

The Impact of Migration and Inflation on Youth Unemployment in Indonesia: An ARDL Approach

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ABSTRACT

Purpose - This study examines migration and inflation in relation to youth unemployment in Indonesia. It covers the period 2000-2024. The outcome concerns people aged 15-24. The focus is the transition from school to work. The analysis distinguishes long-run associations from short-run dynamics.

Design/methodology/approach – Annual BPS-based series are analysed using an autoregressive distributed lag (ARDL) model. Youth unemployment covers ages 15-24. Migration uses the five-year retrospective risen-migration concept. Its annual provenance remains unverified, making migration estimates provisional. ARDL accommodates I(0) and I(1) variables and distinguishes long-run relationships from short-run changes.

Finding/Results – The results provide mixed evidence of a long-run equilibrium relationship. The finite-sample bounds test points to cointegration, but the asymptotic test is inconclusive and the insignificant error-correction term indicates that adjustment toward equilibrium is not statistically reliable. In the long run, migration is negatively associated with youth unemployment, whereas inflation is positively associated with it. The short-run effects are not statistically robust and therefore require cautious interpretation.

Originality/Value – This study examines migration, inflation, and youth unemployment jointly in Indonesia. Its focus is youth labour-market dynamics. It considers mobility alongside macroeconomic price pressure. The results inform discussion of labour matching and price stability. The contribution remains conditional on the model and data limitations.

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1. Introduction

The problem of youth unemployment reflects broader changes in both the global economy and the domestic labour market. It represents more than a temporary labour-market imbalance because excluding young people from work also wastes their human capital, innovative capacity, and future productivity potential (Fergusson & Yeates, 2021). Evidence from the Association of Southeast Asian Nations (ASEAN) shows that youth unemployment is associated with weaker economic performance over the long run (Fung & Nga, 2022). This challenge becomes more difficult to address when uncertainty in trade and investment constrains employment creation, a concern situated within the wider development debate by the United Nations Conference on Trade and Development (UNCTAD, 2024). Understanding the pressures on young labour-market entrants therefore requires attention to both structural employment barriers and macroeconomic conditions.

Indonesia is undergoing a demographic transition in which working-age people constitute a large share of the population. This demographic bonus can promote development only when the economy is capable of absorbing the growing labour force into productive and decent work (Nainggolan & Budiman, 2024). The employment-policy discussion in Indonesia Employment Outlook 2024 places labour absorption within the broader challenge of strengthening employment after the pandemic (Muhyyiddin, 2023). When employment growth falls behind labour-force growth, the demographic opportunity may instead be accompanied by underemployment, stagnation, and social pressure. The demographic context consequently makes the transition of young people into stable work a central concern for the present study.

Indonesia's labour-force statistics illustrate why youth unemployment warrants analysis separately from the national unemployment rate (Badan Pusat Statistik, 2024). In August 2024, the National Labour Force Survey, or Survei Angkatan Kerja Nasional (SAKERNAS), recorded 152.11 million people in Indonesia's labour force. Unemployment reached 21.68% among those aged 15-19 and 14.83% among those aged 20-24, substantially exceeding the national average. These age-specific figures describe different stages of entry into employment and should not be treated as interchangeable with the combined unemployment rate for people aged 15-24. They provide descriptive context for the youth-focused dependent variable without constituting additional observations in the annual model.

Young people often enter the labour market with limited work experience, weak job-search networks, and skills that do not fully match employer demand. Evidence from Indonesian Sakernas-based studies shows that education, training, work experience, gender, and rural-urban location shape young educated unemployment (Sitompul & Athoillah, 2023; Yanindah, 2021). Skills supply and labour demand also remain misaligned in Indonesia, which makes the transition from school to work more difficult for new labour-market entrants (Di Gropello et al., 2011). For example, access to a vacancy is unlikely to translate into employment when an applicant cannot demonstrate the skills or experience required for the position. Within this broader context, migration and inflation are relevant macroeconomic factors for explaining youth employment outcomes.

Migration can influence youth unemployment through spatial labour reallocation, as discussed in the literature on rural-urban migration (Selod & Shilpi, 2021). Rural-to-urban and interregional mobility may improve job matching when destination areas offer stronger labour demand, but it can also increase labour-market congestion when job creation fails to absorb

incoming workers. The discussion of density in Java provides a relevant spatial context for considering such destination pressures (De Koninck & Hai, 2025). Inflation introduces a different pressure through purchasing power, production costs, and firms' recruitment decisions, potentially compounding the employment barriers faced by inexperienced entrants. Considering mobility and prices together therefore connects the geography of employment opportunities with the economic conditions under which firms hire.

Existing studies commonly isolate migration from inflation or embed both in broader unemployment models. Estimating them jointly changes the interpretation because each coefficient is conditional on the other macroeconomic pressure: the migration estimate speaks to whether spatial matching dominates destination-market congestion at a given inflation rate, while the inflation estimate captures price pressure after accounting for labour mobility. This is especially relevant for young people, whose unemployment is shaped by first-job barriers, limited experience, weaker bargaining power, and greater exposure to entry-level hiring cycles. The contribution is therefore not ARDL as a technique, but a youth-specific examination of competing mobility mechanisms under macroeconomic price pressure in Indonesia. The following analysis develops these mechanisms and evaluates whether the reported annual associations are consistent with their expected directions.

The study's national perspective is intended to identify an aggregate relationship rather than to describe the employment experience of every young migrant. An annual national series combines people living in different provinces, working in different sectors, and facing different barriers to entry into employment. Consequently, the estimated association can coexist with substantial differences between origin and destination areas or between young people with different educational backgrounds. For example, mobility that helps one group access employment may coincide with more intense competition for another group in the same destination labour market. This distinction defines the scope of the contribution and guides the cautious interpretation of the empirical results.

2. Literature Review and Hypothesis Development

Youth unemployment remains a central development challenge in many developing economies. High youth unemployment can reduce future income, increase social vulnerability, and weaken political and economic stability (Hailu Demeke, 2022). Unlike general unemployment, youth unemployment is strongly connected to the transition from education to work. Young workers often enter the labour market with limited experience, weaker bargaining power, and skills that may not match the requirements of employers (Michael & Geetha, 2020; Papík et al., 2022). These characteristics explain why the same macroeconomic conditions may have different implications for young entrants and established workers.

Skill mismatch remains a serious issue in Indonesia, where preparation for employment does not always correspond to the opportunities available to new entrants (Di Gropello et al., 2011). Vocational and higher education are intended to prepare young people for work, yet many graduates still encounter barriers to formal employment (Husin et al., 2021). The International Labour Organization (2024) also highlights young people who are not in employment, education, or training, commonly referred to as NEET, within the broader assessment of youth labour-market exclusion. NEET status and unemployment are distinct indicators, so the former provides background rather than a substitute for the unemployment variable analysed

here. The present analysis therefore retains youth unemployment as its outcome while recognising the wider difficulties surrounding the transition into work.

Migration creates two competing youth-labour-market mechanisms in the literature on mobility and employment (Belmonte et al., 2020; Huynh & Vo, 2023; Selod & Shilpi, 2021). The spatial-matching mechanism predicts lower unemployment when young workers move toward vacancies, training opportunities, and expanding sectors. The congestion mechanism predicts higher unemployment when inflows outpace destination-area job creation. Young entrants are particularly exposed because they have less occupation-specific experience and weaker job-search networks. A negative conditional coefficient would therefore be consistent with matching dominating congestion at the national level, whereas a positive coefficient would be consistent with destination-market pressure dominating.

The spatial-matching argument depends on the ability of young people to convert geographical movement into a productive employment match. Moving can widen the set of employers that a job seeker can approach, but it does not itself supply information about vacancies, reliable credentials, or occupation-specific experience. Search costs and the time needed to learn about a destination can therefore delay the employment benefits that mobility might otherwise offer. A young person who relocates before obtaining a job may initially remain unemployed even when the move improves access to opportunities over a longer horizon. This sequence provides a conceptual reason to distinguish the immediate migration association from its conditional long-run counterpart.

The congestion argument emphasises the demand side of destination labour markets rather than assuming that an increase in labour supply automatically creates jobs. When employers cannot expand production or recruitment at the same pace as arrivals, more applicants may compete for the existing pool of entry-level positions. The outcome can depend on how closely the skills of new arrivals correspond to vacancies and on whether expanding sectors can absorb inexperienced workers. Conversely, an inflow that meets an unmet skill requirement need not produce the same pressure as an inflow into an already crowded occupation. The expected migration coefficient is consequently an aggregate balance of competing processes rather than a universal judgement about the desirability of mobility.

The expected inflation-unemployment relationship depends on the inflation regime, a distinction relevant to interpreting evidence for Indonesia (Wulandari et al., 2019). Demand-driven inflation can coincide with stronger output and lower unemployment in conventional short-run Phillips-curve reasoning. By contrast, cost-push inflation arising from food and energy shocks, exchange-rate depreciation, distribution bottlenecks, or administered prices can raise production costs, compress household purchasing power, and weaken hiring. The latter mechanism is especially relevant to Indonesian youth because firms can postpone entry-level recruitment or rely on more experienced workers when costs and uncertainty rise. H2 therefore concerns a persistent supply-side and cost-push channel rather than claiming that every inflation episode increases unemployment.

Price pressure may affect youth employment through both household decisions and the recruitment decisions of firms. For households, a reduction in purchasing power can limit the resources available for transport, relocation, training, and a prolonged search for suitable employment. For firms, higher input costs can make the expected return from an additional employee less certain, particularly where output prices cannot adjust fully. These channels

may operate simultaneously, leaving young applicants with fewer search resources at the same time that employers become more selective. They offer a possible interpretation of a positive inflation coefficient, while remaining mechanisms that the aggregate model does not identify separately.

Research hypotheses

H1: Migration has a negative long-run effect on youth unemployment in Indonesia because, over time, spatial labour reallocation improves the matching of workers to jobs.

H2: Inflation has a positive long-run effect on youth unemployment in Indonesia because sustained price pressure weakens purchasing power, investment, and labour absorption.

H3: Migration and inflation exert stronger effects on youth unemployment in the long run than in the short run because labour-market and macroeconomic adjustments occur gradually.

H3 is interpreted as a temporal expectation rather than a separately tested cross-horizon hypothesis. The associations of migration and inflation may be clearer in the long run because spatial reallocation, vacancy matching, cost pass-through, and hiring responses take time. This expectation is assessed descriptively by comparing the patterns and uncertainty of the long-run and short-run estimates. No formal cross-horizon equality test is conducted, and differences in individual significance levels alone do not establish that the underlying effects differ statistically. The empirical assessment therefore distinguishes directional consistency with the hypotheses from stronger claims about causal effects or adjustment speeds.

3. Methodology

This study applies a quantitative annual time-series design to Indonesia for 2000-2024, comprising 25 observations. Youth unemployment (Y) denotes the national unemployment rate for ages 15-24; migration (X1) is identified in the estimation archive as the risen in-migration rate; and inflation (X2) is annual national Consumer Price Index (CPI) inflation. Table 1 summarises the definitions, units, and data sources. Because the sample is short, a highly parameterised lag structure substantially reduces the degrees of freedom available for estimation and inference. All long-run findings are therefore interpreted as conditional associations rather than causal effects.

Table 1. Data sources, variable definitions, and measurement units

Variable	Symbol	Operational definition	Unit	Main source
Youth unemployment	Y	Unemployment rate among young workers, following the standard labour-force definition of unemployed persons relative to the youth labour force. The empirical series should be consistently constructed for the 15-24 age group or clearly stated age bands.	Percent of labour force aged 15-24 (%)	Badan Pusat Statistik (2024) , SAKERNAS

Variable	Symbol	Operational definition	Unit	Main source
Migration	X1	Risen In-Migration Rate (per 100 population). The number of residents aged five years and over in an administrative area who five years previously lived in a different administrative area, calculated per 100 residents	Percent per year (%)	Badan Pusat Statistik (2023)
Inflation	X2	National CPI-based inflation rate reflecting annual changes in consumer prices.	Percent per year (%)	Badan Pusat Statistik (2025), CPI and inflation statistics

[Badan Pusat Statistik \(2023\)](#) provides the migration reference used to clarify the internal-mobility concept associated with X1. Its migration statistics distinguish lifetime migration from recent, or risen, migration, so these concepts should not be used interchangeably when interpreting the empirical variable. The five-year retrospective definition concerns a change in residence over a reference interval and is not, by itself, a directly observed annual migration flow. Because the year-specific provenance and annualisation log of the estimation series are unavailable, the reported migration coefficient remains provisional and its interpretation is conditional on the recorded measurement. The publication identifies the relevant statistical concept without independently verifying every annual value used in the existing estimation archive.

[Badan Pusat Statistik \(2025\)](#) provides a corresponding reference for the CPI information underlying the interpretation of inflation. The publication presents national and provincial CPI developments during 2024 and uses the reference year 2022=100. An inflation rate measures a change in consumer prices, whereas the CPI level expresses prices relative to the reference year, so the two should not be treated as the same regressor. The present model retains the annual national inflation series described in the estimation archive, rather than introducing provincial CPI levels or reconstructing historical observations from the latest publication. Accordingly, the source citation clarifies the price concept and reporting context while preserving the original variable and estimation period.

The unemployment rate measures the share of the relevant labour force that is unemployed, rather than the share of all young people without a job. Its denominator excludes young people outside the labour force, making participation decisions relevant to the interpretation of changes in the measured rate. A lower youth unemployment rate therefore cannot automatically be interpreted as an equivalent increase in the proportion of all young people who are employed. For example, movements between education, job search, employment, and inactivity can change the labour-force composition even when the national population in the age group changes little. The empirical outcome is accordingly kept distinct from employment levels, labour-force participation, and the broader NEET concept discussed earlier.

The autoregressive distributed lag (ARDL) approach is selected because it estimates long-run and short-run relationships when the variables are I(0), I(1), or a combination of both, provided that none is I(2) ([Pesaran et al., 2001](#); [Natsiopoulos & Tzeremes, 2022](#)). Prior to ARDL estimation, the Augmented Dickey-Fuller (ADF) unit-root test is used to verify that every

variable meets the required order of integration (Dickey & Fuller, 1979). The optimal lag structure is chosen using the Akaike Information Criterion (AIC), which balances goodness of fit and parsimony. The estimation then distinguishes the reported level relationship from the coefficients describing changes over the shorter observation horizon. This sequence makes the interpretation of each result dependent on the integration checks, lag specification, and subsequent diagnostic evidence.

3.1 Stationarity test

Stationarity must be examined because ARDL estimation permits $I(0)$ and $I(1)$ variables, including a mixture of the two, but does not permit an $I(2)$ variable (Pesaran et al., 2001). Accordingly, the Augmented Dickey-Fuller (ADF) unit-root test is used to determine the integration order of youth unemployment, migration, and inflation before conducting the bounds test (Dickey & Fuller, 1979). The level tests assess whether the original series display evidence against a unit root, while the first-difference tests assess the transformed series. Rejection at the first difference, following non-rejection at the level, supports treating a variable as $I(1)$ within the reported testing specification. The stationarity results therefore establish the preliminary statistical conditions for applying the selected ARDL framework.

3.2 Determining the optimal lag

Determining the optimal lag is necessary to represent the relationship between current outcomes and past values without including unnecessary parameters (Lütkepohl, 2005; Pesaran et al., 2001). In an ARDL model, the dependent variable and the explanatory variables may enter with different lag lengths. Information criteria compare candidate specifications by combining a measure of fit with a penalty for model complexity, and this study uses AIC for selection. The Schwarz Information Criterion offers an alternative comparison, but no additional selection result is inferred where it is not reported in the original output. The selected lag structure is consequently retained while its implications for the short annual sample are considered during interpretation.

3.3 Cointegration test

Cointegration is evaluated through the ARDL bounds-testing procedure (Pesaran et al., 2001). The estimated F-statistic is assessed against the $I(0)$ lower-bound and $I(1)$ upper-bound critical values. A statistic above the upper bound leads to rejection of the null of no long-run level relationship, whereas a statistic below the lower bound does not reject the null. A statistic between the two bounds produces an inconclusive result, and the comparison must use critical values appropriate to the deterministic specification and number of regressors. The bounds decision is therefore assessed together with the reported error-correction evidence rather than being treated as a complete assessment of model reliability.

The distinction between a bounds decision and the precision of individual coefficients is central to the empirical interpretation. The bounds test concerns a joint level relationship among the included variables, while a coefficient test concerns a particular estimated parameter within the chosen specification. A model can therefore yield individually significant coefficients without supplying equally strong evidence about its adjustment mechanism or its stability under alternative specifications. In a short sample, these differences deserve particular attention because a small number of observations must support several lagged terms and diagnostic comparisons. Keeping the tests conceptually separate prevents the

interpretation of one favourable statistic from replacing an assessment of the full set of reported results.

3.4 Model Suitability Test with Classical Assumption Test

Model adequacy is evaluated using residual diagnostic tests that are standard in time-series econometrics. Normality is examined using the Jarque-Bera test, heteroscedasticity using the Breusch-Pagan-Godfrey test, and serial correlation using the Breusch-Godfrey LM test (Breusch & Pagan, 1979; Godfrey, 1978; Jarque & Bera, 1980). These tests examine different properties of the fitted residuals and consequently address different potential sources of unreliable inference. For example, residual variance can appear stable even when serial dependence or an imprecisely estimated adjustment coefficient remains a concern. The diagnostics are therefore interpreted jointly and do not eliminate the limitations caused by a short annual sample.

3.5 Normality test

The Jarque-Bera normality test evaluates whether residual skewness and kurtosis deviate from the normal distribution (Jarque & Bera, 1980). The null hypothesis is that the residual distribution is consistent with normality in these respects. A probability value greater than 0.05 indicates that this null hypothesis is not rejected at the 5% significance level. Such a result does not prove exact normality, especially when the number of residual observations available for testing is small. The test therefore provides one diagnostic check on the fitted model rather than a guarantee that all coefficient-based inferences are reliable.

3.6 Heteroscedasticity test

The Breusch-Pagan-Godfrey test is used to detect heteroscedasticity, namely unequal error variance across observations (Breusch & Pagan, 1979). Its null hypothesis is that the residual variance is constant under the tested specification. A probability value greater than 0.05 indicates that the null hypothesis of homoscedastic residuals is not rejected at the 5% significance level. The decision refers to the particular variance pattern examined by the test and does not establish that every possible form of heteroscedasticity is absent. The reported outcome is therefore considered alongside the remaining diagnostics and the limitations of the annual sample.

3.7 Autocorrelation test

The Breusch-Godfrey LM test examines whether residuals are serially correlated over time (Godfrey, 1978). The null hypothesis is that no residual serial correlation is present at the lag order examined by the test. If the probability value is higher than 0.05, this null hypothesis is not rejected at the 5% significance level. The check is relevant because unexplained dependence between successive observations can affect the interpretation of estimated dynamic relationships. Its result helps assess the selected lag specification but does not establish that every alternative dynamic model would produce the same coefficients.

3.8 Model stability test

Model stability is assessed using CUSUM and CUSUM of Squares tests (Brown et al., 1975). These residual-based tests indicate whether the plotted statistics remain within the 5% stability boundaries over the sample period. Statistics that remain within these boundaries do not reveal visible instability under the respective diagnostic procedures. However, these are not

full substitutes for formal structural-break tests such as the Zivot-Andrews or Bai-Perron procedures (Zivot & Andrews, 1992; Bai & Perron, 2003). The stability evidence is therefore used to qualify the interpretation of the existing estimates without claiming that formal break-sensitive re-estimation has been undertaken.

3.9 ARDL model estimation

The ARDL model provides a framework for examining a long-run relationship alongside short-run dynamics under the relevant integration and specification conditions (Nkoro & Uko, 2016). This flexibility makes it suitable for analysing variables with potentially different lagged responses within a single empirical framework. ARDL allows different lag lengths for each variable, although this flexibility does not remove the need to consider parameter uncertainty in a small sample. Based on these considerations, this study retains the ARDL model to examine the short-run and long-run associations between migration, inflation, and youth unemployment. The following expression summarises the long-run relationship using the notation of the original specification.

$$YU_t = \theta_1 MIG_t + \theta_2 INF_t + \varepsilon_t \quad (1)$$

YU_t = Youth Unemployment
 MIG_t = Migration
 INF_t = Inflation
 θ_1, θ_2 = Long-run coefficient
 ε_t = Error term

In the short run, the Error Correction Term (ECT) represents the adjustment of youth unemployment following a deviation from the specified long-run relationship. The ECT coefficient is expected to be negative and statistically significant if the estimated equation provides evidence of convergence toward that relationship. A negative coefficient alone is insufficient to establish a reliable speed of adjustment when its uncertainty is substantial. The interpretation must therefore consider the sign and probability value together rather than translate an insignificant estimate into a definitive annual correction rate. The following error correction model (ECM) expresses this distinction between changes in the variables and the lagged disequilibrium term.

$$\Delta YU_t = \beta_0 + \sum_{i=1}^p \beta_1 \Delta YU_{t-i} + \sum_{i=1}^q \beta_2 \Delta MIG_{t-i} + \sum_{i=1}^r \beta_3 \Delta INF_{t-i} + \phi ECT_{t-1} + e_t \quad (2)$$

Δ = change (difference)
 β_0 = Constant
 $\beta_1, \beta_2, \beta_3$ = Short-run coefficient
 ECT_{t-1} = Error Correction Term in the long run
 ϕ = Adjustment coefficient (must be negative and significant)
 e_t = error term

4. Result and Discussion

4.1 Stationarity test

The stationarity test results in Table 2 show that all variables have ADF probability values at their respective levels of 0.8621, 0.7034, and 0.4513, all of which are greater than $\alpha = 0.05$. At the first difference, the ADF probability values are recorded at 0.0006, 0.0098, and 0.0000, all of which are below $\alpha = 0.05$. Thus, these results indicate that the three variables meet the stationarity requirement at the first difference. Within the reported test specification, this pattern supports treating youth unemployment, migration, and inflation as I(1) variables rather than assuming that their levels are stationary. The results provide the preliminary basis for proceeding to lag selection and the bounds analysis.

Table 2. Stationarity test

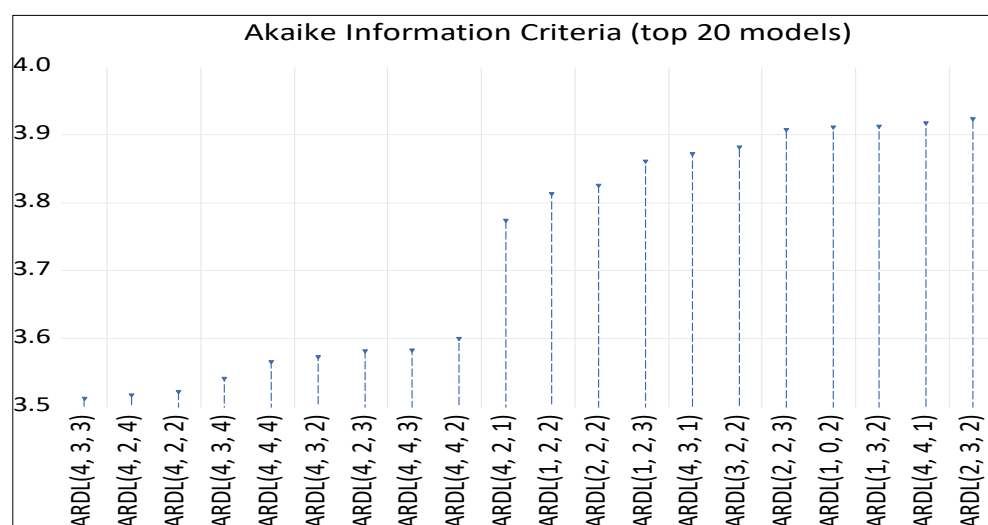
Variable	Unit Root Test	ADF Test Statistic	Prob ADF	Description
Youth	Level	-0.556895	0.8621	Non-stationary
Unemployment (Y)	First Difference	-5.007905	0.0006	Stationary
Migration (X1)	Level	-1.087885	0.7034	Non-stationary
	First Difference	-3.763892	0.0098	Stationary
Inflation (X2)	Level	-1.629675	0.4513	Non-stationary
	First Difference	-7.625990	0.0000	Stationary

Source: Processed data, 2025

4.2 Determining the optimal lag

Figure 1 displays the 20 highest-ranked ARDL specifications generated automatically in EViews according to the Akaike Information Criterion (AIC). ARDL(4,3,3) produces the lowest AIC value and is therefore selected for the subsequent estimation. The selected specification includes a relatively extensive lag structure for the available annual sample. Its ranking indicates a preference within the examined candidate set, rather than demonstrating that every alternative model or lag restriction would lead to identical inferences. Given the small sample, this lag structure is interpreted cautiously in the short-run analysis.

Figure 1. Optimal lag selection



Source: Processed data, 2025

4.3 Cointegration test

As reported in Table 3, the ARDL bounds test yields an F-statistic of 4.6197, which is above the reported 5% upper critical value of 3.87. Using the critical values reproduced in that table, the null hypothesis of no long-run relationship is rejected. This comparison supports examining the conditional level relationship among youth unemployment, migration, and inflation within the reported specification. It should nevertheless be read alongside the manuscript's differing bounds assessments and the statistically insignificant error-correction coefficient reported below. The bounds comparison therefore motivates the long-run analysis without resolving all uncertainty about the model's equilibrium interpretation.

Table 3. Results of the cointegration bounds testing approach

Test Statistic	Value	Signif.	I(0)	I(1)
Asymptotic: n = 100				
F-Statistic	4.619700	10%	2.63	3.35
k	2	5%	3.1	3.87
		2.5%	3.55	4.38
		1%	4.13	5

Source: Processed data, 2025

4.4 ARDL model estimation

4.4.1 Long-run ARDL test

The long-run ARDL coefficients are presented in Table 4. Migration (X1) has a coefficient of -0.00007 and a probability value of 0.0405, showing a negative and statistically significant long-run association with youth unemployment. If X1 is measured as a rate per 100 population, a one-unit rise in the migration rate corresponds to a 0.00007 percentage-point decline in youth unemployment. Because this per-unit magnitude is small, its economic interpretation should emphasise the direction of the association while retaining the qualification about the measurement of X1. The coefficient is consequently read as a conditional national association rather than a verified individual employment benefit from migration.

Inflation (X2) has an estimated coefficient of 0.487153 and a probability value of 0.0249. The positive and statistically significant estimate means that, holding the other included explanatory variable constant, a one-percentage-point increase in inflation is associated with an approximately 0.487 percentage-point rise in long-run youth unemployment. The constant is statistically insignificant, with a probability value of 0.2870 in Table 4. The inflation coefficient therefore concerns the rate of youth unemployment expressed in percentage points, rather than a percentage change in the number of unemployed young people. The following expression reproduces the reported error-correction relationship for comparison with the coefficient table.

$$EC = (Youth\ Unemployment) - (0.00007 \cdot D(Migration)) + 0.487153 \cdot D(Inflation) - 0.161590$$

Table 4. Long-run coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
X1	-7.00E-05	2.79E-05	-2.508944	0.0405
X2	0.487153	0.171233	2.844973	0.0249
C	-0.161590	0.140231	-1.152310	0.2870
EC = (Y) - ((-0.00007)*D(X1) + 0.487153*D(X2) - 0.161590)				

Source: Processed data, 2025

4.4.2 Short-run ARDL test

Table 5 reports the short-run estimates from ARDL(4,3,3). The lagged changes in youth unemployment, $D(Y(-1))$ and $D(Y(-4))$, are statistically significant and have negative coefficients of -0.831561 and -0.724566, respectively. These estimates indicate short-run persistence and partial correction in the youth unemployment series, whereas the other lagged dependent variables are statistically insignificant. The negative signs describe the conditional relationship between the included lagged changes and the current change in youth unemployment. They do not independently establish a reliable return to long-run equilibrium, which requires consideration of the separate ECT estimate.

Variable labels are consistent with the long-run specification: X1 represents migration and X2 represents inflation. Accordingly, $D(X1)$ and its lags refer to migration, whereas $D(X2)$ and its lags refer to inflation. Most short-run migration terms are insignificant; the exception is $D(X1(-2))$, whose coefficient is -0.000101 and is significant at the 5% level. For inflation, $D(X2(-1))$ is positive and significant with a coefficient of 0.561334, while $D(X2(-2))$ is marginally significant at the 10% level. These individual short-run estimates must nevertheless be interpreted cautiously because the model is not jointly significant and the number of observations is limited.

The short-run regression reports an F-test probability of 0.178352; thus, the differenced regressors are not jointly significant at conventional levels. The R-squared is 0.776230, but the adjusted R-squared declines to 0.392623 because ARDL(4,3,3) estimates many parameters relative to the available observations. $ECT(-1)$ is negative at -0.406089 but statistically insignificant ($p = 0.2678$). Consequently, the bounds comparisons and the ECM do not offer fully consistent evidence: the manuscript reports support from the nearest $n = 30$ finite-sample critical bound, with reference to [Narayan \(2005\)](#), alongside an inconclusive Case-II asymptotic assessment and a statistically unreliable adjustment coefficient. The long-run coefficients are therefore treated as conditional and specification-sensitive, while the short-run estimates remain exploratory.

The combination of individual significance and joint insignificance limits the strength of conclusions drawn from the short-run equation. The probability value for an individual lagged term evaluates that coefficient conditional on the other included regressors, whereas the reported F-test evaluates the joint restriction represented by the model statistic. Finding one significant migration lag or one significant inflation lag therefore does not mean that the short-run model as a whole is strongly supported. The considerable difference between R-squared and adjusted R-squared also cautions against equating a relatively high fitted proportion with a precise or parsimonious dynamic explanation. The individual lag patterns are consequently discussed as exploratory features of the selected specification rather than as firm timing rules for policy.

Table 5. ARDL short-run regression coefficients

Case 2: Restricted constant and no trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
$D(Y(-1))$	-0.831561	0.343118	-2.423542	0.0459
$D(Y(-2))$	0.034451	0.246361	0.139841	0.8927
$D(Y(-3))$	0.008591	0.206588	0.041584	0.9680
$D(Y(-4))$	-0.724566	0.283671	-2.554250	0.0379

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
D(X1)	-8.22E-05	5.86E-05	-1.404534	0.2029
D(X1(-1))	7.49E-05	4.56E-05	1.642917	0.1444
D(X1(-2))	-0.000101	3.57E-05	-2.822159	0.0257
D(X1(-3))	-6.77E-05	5.95E-05	-1.137569	0.2927
D(X2)	0.139676	0.130137	1.073302	0.3187
D(X2(-1))	0.561334	0.167016	3.360964	0.0121
D(X2(-2))	0.387246	0.188100	2.058720	0.0785
D(X2(-3))	0.136001	0.123088	1.104912	0.3057
CointEq(-1)* / ECT(-1)	-0.406089	0.337329	-1.203837	0.2678
R-squared	0.776230	Mean dependent var	-0.524000	
Adjusted R-squared	0.392623	S.D. dependent var	1.586036	
S.E. of regression	1.236067	Akaike info criterion	3.511924	
Sum squared resid	10.69503	Schwarz criterion	4.159150	
Log likelihood	-22.11924	Hannan-Quinn criter.	3.638270	
F-statistic	2.023505	Durbin-Watson stat	1.560191	
Prob(F-statistic)	0.178352			

Source: Processed data, 2025

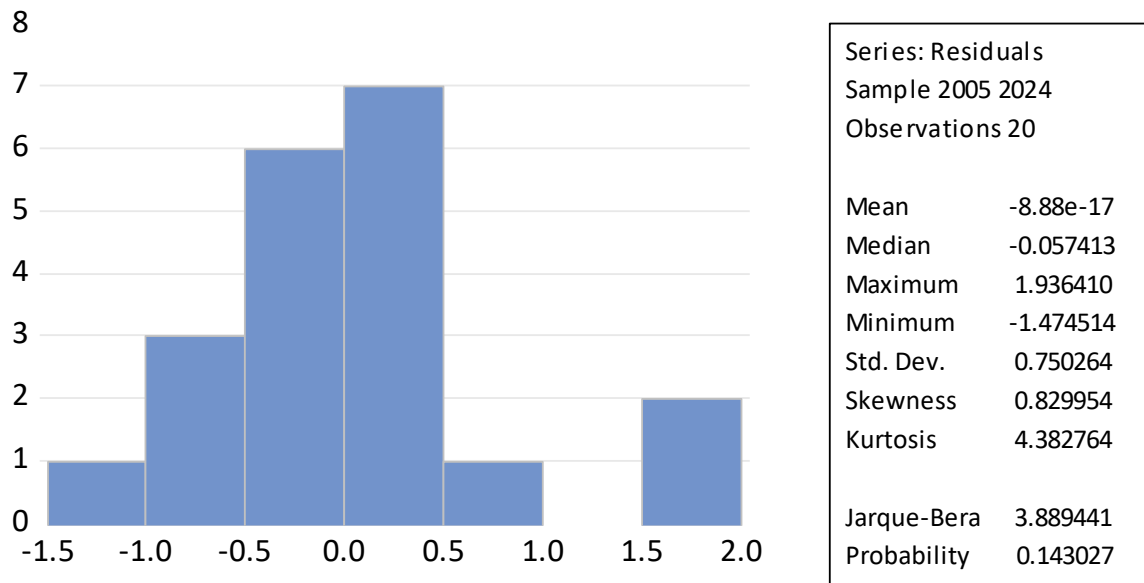
4.4.3 Model suitability test

The reported residual diagnostics do not reveal conventional normality, heteroscedasticity, serial-correlation, or CUSUM instability problems at the stated thresholds. Each diagnostic addresses a specific property of the fitted residuals or estimated relationship and therefore contributes a different piece of information. Passing these tests does not resolve the small-sample burden, the unverified construction of X1, the differing bounds assessments, or the insignificant ECT(-1). Likewise, acceptable diagnostics do not substitute for parsimonious-lag and break-sensitive re-estimation, neither of which is reported in the existing analysis. The following tests should therefore be understood as checks on the retained specification rather than comprehensive evidence of robustness.

Normality Test

Figure 2 presents the Jarque-Bera normality test, which reports a probability value of 0.143027, greater than 0.05. Therefore, the null hypothesis of normally distributed residuals is not rejected at the 5% significance level. The result indicates that the reported skewness and kurtosis do not provide sufficient evidence against normality under this test. However, the small number of observations limits how strongly non-rejection can be interpreted as evidence about the underlying residual distribution. The normality result is consequently considered together with the variance, serial-correlation, and stability diagnostics.

Figure 2. Normality test



Source: Processed data, 2025

Heteroscedasticity Test

Table 6 reports the Breusch-Pagan-Godfrey heteroscedasticity test, with an Obs*R-squared probability value of 0.8575, greater than 0.05. The null hypothesis of homoscedastic residuals is therefore not rejected at the 5% significance level. The F-statistic probability of 0.9621 and the scaled explained sum-of-squares probability of 0.9999 are also above this threshold. These reported comparisons provide no evidence of the tested heteroscedasticity pattern, although they do not guarantee constant variance under every possible alternative specification. The result supports the residual assessment of the retained model while leaving its broader estimation limitations unchanged.

Table 6. Heteroscedasticity Test

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	0.314219	Prob. F(12, 7)	0.9621
Obs*R-squared	7.001689	Prob. Chi-Square(12)	0.8575
Scaled explained SS	1.450710	Prob. Chi-Square(12)	0.9999

Source: Processed data, 2025

Autocorrelation test

Table 7 presents the Breusch-Godfrey serial correlation LM test, which reports an Obs*R-squared probability value of 0.1009. Since this value is greater than 0.05, the null hypothesis of no serial correlation is not rejected at the 5% significance level. The reported F-test probability is 0.5213, which also exceeds the same threshold. The conclusion concerns the two-lag test displayed in the table and should not be extended to all possible lag orders without additional testing. The retained model consequently shows no detected serial correlation under this diagnostic, subject to the limited size of the estimation sample.

Table 7. Breusch-Godfrey serial correlation LM test for autocorrelation

Breusch-Godfrey Serial Correlation LM Test

F-statistic	0.744185	Prob. F(2,5)	0.5213
Obs*R-squared	4.587807	Prob. Chi-Square(2)	0.1009

Source: Processed data, 2025

Model stability test

Figures 3 and 4 present the CUSUM and CUSUM of Squares tests used to assess parameter stability over the observation period. Both plotted statistics stay within the 5% significance boundaries, so no visible parameter instability is detected. The plots therefore do not provide a visual signal of instability under the two reported procedures. However, because the sample covers major shocks, including the global financial crisis and the COVID-19 period, these stability diagnostics should not be regarded as substitutes for formal structural-break tests. The figures support a qualified assessment of the existing specification without establishing that its coefficients are invariant to every possible change in economic conditions.

Figure 3. CUSUM stability test

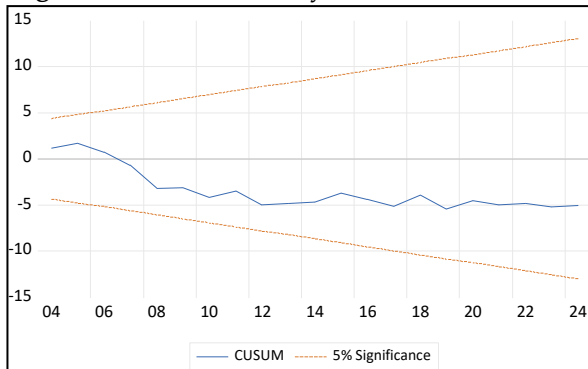
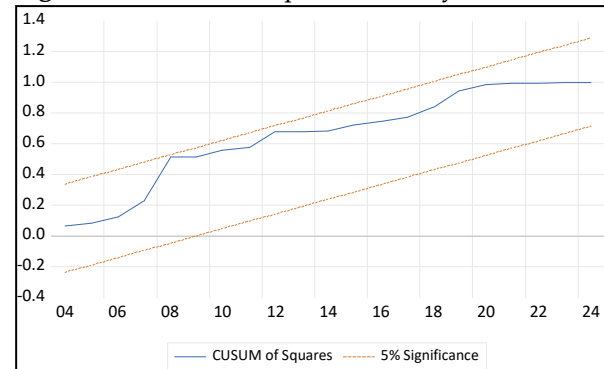


Figure 4. CUSUM of Squares stability test



Source: Processed data, 2025

Discussion

The long-run estimates indicate a negative and statistically significant association between migration and youth unemployment. At the national level, this result suggests that internal mobility may facilitate labour-market adjustment by moving workers from areas with fewer opportunities to locations with greater employment potential. This interpretation accords with the spatial labour-matching mechanism discussed in the migration literature ([Selod & Shilpi, 2021](#)). However, the coefficient is economically small per unit and depends on the precise measurement of migration. It should therefore be interpreted as a negative long-run association rather than proof that every form of migration necessarily lowers youth unemployment.

The negative migration coefficient is consistent with H1 only within the measurement and modelling conditions of the present analysis. If the recorded migration variable captures movements that connect available workers with unfilled positions, the sign is compatible with improved allocation across regional labour markets. The model does not observe the vacancies, occupations, search histories, or individual employment transitions required to verify that mechanism directly. It also cannot show whether the estimated national association is driven mainly by particular destinations, sectors, or groups of young workers. The matching mechanism therefore remains a plausible interpretation of the observed sign rather than a separately demonstrated causal pathway.

The distinction between the direction and magnitude of the migration estimate is important for policy interpretation. The coefficient of -0.00007 indicates a negative slope in the units used by the original model, but the practical meaning of a one-unit movement depends on the exact

construction of $X1$. Without the annualisation record, it would be inappropriate to convert this estimate into a predicted number of jobs created or young people removed from unemployment. Similarly, comparing its numerical size directly with the inflation coefficient would be misleading because the two regressors represent different concepts and measurement scales. The defensible conclusion is consequently about a conditional direction of association, with the economic magnitude remaining dependent on verification of the migration series.

The short-run migration effect is not robust. Although $D(X1(-2))$ is statistically significant, the short-run model is jointly insignificant and $ECT(-1)$ is also statistically insignificant. Accordingly, the result does not provide strong evidence that migration immediately lowers youth unemployment or that the model identifies a statistically reliable annual adjustment path. A cautious interpretation is that migration may influence youth employment gradually through labour-market adjustment, sectoral absorption, and spatial matching over longer horizons. This interpretation explains why the significant individual lag should not be converted into a precise timetable for the employment benefits of mobility.

Employment services can be linked to the migration finding through the practical barriers separating movement from successful recruitment. Better information about vacancies may help young people assess whether destination opportunities correspond to their qualifications before they relocate. Vocational preparation and recognition of skills may similarly improve the chance that a wider geographical search produces a suitable match rather than a longer period of unemployment. These measures address the mechanisms discussed in the paper, but their effectiveness cannot be quantified from the migration coefficient or treated as an estimated programme impact. The policy implication is therefore to improve the conditions under which mobility can support employment, while evaluating specific interventions using appropriate additional evidence.

Inflation has a positive conditional long-run coefficient of 0.487153, a result interpreted in relation to the Indonesian inflation-unemployment literature ([Wulandari et al., 2019](#)). In the selected model, this magnitude is economically meaningful: a one-percentage-point rise in inflation corresponds to an increase of approximately 0.487 percentage points in youth unemployment. This result does not reject all Phillips-curve mechanisms. In the short run, demand-driven inflation may coincide with stronger economic activity and lower unemployment, whereas food, energy, exchange-rate, distribution, and administered-price shocks may generate cost-push pressure that reduces purchasing power and limits entry-level recruitment. The estimate is therefore compatible with persistent supply-side pressure, without identifying its components or establishing a universal positive inflation-unemployment relationship.

The inflation result is consistent with H2 as a conditional association rather than a direct test of a specific source of price increases. The annual national inflation measure combines price movements that may arise from demand conditions, supply constraints, or changes in the costs of particular expenditure categories. The model does not decompose these components and therefore cannot assign the positive coefficient to food prices, energy prices, exchange-rate movements, or administered prices individually. Nor does it identify whether the relationship operates mainly through weaker household demand, higher business costs, or a combination of those channels. The cost-push explanation should consequently be understood as a

theoretically motivated interpretation that remains open to more detailed empirical examination.

Young workers may be exposed to price pressure at the point when firms decide whether to open new positions. An employer facing uncertain costs can postpone recruitment without necessarily dismissing existing staff, so the immediate burden may fall on people seeking their first job. Applicants with limited work experience may also have fewer ways to demonstrate productivity when firms become more selective about hiring. This reasoning connects the inflation coefficient to the school-to-work transition without implying that the model contains direct measures of hiring standards or employer expectations. It helps explain the youth-specific relevance of price stability while preserving the distinction between an aggregate estimate and the mechanisms proposed to interpret it.

[Fung and Nga \(2022\)](#) examine youth unemployment and macroeconomic conditions in ASEAN, whereas this study focuses on the conditional relationships involving migration and inflation in Indonesia. The inflation coefficient of 0.487153 is economically meaningful because sustained price pressure is associated with a measurable weakening of youth labour absorption in the selected model. The finding complements the Indonesian inflation-unemployment analysis of [Wulandari et al. \(2019\)](#) while concentrating specifically on young workers. The migration result should also be compared cautiously with [Huynh and Vo \(2023\)](#), whose Asian-country evidence indicates that the migration-unemployment relationship differs across country income groups. Direct comparison of coefficient magnitudes remains limited because earlier studies differ in country coverage, age groups, data frequency, unemployment definitions, and migration measures.

The combined specification contributes by making each reported association conditional on the other included macroeconomic variable. The migration coefficient is estimated alongside inflation, so its sign is not simply a description of the unconditional movement of migration and youth unemployment over time. Likewise, the inflation coefficient is estimated while accounting for the migration variable and the lag structure retained in the model. However, this conditioning does not control for every determinant of unemployment, including the skills, work experience, and location differences discussed in the literature review. The empirical contribution is therefore a focused joint assessment of two relevant pressures, with the remaining sources of variation still outside the specification.

Overall, the reported coefficient patterns suggest clearer conditional associations in the long-run estimates than in the short-run equation. This pattern is theoretically plausible because labour reallocation, price pressures, firms' hiring decisions, and the matching of young workers to jobs take time to affect employment outcomes. Nevertheless, the statistical insignificance of ECT(-1) means that the short-run adjustment mechanism should not be overstated. The descriptive comparison is compatible with the temporal expectation in H3, but it does not establish a statistically tested difference in effect sizes across horizons. Reducing youth unemployment therefore calls for attention to structural labour-market conditions and macroeconomic stability, without relying on the model to prescribe a precise adjustment schedule.

The policy discussion can be organised around improving labour matching while reducing the price pressures that may discourage youth recruitment. Employment agencies can use regional labour-market information to connect training and placement services with the

vacancies that employers actually report. At the same time, supply-chain coordination and attention to food-price conditions address the cost pressures highlighted in the paper's interpretation of inflation. These priorities are complementary because improved mobility may be less effective when destination firms face constraints on hiring, while price stability alone does not resolve skill mismatch. The recommendations therefore concern coordination across existing policy areas rather than the introduction of a new causal mechanism or an unestimated policy target.

Regional coordination matters because a national association does not show how employment opportunities and adjustment costs are distributed across locations. The recommendation to promote investment beyond the largest urban centres is intended to widen the geography of available jobs and reduce reliance on a small number of destinations. Local employment services would still need information about the qualifications sought by employers and the capabilities of young applicants before selecting training or placement priorities. The model cannot rank provinces, identify the best sector for investment, or determine how much funding any location should receive. Those decisions require local evidence, while the present findings provide a national rationale for connecting mobility planning with the expansion of employment opportunities.

5. Conclusion and Suggestion

Using the ARDL approach, this study evaluates the associations of migration and inflation with youth unemployment in Indonesia between 2000 and 2024. The reported bounds comparison provides support for a level relationship, although the overall equilibrium assessment remains qualified by the differing bounds interpretations and the insignificant adjustment coefficient. Migration is negatively and statistically significantly associated with youth unemployment in the long run, whereas inflation has a positive and statistically significant association. These results are consistent with labour mobility facilitating employment adjustment over time and persistent inflation weakening labour absorption. The findings remain conditional on the retained specification and migration measurement, rather than establishing that either relationship is causal.

The short-run evidence is weaker. Several lagged coefficients are statistically significant, but the short-run model is not jointly significant and has limited degrees of freedom because of the small annual sample and the ARDL(4,3,3) lag structure. Although the ECT(-1) coefficient is negative, it is statistically insignificant; thus, the model does not provide reliable statistical evidence of a short-run error-correction adjustment process. The long-run estimates constitute the main empirical contribution, whereas the short-run coefficients and the ECM adjustment require cautious interpretation. The descriptive contrast between horizons consequently supports continued investigation rather than a definitive claim about the comparative strength or speed of the effects.

The policy implication is that youth unemployment should be addressed through coordinated labour-market and macroeconomic policies. Migration policy should improve the planning and absorption of labour mobility rather than impose administrative restrictions on movement. Relevant measures include strengthening the Ministry of Manpower's job-matching services, expanding vocational reskilling and upskilling for young migrants, improving regional labour-market information systems, and promoting investment beyond the largest urban centres through coordination among the National Development Planning

Agency (Bappenas), local governments, and employment agencies. Inflation control should combine supply-chain stabilisation, food-price monitoring, coordination by national and regional inflation-control teams, and measures to protect youth employment when production costs rise. These recommendations follow the study's proposed mechanisms, while their specific effectiveness and quantitative impacts require evidence beyond the reported associations.

6. Limitations and Future Research

The annual frequency of the data also defines what can be learned about the timing of employment responses. A one-year observation interval combines movements occurring at different points within the year and may conceal faster changes in recruitment or job search. The reported lagged coefficients consequently describe relationships between annual observations rather than the exact duration of an individual's search for employment. For the same reason, the analysis cannot identify seasonal migration, monthly price shocks, or the immediate effects of a particular policy announcement. The long-run and short-run distinction should therefore be read within the annual modelling framework rather than translated into a detailed calendar of labour-market events.

Jointly including migration and inflation does not mean that the model estimates an interaction between them. The specification reports separate coefficients for the two variables, with each interpreted conditional on the other and on the retained dynamic terms. It does not include a reported interaction coefficient showing whether the migration association becomes stronger or weaker at different inflation rates. The discussion of complementary labour-market and price-stability policies therefore rests on the proposed mechanisms and the separate estimated associations, rather than on a statistically demonstrated interaction effect. This distinction preserves the value of examining the variables together while preventing the policy interpretation from extending beyond what the original specification estimates.

The negative ECT estimate should not be interpreted as proof that a fixed share of disequilibrium is corrected every year. Its sign points toward adjustment in the fitted equation, but the probability value of 0.2678 does not provide conventional statistical support for a non-zero adjustment coefficient. Reporting a definite convergence rate would therefore give the point estimate more authority than the accompanying uncertainty permits. The same limitation prevents the model from supplying a reliable number of years required to reach a long-run employment outcome following a change in migration or inflation. The appropriate conclusion remains that the proposed adjustment mechanism is not statistically established by the reported ECM.

The residual diagnostics and the substantive limitations of the model need to remain separate in the overall assessment. Figures 2-4 and Tables 6-7 indicate no detected problems under the particular normality, variance, serial-correlation, and stability checks reported in the paper. Those results concern the behaviour of the fitted model and do not verify the construction of the migration series or demonstrate that omitted influences are unimportant. A specification can pass these diagnostic checks while still producing estimates that depend on its lag choices, variable definitions, or limited number of observations. The diagnostic evidence consequently supports a bounded interpretation of the retained model rather than an unrestricted claim that its empirical conclusions are robust.

Further research should examine whether the reported directions remain stable once the unresolved data and specification issues are addressed. The first priority is to document the annual migration observations and their construction so that the meaning of X1 can be reproduced and its coefficient interpreted consistently. Subsequent work could compare more parsimonious lag structures and examine sensitivity to major changes in the observation period. Disaggregated evidence could then explore whether the national relationship reflects differences across regions or groups of young workers that the present annual model cannot distinguish. These extensions would assess the durability and mechanisms of the existing findings without being presented as analyses already completed in this paper.

References

- Badan Pusat Statistik. (2023). *Statistik migrasi Indonesia hasil Long Form Sensus Penduduk 2020*. BPS-Statistics Indonesia.
- Badan Pusat Statistik. (2024). *Keadaan angkatan kerja di Indonesia Agustus 2024*. BPS-Statistics Indonesia.
- Badan Pusat Statistik. (2025). *Consumer price index of 38 provinces in Indonesia 2024 (2022=100)*. BPS-Statistics Indonesia.
- Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. *Journal of Applied Econometrics*, 18(1), 1–22. <https://doi.org/10.1002/jae.659>
- Belmonte, M., Conte, A., Ghio, D., Kalantaryan, S., & McMahon, S. (2020). *Youth and migration: An overview*. Publications Office of the European Union. <https://doi.org/10.2760/625356>
- Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica*, 47(5), 1287–1294. <https://doi.org/10.2307/1911963>
- Brown, R. L., Durbin, J., & Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society: Series B (Methodological)*, 37(2), 149–163. <https://doi.org/10.1111/j.2517-6161.1975.tb01532.x>
- De Koninck, R., & Hai, P. T. (2025). Coping with density: Reflections on Java (1960–2010). *Singapore Journal of Tropical Geography*, 46(3), 371–385. <https://doi.org/10.1111/sjtg.70025>
- Di Gropello, E., Kruse, A., & Tandon, P. (2011). *Skills for the labor market in Indonesia: Trends in demand, gaps, and supply*. World Bank. <https://doi.org/10.1596/978-0-8213-8614-9>
- Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a), 427–431. <https://doi.org/10.1080/01621459.1979.10482531>
- Fergusson, R., & Yeates, N. (2021). *Global youth unemployment: History, governance and policy*. Edward Elgar Publishing. <https://doi.org/10.4337/9781789900422>
- Fung, Y. V., & Nga, J. L. H. (2022). An investigation of economic growth, youth unemployment and inflation in ASEAN countries. *International Journal of Academic Research in Business and Social Sciences*, 12(1), 1731–1755. <https://doi.org/10.6007/IJARBS/v12-i1/12023>

- Godfrey, L. G. (1978). Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables. *Econometrica*, 46(6), 1293–1301. <https://doi.org/10.2307/1913829>
- Hailu Demeke, Y. (2022). Youth unemployment and political instability: Evidence from IGAD member countries. *Cogent Economics & Finance*, 10(1), 2079211. <https://doi.org/10.1080/23322039.2022.2079211>
- Husin, N. A., Rasli, S., Kumar, M. S. G., & Suppiah, G. (2021). Unemployment crisis among fresh graduates. *American International Journal of Social Science Research*, 10(1), 1–14. <https://doi.org/10.46281/aijssr.v10i1.1461>
- Huynh, H. H., & Vo, D. H. (2023). The effects of migration on unemployment: New evidence from the Asian countries. *Sustainability*, 15(14), 11385. <https://doi.org/10.3390/su151411385>
- International Labour Organization. (2024). *Global employment trends for youth 2024: Decent work, brighter futures*. ILO. <https://doi.org/10.54394/ZUUI5430>
- Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, 6(3), 255–259. [https://doi.org/10.1016/0165-1765\(80\)90024-5](https://doi.org/10.1016/0165-1765(80)90024-5)
- Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer. <https://doi.org/10.1007/978-3-540-27752-1>
- Michael, E., & Geetha, C. (2020). Macroeconomic factors that affecting youth unemployment in Malaysia. *Malaysian Journal of Business and Economics (MJBE)*, 7(2), 181–205. <https://doi.org/10.51200/mjbe.vi.2890>
- Muhyiddin, M. (2023). *Indonesia employment outlook 2024: Strengthening employment policy post COVID-19 pandemic and government transition*. Pusat Pengembangan Kebijakan Ketenagakerjaan, Kementerian Ketenagakerjaan Republik Indonesia. <https://doi.org/10.47198/outlook.2024>
- Nainggolan, F. A., & Budiman, M. A. (2024). Analisis potensi dan resiko bonus demografi terhadap pertumbuhan ekonomi di Indonesia. *Jurnal Pendidikan Ekonomi Indonesia*, 6(2), 95–104. <https://doi.org/10.17509/jpei.v6i2.75220>
- Narayan, P. K. (2005). The saving and investment nexus for China: Evidence from cointegration tests. *Applied Economics*, 37(17), 1979–1990. <https://doi.org/10.1080/00036840500278103>
- Natsiopoulou, K., & Tzeremes, N. G. (2022). ARDL bounds test for cointegration: Replicating the Pesaran et al. (2001) results for the UK earnings equation using R. *Journal of Applied Econometrics*, 37(5), 1079–1090. <https://doi.org/10.1002/jae.2919>
- Nkoro, E., & Uko, A. K. (2016). Autoregressive distributed lag (ARDL) cointegration technique: Application and interpretation. *Journal of Statistical and Econometric Methods*, 5(4), 63–91. <https://www.scienpress.com/download.asp?ID=1966>

- Papík, M., Mihaľová, P., & Papíková, L. (2022). Determinants of youth unemployment rate: Case of Slovakia. *Equilibrium. Quarterly Journal of Economics and Economic Policy*, 17(2), 391–414. <https://doi.org/10.24136/eq.2022.013>
- Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289–326. <https://doi.org/10.1002/jae.616>
- Selod, H., & Shilpi, F. (2021). Rural-urban migration in developing countries: Lessons from the literature. *Regional Science and Urban Economics*, 91, 103713. <https://doi.org/10.1016/j.regsciurbeco.2021.103713>
- Sitompul, N. K., & Athoillah, M. (2023). Indonesia's youth unemployment rate: Evidence from Sakernas data. *Journal of International Conference Proceedings*, 6(1), 347–357. <https://doi.org/10.32535/jicp.v6i1.2346>
- UNCTAD. (2024). *Trade and development report 2024: Rethinking development in the age of discontent*. United Nations.
- Wulandari, D., Utomo, S. H., Narmaditya, B. S., & Kamaludin, M. (2019). Nexus between inflation and unemployment: Evidence from Indonesia. *The Journal of Asian Finance, Economics and Business*, 6(2), 269–275. <https://doi.org/10.13106/jafeb.2019.vol6.no2.269>
- Yanindah, A. (2022). An insight into youth unemployment in Indonesia. *Proceedings of the International Conference on Data Science and Official Statistics*, 2021(1), 666–682. <https://doi.org/10.34123/icdsos.v2021i1.229>
- Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the Great Crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business & Economic Statistics*, 10(3), 251–270. <https://doi.org/10.1080/07350015.1992.10509904>