Unpacking the Effect of Foreign Direct Investment on Tanzania's Labor Market

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Abstract

This study examines the impact of foreign direct investment (FDI) on labor market dynamics in Tanzania using a 34-year time series dataset (1990–2023). Advanced econometric methods, including the Autoregressive Distributed Lag (ARDL) model, Johansen Co-integration tests are employed to analyze long-term and short-term effects of FDI on employment creation and productivity. Results reveal a significant positive long-term relationship, with a 1% increase in FDI leading to a 0.305% rise in labor force participation, while short-term findings highlight persistent labor market growth influenced by past employment levels. From a monetary policy perspective, the findings recommend that macroeconomic stability is critical to enhancing FDI's effectiveness. Policymakers should prioritize maintaining low inflation, stable exchange rates, and favorable credit conditions to attract sustainable FDI inflows. Furthermore, aligning monetary policy with fiscal strategies to direct investments into labor-intensive and productivity-enhancing sectors can amplify FDI's impact on job creation. Strengthening institutional frameworks, improving infrastructure, and promoting access to finance for complementary domestic industries are essential for leveraging FDI to achieve inclusive economic growth. These insights provide actionable guidance for optimizing FDI's role in Tanzania's sustainable development trajectory.

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1.Introduction

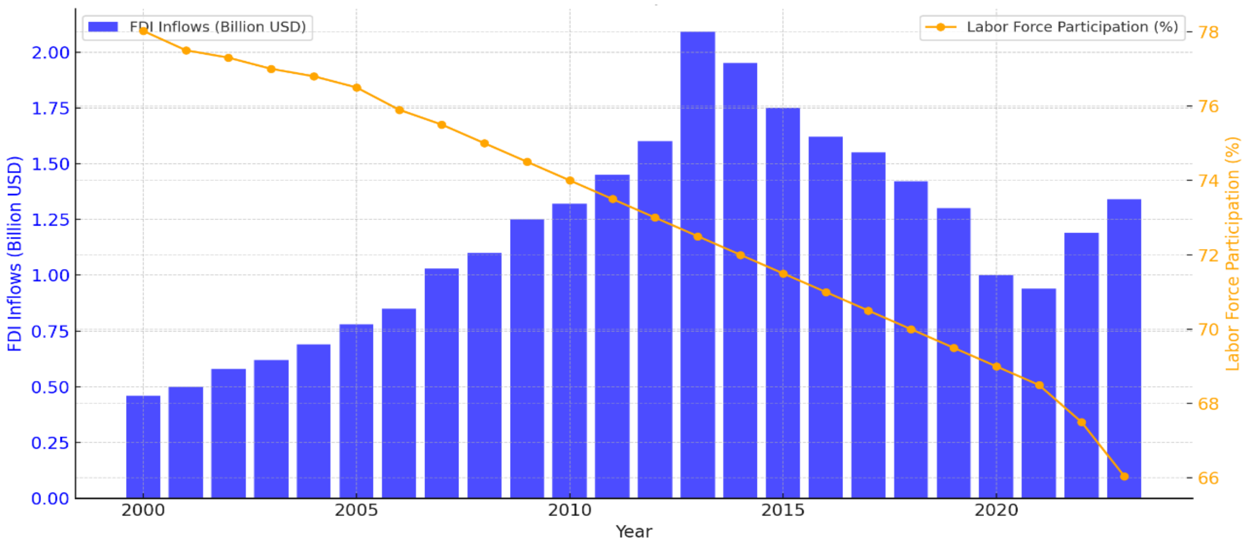
Globally, Foreign Direct Investment (FDI) has played a pivotal role in shaping the global economic landscape. According to the United Nations Conference on Trade and Development (UNCTAD), global FDI flows reached $1.58 trillion in 2021, a 64% recovery from the sharp decline caused by the COVID-19 pandemic (UNCTAD, 2022). Historically, developed economies such as the United States and European Union countries have dominated FDI inflows. However, developing regions, particularly Asia and Africa, have emerged as significant recipients in recent decades, collectively attracting over 50% of global FDI inflows in 2021. This shift signals a redistribution of economic opportunities and challenges across the globe.

Foreign direct investment (FDI), defined as long-term investments by firms or individuals in foreign business interests, is a key driver of economic growth, facilitating capital transfer, technology sharing, and integration into global value chains (World Bank, 2020). In emerging economies, FDI contributes significantly, with up to 30% of GDP in some cases, promoting industrialization and economic transformation. Global FDI trends have shifted dramatically, with developing countries receiving 60% of global inflows by 2021, compared to just 18% in the 1990s (UNCTAD, 2022). This shift has had diverse labor market impacts. For instance, in China, FDI in manufacturing and technology sectors has created millions of jobs while enhancing skill levels (ILO, 2019; Kitole et al., 2024). In Mexico, FDI in the automotive sector generates 5% of national employment and supports exports valued at $100 billion annually (World Bank, 2020). However, FDI also presents challenges. In regions with weaker governance, such as Southeast Asia, it has been associated with exploitative labor practices, low wages, and unsafe working conditions (ILO, 2021). While FDI is celebrated for driving employment and economic growth, its dual effects promoting development while raising concerns about job quality, skill development, and labor rights make it a complex and contentious issue in global labor markets.

Tanzania has experienced steady economic growth, averaging 5.19% in 2023, up from 4.57% in 2022, reflecting a gradual post-pandemic recovery (World Bank, 2022). Tanzania has undertaken significant efforts to create a conducive environment for FDI, including the establishment of the Tanzania Investment Centre (TIC) in 1997 to facilitate and promote investments, and the alignment of labor laws with international standards (UNCTAD, 2021). To attract foreign capital, the government has introduced incentives such as tax exemptions and guarantees, particularly targeting sectors like mining, infrastructure, and energy. Recognizing the potential of FDI to drive job creation and industrialization, the National Five-Year Development Plan (2021–2026) highlights the need to attract investments that support local industries and employment opportunities (World Bank, 2023)

Despite this growth, benefits remain unevenly distributed due to high population growth, estimated at 2.8%–3% annually, which continues to expand the labor force faster than the formal sector can absorb (World Bank, 2023). Consequently, underemployment and a reliance on the informal sector persist, with Tanzania ranked among the poorest countries globally in human development. Official unemployment stood at 2.61% in 2023, but this likely understates labor market challenges, including informal employment and labor inefficiencies (Bank of Tanzania, 2023). Over the past two decades, FDI inflows have fluctuated significantly, rising from $0.46 billion (3.47% of GDP) in 2000 to a peak of $2.09 billion (4.57% of GDP) in 2013, before declining to $0.94 billion (1.43% of GDP) in 2020. Recent years have seen recovery, with FDI inflows reaching $1.19 billion (1.68% of GDP) in 2021 and $1.34 billion (1.69% of GDP) in 2023 (World Bank, 2023). Despite these trends, Tanzania faces declining labor force participation and a persistently low industrial employment share, reflecting structural labor market challenges not captured by low unemployment rate.

Figure 1: FDI inflows and labor force participation in Tanzania (2000 – 2023)



Source: Authors' estimate using World Bank Data, 2023

There is limited understanding of how FDI translates into quality employment, especially for marginalized groups such as youth and women. Key questions remain about whether FDI leads to sustainable job creation, skill development, and income equality, or exacerbates challenges like underemployment and income disparities. Addressing these gaps is critical to optimizing FDI's impact on the labor market. By examining FDI trends and their implications, this study aims to inform strategies for inclusive growth, offering guidance for both developing and developed economies pursuing sustainable development.

Hypothesis

H_0: Foreign direct investment (FDI) has no significant effect on Tanzania's labor market.

2. Review of Related Literature

Neoclassical Growth Theory, developed by Solow (1956) and Swan (1956), provides a foundational framework for analyzing the interplay between foreign direct investment (FDI) and economic growth. This theory identifies capital accumulation, technological progress, and labor productivity as the key drivers of long-term economic expansion. Within this framework, FDI is considered a crucial mechanism for transferring advanced technologies, modern managerial practices, and production efficiencies to host economies, thereby facilitating economic development (Solow, 1956; Swan, 1956; Kitole & Utouh, 2023). Furthermore, the theory posits that economic growth is largely driven by exogenous factors, particularly technological innovation, rather than solely by increases in labor or capital inputs, underscoring the importance of external advancements in shaping the trajectory of growth.

Neoclassical Growth Theory posits that economies with higher absorptive capacities, such as strong institutions, skilled labor, and robust infrastructure, are better positioned to maximize the benefits of FDI. For Tanzania, this means the effectiveness of FDI in improving labor market outcomes depends on its ability to integrate foreign technologies and practices into local industries. Investments in skill-intensive sectors can drive higher wages and skill development, while labor-intensive sectors generate immediate employment but limited long-term productivity gains.

The theory also emphasizes technological progress as a driver of long-term growth, with FDI serving as a vehicle for introducing innovations and modern management practices. In Tanzania, FDI in manufacturing can bring automation and efficiency gains, while investments in services may promote advancements in digital technologies, boosting labor productivity and industrial competitiveness in regional and global markets. However, weak institutions, inadequate infrastructure, or a lack of skilled labor could limit these benefits, and heavy reliance on capital-intensive sectors like mining may restrict FDI's impact on broader employment creation, underscoring the need for governance and workforce development reforms. Studies such as Borensztein et al. (1998) applied the theory to demonstrate how FDI facilitates technological diffusion in developing countries, contingent on the host economy's absorptive capacity. Similarly, Alfaro et al. (2004) extended the theory to highlight the role of sectoral FDI allocation, showing that investments in manufacturing and services yield greater productivity gains compared to primary sectors. However, while the theory provides a robust framework for analyzing FDI-driven growth, it assumes technological progress as an exogenous factor and overlooks the endogenous mechanisms through which FDI might stimulate innovation within host economies. Additionally, the theory does not sufficiently address the role of institutional quality, governance, and infrastructure, which are critical in determining the extent of FDI spillovers.

Empirical Review

Saha (2024) employs system GMM, dynamic panel threshold techniques, and PMG methodology to explore the role of the productive capacity index (PCI) in moderating FDI's effects on labor productivity. The study finds that FDI initially reduces productivity in tradable and non-tradable sectors but enhances it beyond a PCI threshold, particularly in tradable sectors. Similarly, Jude and Silaghi (2015) apply a dynamic labor demand model for Central and Eastern European Countries (CEEC) and reveal a "creative destruction" effect, where FDI initially reduces employment but later fosters long-term job creation, favoring skilled labor. Wahyudi and Palupi (2023) use VECM to analyze the bidirectional causality between FDI, labor force participation, and energy consumption in OECD countries, showing significant long-term relationships but weak short-term effects. Meanwhile, Haaland and Wooton (2007) highlight how labor market flexibility and lower redundancy costs make countries more attractive for FDI, especially in high-risk industries.

Other studies, such as Nguyen (2021) and Mayom (2015), focus on the importance of skilled labor and infrastructure in maximizing FDI benefits. Nguyen finds that manufacturing sectors in Vietnam benefit the most from FDI but warns of potential worker displacement in certain industries. Mayom emphasizes that governance, infrastructure, and skilled labor amplify FDI's positive effects on employment in Sub-Saharan Africa. Additionally, Nosova (2018) underscores FDI's contributions to job creation, wage growth, and technology transfer in Ukraine, though these benefits are unevenly distributed. Across these analyses, the consistent finding is that FDI's positive impact hinges on host countries' absorptive capacities, labor market structures, and sector-specific dynamics, requiring tailored policies to mitigate initial disruptions and ensure equitable growth.

3.Methodology

This study utilized a 34-year time series dataset (1990–2023) from credible sources, such as the World Bank Development Indicators, to investigate the effects of FDI on Tanzania's labor market dynamics available at https://data.worldbank.org/(World Bank, 2023). The analysis was conducted using STATA 17 software, which is well-suited for handling complex time series data and performing advanced econometric modeling. The reliability and validity of the findings are supported by the rigorous data collection and verification processes employed by these organizations (UNCTAD, 2021). Although occasional data gaps, common in developing countries like Tanzania, posed challenges to the completeness of trend analyses and the precision of some model estimates, these limitations were mitigated through robust diagnostic checks and methodological rigor. Advanced econometric techniques ensured that the analysis remained consistent and insightful despite these challenges. The integration of reliable data and robust analytical methods strengthens the study's contribution to understanding the role of FDI in shaping labor market dynamics in Tanzania, providing a valuable foundation for further research and policy development (World Bank, 2023; UNCTAD, 2021).

Analytical Modelling

The data analysis for this study was conducted using STATA 17 software, applying advanced econometric techniques to ensure robust and reliable results. Johansen Co-integration tests were employed to examine long-run relationships among the key variables, while short-run dynamics were analyzed using the Error Correction Model (ECM) to capture adjustments toward equilibrium within co-integrated series. Additionally, Granger Causality tests were applied to investigate the directional relationship between foreign direct investment (FDI) and labor market outcomes, providing insights into causality. Before conducting these estimations, stationarity of the time series data was verified using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to avoid spurious results, as emphasized in econometric literature (Gujarati, 2004; Maddala, 1999; Kitole, 2025).

The study employed an Autoregressive Distributed Lag (ARDL) model, alongside Johansen’s Test of Cointegration and Bound Testing, to robustly analyze long-term relationships between FDI, labor force participation, and productivity. These methods ensured consistency in detecting linkages and enhanced the study’s methodological rigor. Comprehensive post-estimation diagnostics, including stability tests, autocorrelation checks, and normality tests using Jarque-Bera statistics, validated the models' reliability. Univariate analysis was also conducted to assess trends and ensure data normality before the main analysis. This rigorous econometric approach strengthens the study's contribution to understanding FDI's impact on Tanzania’s labor market.

Augmented Dickey-Fuller Tests

The Augmented Dickey-Fuller (ADF) test was employed in this study to determine the stationarity of key time series variables, such as FDI inflows and labor market indicators, ensuring their mean and variance remained stable over time. As an extension of the Dickey-Fuller test, the ADF test adjusts for autocorrelation within residuals by incorporating lagged dependent variables, providing more accurate stationarity checks. This step was crucial for pre-estimation diagnostics, as non-stationary data can lead to spurious regression results and unreliable conclusions. By confirming stationarity, the study validated the use of advanced econometric models, including Error Correction Models (ECM) and Vector Error Correction Models (VECM), to explore long-run and short-run relationships between FDI and labor market dynamics over a 34-year period (1990–2023). The application of the ADF test ensured robust and reliable statistical foundations for the analysis unlike VECM which was not suitable.

This step was integral to the study's methodology, as it provided a solid foundation for subsequent modeling and hypothesis testing, contributing to the reliability of the findings. It can be illustrated as:

$$\Delta X_t = \propto_0 + \propto_1 t + \beta_0 X_{t-1} + \sum_{i=1}^{k} \beta_i \Delta X_{t-i} + \eta_t \quad (1)$$

Where; Δ = difference operator, t= time trend; k= number of lags used, η= the error term; $\alpha_s$and $\beta_s$are parameters to be estimated

Phillips Perron (PP) test

The Phillips-Perron (PP) tests enhance the Dickey-Fuller test by adjusting for serial correlation and heteroscedasticity in the error terms. These tests use a heteroscedasticity and autocorrelation consistent covariance matrix estimator, making them more robust to serial correlation compared to the ADF test (Phillips & Perron, 1988). The PP, Zt and Z statistics share the same asymptotic distributions as the ADF t-statistic and normalized bias statistics but with the advantage of being unaffected by various forms of heteroscedasticity. Additionally, the PP test does not require specifying lag length, offering greater flexibility in its application.

$$y_t = \pi y_{t-1} + (constant, time\ trend) + u_t \quad (2)$$

Autoregressive Distributed Lag (ARDL) Model

The ARDL model is utilized to assess the magnitude of parameters for each specific variable, offering several advantages over the VECM model. Firstly, ARDL model estimate variables with different orders of stationarity, making it versatile for data where variables become stationary at different levels, as long as they do not exceed the third order of integration (Pesaran, 1997). Secondly, the ARDL model is particularly suitable for small sample sizes, with Narayan (2005) providing critical values for samples ranging from 30 to 80 observations. Given that this study uses 34 observations, the ARDL model is appropriate.

Additionally, the ARDL model is advantageous when examining a single long-run relationship, as it clearly distinguishes between independent and dependent variables. This allows for the precise estimation of the impact of one or more exogenous variables on a dependent variable. Furthermore, the ARDL method minimizes the issue of endogeneity, as each variable is treated as a single equation, reducing residual correlation, unlike the VECM model, which involves multiple vectors of equations (Harris & Sollis, 2003).

The linear generalized ARDL model is identified as;

$$Y_t = \alpha_{0j} + \sum_{i=1}^{p} \delta_j Y_{t-1} + \sum_{i=0}^{q} \beta_j' X_{t-1} + \varepsilon_{jt} \quad (3)$$

In this model, δ represents the coefficients of the lags of Y_t' up to $\boldsymbol{p}$ periods, indicating the impact of past values of the dependent variable on its current value. β represents the coefficients of the lags of X_t' up to $\boldsymbol{q}$ periods, capturing the influence of past values of the explanatory variables on Y_t'. ε_{jt} is the error term, assumed to be white noise. This model is particularly useful in econometrics for dealing with variables that might be integrated of different orders, allowing for both short-term and long-term analysis within a single framework (Pesaran et al., 2001).

The explanatory must not be I, even though the ARDL model does not require the unit root pre-testing (2). To ensure that the related variables remain none I, the test for unit roots still be required (2). Equation 4, which is a modified version of Pesaran *et.al.* (2001) generic's equation 3, can be used to present the general ARDL model.

$$\Delta lnFDI_t = \alpha + \sum_{i=1}^{k+d} \beta \Delta lnEMPl_{t-1} + \sum_{i=1}^{k+d} + u_t \quad (4)$$

Whereas k is the stochastic mistake term, and d is the most extreme request for factor incorporation and is the ideal slack request. The first difference operator, denoted by Δ represents the changes in FDI and EMPL, which are expressed in terms of natural logarithms.

Variables Measurement

Table 1 presents the measurement of study variables, sources and expected sign with FDI measured as the Foreign Direct Investment, net inflows and Labour Market as employment created per GDP.

Table 1: Measurement variables and data sources

Variable	Measures	Source	Expected Sign
Foreign Direct Investment	net inflows	World Bank, Bank of Tanzania	
Labour Market	Employment created per/GDP	World Bank	+

Results

The dataset consists of 34 observations, capturing key variables related to labor force and foreign direct investment (FDI). The labor force has an average size of approximately 20.15 million, with a standard deviation of about 5.37 million, indicating significant variation across the observed period. The labor force ranges from a minimum of 12.49 million to a maximum of 31.05 million, reflecting substantial changes in employment levels over time. Similarly, FDI has an average value of 745.2 million USD, with a standard deviation of 590.2 million USD, suggesting considerable variability in investment inflows. The minimum FDI observed is a mere 10,000 USD, while the maximum reaches over 2.08 billion USD, highlighting both the challenges and opportunities in attracting foreign investment.

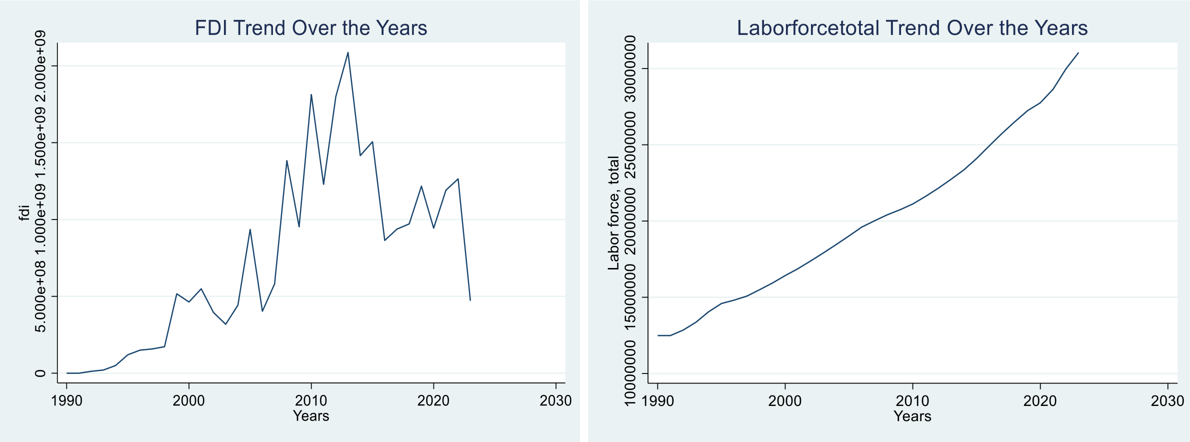
Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Labor force	34	20145242	5366674.6	12489000	31053999
FDI	34	7.452e+08	5.902e+08	10000	2.087e+09
lnLB	34	16.784	.268	16.34	17.251
lnFDI	34	19.38	2.859	9.21	21.459

Source: Author estimates using World Bank data, 2023

The natural logarithms of these variables, lnLB (labor force creation) and lnFDI (foreign direct investment), provide additional insights. The average value of lnLB is 16.784, with minimal variation (standard deviation of 0.268), suggesting relative stability in labor force growth trends. On the other hand, lnFDI has an average of 19.38, with a higher standard deviation of 2.859, reflecting more significant fluctuations in FDI inflows. The range of lnFDI (from 9.21 to 21.459) indicates occasional extremes in investment levels. These findings suggest that while the labor force shows steady growth over time, FDI inflows are more volatile, pointing to potential challenges in maintaining consistent external investment.

Figure 1: Stochastic Trend of FDI inflows and Labor force total



Source: Author estimates using World Bank data, 2023

Test for stationarity

The Augmented Dickey-Fuller (ADF) test results reveal mixed stationarity properties for the variables. The lnLabor Force is not stationary at levels (I(0)) as its test statistic (0.724) is higher than the critical values at the 1%, 5%, and 10% significance levels. However, after first differencing (I(1)), the test statistic becomes -4.373, which is lower than the critical values, indicating that lnLabor Force is stationary at first difference. In contrast, lnFDI is stationary at levels (I(0)), with a test statistic of -4.921, which is lower than the critical values at all significance levels.

Given this combination of variables where one is stationary at levels (lnFDI) and the other becomes stationary at first difference (lnLabor Force) a VECM (Vector Error Correction Model) is not suitable for analyzing the relationship. The VECM requires all variables to be non-stationary at levels (I(1)) but cointegrated, which is not the case here since lnFDI is stationary at levels.

Table 3. Augmented Dickey-Fuller test for Unit Root

Variable	Order of integration	Test statistic	Critical value			Conclusion
			1%	5%	10%	
lnLabor Force	I(0)	0.724	-3.696	-2.978	-2.620	Not stationary
	I(1)	-4.373	-3.702	-2.980	-2.622	Stationary
lnFDI	I(0)	-4.921	-3.696	-2.978	-2.620	Stationary

Source: Author estimates using World Bank data, 2023

Instead, an ARDL (Autoregressive Distributed Lag) model is better suited for this analysis because it accommodates variables with mixed orders of integration (a mix of I(0) and I(1)). Additionally, the lag selection process in ARDL allows for individual lag specifications for each variable, providing a flexible framework for analyzing relationships in such datasets. Thus, based on the stationarity results and the flexibility of lag selection, ARDL is the appropriate model for analyzing the relationship between these variables.

Lag Selection Criterion

Table 4: Lag-Order Selection Criteria

Lag	LL	LR	df	P-value	FPE	AIC	HQIC	SBIC
0	-26.1005	-	-	-	.022319	1.87337	1.90325	1.96678
1	92.473	237.15	4	0.000	.000011	-5.76486	-5.67521	-5.48462
2	97.1588	9.3718	4	0.052	.00001	-5.81059	-5.66117	-5.34352
3	106.605	18.893	4	0.001	7.3e-06	-6.17369	-5.96451	-5.5198*
4	113.271	13.331*	4	0.010	6.2e-06*	-6.3514*	-6.08245*	-5.51068

Note: *=Optimal lag selected by the criterion, *Final prediction error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), Hanna-Quinn Criterion (HQC)*

Cointegration Test

A key requirement for applying the Autoregressive Distributed Lag (ARDL) is that the variables must share a long-run relationship (Johansen, 1995). To verify this, the Bound Cointegration test was conducted to identify the number of Cointegration equations as per Table 5

Table 5: Bound Testing for Cointegration

Test Statistics	**Value**	**Significance**	**Bound Critical Values**		**P_value**	
			I(0)	I(1)	I(0)	I(1)
F-test	5.918	10%	4.04	3.77		
		5%	3.23	4.35	0.017	0.064
		1%	3.69	4.29		
T test	3.756	10%	1.57	2.46		
		5%	2.13	2.05	0.006	0.051
		1%	2.43	2.37		

Source: Author estimates using World Bank data, 2023

The ARDL Bounds Test results show an F-test statistic of 5.918, which exceeds both the I(0) and I(1) critical values at the 10%, 5%, and 1% significance levels (e.g., at 10%: I(0) = 4.04, I(1) = 3.77). This indicates that the null hypothesis of no Cointegration can be rejected, providing strong evidence of a long-term equilibrium relationship between the variables. Additionally, the T-test statistic of 3.756 exceeds the critical values for I(0) and I(1) at the 10%, 5%, and 1% levels (e.g., at 10%: I(0) = 1.57, I(1) = 2.46), with corresponding p-values of 0.006 and 0.051, showing significant adjustment dynamics in the short term. Overall, the results suggest the presence of a long-term relationship between the variables, along with meaningful short-term adjustments, highlighting a stable and cointegrated system.

The Autoregressive Distributed Lag

The moderate explanatory power of the model, indicated by an R-squared of 38.66% and an adjusted R-squared of 32.09%, aligns with findings in studies analyzing complex economic systems, where unobserved factors often influence employment dynamics. For instance, Olczyk and Petreski (2024) reported similar R-squared values in their study of FDI-induced job creation in the EU-27, attributing this to the multifaceted nature of employment growth influenced by regional and sectoral characteristics. Likewise, Bogatinoska et al. (2024) found moderate R-squared values in their examination of FDI and unemployment in former Yugoslav republics, emphasizing the role of external shocks and country-specific factors. Grabinsky and Ukraynets (2024) observed comparable results in their analysis of FDI and digitalization in China, where regional disparities and technological readiness contributed to employment variations beyond the model's scope. Despite these moderate explanatory powers, the low

RMSE of 0.0065 in this model reflects strong predictive accuracy, a characteristic also highlighted by Ali (2023) in his study of FDI impacts on India's manufacturing sector, where targeted policies enhanced labor-intensive benefits. Pal and Ali (2023) further noted that in India's service sector, similar models with moderate R-squared values effectively captured FDI's long-term employment contributions despite limitations in measuring informal labor dynamics.

The Autoregressive Distributed Lag (ARDL) in Table 6 was estimated with a lag structure of (2, 0), and the results provide valuable insights into the short-run and long-run dynamics between the variables lnLB (dependent variable) and lnFDI (independent variable). The regression statistics and estimated coefficients reveal both adjustment mechanisms and the relationships between these variables. The constant term (cons) is estimated at -0.12506, with a standard error of 0.10576 and a t-value of -1.18. The p-value of 0.247 suggests that the constant term is not statistically significant. This result indicates that, in the absence of other explanatory variables, the model does not predict a significant baseline value for lnLB.

The adjustment coefficient for lnLB is 0.01343, with a standard error of 0.12709 and a t-value of 10.87. The p-value of 0.090 indicates that the adjustment term is statistically significant at the 10% level. This positive coefficient suggests that deviations from the long-run equilibrium are corrected at a slow rate, with about 1.3% of the disequilibrium being adjusted in each period. The significance of the adjustment term indicates the presence of a stable long-term relationship between lnLB and lnFDI, which is an essential criterion for the validity of the ARDL model.

In the long run, the coefficient for lnFDI, representing foreign direct investment (FDI), is 0.30521, with a standard error of 0.10949 and a t-value of 2.79, making it statistically significant at the 5% level (p-value 0.009). This result indicates that a 1% increase in FDI is associated with a 0.305% increase in labor force creation or employment creation (lnLB) in the long term, holding other factors constant. These findings suggest that FDI plays a critical role in driving long-term employment creation. By bringing in capital, technology, and expertise, FDI can stimulate economic activity, enhance productivity, and generate job opportunities, thereby supporting labor market growth.

The short-run coefficient for lnLB, representing labor force creation or employment creation, is 0.36861, with a standard error of 0.12809 and a t-value of 2.88, making it statistically significant at the 1% level (p-value 0.008). This indicates that past levels of labor force creation have a positive and significant short-term impact on current levels of employment creation. Specifically, a 1% increase in labor force creation in the previous period results in a 0.369% increase in labor force creation in the current period. This finding suggests a strong inertia or persistence in employment creation, meaning that labor force growth tends to build on itself in the short run.

Table 6 Autoregressive Distributed Lag Model Estimate

ARDL	Variable	Coeff	Std. err.	t-value	P>|t|	95% conf. interval	
ADJ	lnLB	0.01343	0.12709	10.87	0.090*	1.1217	1.6424
Lon Run	lnFDI	0.30521	0.10949	2.79	0.009**	0.0809	0.5295
Short Run	lnLB	0.36861	0.12809	2.88	0.008**	0.1062	0.63099
	cons	-0.12506	0.10576	-1.18	0.247	-0.3417	0.09150

ARDL (2, 0) regression
Number of obs =32 Root MSE = 0.0065
R-squared =0.3866 Sample:1992 - 2023
Adj R-squared = 0.3209

**** p<.01, ** p<.05, * p<.1*

Autocorrelation

The Durbin-Watson d-statistic tests for the autocorrelation of residual-value in the context of regression analysis especially in time series data as shown is Table 7. This statistic varies from 0 to 4; that is, when the value is close to 2, there is no autocorrelation; values less than 2 point to positive autocorrelation, while values above 2 point a negative autocorrelation (Durbin & Watson, 1950). This test is crucial for validating the assumptions of regression models, as autocorrelation in residuals can distort the results and lead to inefficient estimates. Therefore, the calculated d-statistic is 0.1963569, which lie between decision ranges. This suggests that there is no autocorrelation present in the residuals. However, the degree of autocorrelation cannot be determined based on the d-statistic alone, and further tests or analysis may be necessary to fully understand the nature and extent of autocorrelation in the data.

Table 7: Durbin-Watson

Durbin-Watson	0.1963569
Prob > chi2 (2, 33)	
Conclusion	no serial correlation

Source: Author estimates using World Bank data, 2023

Heteroscedasticity

The study employed Cameron & Trivedi's decomposition of IM-test alongside White's test to examine heteroscedasticity, skewness, and kurtosis in the model. Table 8 present the overall chi-squared statistic for White's test as 1.20 with a p-value of 0.5490, indicating no significant evidence of heteroscedasticity. The decomposition revealed that the heteroscedasticity component had the highest chi-squared statistic (1.20), but its p-value of 0.5490 suggested no substantial heteroscedasticity. The skewness and kurtosis components also showed no significant contributions, with high p-values further confirming homoscedasticity. These findings strengthen the reliability and validity of the model's estimation outcomes, affirming that the model adheres to the assumption of homoscedasticity, thereby enhancing the credibility of the study's results.

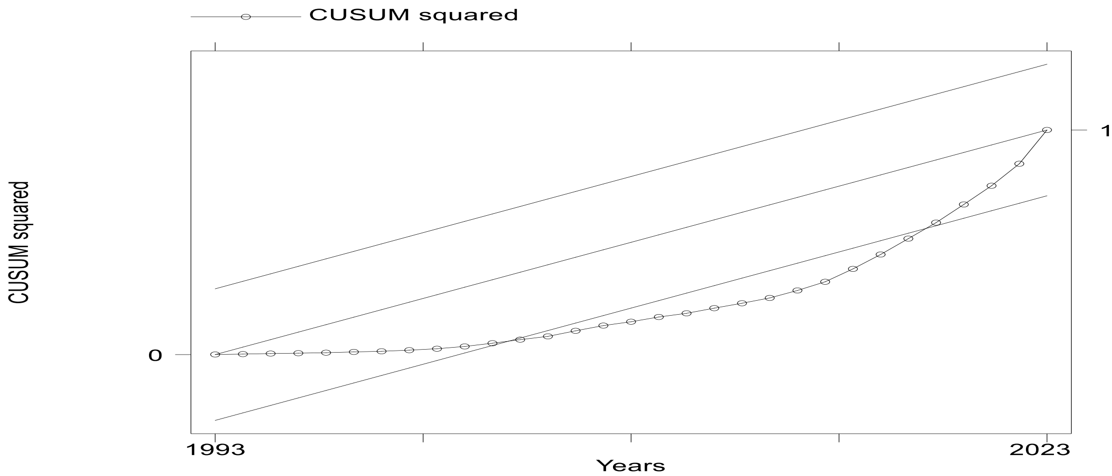
Table 8: Cameron and Trivedi’s IM-test

Source	chi2	df	p
Heteroscedasticity	1.20	2	0.5490
Skewness	2.07	1	0.1505
Kurtosis	4.20	1	0.0404
Total	7.47	4	0.1132

Source: Author estimates using World Bank data, 2023

Model Stability

The stability of the ARDL model was evaluated using the CUSUM squared test, which involves plotting the CUSUM squared statistic against the critical boundaries. For the model to be considered stable, the statistic must remain within these boundaries. However, as shown in the figure, the CUSUM squared statistic crosses the boundaries, indicating significant structural changes in the time series data. This suggests that the model does not meet the criteria for stability. The structural change implies that the underlying relationship between variables has shifted over time, and thus, the current model may not reliably capture the dynamics of the data. Studies by Perron (1989) and Zivot and Andrews (1992) emphasize the impact of structural breaks on model validity, particularly during economic transformations or policy changes. Malik (2019) highlighted that structural changes in industrial policy or external economic shocks could alter the relationship between FDI inflows and employment creation over time. This was particularly evident in emerging economies experiencing transitions in governance, infrastructure, or trade dynamics. Furthermore, Grabinsky and Ukraynets (2024) found that digitalization-induced structural shifts in China caused instability in long-term econometric models analyzing FDI and employment, necessitating adjustments to account for evolving economic conditions.



Source: Author estimates using World Bank data, 2023

Discussions

The long-run coefficient of 0.30521 for lnFDI demonstrates a significant positive relationship between foreign direct investment (FDI) and labor force creation, consistent with existing empirical research. Olczyk and Petreski (2024) highlighted that forward participation in global value chains amplifies the employment benefits of FDI by boosting domestic value addition and production capabilities, which directly enhances labor market opportunities. Similarly, Bogatinoska et al. (2024) found that FDI inflows have contributed significantly to reducing unemployment in the former Yugoslav republics, particularly when aligned with the structural needs of the host economy. Grabinsky and Ukraynets (2024) emphasized that in China, the digital economy magnifies FDI's positive impact on long-term employment creation, particularly in the service sector, underscoring the transformative role of technology in amplifying labor productivity and job growth. Malik (2019) further noted that FDI's long-term employment impact is contingent upon channeling investments into labor-intensive sectors, particularly in manufacturing, to ensure maximum labor absorption. Finally, Pal and Ali (2023) demonstrated that the service sector in India consistently benefits from sustained FDI inflows, which contribute to income growth and job creation over time.

The finding that a 1% increase in past labor force creation leads to a 0.369% increase in current employment creation underscores the significant inertia in labor market growth. This aligns with Olczyk and Petreski (2024), who identified that regions with strong forward GVC participation experience compounding employment effects due to cumulative productivity gains and domestic value creation. Similarly, Bogatinoska et al. (2024) demonstrated that FDI inflows in the former Yugoslav republics significantly impacted labor market dynamics, where previous employment growth facilitated future opportunities. Grabinsky and Ukraynets (2024) further emphasized this persistence effect in China, noting that digitalization enhances the impact of FDI on employment, particularly in less-developed regions, where past job growth fosters sustained labor demand. Ali (2023) observed a similar phenomenon in India's manufacturing sector, where FDI inflows could boost employment if aligned with labor-intensive industries, leveraging previous labor force expansions. Lastly, Pal and Ali (2023) found that in India's service sector, cumulative employment effects emerged through FDI-driven growth, especially in areas with strong prior labor activity.

Conclusion

The ARDL results suggest a significant long-term relationship between lnLB and lnFDI, with FDI playing a crucial role in influencing economic outcomes over time. The short-term dynamics also reveal that past values of the dependent variable contribute positively to current outcomes. However, the adjustment term indicates a slow rate of convergence to equilibrium when deviations occur, suggesting the need for stable and persistent policy interventions to sustain long-term growth. The overall fit of the model is moderate, and while it highlights key relationships, additional variables may need to be incorporated to capture a more comprehensive picture of the dynamics at play.

The findings of this study have significant implications for macro-foundations, particularly in understanding the structural drivers of economic growth and employment creation. The positive long-term impact of FDI on labor force creation suggests that FDI serves as a crucial mechanism for enhancing the productive capacity of an economy by injecting capital, technology, and expertise. This aligns with macro-foundational principles that emphasize the role of external investments in bridging gaps in domestic savings and driving aggregate supply through productivity improvements. The observed persistence in employment creation further implies that FDI fosters dynamic effects within the economy, such as skill development, industrial diversification, and enhanced global competitiveness. To leverage these benefits, policymakers should focus on creating an institutional framework that encourages sustainable FDI inflows, including robust property rights, transparent regulations, and infrastructure development. Moreover, the study highlights the importance of ensuring that FDI aligns with labor-intensive sectors and regional development needs, supporting inclusive growth and reducing disparities. By integrating FDI strategically into the macroeconomic fabric, nations can strengthen their economic foundations, improve labor market resilience, and stimulate long-term growth trajectories.

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