

Article

The Impact of Foreign Direct Investment on Unemployment in Developing Countries: Evidence from Panel ARDL Models

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Abstract

This study examines the impact of Foreign Direct Investment (FDI) on unemployment in 90 developing countries over the period 2000 to 2024. Two assumptions of the FDI impact on unemployment are investigated: the positive externality effects, and the negative effect of both crowding-out of domestic firms and the displacement of local workers. The Panel Autoregressive Distributed Lag ARDL approaches are employed to estimate the long-run and short-run coefficients in three models. The results indicate that all FDI types are associated with unemployment reduction in developing countries. The FDI flow has a high negative association with unemployment, indicating the presence of a strong positive externality of the FDI flow on host developing countries that contributes effectively to reducing unemployment. Moreover, the FDI stock per capita has a highly significant negative relationship with unemployment, consistency with the absence of dominant crowding-out and labor-displacement effects in the long run; therefore, the macroeconomic policies that attract FDI, productivity development of labor, and improvement of management methods are highly recommended in developing economies.

Keywords: FDI; unemployment; developing countries; macroeconomics; panel ARDL; Pooled Mean Group; crowding-out effect-displacement of labor

1. Introduction

Foreign Direct Investment (FDI) is considered an important source for capital, technology, job creation, and organizational and managerial know-how in developing countries (UNCTAD, 1994). However, empirical studies yield divergent results. Although many studies find that FDI contributes to reducing unemployment in specific groups of developing countries, others demonstrate that FDI can increase unemployment. Mkombe et al. (2021) clarified that the foreign investment may lead to the layoff of many workers, especially those who are unqualified, by acquiring and restructuring local firms, substituting workers with machines, or competing with local producers and crowding them out of the market. Saurav et al. (2020) suggest, based on their survey of empirical studies, that FDI affects unemployment through three types of firms: firms owned by foreigners, firms that are suppliers to foreign firms, and firms that compete with foreign firms. Foreign-owned firms can increase employment opportunities by gaining access to new markets and increasing exports; however, they may also increase unemployment by substituting capital-intensive technology in place of labor-intensive technology. Suppliers for foreign firms can increase employment by producing goods and services that foreign firms demand. However, these firms should improve the quality of their goods and services and decrease their costs. This may lead to adopting capital-intensive techniques and a decrease in their need for



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workers. Competing firms increase unemployment due to a decline in their market share. However, some of these firms may increase their market share by benefiting from the technical and managerial expertise of the skilled workers who transfer from the foreign firms. Other studies argue that the problems related to statistical characteristics of the data, sample countries, and estimation methods may lead to biased estimates of FDI effect on unemployment. [Hakim et al. \(2023\)](#) used meta-regression analysis for more than 60 studies that assessed the impact of FDI on unemployment. They indicated that many studies yield bias estimators resulting from the endogeneity and heterogeneity problem.

Although the current empirical studies present valuable insights, they are still limited to a narrow geographical context, as they focus on specific regions like ASEAN, MENA, or selected countries from Sub-Saharan Africa. This fragmentation, localization, and the contradictory results fail to yield a generalizable conclusion about the effect of FDI on unemployment in developing countries. This study differentiates itself from previous empirical literature in two ways. First, instead of depending on a regional lens, it relies on a global perspective by using a comprehensive sample including 90 middle- and low-income countries over 25 years (2000–2024). This extensive geographical coverage allows for eliminating the bias of localized selection and enables us to capture the macroeconomic regularities across various institutional contexts. Second, unlike previous studies that address FDI as a homogeneous variable, this paper distinguishes between two dimensions of FDI: the flow, which captures the short-run financial input (FDI flow), and the stock, which reflects the accumulation of fixed capital assets (FDI stock per capita). This dual approach enables us to analyze both the transitory and the structural effects of FDI on the labor market.

This study examines the impact of FDI on unemployment in 90 developing countries over the period from 2000 to 2024. Two assumptions of the FDI impact on unemployment are investigated in this study. The first assumption is the positive externality effects, as the study assesses this effect using inward FDI flow value, assuming that an increase in the inward FDI flow value leads to a decrease in unemployment. The second assumption is the negative effect of both crowding-out of domestic firms and the displacement of local workers. Following [Acemoglu \(2025\)](#) and [Aitken and Harrison \(1999\)](#), an increase in the foreign capital leads to a decrease in labor demand. This is due to two effects: the automation-displacement effect, as an increase in capital–labor ratio leads to an increase in automation, and consequently, a decrease in labor demand; and the market-stealing effect, as an increase in foreign capital shares in the domestic market leads to a decrease in local firms' productivity, and consequently, a decrease in labor demand. This study aims to empirically investigate the theoretical debate related to the impact of FDI on labor demand within a comprehensive framework. Two theoretical arguments are examined: the positive externality effects of FDI in developing economies versus structural crowding-out mechanisms, namely [Acemoglu's \(2025\)](#) automation-displacement effect and [Aitken and Harrison's \(1999\)](#) market-stealing effect. To assess these different theoretical arguments, two FDI indicators are used. Inward FDI flow, which measures the current movements of foreign capital in the market, is used to assess overall FDI effects in the economy (externality effect). On the other hand, FDI stock per capita, which captures the foreign capital–labor ratio, is used to examine the relationship between foreign capital and human capital, whether they are complementary or competitive, based on the effect of foreign capital on labor demand.

The overall objectives of the study are to examine the effect of FDI on unemployment across the largest possible sample of developing countries, to investigate the theoretical arguments of divergent effects, and to resolve the conflicting findings of previous empirical studies.

The questions of the research are as follows: (1) To what extent does the positive externality effect of FDI mitigate unemployment in developing countries? (2) Does foreign

capital crowd out domestic labor under Acemoglu's automation-displacement effect and Aitken & Harrison's market-stealing effect? (3) Is the effect of FDI on unemployment transitory or structural?

The research hypotheses stem from the theoretical literature; specifically, the first hypothesis derives from positive externality effects, predicting that FDI flow reduces unemployment by raising labor productivity and, consequently, labor demand. The second hypothesis tests whether an increase in the foreign capital–labor ratio leads to an increase in unemployment according to automation-displacement and market-stealing negative effects or whether it reduces unemployment based on the complementary relationship between foreign capital and domestic labor.

The remainder of the study is structured as follows: Section 2 briefly presents the theoretical framework of the expected FDI impact on unemployment. The empirical literature findings are reviewed in Section 3. The data and variables are detailed in Section 4. In Section 5, model specification and empirical results are reported. Finally, the conclusions and policy recommendations are discussed in Section 6.

2. Theoretical Framework

The impact of FDI on unemployment is related to the relationship between FDI and labor productivity. The theoretical economic literature is characterized by diverse debates regarding the prevailing directional effect of FDI on the host countries. This part of the paper presents four theoretical strands that can provide a holistic framework for the role of FDI in the domestic economies of developing countries.

Diminishing returns effect: Within traditional neoclassical growth theory, characterized by diminishing returns to capital and exogenous technological change, FDI represents a transfer of capital from countries with an abundance of capital to others with a scarcity of capital. Consequently, in countries with the same technology and preferences, FDI has no effect on the growth rate and productivity in the long run (Fan, 2003).

Externality effects: Many economists argue that FDI has positive externalities for domestic firms in the host countries, as foreign firms bring superior technology, managerial experience, and other intangible assets to developing countries (Ali et al., 2023). Liu (2008) suggests that FDI affects both productivity level and productivity growth rate. In the short run, FDI potentially has a negative effect on the productivity level as a result of the diversion of resources from pure production process as learning expenditures on new technologies and managerial skills from foreign firms; however, in the long run this new learning can promote the productivity growth rate of domestic firms.

Market-stealing effect: Aitken and Harrison (1999) have suggested that there are negative spillover effects from foreign firms to domestic firms that make the overall positive effect of FDI on domestic productivity smaller. They interpret this negative effect as a market-stealing effect. Multinational firms tend to enter the local market with intangible assets such as technological know-how, managerial skills, and reputation. These assets enable them to increase their productivity and reduce their average cost of production. In the short run, multinational firms typically enter into competition with local firms, forcing them to reduce their output in response to the entry of lower-cost competitors.

Automation effect: Acemoglu and Restrepo (2019) investigated the effect of automation on labor demand. They suggested that automation can affect labor demand in two opposite directions. The first direction is represented by the positive effect of automation on labor demand resulting from increased value added. This leads to an increase in labor demand from non-automated tasks. However, automation tends to displace labor with machines, causing a decrease in labor demand. The net effect of automation on labor demand will be positive or negative depending on which is greater: the positive productivity effect

or the negative displacement effect. [Acemoglu \(2025\)](#) related automation to capital stock, arguing that a high capital stock will increase automation. Consequently, the impact of the accumulation of capital stock on labor demand is potentially negative if the capital stock is directed toward advanced automation activities with a negative net effect on labor demand.

Based on these four theoretical strands, a distinction can be made between the impact of FDI on productivity in the economy as a whole and its impact on the productivity of domestic firms. The expected impact at the macroeconomic level is positive, as foreign firms incentivize workers, managers, and other specialists to improve the skills required to be qualified for hiring by foreign firms. In addition, they encourage domestic firms to improve the quality of their products to compete with those of foreign firms or provide them with intermediate goods and services. Conversely, foreign firms can crowd out domestic firms in terms of market share and decrease the demand for domestic products by producing better and cheaper goods and services. Moreover, one of the potential effects of foreign capital is enhancing automation that leads to displacing labor with machines.

The impact of FDI on unemployment is consistent with its impact on productivity, as FDI can improve the demand for labor in the economy as a whole, especially highly qualified workers; however, competition from foreign firms can decrease the domestic firms' labor demand. This paper explores the two-directional impact of FDI on unemployment, as will be discussed in Section 5.

3. Empirical Literature Review

The empirical studies regarding the impact of FDI on unemployment remain highly fragmented. These inconsistent findings result from methodological heterogeneity, indicator composition, and data-scale limitations rather than regional structural patterns ([Hakim et al., 2023](#)). To clarify these dynamics, this section presents a critical analysis of previous studies according to their main theoretical perspectives, discussing how the variation in research design impacts empirical findings.

3.1. Driving Labor Demand and the Positive Externality Perspective

Based on endogenous growth theory, the dominant strand assumes that FDI inflow injects technological transfer, managerial experts, and other intangible assets into host economies, thereby raising productivity and increasing labor demand. The perspective is supported by a lot of empirical evidence. For instance, [Vacaflares \(2011\)](#) employs a dynamic system GMM across 12 Latin American countries for the period 1980–2006, showing a significant positive effect on job creation. This finding is confirmed by [Onanuga and Onanuga \(2018\)](#) using the panel OLS method across 23 emerging economies for the period 2000–2015, indicating that FDI contributes to reducing unemployment in both the current and subsequent periods, as the long-run equilibrium relationship becomes clearer when the model allows for dynamic adjustment. [Alalawneh and Nessa \(2020\)](#) employ a panel VAR approach to six MENA economies over the period 1998 to 2018, as well as fixed-effects and random-effects methods, showing a distinct temporal variation where FDI reduces unemployment in the long run, but in the short run remains causally neutral. Similarly, [Ogbonnaya and Ebubechima \(2025\)](#) utilized non-linear Panel ARDL frameworks to capture asymmetric transmission channels in 25 Sub-Saharan African countries for the period 2000–2021, demonstrating that positive shocks to FDI systematically reduce aggregate unemployment. Other work shows that this positive effect relies heavily on model specification and variable sub-components. Employing one-way analysis of variance (ANOVA), [Kukaj et al. \(2022\)](#) demonstrate the importance of FDI in mitigating unemployment for six Balkan countries. [H. T. Nguyen et al. \(2024\)](#) contrast pooled OLS, the fixed-effects model, the random-effects model, and GMM estimator across 29 Asia-Pacific countries,

demonstrating a significant positive association with employment. Crucially, [Jovanović and Weiss \(2022\)](#) introduce a sectoral dimension across 17 European developing economies, revealing that driving labor demand is exclusive to secondary-sector FDI and manifests with a two-year lag, especially when the foreign companies start to reinvest their profits.

3.2. *The Domestic Crowding-Out and Automation-Displacement Paradox*

In contrast, a substantial body of the empirical literature rejects the positive externality assumption, suggesting that FDI may lead to labor displacement through automation or by crowding out vulnerable local firms. Works within this framework employ estimation methods that accommodate structural breaks or cross-sectional dependencies. For instance, [Bayar and Sasmaz \(2017\)](#) utilized the Augmented Mean Group (AMG) estimator across 21 emerging economies, showing that FDI increases unemployment due to the domestic crowding-out effect. Similarly, [Dhanoon et al. \(2020\)](#) employ the Seemingly Unrelated Regression (SUR) technique on a panel of MENA countries, indicating a net increase in unemployment. This finding is confirmed by [Ikani \(2024\)](#) via Panel ARDL approach for 16 West African states, revealing that long-run capital injection worsens host country unemployment, while neutral in the short run.

3.3. *The Statistical Neutrality Strand*

A third strand of empirical studies reports a statistically insignificant nexus between FDI inflows and domestic labor demand, noting that the choice of econometric model heavily affects findings. For instance, [Mkombe et al. \(2021\)](#) compare fixed-effect, FGLS-Parks, and PCSE estimators across six Southern African countries, showing no statistically significant effect on youth unemployment. Similarly, [Othman et al. \(2024\)](#) employ a Panel ARDL model across five ASEAN emerging economies, confirming the FDI inflows neutrality regarding youth unemployment. In the same direction [A. T. Nguyen \(2022\)](#) utilizes a traditional VAR model across five South Asian nations, finding no significant effect on unemployment. However, the Granger Causality test suggests that FDI causes unemployment in the short run.

3.4. *FDI Stock vs. FDI Flow*

The final and most recent strand of the literature utilizes FDI stock indicators to measure the structural effect of FDI. [Irshad and Qayed \(2022\)](#) evaluate the FDI effect on unemployment in five BRICS and nine ASEAN economies producing contradictory outcomes within the exact same sample using different estimates. Their Panel-Corrected Standard Errors (PCSE) specification reveals that FDI stock increases unemployment—validating [Acemoglu's \(2025\)](#) automation-displacement and [Aitken and Harrison's \(1999\)](#) market-stealing assumption—while using Feasible Generalized Least Squares (FGLS) specification yields an opposite outcome. Conversely, [Kaan and Christina \(2026\)](#) apply Panel ARDL across OECD economies, showing that inward and outward FDI stock significantly reduce unemployment, contradicting the automation-displacement theorem.

While the preceding studies reveal high divergence in their findings, the structural reasons behind these contradictions are still largely unaddressed. Prior research suffers from severe methodological limitations in addressing endogeneity and heterogeneity problems, resulting in biased estimators ([Hakim et al., 2023](#)). In addition, these studies were limited to a narrow geographic scope, focusing only on specific country groups or individual nations. The most important issue is that the existing evidence remains inconclusive since prior studies fail to distinguish between external and structural effects of foreign capital on the host labor market. Consequently, a comprehensive reassessment is required to address these contradictory findings of previous empirical studies.

4. Data and Variables Descriptions

4.1. Data Descriptions

The data used in this study covers 90 developing countries. Selection was based on data availability to form a balanced panel. The study spans the period 2000 to 2024 to include the most recent available data with a moderate length of span, avoiding the problems of structural change and high economic volatility that appear with long period data, causing breaks in parameters of the panel data model (Okui & Wang, 2021; Ditzen & Karavias, 2025). All selected nations are classified as middle- or low-income economies, excluding any high-income countries (see Appendix A, Table A1 for the country list). Table 1 presents the descriptive statistics of raw data. The lowest rate of unemployment is around 0.12% in Cambodia in 2019, while the highest rate is 34% in South Africa in 2021 through the COVID-19 period. The mean value of unemployment across countries and years is 7.20%. The highest FDI flow value is about 189,000 million US\$ in China in 2022. Conversely, the lowest FDI flow value is −7400 million US\$ in Angola in 2017. The average value of FDI flow is 3450 million US\$. The FDI stock per capita records its highest value of 15,944.540 US\$ in Cabo Verde in 2017, while the lowest value is 0.935 US\$ in Guinea-Bissau in 2006. The mean value of FDI stock per capita is about 1312 US\$. The highest value of real GDP per capita is 39,995 PPP (constant 2021 international \$) in Equatorial Guinea in 2008; the lowest value is about 712 PPP in Mozambique in 2000, and the average value is about 8634 PPP. The highest value for openness is 192% in Malaysia in 2000, while the lowest value is 12% in Nigeria in 2020, and the mean value is 57%. The highest value of inflation is 550% in Congo, Dem. Rep. in 2000, while the lowest value is −8% in Ethiopia in 2001, and the mean value is 8%. The high standard deviation value of most variables indicates a high volatility in raw variable values due to some extreme values. To reduce the effect of the extreme values and high volatility, the study transforms the data into logarithm formulation and normalizes those variables with negative minimum values, as shown in the next section.

Table 1. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
UEM	2250	7.20%	5.71%	0.12%	34.01%
FDIF	2250	3,450,000,000	13,400,000,000	−7,400,000,000	189,000,000,000
FDIS	2250	1311.954	1881.433	0.935	15,944.540
GDPC	2250	8634	7051	712	39,995
OPN	2250	57%	28%	12%	192%
INF	2250	8%	19%	−8%	550%

Source: Author's compilation from Stata 17.

4.2. Variables Descriptions

Based on the theoretical framework related to the channels of FDI effects on unemployment, this study introduces a distinction between the appropriate indicators for each potential channel. Within the theoretical framework of the study, there are positive external-ity channels, such as technology transfer and managerial expertise, and, at least theoretically, negative effect channels, such as crowding-out domestic firms and labor-displacement by machines. It is illogical to combine two contradictory channels in one indicator. Therefore, the study utilizes FDI indicators for each channel. FDI inflow is appropriate to proxy foreign capital injections, technology transfer, and other intangible assets, while FDI stock per capita is an indirect proxy for the accumulated foreign capital through which labor displacement by machines and the expansion of foreign companies' market share may operate, rather than a direct measure of automation intensity or competitive displacement.

To examine the impact of FDI on unemployment, this study employs the following functional form:

$$UEM_{it} = f(FDIF_{it}, FDIS_{it}, GDPC_{it}, OPN_{it}, INF_{it}) \quad (1)$$

where *UEM* represents the unemployment rate.

FDIF represents inward foreign direct investment flow—this indicator is commonly used in the empirical literature to assess the externality effects of FDI inflow; *FDIS* represents inward FDI stock per capita, an indirect proxy for the foreign capital–labor ratio, through which the potential automation-displacement effect of Acemoglu (2025) and the market-stealing effect of Aitken and Harrison (1999) are evaluated; and *GDPC*, *OPN*, *INF* represent real GDP per capita, openness, and inflation respectively. These variables follow the existing literature on the determinants of unemployment. Table 2 presents descriptions of the variables.

Table 2. Variables descriptions.

Variable	Definition	Theoretical Expected Sign	Data Source	Variable	Obs	Mean	Max
Dependent variable				UEM	2250	7.20%	34.01%
UEM	Total unemployment (% of total labor force) (modeled ILO estimate)	—	World Development indicators (WDIs)	FDIF	2250	3,450,000,000	189,000,000,000
Independent variables—key variables				FDIS	2250	1311.954	15,944.540
FDIF	Foreign direct investment flow (US\$ at current prices)	Externality effect (–)	UNCTADstat Data centre	GDPC	2250	8634	39,995
FDIS	Foreign direct investment stock per capita (US\$ at current prices)	Automation & market-stealing effects (+)	UNCTADstat Data centre	OPN	2250	57%	192%
Control variables				INF	2250	8%	550%
GDPC	GDP per capita, PPP (constant 2021 international \$)	Labor demand effect (–)	World Development Indicators (WDIs)				
OPN	Openness (sum of exports and imports of goods and services as a percentage of GDP)	Labor demand effect (–)	World Development Indicators (WDIs)				
INF	Headline consumer price inflation, annual	Labor demand effect (–)	A global database of inflation				

Source: Author’s elaboration based on UNCTAD (n.d.) and World Bank (n.d.-a, n.d.-b) data.

In the baseline linear specification, all variables are transformed into natural logarithms, and the values of *FDIF* and *INF* are normalized to the (0, 1) interval prior to this transformation to avoid undefined values.

The normalized values are calculated according to the following UNDP normalized method (UNDP, 2025):

$$\text{normalized value} = \frac{\text{actual value} - \text{minimum value}}{\text{maximum value} - \text{minimum value}}$$

The following is the baseline model:

$$\ln UEM_{it} = \beta_1 + \beta_{11} \ln FDIF_{it} + \beta_{12} \ln FDIS_{it} + \beta_{13} \ln GDPC_{it} + \beta_{14} \ln OPN_{it} + \beta_{15} \ln INF_{it} + u_{1it} \quad (2)$$

where β_1 – β_{15} are parameters, i denotes the cross-sectional unit, and t denotes the time period. Two other models are used to confirm the effect of FDI on unemployment. The first one excludes the FDIS variable, and the second one excludes the FDIF variable, as shown in the following equations.

$$\ln UEM_{it} = \beta_2 + \beta_{21} \ln FDIF_{it} + \beta_{22} \ln GDPC_{it} + \beta_{23} \ln OPN_{it} + \beta_{24} \ln INF_{it} + u_{2it} \quad (3)$$

$$\ln UEM_{it} = \beta_3 + \beta_{31} \ln FDIS_{it} + \beta_{32} \ln GDPC_{it} + \beta_{33} \ln OPN_{it} + \beta_{34} \ln INF_{it} + u_{3it} \quad (4)$$

4.3. Correlation Analysis

The correlation matrix presented in Table 3 demonstrates the presence of linear associations among the variables of the study. Most correlation coefficients are significantly different from zero. The highest coefficient of correlation (0.732) is between GDP per capita and FDI stock. All coefficients are less than 0.8; this indicates that there is no problematic multicollinearity among the variables of the model. Most correlation coefficients are positive. This is due to the fact that correlation analysis does not account for the time and individual dimensions of the data.

Table 3. Correlation matrix (*p*-values in italics).

	lnUEM	lnFDIF	lnFDIS	lnGDPC	lnOPN	lnINF
lnUEM	1.000					
lnFDIF	−0.021 (0.309)	1.000				
lnFDIS	0.225 (0.000)	0.121 (0.000)	1.000			
lnGDPC	0.340 (0.000)	0.219 (0.000)	0.732 (0.000)	1.000		
lnOPN	0.066 (0.002)	−0.052 (0.013)	0.448 (0.000)	0.312 (0.000)	1.000	
lnINF	0.074 (0.001)	−0.033 (0.120)	−0.100 (0.000)	−0.027 (0.197)	−0.086 (0.000)	1.000

p-values are in parentheses. Source: Author's compilation from Stata 17.

5. Empirical Method

5.1. Preliminary Tests

5.1.1. Cross-Sectional Dependence Test

The existence of cross-sectional dependence in the error terms in the panel data model makes the estimators of conventional panel data estimation methods such as fixed or random effects inconsistent and leads to misleading inference. However, if the cross-sectional dependence of errors is weak, the consequence for the consistency of conventional panel estimation methods can be neglected. Therefore, the test of cross-sectional correlation

of panel residuals is an important issue (Chudik & Pesaran, 2013). M. Pesaran (2015) developed the following test for weak cross-sectional dependence:

$$CD = \left[\frac{TN(N-1)}{2} \right]^{1/2} \hat{\rho}_N \quad (5)$$

where

$$\hat{\rho}_N = \frac{2}{N(N-1)} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \quad (6)$$

By rearranging the two equations,

$$CD = \sqrt{\frac{2T}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^N \hat{\rho}_{ij} \quad (7)$$

where $\hat{\rho}_{ij}$ is the sample estimate of pairwise correlation between the i -th and j -th units. The tests for weak cross-sectional dependence of the three baseline models (Equations (2)–(4)) are represented in Table 4. All results accept the null hypothesis of weak cross-sectional dependence. This outcome suggests that the cross-sectional dependence between the error terms of countries can be neglected, and the impact of global shocks on unemployment across countries has no significant effects. Under this outcome of the CD test, the first-generation cointegration test and panel estimation methods can be justified.

Table 4. M. Pesaran (2015) test for weak cross-sectional dependence. H_0 : errors are weakly cross-sectionally dependent.

Models	CD	<i>p</i> -Value
Model (1) (Equation (2))	−0.740	0.459
Model (2) (Equation (3))	−0.642	0.521
Model (3) (Equation (4))	−0.668	0.504

Source: Author's compilation from Stata 17.

5.1.2. Unit-Root Test

Two generations of unit-root tests are used to allow for coefficient heterogeneity across cross-sections: the Im–Pesaran–Shin (IPS) test (without cross-sectional dependency), and the Pesaran panel unit-root test in the presence of cross-section dependence (CIPS). Table 5 presents the results of the two tests with and without trend, evaluated at both levels and first differences. The results show that all variables are stationary at the level or after first differencing. This justifies the employment of Panel ARDL to estimate the long-run and short-run effects of FDI on unemployment.

Table 5. Unit-root test results.

Variables	Level: With Constant	Level: With Constant & Trend	1st Diff.: With Constant	1st Diff.: With Constant & Trend
Im–Pesaran–Shin (IPS)				
lnUEM	−3.5303 ***	−2.5651 ***	−28.4629 ***	−24.1118 ***
lnFDIF	−6.1009 ***	−7.9924 ***	−42.5506 ***	−37.5519 ***
lnFDIS	−6.1677 ***	2.862	−24.0247 ***	−22.8683 ***
lnGDPC	0.6284	0.9601	−26.2719 ***	−25.0315 ***
lnOPN	−4.0642 ***	−4.8198 ***	−36.2388 ***	−31.2036 ***
lnINF	−21.8111 ***	−17.5913 ***	−43.3388 ***	−38.59 ***

Table 5. Cont.

Variables	Level: With Constant	Level: With Constant & Trend	1st Diff.: With Constant	1st Diff.: With Constant & Trend
Pesaran panel unit-root test in the presence of cross-section dependence (CIPS)				
lnUEM	−1.617	−2.231	−3.956 ***	−4.170 ***
lnFDIF	−2.801 ***	−3.293 ***	−5.207 ***	−5.381 ***
lnFDIS	−2.444 ***	−2.966 ***	−4.131 ***	−4.323 ***
lnGDPC	−1.769	−2.473	−3.772 ***	−3.955 ***
lnOPN	−1.780	−2.590 *	−4.465 ***	−4.570 ***
lnINF	−3.536 ***	−3.887 ***	−5.368 ***	−5.378 ***

* $p < 0.1$, *** $p < 0.01$. Source: Author's compilation from Stata 17.

5.1.3. Pedroni Cointegration Test

This study employs the Pedroni cointegration test, as it allows for heterogeneity in the cointegration vectors. The results of the Pedroni cointegration test presented in Table 6 show that the null hypothesis of no cointegration in the three models with trend, as well as in Model (1) without trend, is rejected at a 5% level of significance according to the t-statistics of the Modified Phillips–Perron and Augmented Dickey–Fuller tests. Meanwhile, in Models (2) and (3) without trend the null hypothesis of no cointegration is rejected at a 10% level of significance according to the same tests. These results suggest that there is evidence of an existing long-run cointegrating relationship in the three models according to at least two of the three Pedroni panel statistics.

Table 6. Pedroni test for cointegration. H_0 : no cointegration. H_a : all panels are cointegrated.

	M1: Trend	M1: No Trend	M2: Trend	M2: No Trend	M3: Trend	M3: No Trend
Modified Phillips–Perron t	10.043 ***	8.612 ***	8.831 ***	7.199 ***	8.571 ***	7.465 ***
Phillips–Perron t	−1.057 n.s.	−0.592 n.s.	−0.429 n.s.	−0.682 n.s.	−0.912 n.s.	0.234 n.s.
Augmented Dickey–Fuller t	−4.316 ***	−2.748 ***	−1.793 **	−1.62 *	−4.076 ***	−1.34 *

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; n.s. = not significant. Source: Author's compilation from Stata.

5.1.4. Multicollinearity Test

This study employs the Variance Inflation Factor (VIF) test for multicollinearity. Table 7 presents the VIF test results, which reveal that all VIF values are less than 5, indicating an absence of multicollinearity.

Table 7. Variance Inflation Factor (VIF) results.

Variable	VIF	1/VIF
lnOPN	2.46	0.406816
lnGDPC	2.25	0.444715
lnFDIS	1.27	0.786050
lnFDIF	1.07	0.934513
lnINF	1.02	0.981965
Mean VIF	1.61	

Source: Author's compilation from Stata 17.

5.2. Estimation Method

Model Specification

To overcome the limitations identified in the previous empirical work, this study uses a broad sample of 90 developing countries over a 25-year period. This extensive dataset produces more robust results that can be generalized, on average, across diverse developing economies, conditional on the long-run homogeneity restriction supported by the Hausman test. Statistically, employing the Pooled Mean Group (PMG) method for estimating the ARDL approach allows this study to capture the heterogeneous short-run dynamics unique to each individual nation, while simultaneously estimating the common long-run effects across the entire panel. The validity of this long-run homogeneity assumption is verified empirically using the Hausman specification test (M. H. Pesaran et al., 1998). Accordingly, substantial differences in institutional and structural aspects across countries are absorbed mainly by country-specific short-run dynamics and intercepts. However, if the heterogeneity persists in the long run, the sample can be divided into subsamples according to regions, income per capita, or other criteria. Nonetheless, each subsample must undergo a comprehensive econometric analysis; moreover, the same analytical approach often cannot be applied uniformly across all subsamples due to the divergence of their statistical properties post-fragmentation. Rather than segmenting the sample, we compare our results with the findings of other studies examining the relationship between FDI and unemployment in specific regions, income groups, or other specialized cohorts. Accordingly, the estimated long-run coefficients should be interpreted as average equilibrium relationships across the panel rather than country-specific effects, and their applicability to any individual country remains conditional on structural characteristics. Furthermore, our empirical strategy explicitly distinguishes between the external effects and structural dimensions of foreign investment by deploying two distinct FDI indicators. We utilize inward FDI flow to isolate transitory external effects, such as immediate technology transfer and liquidity injections. Conversely, we incorporate inward FDI stock per capita to test the potential long-run structural negative effects associated with the crowding out of domestic labor via automation-displacement and market-stealing mechanisms.

The PMG approach is used to estimate both long-run and short-run effects of the FDI variables and control variables on unemployment in the three baseline models. In this approach, the short-run coefficients, intercept, and error terms differ across countries, while the long-run coefficients are restricted to be the same (M. H. Pesaran et al., 1998). The Panel ARDL model with lags orders ($p, q_1, q_2, q_3, q_4, q_5$) can be presented as follows:

$$\begin{aligned} \Delta \ln UEM_{it,1} = & \phi_{i1}(\ln UEM_{it-1} - \theta_{01} - \theta_{11} \ln FDI_{it} - \theta_{12} \ln FDIS_{it} - \\ & \theta_{13} \ln GDPC_{it} - \theta_{14} \ln OPN_{it} - \theta_{15} \ln INF_{it}) + \sum_{j=1}^{p_1-1} \lambda_{ij1} \Delta \ln UEM_{it-j} + \\ & \sum_{j=0}^{q_{11}-1} \gamma_{ij11} \Delta \ln FDI_{it-j} + \sum_{j=0}^{q_{12}-1} \gamma_{ij12} \Delta \ln FDIS_{it-j} + \\ & \sum_{j=0}^{q_{13}-1} \gamma_{ij13} \Delta \ln GDPC_{it-j} + \sum_{j=0}^{q_{14}-1} \gamma_{ij14} \Delta \ln OPN_{it-j} + \\ & \sum_{j=0}^{q_{15}-1} \gamma_{ij15} \Delta \ln INF_{it-j} + \epsilon_{it1} \end{aligned} \quad (8)$$

where i and t denote the cross-section unit and the time period, respectively; j represents the lag sequence; the subscript 1 indexes the first baseline model; and the subsequent numerical identifiers 1 to 5 index the explanatory variables in the initial functional form (Equation (1)), respectively.

ϕ_{i1} is the error-correction term, $\theta_{01}, \theta_{11}, \dots, \theta_{15}$ are the long-run parameters, $\gamma_{ij11}, \dots, \gamma_{ij15}$ are the short-run parameters, $p-1, q_{11}-1, \dots, q_{15}-1$ are the lengths of lags for the first differenced regressors, and ϵ_{it1} is the error term.

Following the first baseline model, the second and third baseline models can be transformed into Panel ARDL models as follows:

$$\begin{aligned} \Delta \ln UEM_{it,2} = & \phi_{i2}(\ln UEM_{it-1} - \theta_{02} - \theta_{21} \ln FDI_{it} - \theta_{23} \ln GDPC_{it} - \theta_{24} \ln OPN_{it} - \\ & \theta_{25} \ln INF_{it}) + \sum_{j=1}^{p_2-1} \lambda_{ij2} \Delta \ln UEM_{it-j} + \sum_{j=0}^{q_{21}-1} \gamma_{ij21} \Delta \ln FDI_{it-j} + \\ & \sum_{j=0}^{q_{23}-1} \gamma_{ij23} \Delta \ln GDPC_{it-j} + \sum_{j=0}^{q_{24}-1} \gamma_{ij24} \Delta \ln OPN_{it-j} + \sum_{j=0}^{q_{25}-1} \gamma_{ij25} \Delta \ln INF_{it-j} + \epsilon_{it2} \end{aligned} \quad (9)$$

$$\begin{aligned} \Delta \ln UEM_{it,3} = & \phi_{i3}(\ln UEM_{it-1} - \theta_{03} - \theta_{32} \ln FDIS_{it} - \theta_{33} \ln GDPC_{it} - \theta_{34} \ln OPN_{it} - \\ & \theta_{35} \ln INF_{it}) + \sum_{j=1}^{p_3-1} \lambda_{ij3} \Delta \ln UEM_{it-j} + \sum_{j=0}^{q_{32}-1} \gamma_{ij32} \Delta \ln FDIS_{it-j} + \\ & \sum_{j=0}^{q_{33}-1} \gamma_{ij33} \Delta \ln GDPC_{it-j} + \sum_{j=0}^{q_{34}-1} \gamma_{ij34} \Delta \ln OPN_{it-j} + \sum_{j=0}^{q_{35}-1} \gamma_{ij35} \Delta \ln INF_{it-j} + \epsilon_{it3} \end{aligned} \quad (10)$$

where the parameters represent the same coefficients in the model (8). To distinguish between the three baseline models, the model subscripts change to 2 and 3 respectively.

A potential concern in estimating Equations (8)–(10) is the endogeneity between FDI and unemployment, arising from reverse causality—as foreign investors direct their investment toward markets with lower unemployment, indicating a high quality of labor market performance and macroeconomic stability—and from omitted variables that simultaneously affect both FDI and unemployment, such as institutional quality and political stability. The Panel ARDL model mitigates this bias by introducing lags for both dependent and independent variables, where extending the lag periods to an appropriate length can correct the reverse causality associated with independent variables and the autocorrelation among errors.

5.3. Results and Discussion

5.3.1. Regression Results and Discussion

The PMG estimators' results are presented in Table 8. All variables are transformed into logarithmic form. The FDI flow and inflation variables are normalized to the (0, 1) interval prior to logarithmic transformation to prevent mathematical undefinedness. Therefore, the coefficients of these two variables do not reflect the exact elasticity value of the response of unemployment to the change in them. Their coefficients preserve the same signs of effect (positive/negative) and *p*-value of statistical significance as those of the original variables (before normalization). In Model (1), the long-run coefficient of the FDI flow variable reveals a highly statistically significant effect, indicating that a higher level of FDI flow is associated with a lower level of unemployment; this effect remains highly significant in Model (2) after excluding the FDI stock variable. These results align with the theoretical and empirical literature confirming the positive externality effect of FDI on host countries achieved by spillover technological progress, administrative expertise, and other intangible assets that increase productivity and raise labor demand (Ali et al., 2023; Liu, 2008).

Table 8. Panel ARDL estimators' results. Dependent variable: D.lnUEM.

Variables	M1 PMG	M1 MG	M2 PMG	M2 MG	M3 PMG	M3 MG
Long run						
lnFDIF	−6.448 *** (−4.55)	−1.952 (−0.02)	−7.000 *** (−4.57)	99.41 (0.86)		
lnFDIS	−0.0283 ** (−2.44)	0.214 * (1.87)			−0.214 *** (−8.85)	0.168 (1.48)
lnGDPC	−0.480 *** (−9.24)	−0.409 (−0.68)	−0.539 *** (−16.13)	1.363 (0.74)	−0.177 *** (−2.65)	−0.878 ** (−2.24)
lnOPN	−0.0525 * (−1.79)	−0.117 (−0.56)	−0.0766 ** (−2.95)	−0.931 (−0.86)	−0.0607 (−1.40)	−0.243 (−1.14)
lnINF	−0.516 *** (−4.03)	−1.287 ** (−2.34)	−0.244 ** (−2.28)	0.408 (0.19)	−0.311 ** (−2.00)	−0.883 * (−1.93)

Table 8. Cont.

Variables	M1 PMG	M1 MG	M2 PMG	M2 MG	M3 PMG	M3 MG
Short run						
ECT	−0.174 *** (−10.43)		−0.162 *** (−10.09)		−0.151 *** (−8.76)	
D.lnFDIF	−3.107 (−0.23)	−14.58 (−0.80)	3.916 (0.28)	−5.157 (−0.29)		
D.lnFDIS	0.0325 (0.47)	−0.00416 (−0.05)			0.0511 (1.14)	−0.00348 (−0.08)
D.lnGDPC	−1.295 *** (−5.74)	−1.077 *** (−5.00)	−1.299 *** (−6.79)	−1.251 *** (−5.63)	−1.299 *** (−6.83)	−1.000 *** (−4.67)
D.lnOPN	−0.0196 (−0.42)	−0.0420 (−0.77)	0.00603 (0.13)	−0.0237 (−0.46)	−0.0280 (−0.67)	−0.00755 (−0.14)
D.lnINF	−0.109 (−1.38)	0.0362 (0.30)	−0.119 (−1.62)	0.00542 (0.05)	−0.147 ** (−2.04)	−0.0231 (−0.20)
ec (MG)		−0.484 *** (−16.34)		−0.391 *** (−14.72)		−0.442 *** (−15.66)
_cons	−1.361 *** (−9.91)	10.20 (0.28)	−0.991 *** (−9.52)	13.65 (0.40)	−0.336 *** (−5.81)	0.323 (0.18)
Number of observations	2160	2160	2160	2160	2160	2160

t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's compilation from Stata 17.

Similarly, the coefficient of the FDI stock per capita variable has a highly significant effect on reducing unemployment in Model (1) while including the FDI flow variable, as a 1% increase in FDI stock per capita is associated with a 0.03% decrease in unemployment. When excluding the FDI flow variable in Model (3), the coefficient of FDI stock per capita remains highly statistically significant, indicating that a 1% increase in FDI stock per capita is associated with a 0.21% decrease in unemployment. This suggests that the FDI stock per capita has a robust contribution to reducing unemployment in developing countries. The coefficients of FDI stock per capita demonstrate the impact of the foreign capital–labor ratio on unemployment. The results suggest that an increase in the foreign capital–labor ratio contributes to reducing unemployment in developing countries. This outcome is consistent with the absence of dominant market-stealing (Aitken & Harrison, 1999) and automation-displacement (Acemoglu, 2025) effects at the aggregate level in the long run; that is, if these negative mechanisms operate, they are outweighed by the complementary relationship between accumulated foreign capital and domestic labor, as the accumulation of foreign physical assets expands production capacity and, consequently, labor demand.

Overall, both FDI indicators are associated with unemployment reduction in developing countries, as most of these countries are characterized by an investment shortage and high unemployment rates. Each indicator operates through its own channel: the flow by injecting capital and intangible assets that raise labor productivity, and the stock by expanding the productive capacity that absorbs surplus labor. Therefore, inward FDI incentivizes labor demand by financing new and existing businesses, increasing labor productivity, and generating more income that accelerates economic growth. However, in the short run, FDI flow and stock have no significant effects on unemployment. This suggests that workers need a period of time to meet the qualifications required by new job opportunities. Beyond the period needed by workers to improve their skills, this result can be attributed to the project preparation period before reaching the operational stage, the lag period between the announcement and realization of the investment, labor market rigidities that slow employment adjustment, the delay of technology diffusion to domestic firms, and training costs; indeed, Liu (2008) suggests that training expenditures may reduce productivity in the short term before enhancing it in the long term. This finding is consistent with previous

studies demonstrating an insignificant effect in the short-run, including Alalawneh and Nessa (2020) and Ikani (2024), and the two-year lags identified by Jovanović and Weiss (2022), which collectively support the long-term impact of FDI on unemployment.

Additionally, the results show that GDP per capita has a statistically significant effect on unemployment in both the long and short run in the three models. In the long run, the results show that a 1% increase in GDP per capita is associated with a 0.48%, 0.54%, and 0.18% decrease in unemployment in the three models respectively. Conversely, in the short run, a 1% increase in GDP per capita is associated with a larger contraction in unemployment of 1.3% in the three models. These results agree with the findings of CM et al. (2025), as economic growth drives industrial and service expansion, which generates many job opportunities in developing countries.

Moreover, the results show that openness contributes to reducing unemployment in the first and second models, as a 1% increase in openness leads to a 0.05% decrease in unemployment at the 10% level of significance in the long run in Model (1), and leads to a 0.08% decrease in unemployment at the 5% level of significance in the long run in Model (2). Numerous empirical studies (Gonese et al., 2023; Jain et al., 2025; CM et al., 2025) support this result across various developing countries, as trade openness contributes to an increase in labor demand by expanding global networks with international markets, reallocating resources toward more productive activities, and enhancing technological progress by increasing high-tech imports.

Furthermore, the coefficients of the inflation variable reveal a statistically significant effect on unemployment in the three models in the long run, and in the third model in the short run, indicating that a higher level of inflation is associated with a lower level of unemployment. These results are consistent with the preceding empirical study of CM et al. (2025); however, other studies find different results, demonstrating that the inflation rate contributes to increasing unemployment (Škare & Caporale, 2014).

The coefficients of the error correction term in the three models are highly statistically significant with negative signs, validating the presence of the long-run equilibrium relationships among the variables. The values of these coefficients demonstrate that around 17%, 16%, and 15% of disequilibrium are adjusted in each period in the three models, respectively, reflecting a relatively slow speed of adjustment back to the equilibrium relationship.

Finally, to ensure that PMG estimators, which are restricted to being homogeneous across countries in the long run, are efficient in the three models, the study estimates the Mean Group (MG) coefficients and compares the long-run coefficients of MG vs. PMG approaches using the Hausman test. The results presented in Table 9 reveal that there are no significant differences between the long-run coefficients of both MG and PMG approaches at the 5% level of significance in the three models, which justifies the choice of the PMG estimator as more efficient relative to that of the MG Panel ARDL approach.

Table 9. Hausman test results for MG vs. PMG models.

Model	χ^2 (df)	<i>p</i> -Value	Decision
M1	2.06 (4)	0.841	PMG preferred
M2	1.71 (4)	0.789	PMG preferred
M3	9.25 (4)	0.055	PMG preferred

Source: Author's compilation from Stata 17.

Based on these findings, our understanding of the FDI–unemployment relationship is improved in two respects. First, they demonstrate the importance of FDI in reducing unemployment across a wide sample of developing countries over the last 25 years. These crucial results resolve partially the divergence in the empirical literature, suggesting that

the conflicting results of previous studies are largely due to their sample limitation to a specific region or groups of countries. Second, the findings indicate that at the aggregate level, the negative effects predicted by the automation-displacement and market-stealing arguments are not supported in developing countries. This suggests that the negative effects of automation and market-stealing may be limited to specific fields of investment. However, the complementary relationship between foreign capital and domestic labor demand is dominant.

Accordingly, the results provide supportive evidence—within the limitations of observational analysis—for the feasibility of macroeconomic policies aimed at attracting FDI to reduce unemployment in developing economies in the long run.

5.3.2. Economic Interpretation

Economically, we can interpret the long-run coefficients in Table 8 as elasticities since the variables are in logarithmic form (except for the coefficient of FDI flow, which was normalized prior to logarithmic transformation, preserving its sign and significance but not the exact elasticity value). Nonetheless, we can calculate the elasticity at each value of FDI flow. For example, the elasticity at the sample mean can be derived as $(\text{Elasticity} = \beta \times [\text{FDIF}/(\text{FDIF} - \text{min})])$, which is equivalent to -2.05 and -2.23 in Models 1 and 2. Accordingly, a 10% increase in FDI flow is associated with a long-run reduction in unemployment of about 1.5 and 1.6 percentage points, respectively, at the sample mean.

The elasticities of FDI stock per capita in Models (1) and (3) are -0.028 and -0.214 , indicating that a 10% increase in FDI stock per capita is associated with a 0.3% and 2.1% decrease in unemployment in the long run, respectively. Evaluated at the sample mean of the unemployment rate (7.20%) and FDI stock per capita (1312 USD), a 130 USD increase in FDI stock per capita is associated with an approximate 0.02 and 0.15 percentage point long-run reduction in the unemployment rate.

For comparison, the elasticities of GDP per capita (-0.48 , -0.54 , and -0.18 in Models 1 to 3) imply that a 10% increase in income per capita reduces unemployment by about 0.35, 0.39, and 0.1 percentage points, respectively, at the sample mean. The elasticities of openness (-0.05 and -0.08 in Models 1 and 2) imply that a 10% increase in openness contributes to a reduction in unemployment of about 0.04 and 0.06 percentage points, respectively, at the sample mean. Finally, the elasticities of inflation (-0.52 , -0.24 , and -0.31 in Models 1 to 3) imply that a 10% increase in inflation is associated with a decrease in unemployment of about 0.4, 0.17, and 0.2 percentage points, respectively, at the sample mean. These magnitudes are meaningful economically, as the observed reductions are substantial relative to the sample mean of the unemployment rate of 7.20% and are achievable through realistic policy objectives; indeed, a 10% increase in FDI flow at the mean corresponds to approximately 345 million USD. Furthermore, these effects are cumulative and persistent in the long run, where the error correction coefficients reveal that roughly half of any disequilibrium is corrected within four to five years. The practical interpretation of these elasticities demonstrates that the FDI flow contributes the highest marginal effect in reducing unemployment compared to the remaining determinants; accordingly, macroeconomic policies designed to attract FDI constitute an important instrument for reducing unemployment in developing economies. Nonetheless, this elasticity is point-specific, indicating that the FDI flow returns are higher in countries that have already established a minimum threshold of FDI inflow. Furthermore, the smaller but stronger elasticity of FDI stock per capita indicates that the persistent accumulation and retention of foreign capital, through reinvesting profits and a stable investment environment, complements the attraction of new foreign capital. Finally, FDI attraction policies can be more efficient when combined with growth-enhancing and trade openness policies. In addition, policies aimed

at improving labor skills are necessary to reduce the adjustment period revealed by the insignificant short-run coefficients.

5.3.3. Robustness and Sensitivity Testing

To address the remaining endogeneity and to confirm the robustness of estimation results using the PMG approach, the study employs the two-step [Blundell and Bond \(1998\)](#) System Generalized Method of Moments (System GMM) estimator, which treats the FDI indicators as endogenous variables by using lags of their own level and of their differenced values as instruments, which are correlated with endogenous regressors, but uncorrelated with errors. To meet the stationarity condition of the variables included in the model, GDP per capita is replaced by its first differenced value. Table 10 reports the results of the System GMM estimator.

Table 10. System GMM results. Dependent variable: lnUEM.

Variables	(1)	(2)	(3)
L.lnUEM	0.920 *** (443.98)	0.926 *** (733.04)	0.915 *** (920.70)
lnFDIF	−0.599 *** (−5.51)	−1.040 *** (−5.71)	
lnFDIS	−0.00671 *** (−6.92)		−0.00971 *** (−12.74)
D.lnGDPC	−0.963 *** (−69.23)	−0.971 *** (−62.74)	−0.977 *** (−52.50)
lnOPN	−0.155 *** (−40.85)	−0.156 *** (−39.85)	−0.156 *** (−43.49)
lnINF	−0.164 *** (−12.31)	−0.167 *** (−10.44)	−0.156 *** (−8.87)
_cons	−1.917 *** (−11.34)	−2.362 *** (−9.28)	−1.325 *** (−11.15)
Number of observations	2160	2160	2160

t-statistics in parentheses. *** $p < 0.01$. Source: Author's compilation from Stata 17.

The consistency of signs and the significance of coefficients across the two approaches indicate that the estimated negative effect of FDI on unemployment is unlikely to be driven by reverse causality or omitted variables. Beyond the endogeneity concern addressed by the System GMM estimator, we examine the results' sensitivity to the omission of other determinants of unemployment by adding three additional variables to the baseline model, as reported in Table 11. These variables are population growth (PG) sourced from the World Bank (WDI) database, institutional quality (INS) and human capital (HC) sourced from the UNCTAD datacenter ([UNCTAD, n.d.](#)). The three variables were transformed into their logarithmic values. Population growth and institutional quality are stationary at level $I(0)$, while the human capital variable is stationary in first differences $I(1)$. This indicates that the FDI coefficients are robust to the inclusion of institutional quality, human capital, and demographic determinants. The coefficients of institutional quality and human capital are positive and significant, consistent with the puzzle of educated unemployment ([Girsberger & Méango, 2022](#)), and the paradox of the negative effect of working institutions on unemployment ([Vandenberg, 2010](#)). Meanwhile, GDP per capita and inflation lose their long-run significance in the augmented model, indicating the presence of high correlation with the augmented variables; this supports the reduced specification of the baseline models.

Table 11. Sensitivity analysis results.

	Coefficient	Std. Err.	z	p > z
ECT				
lnFDIF	−8.133242	1.078366	−7.54	0
lnFDIS	−0.0655431	0.0088755	−7.38	0
lnGDPC	−0.020069	0.0285341	−0.7	0.482
lnOPN	−0.0825069	0.0240926	−3.42	0.001
lnINF	0.1062682	0.1023197	1.04	0.299
PG	0.0073298	0.0088731	0.83	0.409
lnINS	0.3791268	0.0784676	4.83	0
lnHC	0.2060644	0.0428828	4.81	0
SR				
ECT	−0.1977205	0.0195795	−10.1	0
D1.lnFDIF	−13.95162	15.16979	−0.92	0.358
D1.lnFDIS	0.0522474	0.0646221	0.81	0.419
D1. lnGDPC	−1.073306	0.2212327	−4.85	0
D1. lnOPN	−0.0256823	0.0543749	−0.47	0.637
D1. lnINF	−0.1300724	0.086015	−1.51	0.13
D1.PG	0.1312308	0.1143084	1.15	0.251
D1.lnINS	−0.0308116	0.1253362	−0.25	0.806
D1.lnHC	−0.0056907	0.1411555	−0.04	0.968
_cons	−2.209913	0.2217239	−9.97	0

Source: Author's compilation from Stata 17.

6. Conclusions and Policy Implications

The study examines the impact of foreign direct investment on unemployment in 90 developing countries for the period 2000–2024, employing the PMG approach of Panel ARDL. Three baseline models were adopted to investigate two theoretical assumptions of the FDI impact on unemployment: the first is a positive externality effect, such as technological progress spillover and managerial experience development, as well as addressing the domestic investment shortage; the second is the negative effect of crowding out local firms by stealing their market share or displacing the labor force with machines (the automation effect). To assess these effects, two key variables have been used: inward FDI flow for the first effect, and inward FDI stock per capita for the second effect. In addition, the models include three other control variables. The PMG estimation results show a highly significant, long-run negative association between all analyzed variables and unemployment, confirming their collective role in mitigating labor market slack. The FDI flow has a high negative association with unemployment, indicating the presence of a strong positive externality of FDI flow on host developing countries that contributes effectively to reducing unemployment. Moreover, the FDI stock variable has a highly significant negative relationship with unemployment, consistent with the absence of a dominant crowding-out of domestic firms by foreign companies in the long run, as the inflow of foreign investment incentivizes the workers and the local firms to improve their skills and administrative expertise, which qualifies them to be employed by or supply goods and services to the foreign companies. Furthermore, the results suggest that increasing GDP per capita, expanding international trade, and rising inflation contribute to reducing unemployment in developing countries. The results obtained by applying the PMG approach were confirmed by employing the System GMM method and proved robust to the inclusion of institutional, human capital, and demographic determinants.

Based on these results, several important policies can be recommended. First, FDI flows and stocks can effectively support the developing countries' efforts to reduce unemployment. Therefore, the macroeconomic policies that attract FDI are highly recommended

in developing economies. In addition, improving labor skills, modernizing management methods, developing education, enhancing research and development activities, and promoting intellectual property rights are necessary conditions for creating an attractive investment environment for foreign companies. Some strategies can serve in this context, including (a) prioritizing labor-intensive, export-oriented FDI, encouraging the reinvestment of profits given the significant effect of the FDI stock; (b) aligning vocational training and education curricula with the skills needed by foreign companies to shorten the adjustment period revealed by the insignificant short-run coefficients; (c) enhancing intellectual property rights, contract enforcement, and investment environment stability to sustain foreign capital accumulation; and (d) strengthening the domestic firms' absorptive capacity through supporting research and development activities and supplier-linkage programs that qualify local firms to provide foreign companies with goods and services.

Although this study indicates that both FDI flow and stock have a significant negative association with unemployment in a wide sample of developing countries, it remains subject to several limitations. First, although the potential endogeneity between FDI and unemployment is mitigated by the lag structure of the Panel ARDL model and the internal instrument of the System GMM estimator, the absence of external instruments precludes a definitive causal interpretation. Second, the long-run coefficients estimated by the PMG approach represent average equilibrium relationships; although the Hausman test supports the homogeneity condition, the findings may imply unobserved differences among subgroups of developing countries, such as regional and income groups. Third, the study employs aggregate measures for FDI, which distinguish neither the sectoral composition of FDI nor the entry mode of new investment versus mergers and acquisitions (M&A) activities, despite their potentially different effects on labor demand. Fourth, the FDI stock per capita is an indirect proxy for the foreign capital–labor ratio rather than a direct measure of automation intensity or competitive displacement, since direct measures of these mechanisms, such as industrial robot adoption or foreign affiliates' market shares, lack adequate coverage for a broad, balanced panel of developing countries over the study period.

Addressing these dimensions, together with the disaggregation of unemployment categories (e.g., youth, female, male, skilled, and unskilled), constitutes a promising avenue for future research.

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Conflicts of Interest: The author declares no conflicts of interest.

Appendix A

Table A1. The study's countries.

Region	Countries
East Asia & Pacific	Cambodia, China, Fiji, Lao PDR, Malaysia, Myanmar, Papua New Guinea, Philippines, Samoa, Solomon Islands, Thailand, Vanuatu, Vietnam
South Asia	Bangladesh, India, Maldives, Nepal, Sri Lanka

Table A1. Cont.

Region	Countries
Middle East & North Africa	Algeria, Egypt, Iran, Jordan, Morocco, Pakistan, Tunisia
Europe & Central Asia	Albania, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Georgia, Kazakhstan, Kyrgyz Republic, Moldova, Tajikistan, Türkiye, Turkmenistan, Uzbekistan
Sub-Saharan Africa	Angola, Benin, Botswana, Burkina Faso, Cabo Verde, Cameroon, Central African Republic, Chad, Comoros, Congo Dem. Rep., Congo, Côte d'Ivoire, Equatorial Guinea, Ethiopia, Gambia, Ghana, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, South Africa, Tanzania, Togo, Uganda, Zambia
Latin America & Caribbean	Argentina, Belize, Bolivia, Colombia, Dominican Republic, Ecuador, El Salvador, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Paraguay, Peru

Source: Author.

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