

The Dynamics of Poverty Transitions in Indonesia: A Multilevel Analysis of Household Entry Into and Exit From Poverty

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Submitted: 1 January 2026. Accepted: 15 June 2026. Published: 24 July 2026

Volume 35, 2027. pp. 533–557. <http://doi.org/10.25133/JPSSv352027.027>

Abstract

Indonesia's aggregate poverty rate masks substantial household-level mobility. This study investigates the determinants of entry into and exit from poverty using panel data from the National Socioeconomic Survey (SUSENAS) 2022–2024. Multilevel binary logistic regression is applied to model transition probabilities across 34 provinces. Results show that education level and employment sector are the strongest household-level predictors: higher-educated heads working in services or manufacturing face a lower risk of entering poverty and greater prospects of exiting poverty. Provincial economic capacity and income inequality independently shape transition outcomes, with an intraclass correlation of 0.313 indicating that nearly one-third of the variation in entry risk is attributable to intraclass effects. Age effects are non-linear, with entry risk following a U-shaped curve minimized around age 51 and exit likelihood peaking near age 37, suggesting that poverty programs benefit from differentiation across life-cycle stages. Findings reflect associations from an observational design and should not be interpreted causally. The evidence points to the need for anticipatory social protection targeting near-poor households and sustained investment in secondary and vocational education as structural pathways out of poverty.

Keywords

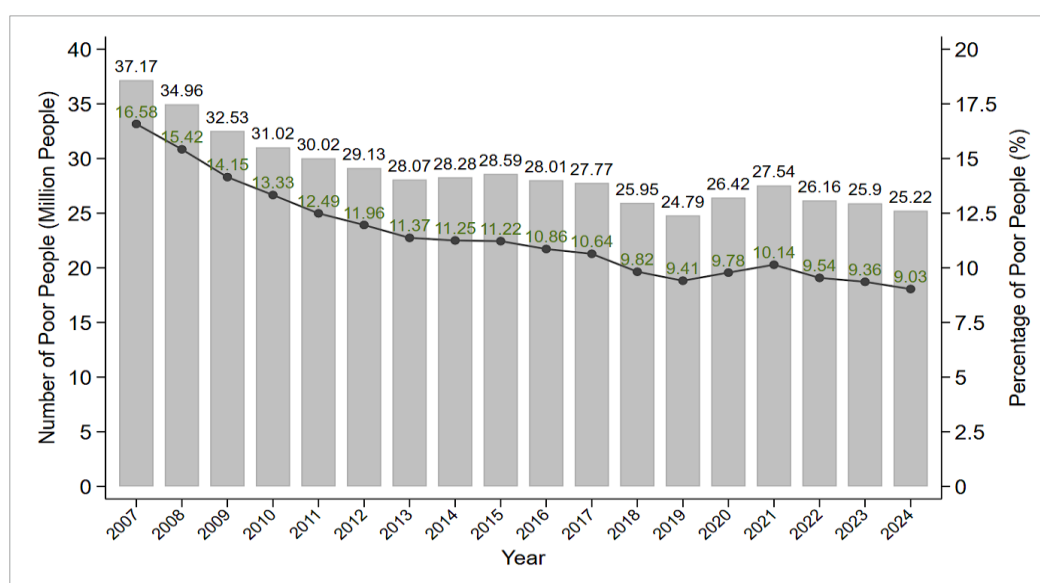
Indonesia; multilevel logistic regression; panel data; poverty dynamics; poverty transitions

Introduction

Poverty is one of the most pressing development challenges globally (World Bank, 2025), as reflected in the first Sustainable Development Goal commitment to end extreme poverty (United Nations, 2023). Much of the literature demonstrates that static indicators, such as the headcount ratio, cannot fully capture the dynamics of household welfare (Calvo & Dercon, 2013). Measuring poverty with the headcount ratio focuses solely on determining poor and non-poor status at a single point in time (Ouoya, 2021), which can obscure the rapid fluctuations experienced by vulnerable households living just above the poverty line (Bandyopadhyay, 2016).

Poverty vulnerability is widely recognized as a key factor behind the slowdown in poverty reduction in Indonesia during 2007–2024 (BPS-Statistics Indonesia, 2024c; Calvo & Dercon, 2007; Jellema & Noura, 2012; Morduch, 1994). All Indonesian RPJMN planning documents from 2004–2009 through the most recent 2020–2024 cycle have failed to achieve their poverty reduction targets (Ministry of Finance of the Republic of Indonesia, 2023). Figure 1 illustrates this long-run declining trend alongside its decelerating pace (BPS-Statistics Indonesia, 2025, 2026).

Figure 1: Number and Percentage of Poor People in Indonesia from 2007 to 2024

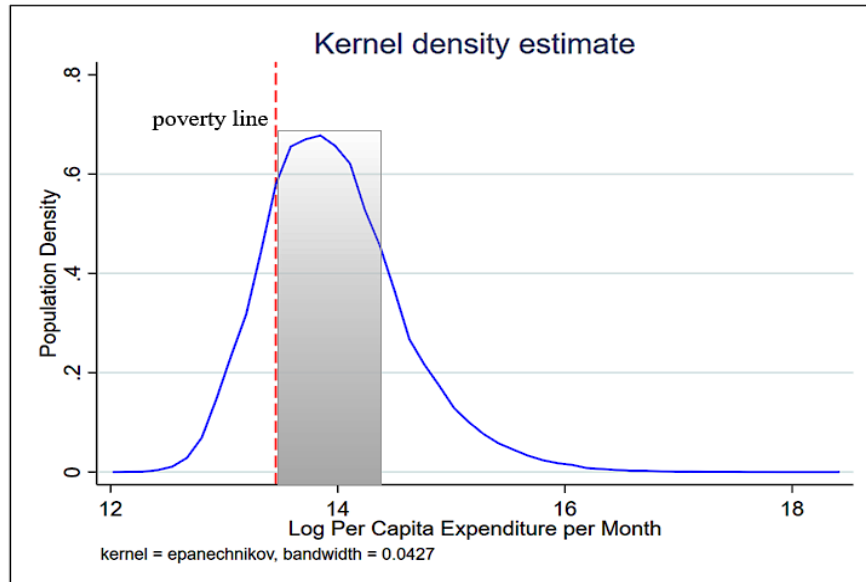


Note: BPS-Statistics Indonesia (2024a, 2024c)

Indonesia experienced a COVID-19-driven spike in poverty to 10.14% in 2021, followed by a partial recovery to 9.03% by 2024 (BPS-Statistics Indonesia, 2024b). This aggregate recovery, however, masks highly volatile household-level transitions. The 2022–2024 period represents the critical post-pandemic recovery window where transient poverty episodes are known to be concentrated (Dang & Lanjouw, 2013; Purwono et al., 2021). Understanding which households are at risk of falling back into poverty and which are positioned to exit sustainably is directly relevant to Indonesia's RPJMN 2025–2029 targets, which remain ambitious and historically unmet (Republic of Indonesia, 2020).

Figure 2 highlights a further structural challenge: most of the Indonesian population remains concentrated close to the poverty line, making them highly vulnerable to being pushed into poverty by even minor income, health, or employment shocks (Chaudhuri et al., 2002).

Figure 2: Distribution Curve of Indonesian Population Expenditure in 2024



Note: BPS-Statistics Indonesia (2024a)

While a substantial global literature on poverty transitions exists (Alwang et al., 2001; Dutta et al., 2025; Mechanic & Tanner, 2007), significant gaps remain in the Indonesian context. This study addresses three specific gaps. First, previous Indonesian studies, encompassing Suryahadi and Sumarto (2001), who used the 100 Village Survey (1997–1999), Mukhanif (2009), who used SUSENAS Panel 2005–2007, Dartanto and Nurkholis (2013), and Dartanto and Otsubo (2013), who used IFLS, have not modeled entry and exit from poverty as separate, asymmetric processes within a single multilevel framework. Second, most existing studies rely on outdated data; the most recent panel-based analysis of post-pandemic poverty dynamics is Tantriana (2024), which covered only the pandemic period 2019–2020. Third, the integration of provincial contextual factors alongside household-level determinants in a formal multilevel model has not been applied to Indonesia using recent nationally representative panel data (Callens & Croux, 2009).

This study fills these gaps by constructing a nationally representative SUSENAS panel for 2022–2024 using the record linkage methodology of Dang and Lanjouw (2013), modeling entry and exit from poverty as separate multilevel logistic regression models, and simultaneously incorporating both household- and provincial-level determinants. This advances the work of Mukhanif (2009) and Dartanto and Nurkholis (2013) by using more recent data, a formal asymmetric modeling structure, and a provincial contextual layer within the multilevel framework.

By integrating demographic factors, event-transition variables capturing changes in household composition and labor market status, government social assistance, and provincial contextual conditions, this study provides a comprehensive empirical portrait of poverty dynamics in post-pandemic Indonesia. The two-model asymmetric approach directly tests whether the mechanisms driving households into poverty differ fundamentally from those

enabling their exit from poverty, a hypothesis grounded in Life Course Theory (Elder, 1998) and supported by the international literature (McKay & Lawson, 2003; McKernan & Ratcliffe, 2005).

Literature review and conceptual framework

Poverty dynamics: Concepts and measurement approaches

Poverty has long been conceptualized as a multidimensional condition involving not only material deprivation but also powerlessness, physical weakness, vulnerability, and isolation (Chambers, 1987; World Bank, 2001). While conventional poverty analysis focuses on static indicators such as the headcount ratio at a single point in time, a growing body of literature argues that this approach obscures the volatile fluctuations experienced by households near the poverty line (Calvo & Dercon, 2013; Ouoya, 2021). Dynamic poverty analysis, which requires longitudinal or panel data, examines how poverty status changes over time for the same households, capturing both entry into and exit from poverty as distinct phenomena (Ellwood & Bane, 1983; McKay & Lawson, 2002).

The literature distinguishes four main analytical approaches to poverty dynamics. The component approach decomposes total poverty into chronic and transient components, where chronic poverty represents persistent deprivation over time and transient poverty reflects short-term fluctuations around the poverty line (Jalan & Ravallion, 1998, 2002). The spell approach examines the duration and frequency of poverty episodes, identifying how long households remain poor and how frequently they re-enter poverty (McKay & Lawson, 2003). The chronic-transient poverty framework classifies households by the persistence of their poverty status across multiple periods, with chronically poor households remaining below the poverty line in all observed periods, while transiently poor households move in and out of poverty (Purwono et al., 2021; Suryahadi & Sumarto, 2001). The vulnerability-to-poverty framework shifts the focus to the ex-ante probability of falling into poverty, treating poverty as a risk outcome shaped by both household-level assets and macro-level shocks (Calvo & Dercon, 2013; Chaudhuri et al., 2002; Dutta et al., 2025).

This study employs a poverty transition approach to examine the entry-exit mechanism nested within the vulnerability-to-poverty framework. This approach is particularly appropriate for short panel data in which duration-based measures of chronic poverty cannot be estimated robustly, and for policy applications requiring household-level risk profiling. One important terminological clarification follows: households remaining in poverty across both transition periods in this study are described as persistently poor within this observational window, not chronically poor in the strict sense. Chronic poverty requires a longer longitudinal record to identify persistent deprivation (McKay & Lawson, 2002), and the two-year panel here is insufficient for that determination.

Determinants of poverty dynamics

The determinants of poverty entry and exit operate through three interconnected channels: household-level characteristics, event-transition variables capturing changes in those characteristics over time, and macro-level contextual conditions. Research by Smith and Middleton (2007) and Creedy and Gemmell (2022) consistently showed that approximately

60% of episodes of entry into poverty are associated with income declines, with job loss as the primary trigger. Changes in household composition, including the birth of children, the addition of household members, and transitions from two-parent to single-parent households, constitute a second major pathway into poverty (Jenkins et al., 2000; Smith & Middleton, 2007). Conversely, transitions into employment and increases in working hours are the dominant drivers of poverty exit, with Vaalavuo and Sirniö (2022) finding that gaining employment increases the probability of exiting poverty by 30–33 percentage points in European contexts.

In the Indonesian context, Mukhanif (2009) demonstrated using SUSENAS Panel 2005–2007 that education, household size, and employment sector are significant determinants of poverty transitions using multilevel logistic regression. Dartanto and Nurkholis (2013) found using IFLS data that household head education, per capita expenditure, and asset ownership are the strongest predictors of poverty exit, while adverse shocks drive entry. Dartanto and Otsubo (2016) further documented the role of income inequality in amplifying poverty risks at the provincial level. Purwono et al. (2021) applied three analytical approaches, including component, spell, and vulnerability methods, to SUSENAS cross-sectional data and confirmed that vulnerability is highest among households in the agricultural sector and those with low education. Tantriana (2024) extended this analysis to the pandemic period using SUSENAS 2019–2020 and found that COVID-19 substantially increased poverty entry rates, particularly among urban near-poor households. However, none of these studies simultaneously model entry and exit as separate asymmetric processes using a formal multilevel framework with recent national panel data, which is the contribution of this study.

Government social assistance constitutes a critical external intervention in poverty dynamics. In Indonesia, social assistance programs are designed to prevent entry into poverty and accelerate exit by maintaining household consumption during economic shocks (Coordinating Ministry for Community Empowerment, 2024; Ministry of Finance of the Republic of Indonesia, 2020). However, the endogenous nature of social assistance targeting, where the most vulnerable households are those most likely to receive assistance, creates identification challenges that require careful interpretation rather than causal inference (Langi et al., 2023; Syata, 2025).

Conceptual framework

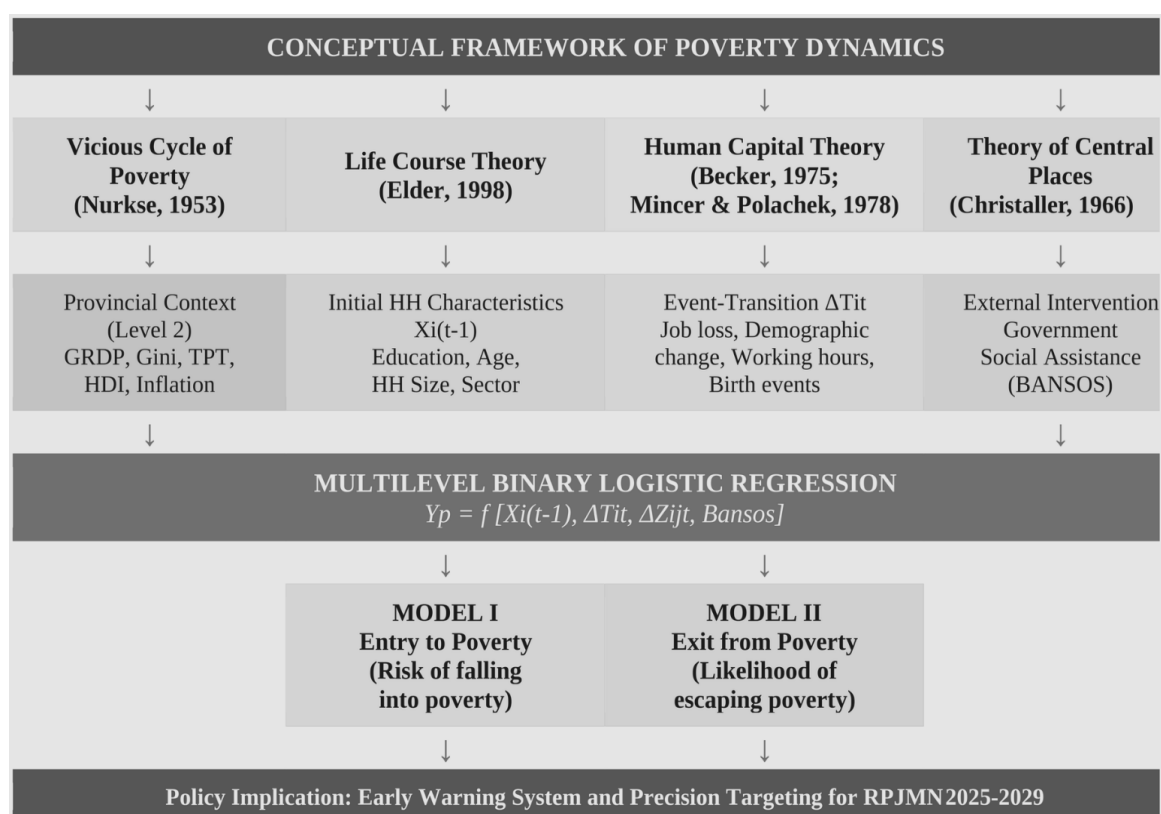
This study is grounded in four theoretical foundations that together explain the mechanisms of poverty entry and exit. First, Nurkse's (1953) Vicious Cycle of Poverty explains why low productivity and weak economic structures perpetuate poverty, providing the macroeconomic rationale for including provincial-level GRDP and inequality as contextual determinants. Second, Life Course Theory (Elder, 1998) posits that the intersection of macro-level context and micro-level life events shapes individual welfare trajectories. This theory provides the theoretical justification for incorporating event-transition variables capturing labor market changes and demographic shocks, while also supporting the modeling of entry and exit as asymmetric processes shaped by different life-course triggers. Third, Human Capital Theory (Becker, 1975; Mincer & Polachek, 1978) explains how education, occupation, and workforce participation shape lifetime earnings and poverty resilience. This directly grounds the inclusion of education level, employment sector, working hours, and labor market transition variables in the models. Fourth, the Theory of Central Places (Christaller, 1966) explains why geographic location generates independent variation in welfare

opportunities, providing the theoretical basis for the multilevel structure that separates household-level (Level 1) from provincial-level (Level 2) effects.

Building on these foundations, this study employed a poverty transition approach embedded within the vulnerability-to-poverty framework (Calvo & Dercon, 2013; Chaudhuri et al., 2002; Dutta et al., 2025). This approach is distinct from but related to the component approach (Jalan & Ravallion, 1998, 2002), the spell approach (Ellwood & Bane, 1983; McKay & Lawson, 2003), and the chronic-transient poverty framework (Purwono et al., 2021; Suryahadi & Sumarto, 2001). The transition approach is particularly appropriate for short panel data in which duration-based measures of chronic poverty cannot be estimated robustly, and for policy applications that require household-level risk profiling. The probability of entering poverty (entry to poverty) and exiting poverty (exit from poverty), denoted Y_p , is modeled as a function of initial household characteristics $X_i(t-1)$, event-transition changes in household characteristics ΔT_{it} , macro-level provincial contextual changes ΔZ_{ijt} , and social assistance interventions.

One important terminological clarification: households that remain in poverty across both transition periods in this study are described as persistently poor within this observational window, not as chronically poor in the strict sense. Chronic poverty requires a longer longitudinal record to identify persistent deprivation (Denisova, 2007; McKay & Lawson, 2003), and the two-year panel in this study is insufficient for that determination.

Figure 3: Conceptual Framework of Poverty Dynamics



Note: Adapted from Nurkse (1953), Becker (1975), Elder (1998), McKernan and Ratcliffe (2005), and Mukhanif (2009)

Methods

Data overview

This study used data from the National Socioeconomic Survey (SUSENAS) Panel conducted by the Central Statistics Agency (BPS-Statistics Indonesia) in 2022, 2023, and 2024. The SUSENAS Panel covered a sample of 282,552 households with a matching success rate of 83.21% for the 2022–2023 period and 288,503 households for the 2023–2024 period with a matching success rate of 84.41%. Household tracking was conducted using seven stable matching key variables following the probabilistic record linkage principle of Fellegi and Sunter (1969): Province Code (R101), Regency Code (R102), Urban/Rural Classification (R105), Sex of Household Head (R405), Date of Birth (R406A), Month of Birth (R406B), and Year of Birth (R406C).

Geographic variables (R101, R102, R105) ensured that matches occurred within the same administrative unit, preventing false matches across different regions. Demographic variables of the household head (R405, R406A, R406B, R406C) served as biologically stable, unique identifiers. Unmatched households were excluded from the panel subsample. A comparison of baseline characteristics between matched and unmatched households revealed no statistically significant systematic differences, suggesting that attrition is largely random. The matching rates of 80–84% were consistent with rates reported for constructed panels in comparable developing-country settings (Dang & Lanjouw, 2013; Tantriana, 2024).

The two transition periods were pooled into a single analytical dataset of 571,055 household observations, yielding greater statistical power for the multilevel models. The pooling decision was supported by a statistical test: a period dummy variable (coded 1 for the 2023–2024 transition and 0 for 2022–2023) was included in preliminary models for both Model I and Model II. The dummy was not statistically significant in either model: Model I showed an OR of 0.98 ($p = 0.41$), and Model II showed an OR of 1.02 ($p = 0.58$). This confirms that no systematic period-specific bias is present and that pooling is statistically justified. Three layers of panel validation are presented in the Appendix, encompassing a time-invariant stability test, a robustness check across model specifications, and an external validation against official BPS-Statistics Indonesia poverty figures.

To examine poverty dynamics, the sample was divided into two subsamples. The first subsample includes households that were non-poor in year $t-1$ but became poor in year t (entry into poverty). The second subsample includes households that were poor in year $t-1$ but became non-poor in year t (exit from poverty). The decomposition of these poverty transitions is presented in Table 1, with the relevant categories highlighted in bold.

Table 1: Scheme of Dynamic Poverty Decomposition from Year $t-1$ to Year t

	Year t		
		Non-Poor	Poor
Year $t-1$	Non-Poor	Never Poor	Entry into Poverty
	Poor	Exit from Poverty	<i>Persistently Poor</i>

Note: Author's own elaboration, adapted from McKay and Lawson (2003)

The dependent variables are divided into two transition probability models: Model I (Entry into Poverty) and Model II (Exit from Poverty). Variable groups for each model are summarized in Tables 2 and 3 below; full operational definitions with scales and coding are provided in Tables A4 and A5 in the Appendix.

Table 2: Summary of Variable Groups for Model I (Entry to Poverty)

Variable Group	Variables	Notation
Household Head Characteristic	Area, Age, Sex, Education	<i>REGION_1, AGEKRT_1, SEXKRT_1, EDUKRT_1</i>
Household Characteristic	HH size, Working members, Economic sector, Initial welfare depth	<i>HHSIZE_1, ARTWORK_1, SECTORRT_1, LEVELP_1</i>
Labor Market Event	Members quitting job, Change in working hours	<i>OUT_JOB_1, CH_HOUR_1</i>
Demographic Event	Birth events, Changes in HH composition and head	<i>BIRTH_1, A_ART_1, A_TODD_1, A_TEEN_1, A_ADULT_1, CH_KRT_1, CH_SEX_1</i>
External Intervention	Social assistance received	<i>BANSOS_1</i>
Provincial Context (Level 2)	TPT, Inflation, HDI, GRDP per capita, Gini ratio	<i>TPT_1, INF_1, IPM_1, lnGRDP_1, RGINI_1</i>

Note: Reference categories – Education: Primary school or below; Sector: Income recipient (non-agricultural); Social assistance: No assistance received; Job loss: 2 or more members lost jobs. Full operational definitions, notation, and coding scales are provided in Table A4 (Appendix).

Table 3: Summary of Variable Groups for Model II (Exit from Poverty)

Variable Group	Variable	Notation
Household Head Characteristic	Area, Age, Sex, Education	<i>REGION_2, AGEKRT_2, SEXKRT_2, EDUKRT_2</i>
Household Characteristic	HH size, Working members, Economic sector, Poverty depth	<i>HHSIZE_2, ARTWORK_2, SECTORRT_2, LEVELP_2</i>
Labor Market Event	Members entering labor market, Change in working hours	<i>IN_JOB_2, CH_HOUR_2</i>
Demographic Event	Birth events, Changes in HH composition and head	<i>BIRTH_2, R_ART_2, R_TODD_2, R_TEEN_2, R_ADULT_2, CH_KRT_2, CH_SEX_2</i>
External Intervention	Social assistance received	<i>BANSOS_2</i>
Provincial Context (Level 2)	TPT, Inflation, HDI, GRDP per capita, Gini ratio	<i>TPT_2, INF_2, IPM_2, lnGRDP_2, RGINI_2</i>

Note: Reference categories – Education: Primary school or below; Sector: Income recipient (non-agricultural); Social assistance: No assistance received; Member reduction: 2 or more members reduced. Full operational definitions, notation, and coding scales are provided in Table A5 (Appendix).

All data processing was executed using Stata 17 and R. The authors affirm that generative AI was employed solely as a technical aid for language refinement and grammatical editing.

Statistical analysis

To model the probabilities of entry and exit into poverty, this study employed multilevel binary logistic regression (Diez Roux, 2002; Rabe-Hesketh & Skrondal, 2008). The nested structure of households within provinces necessitates this approach to avoid biased estimates arising from violations of the independence assumption in standard logistic regression. Consistent with the Life Course Theory framework (Elder, 1998), two separate random-intercept models were estimated: one for poverty entry (Model I) and one for poverty exit (Model II). This reflects the theoretically and empirically established asymmetry of these processes (Dartanto & Nurkholis, 2013; McKernan & Ratcliffe, 2005).

Model I: Probability of poverty entry

$$\log it(P_{ij}) = \ln \left(\frac{P_{ij}}{1 - P_{ij}} \right) \quad (1)$$

$$P_{ij} = \frac{\exp(\beta_{0j} + \sum \beta_k X_{kij})}{1 + \exp(\beta_{0j} + \sum \beta_k X_{kij})} \quad (2)$$

Where the intercept, β_{0j} , varies across provinces (Level 2):

$$\beta_{0j} = \gamma_{00} + \sum \gamma_m Z_{mj} + u_{0j} \quad (3)$$

Substituting (3) into the level-1 equation yields the combined model:

$$\log it(P_{ij}) = \gamma_{00} + \sum \beta_k X_{kij} + \sum \gamma_m Z_{mj} + u_{0j} + e_{ij} \quad (4)$$

Specifically, the full specification for Model I (Entry) is:

$$\begin{aligned} \log it(P(\text{Entry}_{ij})) = & \gamma_{00} + \beta_1 \text{Area}_{ij} + \beta_2 \text{Age}_{ij} + \beta_3 \text{Sex}_{ij} + \beta_4 \text{Edu}_{ij} + \beta_5 \text{Size}_{ij} \\ & + \beta_6 \text{Work}_{ij} + \beta_7 \text{Sector}_{ij} + \beta_8 \text{InitialWelfare}_{ij} + \beta_9 \text{Bansos}_{ij} \\ & + \beta_{10} \text{JobLoss}_{ij} + \beta_{11} \text{DemoShock}_{ij} + \gamma_1 \text{TPT}_j + \gamma_2 \text{Inflation}_j \\ & + \gamma_3 \text{HDI}_j + \gamma_4 \ln \text{GRDP}_j + \gamma_5 \text{Gini}_j + u_{0j} + e_{ij} \end{aligned} \quad (5)$$

Model II: Probability of poverty exit

$$\begin{aligned} \log it(P(\text{Exit}_{ij})) = & \gamma_{00} + \beta_1 \text{Area}_{ij} + \beta_2 \text{Age}_{ij} + \beta_3 \text{Sex}_{ij} + \beta_4 \text{Edu}_{ij} + \beta_5 \text{Size}_{ij} \\ & + \beta_6 \text{Work}_{ij} + \beta_7 \text{Sector}_{ij} + \beta_8 \text{InitialPovDepth}_{ij} + \beta_9 \text{Bansos}_{ij} \\ & + \beta_{10} \text{JobGain}_{ij} + \beta_{11} \text{Demo Reduction}_{ij} + \gamma_1 \text{TPT}_j + \gamma_2 \text{Inflation}_j \\ & + \gamma_3 \text{HDI}_j + \gamma_4 \ln \text{GRDP}_j + \gamma_5 \text{Gini}_j + u_{0j} + e_{ij} \end{aligned} \quad (6)$$

In both specifications, e_{ij} (Level-1 random effect) captures residual variation between households, while u_0j (Level-2 random effect) captures inter-provincial heterogeneity (Diez Roux, 2002; Rabe-Hesketh & Skrondal, 2008).

The household head age variable (AGEKRT) is included in both models with a quadratic specification to capture potential life-cycle non-linearity consistent with Human Capital Theory (Mincer & Polachek, 1978). The quadratic term (age^2) was formally tested and found to be statistically significant in both models ($p < .001$), confirming a non-linear relationship between age and poverty transitions. In Model I (Entry), the linear term shows a negative association ($OR = 0.9332$; $p < .001$), and the quadratic term a positive association ($OR = 1.0007$; $p < .001$), producing a U-shaped curve with a turning point at approximately 51 years, indicating that poverty entry risk declines through peak productive years before rising again in older age. In Model II (Exit), the linear term is positive ($OR = 1.0168$; $p = .001$) and the quadratic term negative ($OR = 0.9998$; $p < .001$), yielding an inverted-U pattern with a turning point at approximately 37 years, whereby exit likelihood rises during early working life before declining as aging reduces labor market flexibility.

Results

Indonesia's reported decline in the poverty rate, based on annual cross-sectional headcount ratios (Pape & Ali, 2023), masks the volatile household-level transitions that static indicators cannot capture (Calvo & Dercon, 2013; McKernan & Ratcliffe, 2002)—grounded in the vulnerability-to-poverty framework (Chaudhuri et al., 2002), which posits that households near the poverty line face persistent reciprocal risks of both entry and exit, Tables 4 and 5 present poverty-status transitions across the two panel periods.

Table 4: Changes in Poverty Status, 2022–2023 Period

Number of Households		2023	
		Non-Poor	Poor
2022	Non-Poor	244,516 (94.97%)	12,956 (5.03%)
	Poor	15,169 (60.48%)	9,911 (39.52%)

Note: Processed from SUSENAS Panel Data 2022–2023 (BPS-Statistics Indonesia). Bold cells indicate the poverty transition subsamples.

Table 5: Changes in Poverty Status, 2023–2024 Period

Number of Households		2024	
		Non-Poor	Poor
2023	Non-Poor	252,707 (95.05%)	13,153 (4.95%)
	Poor	13,175 (58.19%)	9,468 (41.81%)

Note: Processed from SUSENAS Panel Data 2023–2024 (BPS-Statistics Indonesia). Bold cells indicate the poverty transition subsamples.

In the 2022–2023 period, 15,169 households exited poverty while 12,956 fell into it. In the 2023–2024 period, the entry rate increased to 13,153, while exits slightly declined to 13,175, resulting in a near-equilibrium between inflows and outflows. This pattern is consistent with the revolving door of poverty phenomenon documented by Ward (2016) and McKernan and Ratcliffe (2005), and with the argument of Dang and Lanjouw (2013) that, in developing

countries, near-poor households are highly vulnerable to entry into poverty due to inadequate social protection.

The proportion of households remaining in poverty (persistently poor within this observational window) increased from 39.52% in 2022–2023 to 41.81% in 2023–2024, suggesting a deepening poverty trap among the poorest groups during the post-pandemic recovery period (Hamilton et al., 2019).

This descriptive analysis clearly shows the pattern of inflows and outflows around the poverty line. However, it cannot explain why these factors shape poverty dynamics (determinants) and where (regional context) they do so (Chaudhuri, 2003). The following multilevel logistic regression analysis addresses these questions by separating household-level effects at Level 1 from provincial contextual effects at Level 2 (Rabe-Hesketh & Skrondal, 2008).

Determinants of entry into poverty (Model I)

Before discussing variable significance at Level 1, a Likelihood Ratio (LR) test was conducted to validate the multilevel model against a standard single-level logistic model (Hox & Kreft, 1994). The test results are shown in Table 6.

Table 6: Multilevel Logit Model Estimation Results and Random Effects Testing

Variable	Odds	Std. Err.	z	p> z	CI Lower	CI Upper
cons	0.0295967	0.0062374	-16.70	0.00	0.0195819	0.0447335
PROP_CODE						
var(_cons)	1.498958	0.3739506			0.9192577	2.444229
Wald chi-squared (0) = 0.000						
Log likelihood = -97825.181				Prob > chi2	= 0.000	
Note: Estimates are transformed only in the first equation to odds.						
LR test vs. logistic model: chi-square(01) = 11789.06 Prob >= chi-square = 0.0000						
Note: Estimation uses multilevel logistic regression (melogit) in Stata 17. The LR test rejects the null hypothesis that between-province variance equals zero.						

The LR test shows strong significance (Prob >= chibar2 = 0.0000), confirming that the multilevel model with random provincial intercepts far outperforms the single-level alternative. Ignoring regional context when analyzing poverty dimensions in Indonesia can yield biased estimates because it fails to account for intraclass correlations (Rabe-Hesketh & Skrondal, 2008). The magnitude of regional influence is reflected in the Intraclass Correlation Coefficient (ICC) shown in Table 7.

Table 7: Intraclass Correlation Coefficient (ICC) Values at the Provincial Level

Level	ICC	Std. Err.	CI Lower	CI Upper
PROP_CODE	0.313012	0.053646	0.218396	0.426262
Note: The ICC value is 0.313, indicating that 31.3% of the total variation in poverty entry risk is attributable to between-province differences.				

The ICC of 0.313 indicates that 31.3% of total variation in poverty entry risk is attributable to between-province differences, while the remaining 68.7% reflects household-level variation.

This substantial provincial contribution confirms that poverty alleviation policies must be geographically differentiated rather than uniformly applied across Indonesia (Hamilton et al., 2019). This finding is consistent with the theoretical prediction of the Theory of Central Places (Christaller, 1966; Parr, 2025) that geographic location generates independent variation in welfare opportunities. The results of Model I are presented in Table 8.

Table 8: Multilevel Logistic Regression Results on Poverty Entry (Model I)

Variable	Category / Label	Odds Ratio	Std. Err.	z	$p > z $
REGION_1	Urban	0.9629	0.0156	-2.34	0.019
AGEKRT_1	(Continuous)	0.9332	0.0031	-20.73	0.000
AGEKRT_1_sq	(Continuous)	1.0007	0.00003	21.54	0.000
SEXKRT_1	Male	0.9215	0.0209	-3.61	0.000
EDUKRT_1	Junior High	0.7793	0.0147	-13.25	0.000
	Senior High	0.6460	0.0123	-22.98	0.000
	Higher Education (PT)	0.4619	0.0165	-21.59	0.000
HHSIZE_1	(Continuous)	1.3281	0.0071	53.11	0.000
ARTWORK_1	(Continuous)	0.7326	0.0079	-28.97	0.000
SECTORRT_1	Agriculture	1.2973	0.0562	6.01	0.00
	Manufacturing	1.0186	0.0460	0.41	0.684
	Services	0.8160	0.0360	-4.61	0.000
LEVELP_1	Non-Near Poor	0.2104	0.0038	-86.72	0.000
OUT_JOB_1	Job loss: 1 member	0.9888	0.0401	-0.28	0.781
	No job loss	0.8104	0.0346	-4.92	0.000
CH_HOUR_1	(Continuous)	0.9967	0.0002	-20.15	0.00
BANSOS_1	Receives 1-2 types	1.33	0.0262	14.47	0.00
	Receives ≥ 3 types	1.5636	0.0336	20.82	0.00
CH_SEX_1	Sex Unchanged	0.4906	0.0436	-8.01	0.000
CH_KRT_1	Did not become single	1.9426	0.1405	9.18	0.000
BIRTH_1	No Birth	0.7176	0.0167	-14.28	0.000
A_ART_1	Added 1 member	0.4829	0.0161	-21.86	0.00
	No members added	0.2367	0.0100	-34.2	0.000
A_TODD_1	No toddler added	0.825	0.0272	-5.84	0.000
A_TEEN_1	No child/teen added	0.6482	0.0143	-19.68	0.000
A_ADULT_1	No adult added	0.9109	0.0237	-3.59	0.000
TPT_1	(Macro)	1.1048	0.0445	2.47	0.013
INF_1	(Macro)	0.9465	0.0096	-5.42	0.000
IPM_1	(Macro)	0.9489	0.0453	-1.1	0.272
lnGRDP_1	(Macro)	0.4901	0.1291	-2.71	0.007
RGINI_1	(Macro)	9.6969	13.3673	1.65	0.099
_cons	Constant	8935.1	24336.9	3.34	0.001
PROP_CODE	var(_cons)	0.7655	0.2180		

Note: Reference categories: Education = Primary school or below; Sector = Income recipient (non-agricultural); Social assistance = No assistance received; Job loss = 2 or more members lost jobs. Variable lnGRDP_1 refers to the natural log of per capita Gross Regional Domestic Product. $N = 523,332$ (Model I analytical subsample: households non-poor at $t-1$, pooled 2022–2024).

At the provincial level (Level 2), consistent with Nurkse's (1953) Vicious Cycle of Poverty, per capita GRDP (lnGRDP_1) shows a strong negative association with poverty entry risk: each unit increase in log GRDP per capita is associated with a 0.49-fold reduction in poverty entry odds (OR = 0.49; $p < .01$). This supports the trickle-down effect hypothesis whereby regions with stronger economic capacity provide positive externalities protecting households from poverty (Dantas et al., 2023; Sumarto et al., 2024). The Gini ratio (RGINI_1), although only

moderately significant ($p < .10$), shows an OR of 9.69, indicating that households in provinces with high income inequality face a substantially elevated risk of entering poverty (Dartanto & Otsubo, 2013; Haughton & Khandker, 2009).

At the household level (Level 1), consistent with Human Capital Theory (Becker, 1975; Mincer & Polachek, 1978), the education of the household head is the most consistent structural determinant. Using primary school or below as the reference category, the model shows a monotonic risk reduction: junior high school graduates face 0.78 times the poverty entry odds (OR = 0.779), senior high school graduates 0.65 times (OR = 0.646), and higher education graduates 0.46 times (OR = 0.461; $p < .001$). Higher education functions as a productive asset, enabling access to more stable formal employment and providing resilience against economic shocks (Chiswick, 2003).

The social assistance variable (BANSOS_1) shows a positive association with the risk of entering poverty (OR = 1.56 for recipients of 3 or more types). This association should not be interpreted as evidence that social assistance increases the risk of poverty. Rather, it reflects successful government targeting: the most chronically poor and vulnerable households are precisely those most likely to receive multiple types of assistance (Langi et al., 2023; Syata, 2025). This endogeneity issue would require an instrumental variable approach or natural experiment design to resolve definitively, which is beyond the scope of this observational study.

In terms of labor market dynamics, consistent with Life Course Theory's prediction that employment transitions are key poverty-entry triggers (Elder, 1998), households that maintained their members' employment (no job losses) faced a 19% lower risk of entry (OR = 0.810) compared to households experiencing double layoffs (Günther & Harttgen, 2009). Regarding household composition, reflecting the life-course event-transition mechanism, births (BIRTH_1) and additions of new household members (A_TODD_1, A_TEEN_1, A_ADULT_1) significantly increase the probability of entering poverty. At the macro level, the Open Unemployment Rate (TPT_1) increases entry risk by 1.10 times per unit increase.

Determinants of exit from poverty (Model II)

While Model I highlights the fragility of household defenses that can lead to entry into poverty, Model II reveals structural factors that enable poor households to exit poverty. Consistent with the theoretical framework, variables enabling exit are largely determined by long-term asset accumulation and economic structural transformation (McKernan & Ratcliffe, 2005). Model II results are presented in Table 9.

At the household level (Level 1), grounded in Human Capital Theory (Becker, 1975; Mincer & Polachek, 1978), human capital plays a central role. Using primary school or below as the reference, exit likelihood increases with education: junior high graduates have 1.13 times greater exit odds (OR = 1.13), senior high graduates 1.24 times (OR = 1.24), and higher education graduates 1.22 times (OR = 1.22). These findings confirm that investment in primary and secondary education is an absolute prerequisite for breaking the intergenerational poverty cycle (Baidybekova et al., 2022; Møller et al., 2024).

The non-linear age effects extend beyond the marginal associations suggested by linear specifications. The U-shaped entry risk profile, with a turning point at 51 years, aligns with life-cycle theory in that household heads approaching this threshold have typically

accumulated sufficient human capital and household assets to buffer poverty shocks, while those beyond it face rising vulnerability as physical capacity and labor market adaptability decline (Becker, 1962; Dartanto & Otsubo, 2016). The inverted-U exit pattern, peaking at age 37, reflects a parallel dynamic whereby younger household heads benefit from accumulating work experience and earning capacity. At the same time, those past their late thirties encounter structural barriers, including limited retraining opportunities and higher dependency burdens. These findings suggest that poverty intervention programs should differentiate by life-cycle stage, directing preventive support toward older near-poor households aged 51 and above and exit-facilitation programs toward prime-age poor households aged below 37.

Table 9: Multilevel Logistic Regression Results on Poverty Exit (Model II)

Variable	Category / Label	Odds Ratio	Std. Err.	z	$p > z $
REGION_2	Urban	0.9532	0.0236	-1.94	0.053
AGEKRT_2	(Continuous)	1.0167	0.0052	3.24	0.001
AGEKRT_2_sq	(Continuous)	0.9997	0.00004	-4.72	0.000
SEXKRT_2	Male	1.1551	0.0407	4.09	0.000
EDUKRT_2	Junior High	1.13	0.0318	4.34	0.00
	Senior High	1.2414	0.0359	7.47	0.00
	Higher Education (PT)	1.2224	0.0710	3.46	0.001
HHSIZE_2	(Continuous)	0.7137	0.0060	-40.21	0.000
ARTWORK_2	(Continuous)	1.2195	0.0169	14.36	0.000
SECTORRT_2	Agriculture	1.0332	0.0653	0.52	0.606
	Manufacturing	1.2460	0.0828	3.31	0.001
	Services	1.4441	0.0944	5.62	0.000
LEVELP_2	Severely Poor	0.4589	0.0104	-34.5	0.000
IN_JOB_2	Entered Labor Market	1.2081	0.032	7.08	0.00
CH_HOUR_2	(Continuous)	1.0038	0.0002	15.2	0.00
BANSOS_2	Receives 1-2 types	0.8956	0.0276	-3.58	0.000
	Receives ≥ 3 types	0.8440	0.0274	-5.22	0.00
CH_SEX_2	Sex Unchanged	0.9141	0.1455	-0.56	0.572
CH_KRT_2	Remains Single Parent	1.0263	0.143	0.19	0.85
BIRTH_2	No Birth	1.4688	0.0443	12.75	0.000
R_ART_2	Reduced 1 Member	0.3958	0.0205	-17.92	0.000
	No Reduction	0.2001	0.0138	-23.4	0.000
R_TODD_2	Toddler not reduced	0.9268	0.0300	-2.35	0.019
R_TEEN_2	Child/Teen not reduced	0.768	0.0291	-6.94	0.000
R_ADULT_2	Adult not reduced	0.7549	0.0376	-5.64	0.000
TPT_2	(Macro)	1.0761	0.0439	1.8	0.072
INF_2	(Macro)	1.0404	0.0099	4.15	0.000
IPM_2	(Macro)	0.9924	0.0267	-0.28	0.776
lnGRDP_2	(Macro)	1.4562	0.2489	2.2	0.028
RGINI_2	(Macro)	0.2025	0.3706	-0.87	0.383
_cons	Constant	1.8157	3.4637	0.31	0.755
PROP_CODE	var(_cons)	0.1583	0.0613		

Note: Reference categories: Education = Primary school or below; Sector = Income recipient (non-agricultural); Social assistance = No assistance received; Member reduction = 2 or more members reduced. Variable lnGRDP_2 refers to the natural log of per capita Gross Regional Domestic Product. N = 47,723 (Model II analytical subsample: households poor at t-1, pooled 2022–2024).

Sectoral analysis shows that economic transformation from the agricultural sector to modern sectors is the most effective exit pathway, consistent with the structural transformation component of the Vicious Cycle of Poverty framework (Nurkse, 1953). Households in the

services sector enjoy the greatest poverty exit opportunity ($OR = 1.44$; $p < .001$), followed by manufacturing ($OR = 1.24$; $p < .01$). The agricultural sector does not show a statistically significant exit advantage ($OR = 1.03$; $p > .05$), indicating persistent productivity stagnation (Ayantoye et al., 2024).

At the provincial level (Level 2), consistent with Human Capital Theory and the trickle-down effect argument, per capita GRDP ($\ln GRDP_2$) is positively associated with exit likelihood ($OR = 1.46$; $p < .05$). Inflation (INF_2) is also positively associated with exit ($OR = 1.04$), reflecting that moderate inflation during this post-pandemic period likely represents demand-pull dynamics creating employment and business opportunities for the poor (Gábos et al., 2024; Webb et al., 2020).

Discussion

The results of both models confirm the fundamental asymmetry of poverty entry and exit mechanisms, the central theoretical prediction of Life Course Theory (Elder, 1998), and the empirical poverty dynamics literature (Dartanto & Nurkholis, 2013; Mukhanif, 2009). Poverty entry is predominantly driven by short-term shocks, including labor market disruptions, changes in household composition, and increased consumption burdens. Poverty exit, by contrast, is primarily associated with long-term structural assets, including education, occupational sector, and regional economic capacity. This pattern of asymmetric mobility is consistent with the transient-chronic poverty framework (Calvo & Dercon, 2013; Jalan & Ravallion, 1998) and advances the argument of Dartanto and Otsubo (2016) that Indonesian poverty dynamics are driven by fundamentally different mechanisms on the entry and exit sides.

Education of the household head is the most consistent determinant across both models, validating the predictions of Human Capital Theory (Becker, 1975; Mincer & Polachek, 1978). This finding aligns with the Indonesian literature (Mukhanif, 2009; Purwono et al., 2021) and international evidence from Vietnam, Bangladesh, and India (Baidybekova et al., 2022; Møller et al., 2024): secondary and tertiary education functions as both a protective buffer against poverty entry and a productive asset enabling poverty exit.

The ICC of 31.3% confirms that provincial context accounts for nearly one-third of total variation in poverty entry risk. Grounded in the Theory of Central Places (Christaller, 1966), which predicts that geographic location generates independent variation in welfare opportunities, this finding is further supported by the significant GRDP associations in both models. Together, these results reinforce the case for geographically differentiated poverty policies (Callens & Croux, 2009; Dartanto & Otsubo, 2016; Suryahadi et al., 2020).

Although the Gini ratio is not statistically significant in Model II, its large odds ratio in Model I ($OR = 9.69$) suggests that income inequality is associated with a substantially elevated risk of entering poverty in provinces with high income concentration. This is consistent with the Vicious Cycle of Poverty (Nurkse, 1953) prediction that systemic inequality perpetuates poverty traps, and with Dartanto and Otsubo (2016), who documented the role of inequality in Indonesian poverty dynamics (Haughton & Khandker, 2009).

The initial poverty depth variable ($LEVELP_2$) indicates that severely poor households face a substantially lower likelihood of exiting ($OR = 0.46$), confirming a persistent poverty trap

consistent with the low-asset equilibrium literature (Hamilton et al., 2019; Vieira et al., 2020). In Indonesia, this pattern helps explain why extreme poverty rates are difficult to reduce even during periods of stable economic growth (Darma et al., 2024; Dartanto et al., 2020).

This study has several important limitations. First, the observational multilevel logistic regression design establishes associations rather than causal effects. Key variables, encompassing social assistance, employment status, household composition, and regional economic conditions, are likely endogenous to poverty transitions. Addressing these endogeneity concerns would require household fixed-effects analyses, instrumental-variables approaches, or natural experiments. Second, the 2- to 3-year observation window is insufficient to classify households as chronically poor in the strict sense; longer panels are needed for duration-based analyses of chronic poverty. Third, the 80–84% matching rate means approximately 16–17% of households could not be tracked, which may limit representativeness if attrition is non-random in ways not captured by our baseline checks.

Conclusion

This study demonstrates that Indonesia's static poverty rate conceals highly volatile household-level mobility. Panel data from 2022–2024 reveal substantial inflows and outflows at the poverty line, a pattern consistent with the revolving door of poverty in which households near the poverty threshold move in and out of poverty rapidly in response to economic shocks. The near-poor group is particularly exposed, confirming that poverty in Indonesia is fundamentally a dynamic phenomenon that requires policy approaches extending well beyond conventional social assistance programs.

At the household level, the education of the household head and employment in the service or manufacturing sectors are the most consistent factors associated with both a lower risk of entering poverty and a higher likelihood of exiting poverty. Provincial contextual conditions, particularly per capita GRDP, further shape these transitions. The corrected ICC of 31.3% confirms that provincial context accounts for a substantial share of variation in poverty risk, underscoring the importance of geographically differentiated, rather than uniform, poverty reduction strategies.

Policy implications are twofold. First, preventive strategies should target near-poor households through early-warning identification systems built on the multilevel predictive framework developed here, enabling anticipatory rather than reactive intervention. Second, transformative investments in secondary and vocational education, combined with job creation in non-agricultural sectors, are essential to enable a sustainable exit from poverty. Taken together, these findings provide an empirical foundation for Indonesia's RPJMN 2025–2029 poverty reduction agenda and strengthen the case for precision-targeted poverty policy grounded in dynamic, household-level evidence.

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Appendix

Panel data validation and full variable definitions

A. Panel data validation

Three layers of validation were conducted on the constructed panel data following Dang et al. (2014) and Dang and Lanjouw (2013), providing comprehensive evidence that the panel is reliable and the pooled analytical approach is appropriate. Table A1 presents the Time-Invariant Characteristic Stability Test, which validates the matching process by checking consistency of biologically stable characteristics across periods (Antman & McKenzie, 2007; Dang et al., 2014).

Table A1: Time-Invariant Characteristic Stability Test, Constructed SUSENAS Panel Data 2022–2024

Panel Period	Consistency Parameter	Consistency Rate (%)	Conclusion
2022–2023	Sex of Household Head	98.54	Very Consistent
	Birth Year of Household Head	95.69	Very Consistent
2023–2024	Sex of Household Head	98.60	Very Consistent
	Birth Year of Household Head	96.56	Very Consistent
Sample Status	Strongly Balanced	100.00	Valid
Total Obs. (N)	571,055		

Note: Remaining inconsistencies are largely attributable to head replacement phenomena (death, divorce, migration), which are substantive events rather than matching errors (Baulch & Hoddinott, 2000; Dercon & Krishnan, 2000). All 571,055 observations are strongly balanced (Verbeek & Nijman, 1992): Stata 17 output from SUSENAS Panel Data 2022–2024.

Table A2 presents the Robustness Check using five core predictor variables across three model specifications. Dynamic variables were intentionally excluded to avoid confirmation bias in matching quality assessment (Bound et al., 1994).

Table A2: Robustness Check, Constructed SUSENAS Panel Data 2022–2024

Variable	Full Model (N = 565,104)	Restricted Model (N = 539,428)	Strict Model (N = 539,428)
EDUKRT	-0.081***	-0.082***	-0.082***
HH_SIZE	0.515***	0.518***	0.518***
WORKHOUR	-0.009***	-0.009***	-0.009***
PKH	0.276***	0.275***	0.275***
BPNT	0.367***	0.368***	0.368***

Variable	Full Model (N = 565,104)	Restricted Model (N = 539,428)	Strict Model (N = 539,428)
Constant	-3.419***	-3.431***	-3.431***
Log PseudoLL	-144,216.57	-136,565.03	-136,565.03
Pseudo R ²	0.1213	0.1220	0.1220
Wald Chi ²	29,703.28	28,139.83	28,139.83

*Note: *** $p < .01$. Robust standard errors clustered at `id_panel`. Restricted Model excludes observations with inconsistent sex or birth year of household head. Strict Model additionally filters for education inconsistency. Maximum coefficient variation across specifications is 0.003 (HH_SIZE). No variable changes sign or loses significance. Pseudo R² stable at 0.121–0.122: Stata 17 output from SUSENAS Panel Data 2022–2024.*

Table A3 presents the External Validation, comparing constructed panel poverty estimates against official BPS-Statistics Indonesia figures for the same periods (Bourguignon et al., 2004; Dang et al., 2014).

Table A3: External Validation: Constructed Panel Poverty Estimates vs. Official BPS-Statistics Indonesia Figures, 2022–2024

Year	Constructed Panel Estimate (%)	Official BPS-Statistics Indonesia Estimate (%)	Gap
2022 (Set 1)	9.26	9.54	-0.28
2023 (Set 1)	9.03	9.36	-0.33
2024 (Set 2)	9.05	9.03	+0.02

Note: The small, consistent undershooting in 2022–2023 is consistent with findings by Dang and Lanjouw (2013) that constructed panels tend to slightly underestimate poverty rates due to exclusion of high-mobility households (Dercon & Krishnan, 2000; Tarozzi, 2007), based on comparison of the Stata 17 output with the official poverty rates published by Statistics Indonesia (BPS).

B. Full operational variable definitions

Table A4 and Table A5 provide the full operational definitions, notation, and coding scales for all variables used in Model I and Model II, respectively.

Table A4: Full Operational Variables for Model I (Entry to Poverty)

Variable	Notation	Scale
Provincial Code	PROP_CODE	Numeric
Change in Household Poverty Status	CH_PVRTY_1	0 = Remains non-poor; 1 = Becomes poor
Household Head's Age	AGEKRT_1	Numeric
Household Head's Sex	SEXKRT_1	0 = Female; 1 = Male

Variable	Notation	Scale
Household Head's Education	EDUKRT_1	0 = Primary or below; 1 = Junior High; 2 = Senior High; 3 = Higher Education
Area of Residence	REGION_1	0 = Rural; 1 = Urban
Household Size	HHSIZE_1	Numeric
Number of Working Members	ARTWORK_1	Numeric
Household Economic Sector	SECTORRT_1	0 = Income Recipient; 1 = Agriculture; 2 = Manufacturing; 3 = Services
Initial Household Economic Depth	LEVELP_1	0 = Near poor; 1 = Not near poor
Social Assistance Received	BANSOS_1	0 = None; 1 = Receives 1-2 types; 2 = Receives 3 or more types
Change in Head's Composition	CH_KRT_1	0 = Becomes single; 1 = Does not become single
Change in Head's Sex	CH_SEX_1	0 = Sex changed; 1 = Sex unchanged
Members Quitting Job	OUT_JOB_1	0 = 2 or more members out; 1 = 1 member out; 2 = No members out
Change in Working Hours	CH_HOUR_1	Numeric
Birth Event	BIRTH_1	0 = Birth occurred; 1 = No birth
Additional Members	A_ART_1	0 = Added 2 or more; 1 = Added 1; 2 = No members added
Additional Toddlers	A_TODD_1	0 = Toddler added; 1 = No toddler added
Additional Children and Teens	A_TEEN_1	0 = Child/Teen added; 1 = No child/teen added
Additional Adults	A_ADULT_1	0 = Adult added; 1 = No adult added
Open Unemployment Rate (TPT)	TPT_1	Numeric
Annual Inflation	INF_1	Numeric
Human Development Index (HDI)	IPM_1	Numeric
GRDP Per Capita	lnGRDP_1	Numeric
Gini Ratio	RGINI_1	Numeric

Note: This study is based on the SUSENAS Kor questionnaire items. Reference category for Education: Primary school or below; Sector: Income recipient; Social assistance: No assistance received; Job loss: 2 or more members lost jobs.

Table A5: Full Operational Variables for Model II (Exit from Poverty)

Variable	Notation	Scale
Provincial Code	PROP_CODE	Numeric
Change in Household Poverty Status	CH_PVRTY_2	0 = Remains poor; 1 = Exits poverty
Household Head's Age	AGEKRT_2	Numeric

Variable	Notation	Scale
Household Head's Sex	SEXKRT_2	0 = Female; 1 = Male
Household Head's Education	EDUKRT_2	0 = Primary or below; 1 = Junior High; 2 = Senior High; 3 = Higher Education
Area of Residence	REGION_2	0 = Rural; 1 = Urban
Household Size	HHSIZE_2	Numeric
Number of Working Members	ARTWORK_2	Numeric
Household Economic Sector	SECTORRT_2	0 = Income Recipient; 1 = Agriculture; 2 = Manufacturing; 3 = Services
Initial Poverty Depth	LEVELP_2	0 = Moderately poor; 1 = Severely poor
Social Assistance Received	BANSOS_2	0 = None; 1 = Receives 1-2 types; 2 = Receives 3 or more types
Change in Head's Composition	CH_KRT_2	0 = Becomes spouse; 1 = Remains single
Change in Head's Sex	CH_SEX_2	0 = Sex changed; 1 = Sex unchanged
Members Entering Labor Market	IN_JOB_2	0 = No new workers; 1 = New workers exist
Change in Working Hours	CH_HOUR_2	Numeric
Birth Event	BIRTH_2	0 = Birth occurred; 1 = No birth
Reduction of Members	R_ART_2	0 = Reduced 2 or more; 1 = Reduced 1; 2 = No members reduced
Reduction of Toddlers	R_TODD_2	0 = Toddler reduced; 1 = Toddler not reduced
Reduction of Children and Teens	R_TEEN_2	0 = Child/Teen reduced; 1 = Child/Teen not reduced
Reduction of Adults	R_ADULT_2	0 = Adult reduced; 1 = Adult not reduced
Open Unemployment Rate (TPT)	TPT_2	Numeric
Annual Inflation	INF_2	Numeric
Human Development Index (HDI)	IPM_2	Numeric
GRDP Per Capita	lnGRDP_2	Numeric
Gini Ratio	RGINI_2	Numeric

Note: This study is based on the SUSENAS Kor questionnaire items. Reference category for Education: Primary school or below; Sector: Income recipient; Social assistance: No assistance received; Member reduction: 2 or more members reduced.