.984
Disaster intensity (DIS_Intensity)	-0.002***	(0.000)	0.998
Multidimensional Poverty			
Constant	26.70***	(6.887)	—
Education (Edu)	0.030***	(0.011)	1.031
Age	-0.023***	(0.007)	0.978
Gender	-0.046	(0.084)	0.955
Generation X	-0.240*	(0.142)	0.787
Millennial (Gen Y)	-1.043***	(0.217)	0.352
Generation Z	-1.780***	(0.630)	0.169
Married	0.058	(0.123)	1.060
Household size (HHSIZE)	-0.807***	(0.025)	0.446
Employment status (Work)	-0.019	(0.127)	0.981
Sector (Agr)	-0.356***	(0.095)	0.700
Working hours (Hours)	0.007**	(0.003)	1.007
Health insurance (ASKES)	-0.193**	(0.077)	0.824
Credit ownership (Credit)	1.282***	(0.206)	3.604
Village road (Rural_RD)	-0.001	(0.001)	0.999
Distance to health centre (DIST_HC)	0.047***	(0.008)	1.048
Technology access (Tech) ^a	-20.24***	(6.861)	—
Distance to bank (DIST_Bank)	-0.038***	(0.005)	0.962
Disaster intensity (DIS_Intensity)	-0.002***	(0.000)	0.998
Non-poor			
Constant	-7.364	(6.670)	0.001
Education (Edu)	0.292***	(0.011)	1.339
Age	-0.032***	(0.006)	0.969
Gender	-0.066	(0.081)	0.937
Generation X	-0.222	(0.138)	0.801
Millennial (Gen Y)	-1.550***	(0.209)	0.212
Generation Z	-2.132***	(0.609)	0.119

Variable	β	Std. Error	Exp(β)
Married	0.170	(0.120)	1.185
Household size (HHSIZE)	-0.301***	(0.022)	0.740
Employment status (Work)	0.044	(0.122)	1.045
Sector (Agr)	-0.696***	(0.092)	0.499
Working hours (Hours)	0.011***	(0.003)	1.011
Health insurance (ASKES)	2.428***	(0.073)	11.336
Credit ownership (Credit)	1.707***	(0.201)	5.512
Village road (Rural_RD)	0.001	(0.001)	1.001
Distance to health centre (DIST_HC)	0.053***	(0.008)	1.055
Technology access (Tech) ^a	11.78*	(6.645)	—
Distance to bank (DIST_Bank)	-0.053***	(0.005)	0.949
Disaster intensity (DIS_Intensity)	-0.005***	(0.000)	0.995

Notes: Robust standard errors clustered at the village level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Base outcome = combined (monetary and multidimensional) poverty. Model fit: Number of observations = 75,047; Log-likelihood = -32973,914; LR chi-square (48) = 24269,45 ($p < 0.000$); McFadden pseudo $R^2 = 0.2690$.

^a The coefficients on technology access are very large in absolute value for the monetary-poor and non-poor categories. These are flagged as potentially affected by quasi-complete separation and are interpreted only directionally, not as precise odds ratios (see Section 4.3).

Source: SUSENAS 2024; data processed 2025.

4.3 Marginal Effects on Poverty Probability

Because the multinomial logit coefficients are not directly interpretable as effects on probabilities, Table 5 reports the marginal effects of each variable on the probability of belonging to each poverty category, holding the other variables constant. The effects are expressed in percentage points. Following the reviewers' guidance, all effects are interpreted as changes in probability associated with a one-unit change in the variable, ceteris paribus, rather than as causal effects.

Table 5. Marginal Effects on the Probability of Each Poverty Category (percentage points)

Variable	Monetary poor	Multidim. poor	Combined poor	Non-poor
Education (Edu)	-0.28***	-1.47***	-0.26***	2.01***

Variable	Monetary poor	Multidim. poor	Combined poor	Non-poor
Age	0.008	0.05***	0.04***	-0.74***
Gender	0.83***	0.05	0.05	-0.93***
Generation X	0.72**	-0.20	2.16	-7.91*
Millennial (Gen Y)	3.43***	2.32***	2.16***	-7.91***
Generation Z	2.45	0.75	4.33*	-7.54**
Married	-1.77***	-0.52*	-0.11	2.41***
Household size (HHSIZE)	2.87***	-3.31***	0.44***	-0.01
Employment status (Work)	-0.65**	-0.33	-0.10	1.00**
Sector (Agr)	1.60***	1.73***	0.69***	-4.04***
Working hours (Hours)	-0.03***	-0.01**	-0.01***	0.06***
Health insurance (ASKES)	1.57***	-15.12***	-2.15***	15.70***
Credit ownership (Credit)	-2.88***	-1.84***	-1.86***	6.59***
Village road (Rural_RD)	0.01***	-0.01***	0.00	0.00
Distance to health centre (DIST_HC)	-0.21***	-0.01	-0.05***	0.27***
Technology access (Tech)	15.05	-190.39***	-4.33	179.63***
Distance to bank (DIST_Bank)	0.16***	0.05***	0.05***	-0.27***
Disaster intensity (DIS_Intensity)	0.01***	0.01***	0.00***	-0.03***

Notes: Robust standard errors used throughout. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Effects are in percentage points on the probability of each category, ceteris paribus. The technology effects are very large and should be read directionally (see text).

Source: SUSENAS 2024; data processed 2025.

5. Discussion

Poverty is a central development challenge for nearly all developing countries, and reducing it remains a core objective of public policy in Indonesia (Taruno et al.). At the national level, the government has made progress: the headcount poverty rate fell to 9.03 percent in March 2024 from 9.36 percent a year earlier (BPS, 2024). Yet, as the descriptive results show, monetary measures understate deprivation in rural-coastal areas, where multidimensional poverty is more prevalent. The discussion below is organised thematically around the main groups of determinants and closes with policy implications.



5.1 Human Capital and Poverty Mobility

Education emerges as the most consistent determinant of poverty mobility. An additional year of education is associated with a reduction of about 1.47 percentage points in the probability of being multidimensionally poor and an increase of about 2.01 percentage points in the probability of being non-poor, *ceteris paribus*. Higher education enables households to earn more and to make better use of health, sanitation, and other services, consistent with the view that education is a primary lever for breaking the poverty cycle (Sinha & Ramadas, 2021; Wei et al., 2021; Y. Zhang & Huai, 2023). Age and generation also shape mobility. Older heads of household face a higher probability of multidimensional and combined poverty, in line with evidence that declining productivity and weaker labour-market attachment raise multidimensional poverty risk among the elderly (Q. Wang et al., 2023; Septa et al., 2024; Nguyen et al., 2023). Younger cohorts, particularly millennials and Generation Z, show the lowest probability of being non-poor, suggesting that productive-age coastal workers face structural barriers to escaping poverty; this because work on the intergenerational transmission of poverty (Behrman et al., 2017; Chan, 2022). Marriage is associated with a lower probability of poverty and a higher probability of being non-poor, consistent with the stabilizing economic role of stable family relationships (Stewart et al., 2025; Witkin, 2022). Employment is associated with lower poverty across categories, but working in the fisheries sector is associated with higher poverty, reflecting the low and uncertain incomes typical of coastal fishing livelihoods, while longer working hours are associated with modest reductions in poverty (Damaske et al., 2017; Park et al., 2017).

5.2 Financial and Health Access

Access to finance and health protection is strongly associated with poverty status. Credit ownership is associated with a higher probability of being non-poor (a marginal effect of about 6.59 percentage points) and lower probabilities across the poverty categories, supporting the view that financial inclusion helps marginalized households manage risk, smooth consumption, and accumulate assets (Dawood et al., 2019; Zia & Prasetyo, 2018). Greater distance to a bank is associated with higher poverty in every category, consistent with the idea that physical proximity to financial services facilitates the transactions and savings that underpin escape from poverty. Health insurance shows a more nuanced pattern. Holding insurance is associated with a sizeable increase in the probability of being non-poor (about 15.70 percentage points) and a large reduction in multidimensional poverty, in line with evidence that insurance buffers households against health-related financial shocks and poverty traps (Atake, 2018; Liao et al., 2022). At the same time, its positive association with

the monetary-poor category likely reflects the premium burden borne by lower-income households, indicating that insurance coverage alone does not eliminate monetary strain. Proximity to a health centre is likewise associated with a higher probability of being non-poor, as nearby facilities ease access to care and health information.

5.3 Infrastructure, Technology, and Disaster Risk

Village-level infrastructure and exposure to risk also matter. Poorer main-road conditions are associated with a modestly higher probability of monetary poverty, consistent with evidence that investment in rural roads raises agricultural productivity, lowers transport costs, and improves market access (Asher & Novosad, 2018). Access to information and communication technology is robustly associated with lower multidimensional poverty and a higher probability of being non-poor; although the estimated magnitude is unreliable owing to quasi-complete separation (Section 4.3), the direction is clear and aligns with the broader finding that digital access widens households' reach to information, services, and markets. Finally, disaster intensity is associated with higher poverty across all categories: coastal households in disaster-prone villages are more likely to lose assets, shelter, and access to services, deepening both monetary and non-monetary deprivation. This is consistent with a substantial literature linking disaster exposure to entrenched poverty (Hallegatte et al., 2020; Kyne & Kyei, 2024; Padli et al., 2019), a concern that climate change is likely to intensify.

5.4 Policy Implications for Rural-Coastal Sumatra

Taken together, the results imply that sectoral, single-instrument interventions are unlikely to reduce poverty across the board in rural-coastal Sumatra. Because multidimensional poverty exceeds monetary poverty and because financial access, technology, and basic-service proximity distinguish the non-poor from the combined poor, an integrated, place-based approach is needed. Such an approach would combine human-capital investment, the expansion of safe and productive financial access, the integration of health and social protection, improvements in digital and physical infrastructure, and disaster-risk reduction, with particular attention to young workers in the fisheries sector. These region-specific implications are developed as concrete recommendations in the Conclusion.

6. Conclusion and Suggestions

6.1 Conclusion

This study examined the determinants of monetary, multidimensional, and combined poverty among 75,047 rural-coastal households in six provinces of Sumatra, combining 2024



SUSENAS household microdata with 2024 PODES village data and estimating a multinomial logit model with combined poverty as the base outcome. Three main findings stand out. First, multidimensional poverty (9.52 percent) is more prevalent than monetary poverty (5.85 percent) in rural-coastal Sumatra, so that monetary measures alone understate deprivation. Second, education is the most consistent correlate of poverty mobility: an additional year of education is associated with a reduction of about 1.47 percentage points in the probability of multidimensional poverty and an increase of about 2.01 percentage points in the probability of being non-poor, *ceteris paribus*. Third, access to credit and health insurance is associated with a substantially higher probability of being non-poor, while disaster intensity is associated with higher probabilities of poverty across all categories. Younger cohorts working in the fisheries sector remain among the least likely to escape poverty, pointing to structural barriers to decent work and social protection for productive-age coastal workers.

6.2 Policy Recommendations

The findings suggest several concretes, region-specific policy directions for rural-coastal Sumatra:

1. Strengthen vocational education and training tailored to coastal and fisheries households, to translate schooling into higher and more stable incomes.
2. Expand access to safe and productive credit, paired with financial literacy, so that borrowing supports income generation rather than mere consumption smoothing.
3. Integrate health insurance with broader social-protection programmers, and ease premium burdens for low-income households, so that coverage reduces rather than adds to monetary strain.
4. Improve digital infrastructure and digital literacy in coastal villages, given the robust association between technology access and lower deprivation.
5. Reduce the distance and transaction costs of reaching banks and health centers, through mobile services, agent banking, and outreach health posts.
6. Strengthen disaster mitigation and adaptation in coastal villages, including early-warning systems, resilient infrastructure, and asset-protection schemes.
7. Design targeted programmers for young workers in the fisheries sector, combining skills, social protection, and access to productive assets.

6.3 Limitations and Future Research

This study is limited by its cross-sectional design; therefore, the findings should be interpreted as associations rather than causal effects. The analysis is confined to the rural-coastal areas of six Sumatran provinces in a single year, which limits generalizability to other regions and over time. In addition, the very large coefficients on technology access reflect quasi-complete separation, so the magnitude of that relationship should be read with caution even though its direction is robust. Future research could employ panel or longitudinal data to identify causal effects, extend the analysis to other coastal regions of Indonesia for comparison, examine intra-household and gender dimensions of coastal poverty in greater depth, and apply identification strategies such as instrumental variables to address the endogeneity of credit, insurance, and technology access.

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References

1. Adeleye, B. N., Gershon, O., Ogundipe, A., Owolabi, O., Ogunrinola, I., & Adediran, O. (2020). Comparative investigation of the growth-poverty-inequality trilemma in Sub-Saharan Africa and Latin American and Caribbean Countries. *Heliyon*, 6(12), e05631. <https://doi.org/10.1016/j.heliyon.2020.e05631>
2. Agyeman-Boaten, S. Y. (2024). Determinants of poverty in rural cocoa farming communities in Ghana: unidimensional and multidimensional analysis. *Cogent Economics and Finance*, 12(1). <https://doi.org/10.1080/23322039.2024.2397808>
3. Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics*, 95(7–8), 476–487. <https://doi.org/10.1016/j.jpubeco.2010.11.006>
4. Alkire, S., & Santos, M. E. (2010). Acute multidimensional poverty: A new index for developing countries. OPHI Working Paper No. 38. Oxford Poverty and Human Development Initiative.
5. Alkire, S., & Seth, S. (2015). Multidimensional poverty reduction in India between 1999 and 2006: Where and how? *World Development*, 72, 93–108. <https://doi.org/10.1016/j.worlddev.2015.02.009>

6. Andriesse, E. (2018). Primary sector value chains, poverty reduction, and rural development challenges in the Philippines. *Geographical Review*, 108(3), 345–366. <https://doi.org/10.1111/gere.12287>
7. Asher, S., & Novosad, P. (2018). Rural roads and local economic development. Policy Research Working Paper. The World Bank. <https://doi.org/10.1257/aer.20180268>
8. Atake, E. H. (2018). Health shocks in sub-Saharan Africa: Are the poor and uninsured households more vulnerable? *Health Economics Review*, 8(1). <https://doi.org/10.1186/s13561-018-0210-x>
9. Badan Pusat Statistik. (2024). Profil kemiskinan di Indonesia Maret 2024 (Berita Resmi Statistik No. 47/07/Th. XXVII). Badan Pusat Statistik. <https://www.bps.go.id>
10. Behrman, J. R., Schott, W., Duc, L. T., Mani, S., Fernald, L. C. H., Crookston, B. T., Stein, A. D., & Dearden, K. (2017). Intergenerational transmission of poverty and inequality: Parental resources and schooling attainment and children's human capital in Ethiopia, India, Peru, and Vietnam. *Economic Development and Cultural Change*, 65(4), 657–697. <https://doi.org/10.1086/691971>
11. Brülle, J., Gangl, M., Levanon, A., & Saburov, E. (2019). Changing labour market risks in the service economy: Low wages, part-time employment and the trend in working poverty risks in Germany. *Journal of European Social Policy*, 29(1), 115–129. <https://doi.org/10.1177/0958928718779482>
12. Chan, T. W. (2022). The dynamics of relative poverty in China in a comparative perspective. *Chinese Journal of Sociology*, 8(1), 29–51. <https://doi.org/10.1177/2057150X211068543>
13. Damaske, S., Bratter, J. L., & Frech, A. (2017). Single mother families and employment, race, and poverty in changing economic times. *Social Science Research*, 62, 120–133. <https://doi.org/10.1016/j.ssresearch.2016.08.008>
14. D'Attoma, I., & Matteucci, M. (2024). Multidimensional poverty: An analysis of definitions, measurement tools, applications and their evolution over time through a systematic review of the literature up to 2019. *Quality and Quantity*, 58(4). <https://doi.org/10.1007/s11135-023-01792-8>
15. Dawood, T. C., Pratama, H., Masbar, R., & Effendi, R. (2019). Does financial inclusion alleviate household poverty? Empirical evidence from Indonesia. *Economics and Sociology*, 12(2), 235–252. <https://doi.org/10.14254/2071-789X.2019/12-2/14>
16. Ernawati, & Tajuddin. (2022). The impact of the Covid-19 pandemic on poverty gap in Indonesia. *Proceedings of the International Conference on Sustainable Innovation (ICOSIAMS 2021)*, 201, 38–42. <https://doi.org/10.2991/aebmr.k.211225.007>
17. Feriyanto, N., El Aiyubbi, D., & Nurdany, A. (2020). The impact of unemployment, minimum wage, and real gross regional domestic product on poverty reduction in provinces of Indonesia. *Asian Economic and Financial Review*, 10(10), 1088–1099. <https://doi.org/10.18488/journal.aefr.2020.1010.1088.1099>
18. Gamboa, G., Mingorría, S., & Scheidel, A. (2020). The meaning of poverty matters: Trade-offs in poverty reduction programmes. *Ecological Economics*, 169, 106450. <https://doi.org/10.1016/j.ecolecon.2019.106450>

19. Garcia-Diaz, R., & Prudencio, D. (2016). A Shapley decomposition of multidimensional chronic poverty in Argentina. *Bulletin of Economic Research*, 69(1), 1–19. <https://doi.org/10.1111/boer.12082>
20. Haitao, W. (2015). Income inequality and rural poverty in China: Focusing on the role of government transfer payments. *China Agricultural Economic Review*, 7(1), 92–107. <https://doi.org/10.1108/CAER-09-2013-0124>
21. Hallegatte, S., Vogt-Schilb, A., Rozenberg, J., Bangalore, M., & Beaudet, C. (2020). From poverty to disaster and back: A review of the literature. *Economics of Disasters and Climate Change*, 4(1), 223–247. <https://doi.org/10.1007/s41885-020-00060-5>
22. Heitzmann, K., & Pennerstorfer, A. (2024). Large families and poverty in Austria: What explains their disproportionate risk of experiencing income poverty? *International Journal of Social Welfare*, 34(1), 1–12. <https://doi.org/10.1111/ijsw.12667>
23. Hick, R., & Lanau, A. (2018). Moving in and out of in-work poverty in the UK: An analysis of transitions, trajectories and trigger events. *Journal of Social Policy*, 47(4), 661–682. <https://doi.org/10.1017/S0047279418000028>
24. Kakwani, N., & Son, H. (2022). Economic inequality and poverty. Oxford University Press. <https://doi.org/10.1093/oso/9780198852841.001.0001>
25. Kwadzo, M. (2015). Choosing concepts and measurements of poverty: A comparison of three major poverty approaches. *Journal of Poverty*, 19(4), 409–423. <https://doi.org/10.1080/10875549.2015.1015067>
26. Kyne, D., & Kyei, D. (2024). Understanding associations between disasters and sustainability, resilience, and poverty: An empirical study of the last two decades. *Sustainability*, 16(17). <https://doi.org/10.3390/su16177416>
27. Li, T., Cao, X., Qiu, M., & Li, Y. (2020). Exploring the spatial determinants of rural poverty in the interprovincial border areas of the Loess Plateau in China: A village-level analysis using geographically weighted regression. *ISPRS International Journal of Geo-Information*, 9(6). <https://doi.org/10.3390/ijgi9060345>
28. Li, Y., Jin, Q., & Li, A. (2022). Understanding the multidimensional poverty in South Asia. *Journal of Geographical Sciences*, 32(10), 2053–2068. <https://doi.org/10.1007/s11442-022-2036-z>
29. Liao, P., Zhang, X., & Zhang, W. (2022). Endogenous health risks, poverty traps, and the roles of health insurance in poverty alleviation. *Health Economics Review*, 12(1), 1–15. <https://doi.org/10.1186/s13561-022-00370-2>
30. Ma, L., Ding, T., & Zhang, J. (2024). Research on the capability to prevent returning to poverty and its enhancement path for the ecologically fragile areas: A case study of Enshi Prefecture. *Sustainability*, 16(12). <https://doi.org/10.3390/su16124986>
31. Marrero, G. A., & Servén, L. (2022). Growth, inequality and poverty: A robust relationship? *Empirical Economics*, 63(2), 725–791. <https://doi.org/10.1007/s00181-021-02152-x>
32. Meseret Chanie, A., Yuan Pei, K., Lei, Z., & Bao Zhong, C. (2018). Rural development policy: What does Ethiopia need to ascertain from China's rural development policy to

- eradicate rural poverty? *American Journal of Rural Development*, 6(3), 79–93. <https://doi.org/10.12691/ajrd-6-3-3>
33. Milliano, M. de, & Plavgo, I. (2019). Analysing multidimensional child poverty in sub-Saharan Africa: Findings using an international comparative approach. *Child Indicators Research*, 11(3), 805–833. <https://doi.org/10.1007/s12187-017-9488-1>
34. Mohaqeqi Kamal, S. H., Basakha, M., & Alkire, S. (2024). Multidimensional poverty index: A multilevel analysis of deprivation among Iranian older adults. *Ageing and Society*, 44(2), 337–356. <https://doi.org/10.1017/S0144686X2200023X>
35. Ndirangu, G. (2024). Investment in health care and its impact on poverty reduction. *International Journal of Developing Country Studies*, 6(2), 13–25. <https://doi.org/10.47941/ijdc.2167>
36. Nguyen, D. T., Sen, L. T. H., Hoang, H. G., Tran, T. N., Tran, N. A. T., & Mazancova, J. (2023). Insight into the multidimensional poverty of the mountainous ethnic minorities in Central Vietnam. *Social Sciences*, 12(6). <https://doi.org/10.3390/socsci12060331>
37. Ogutu, S. O., & Qaim, M. (2018). Commercialization of the small farm sector and multidimensional poverty. *World Development*, 114, 281–293. <https://doi.org/10.1016/j.worlddev.2018.10.012>
38. Padli, J., Ahmat, N., & Nawawi, M. N. (2019). The impact of natural disasters, technological change and education on poverty rate: Evidence from developing countries. *Jurnal Ekonomi Malaysia*, 53(2), 21–28. <https://doi.org/10.17576/JEM-2019-5302-2>
39. Park, E. Y., Nam, S. J., & Park, S. H. (2017). Income patterns of households including individuals with intellectual disabilities according to poverty dynamics. *Journal of Policy and Practice in Intellectual Disabilities*, 14(2), 108–117. <https://doi.org/10.1111/jppi.12166>
40. Ratri, T. D., & Sholeh, M. (2019). The influence of education, health and the internet on poverty in Indonesia. *Advances in Social Science, Education and Humanities Research*, 323, 158–163. <https://doi.org/10.2991/icosse-icsmc-18.2019.31>
41. Rizal, R. N., Hartono, D., Dartanto, T., & Gultom, Y. M. L. (2024). Multidimensional energy poverty: A study of its measurement, decomposition, and determinants in Indonesia. *Heliyon*, 10(3), e24135. <https://doi.org/10.1016/j.heliyon.2024.e24135>
42. Salam, A., Pratomo, D. S., & Saputra, P. M. A. (2022). Analisis kemiskinan pada rumah tangga di Jawa Timur melalui pendekatan multidimensi dan moneter. *Jurnal Kependudukan Indonesia*, 16(2), 127. <https://doi.org/10.14203/jki.v16i2.480>
43. Salam, A., & Suwandana, E. (2024). Bekerja tetapi tetap miskin, apakah permasalahan kemiskinan multidimensi? *Jurnal Ekonomi dan Pembangunan Indonesia*, 24(1), 1–18. <https://doi.org/10.21002/jepi.2024.06>
44. Salecker, L., Ahmadov, A. K., & Karimli, L. (2020). Contrasting monetary and multidimensional poverty measures in a low-income sub-Saharan African country. *Social Indicators Research*, 151(2), 547–574. <https://doi.org/10.1007/s11205-020-02382-z>

45. Septa, D., Acharya, R., & Dhanora, M. (2024). Determinants of multidimensional poverty: A study of the rural district of Madhya Pradesh. *Journal of Development Policy and Practice*, 10(2), 145–170. <https://doi.org/10.1177/24551333241285537>
46. Shen, Y. (2022). *Rural poverty, growth, and inequality in China*. Springer International Publishing. <https://doi.org/10.1007/978-981-16-9655-8>
47. Sinha, M., & Ramadas, S. (2021). Correlates of multidimensional poverty in rural Bihar. *Agricultural Economics Research Review*, 34(conf), 51–57. <https://doi.org/10.5958/0974-0279.2021.00014.8>
48. Stewart, K., Patrick, R., & Reeves, A. (2025). A time of need: Exploring the changing poverty risk facing larger families in the UK. *Journal of Social Policy*, 54(1), 75–99. <https://doi.org/10.1017/S0047279422000952>
49. Wang, J., Xiao, H., & Liu, X. (2023). The impact of social capital on multidimensional poverty of rural households in China. *International Journal of Environmental Research and Public Health*, 20(1). <https://doi.org/10.3390/ijerph20010217>
50. Wang, Q., Shu, L., & Lu, X. (2023). Dynamics of multidimensional poverty and its determinants among the middle-aged and older adults in China. *Humanities and Social Sciences Communications*, 10(1), 1–9. <https://doi.org/10.1057/s41599-023-01601-5>
51. Wei, W., Sarker, T., Żukiewicz-Sobczak, W., Roy, R., Monirul Alam, G. M., Rabbany, M. G., Hossain, M. S., & Aziz, N. (2021). The influence of women's empowerment on poverty reduction in the rural areas of Bangladesh: Focus on health, education and living standard. *International Journal of Environmental Research and Public Health*, 18(13), 1–18. <https://doi.org/10.3390/ijerph18136909>
52. Witkin, N. (2022). Is stable marriage associated with greater wealth among low-income households? Evidence from the Survey of Consumer Finances. Working paper.
53. Wolff, J. (2020). Beyond poverty. In V. Beck, H. Hahn, & R. Lepenies (Eds.), *Dimensions of poverty* (pp. 23–39). Springer. https://doi.org/10.1007/978-3-030-31711-9_2
54. Zenebe Ede'o, A., Ketebo, J. H., & Chala, B. W. (2020). Feminization of multidimensional urban poverty in sub-Saharan Africa: Evidence from selected countries. *African Development Review*, 32(4), 632–644. <https://doi.org/10.1111/1467-8268.12466>
55. Zhang, M., & Wu, M. (2024). The impact of rural health insurance on vulnerability to chronic poverty among rural residents in China: Analysis using Probit and IVprobit models. *Frontiers in Public Health*, 12, 1481019. <https://doi.org/10.3389/fpubh.2024.1481019>
56. Zhang, Y., & Huai, J. (2023). A case study of farmers' behavioral motivation mechanisms to crack the fractal multidimensional relative poverty trap in Shaanxi, China. *Agriculture*, 13(11). <https://doi.org/10.3390/agriculture13112043>
57. Zia, I. Z., & Prasetyo, P. E. (2018). Analysis of financial inclusion toward poverty and income inequality. *Jurnal Ekonomi Pembangunan*, 19(1), 114. <https://doi.org/10.23917/jep.v19i1.5879>