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SHIFTING FIELDS: DETERMINANTS OF AGRICULTURAL EMPLOYMENT IN NEXT-TIER EMERGING ECONOMIES

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ABSTRACT

This study examines the determinants of agricultural employment in Next Tier Emerging Economies (Argentina, Bangladesh, Chile, Colombia, Egypt, Iran, Iraq, Malaysia, Pakistan, Peru, Philippines, Poland, Saudi Arabia, South Africa, Thailand, and Vietnam) for the period 1995–2019. These countries, characterized by their transitional economies and significant agricultural sectors, represent a critical segment of global development as they navigate structural shifts from agrarian-based systems to more diversified economies. In the processes of structural transformation, economic growth, and social development, the share of agriculture in employment also stands out as an important indicator. Using Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) methods, the analysis reveals that GDP per capita, average years of schooling, and mechanization (measured as machinery per unit of agricultural land) have significant negative effects on the share of agricultural employment in total employment. Conversely, the value added from agricultural production positively affects on agricultural employment. These findings are important for understanding the interaction between agricultural productivity, economic development, educational attainment, and technological advancement in shaping agricultural labor dynamics, offering significant insights for policy design. In this context, policies could address rural labor displacement caused by mechanization, promote sustainable agricultural productivity, and balance rural education with job creation to alleviate urban migration pressures. This study contributes to a better understanding of structural transformation and labor market shifts within the context of emerging economies.

Keywords: Agricultural Employment, FMOLS, DOLS

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INTRODUCTION

Agriculture has historically been a cornerstone of economic activity, particularly in emerging economies, providing livelihoods for significant portions of the population. As one of the oldest economic activities, agriculture is critical in rural development, food security, and poverty alleviation. However, as economies grow and diversify, the share of agriculture in total employment tends to decline due to structural transformation. This shift, marked by a transition from agrarian-based systems to industrial and service-oriented economies, has been well-documented in the literature, including Kuznets' theory of structural transformation (Kuznets, 1955), which posits that economic growth inevitably leads to a reduction in the reliance on agricultural labor.

Emerging economies, in particular, experience this transformation at varying rates depending on their economic development, urbanization, and technological adoption levels. Timmer (1988) emphasizes that the pace of this transition depends on the agricultural sector's productivity and the capacity of non-agricultural sectors to absorb surplus labor. In many transitional economies, the agricultural sector remains a major employer despite its declining contribution to GDP. This duality creates a complex dynamic where rural areas struggle with labor retention as urban centers and non-agricultural sectors expand.

This study focuses on the determinants of agricultural employment in Next Tier Emerging Economies (NTEEs), a group of countries characterized by their transitional economies and significant agricultural sectors. These countries, including Argentina, Bangladesh, Chile, Colombia, Egypt, Iran, Iraq, Malaysia, Pakistan, Peru, Philippines, Poland, Saudi Arabia, South Africa, Thailand, and Vietnam, represent a critical segment of global development. They have been navigating structural shifts that involve technological advancements, urbanization, and changing economic priorities. Despite these transformations, agriculture remains a key sector in terms of employment and GDP contribution, making it essential to examine the factors influencing its dynamics (Briones & Felipe, 2013; Nin-Pratt et al., 2017; Yeboah & Jayne, 2017).

Previous studies have explored various aspects of agricultural employment, including its relationship with mechanization (Binswanger, 1986; Sidhoum et al., 2019; Yücel & Çalişkan, 2021), education (Schultz, 1964; Porzio & Santangelo, 2019), and economic growth (Byerlee et al., 2005; Headey et al., 2010; Behera & Tiwari). Mechanization, often seen as a driver of agricultural productivity, has been shown to reduce labor demand (Amare & Endalew, 2016; Cauneda & Kala, 2021), while education levels influence labor mobility away from agriculture (Núñez, 2003; Bojnec et al., 2003). Moreover, the value added by agriculture plays a vital role in determining its ability to sustain employment, particularly in economies where agricultural output contributes significantly to national income. This paper builds on these strands of literature to investigate how these factors interact in shaping agricultural employment in NTEEs.

Using data from 1995 to 2019, this study employs Fully Modified Ordinary Least Squares (FMOLS) and Dynamic Ordinary Least Squares (DOLS) methods to analyze the impact of four key variables: GDP per capita, average years of schooling, agricultural value added (% of GDP), and mechanization (machinery per unit of agricultural land) on agricultural employment. These methods are particularly suited for addressing endogeneity and serial correlation in panel data, ensuring robust and reliable results.

The findings of this study shed light on how economic development, education, technological progress, and sectoral productivity interact to shape labor market outcomes in these economies. For instance, GDP per capita, often viewed as a proxy for economic transformation, is expected to negatively affect agricultural employment as higher incomes encourage shifts toward industry and services. Similarly, schooling is anticipated to reduce reliance on agriculture by equipping individuals with skills

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more suited for urban and industrial jobs. Mechanization, while increasing productivity, is likely to reduce labor demand in agriculture, whereas higher agricultural value added may sustain employment by enhancing the economic significance of the sector.

This paper contributes to the literature by comprehensively analyzing agricultural employment dynamics in NTEEs, offering valuable insights for policymakers. It highlights the interplay between modernization and rural livelihoods, emphasizing the importance of inclusive strategies to manage labor transitions effectively. By focusing on a diverse group of emerging economies, this study provides an understanding of agricultural employment trends, contributing to the broader discourse on structural transformation and sustainable development.

MATERIALS AND METHODS

To investigate the determinants of agricultural employment in NTEEs, this study utilizes panel data covering 16 countries over the period 1995–2019. For our study, we employ data on agricultural employment ($AGRI\_EMP$), income level (GDP_{pc}), education level ($SCHOOL$), value added by agriculture ($VALUE\_ADDED$), and agricultural mechanization ($MACHINERY$). All the variables were transformed into natural logarithmic forms to address scale differences and promote distributions that approximate normality. The summary information about the variables used in the analyses and descriptive statistics are presented in Table 1 and Table 2, respectively.

Table 1. Summary of Variables

Target Variable	*Proxy Variable*	*Symbol*	*Definition*	*Source*
Agricultural Employment	Share of the labor force employed in agriculture	$AGRI\_EMP$	Share of the labor force employed in agriculture	Our World in Data*
Economic Growth	Real GDP per capita	GDP_{pc}	GDP per capita (2015 constant prices, $)	The World Bank (WB) – World Development Indicators (WDI)
Education Level	Average years of schooling	$SCHOOL$	Average years of formal education for individuals aged 15-64.	Our World in Data**
Value Added Agriculture	Value added agriculture	$VALUE\_ADDED$	Agriculture, forestry, and fishing, value added (% of GDP)	WB - WDI
Agricultural Mechanization	Farm machinery per unit of agricultural land	$MACHINERY$	Farm machinery is measured in units of horsepower. This is divided by total agricultural land to give the average machinery use per 1000 hectares of agricultural land.	Our World in Data***

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*Our World in Data based on International Labor Organization (via the World Bank) and historical sources – processed by Our World in Data

**Barro and Lee (2015); Lee and Lee (2016) – with major processing by Our World in Data

*** United States Department for Agriculture (USDA) Economic Research Service – processed by Our World in Data

Table 2. Descriptive Statistics

Developing Countries							
Variable	*No. of obs.*	*Mean*	*Std. Dev*	*Min*	*Max*	*Skewness*	*Kurtosis*
EMPLOYMENT	400	2.850	1.143	-2.813	4.204	-2.014	8.174
GDP_{pc}	400	8.393	0.865	6.288	10.081	-0.209	2.600
SCHOOL	400	2.041	0.293	1.024	2.575	-0.814	3.559
VALUE _ ADDED	400	2.066	0.688	0.656	3.324	-0.172	2.132
MACHINERY	400	-0.993	1.246	-3.458	1.970	0.388	2.778

Source: Authors' Calculations

Before proceeding with the analysis, it is essential to determine whether cross-sectional dependency existed among the variables, as this affects the choice of econometric methods. The study employs three tests for cross-sectional dependence. They include the Pesaran (2004) cross-sectional dependence (CD) test, the Friedman (1937) test statistic, and the Frees (1995) test statistic. The application of these tests is due to robustness purposes. Cross-sectional dependency can arise in panel data when countries share similar external shocks, such as global trade dynamics or climatic conditions, leading to interdependence among the observations. The results are presented in Table 3 and indicate no cross-sectional dependence, as the null hypothesis of no dependence cannot be rejected.

Table 3. Cross-Sectional Dependency Tests

Test	*Test İstatistiği*	*P-value*
Pesaran CD	-0.112	0.911
Frees	2.400	0.195
Friedman	18.695	0.228

Source: Authors' Calculations

Identifying the absence of such dependency allowed for using first-generation unit root tests, which assume cross-sectional independence, ensuring the validity of the subsequent econometric analysis. The results showed no cross-sectional dependency among the variables. Furthermore, the Im, Pesaran, and Shin (2003) (IPS) unit root test results, which are presented in Table 4, indicate that all variables are integrated of order one (I(1)). This finding is critical because it ensures that the variables exhibit stationarity only after differencing, a key requirement for using cointegration techniques such as FMOLS and DOLS. The presence of I(1) variables implies that the data have long-run equilibrium relationships, justifying the use of models designed to capture these dynamics while addressing endogeneity and serial correlation issues. By confirming that the variables are I(1), the robustness of the subsequent econometric analysis is enhanced.

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Table 4. IPS Unit Root Test

Im, Pesaran and Shin (IPS)				
Variables	*I(0)*		*I(1)*	
	Stat	P-value	Stat	P-value
EMPLOYMENT	3.213	0.999	-6.875	0.000
GDP_{pc}	2.964	0.999	-8.732	0.000
SCHOOL	0.532	0.703	-6.993	0.000
VALUE _ ADDED	-1.196	0.116	-12.623	0.000
MACHINERY	-1.133	0.129	-9.899	0.000

Prior to estimating the FMOLS and DOLS models, we also conduct cointegration tests to verify the existence of long-run relationships among the variables. The results of the Westerlund (2008), Pedroni (1999 and 2004), and Kao (1999) tests are summarized in Table 5. These results confirm the presence of a long-run equilibrium relationship among the variables, validating the use of FMOLS and DOLS models for estimating the determinants of agricultural employment.

Table 5. Cointegration Tets

Test	Test Statistics
Westerlund	
Variance Ratio	-1.335 (0.091)
Pedroni	
Modified Phillips – Perront	2.871 (0.002)
Phillips – Perront	-1.777 (0.0378)
Augmented Dickey – Fuller t	-2.248 (0.012)
Kao	
Modified Dickey – Fuller t .	4.014 (0.000)
Dickey – Fuller t	5.906 (0.000)
Augmented Dickey – Fuller t	4.801 (0.000)
Unadjusted Modified Dickey – Fuller t	3.998 (0.000)
Unadjusted Dickey – Fuller t	5.847 (0.000)

Note: Probability values in parentheses

Given these findings, further analysis utilizing methods that account for cointegration would be appropriate to capture long-run relationships in the data. This cointegration finding justifies using

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long-run estimation techniques such as FMOLS and DOLS to explore the nature of these relationships. These approaches are suitable for addressing endogeneity and serial correlation issues in panel data, particularly when the variables are cointegrated.

EMPIRICAL RESULTS AND DISCUSSION

The FMOLS and DOLS results are summarized in Table 6.

Table 6. FMOLS and DOLS Results

	FMOLS		DOLS	
Variable	*Coefficient*	*t-statistic*	*Coefficient*	*t-statistic*
GDP_{pc}	-0.90***	-58.01	-1.15***	-28.68
SCHOOL	-1.02***	-29.55	-2.10***	-20.73
VALUE _ ADDED	0.08***	13.91	0.13***	4.39
MACHINERY	-0.57***	6.88	-0.27***	13.47

Note: *** p < 0.01

The empirical findings from both FMOLS and DOLS models consistently demonstrate significant relationships between the selected independent variables and agricultural employment in NTEEs.

The negative coefficients for GDP_{pc} (-0.90 in FMOLS, -1.15 in DOLS) indicates that as GDP per capita increases, the share of agricultural employment in total employment declines. This trend aligns with the structural transformation theory, where economic growth leads to a shift of labor from low-productivity agricultural sectors to higher-productivity industrial and service sectors. For resource-rich economies such as Saudi Arabia and Iraq, the decline in agricultural employment is accelerated due to the dominance of oil revenues, which shift investment and labor towards energy and urban infrastructure sectors. Similarly, industrialized NTEEs such as Poland and Malaysia experience pronounced labor reallocation due to rapid urbanization and industrial development.

The coefficients for *SCHOOL* (-1.02 in FMOLS, -2.10 in DOLS) reflect a significant negative impact of education on agricultural employment. This is consistent with the human capital theory, which suggests that increased educational attainment equips individuals with the skills to transition to non-agricultural sectors. The negative effect is particularly evident in countries such as Bangladesh, Pakistan, and Vietnam, where education reforms have been a priority. Improved educational opportunities have encouraged rural youth to seek employment in urban and industrial sectors, reducing reliance on agriculture.

The positive coefficients for *VALUE _ ADDED* (0.08 in FMOLS, 0.13 in DOLS) indicate that higher agricultural productivity sustains labor demand in agriculture. This finding is particularly relevant for agrarian economies such as Argentina, Peru, and Thailand, where agriculture remains economically significant and a key source of rural employment. The positive impact of agricultural value added highlights the importance of policies that enhance productivity, such as investments in irrigation, crop diversification, and access to markets. These measures help stabilize employment in agriculture despite broader structural shifts.

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The negative coefficients for *MACHINERY* (-0.57 in FMOLS, -0.27 in DOLS) reveal that mechanization reduces the demand for agricultural labor. This effect is more pronounced in technologically advanced NTEEs such as Malaysia and South Africa, where mechanization has replaced manual labor in key agricultural activities. However, in labor-intensive economies such as Egypt and Bangladesh, the adoption of mechanization is slower, moderating its impact on labor displacement. This underscores the heterogeneous effects of mechanization depending on the level of technological adoption and labor market dynamics.

CONCLUSION

This study provides empirical evidence on the determinants of agricultural employment in Next-Tier Emerging Economies, offering valuable insights into the labor dynamics of transitional economies. The results highlight the complex interplay between economic growth, education, mechanization, and agricultural productivity in shaping employment patterns in the agricultural sector.

The negative impact of GDP per capita and schooling on agricultural employment aligns with structural transformation theories, where rising incomes and higher education levels drive labor away from agriculture toward industry and services. Similarly, mechanization reduces the reliance on manual labor, reflecting technological progress in agriculture. However, the positive effect of agricultural value added emphasizes the continued importance of the sector in sustaining rural employment when it remains productive and economically significant.

These findings have important policy implications. Policymakers must address the challenges of mechanization and rural labor displacement through targeted interventions such as skill development programs, rural job creation initiatives, and investment in sustainable agricultural practices. Balancing rural education with local employment opportunities is critical to preventing excessive urban migration and ensuring equitable growth.

This study contributes to understanding structural transformation and labor market shifts in emerging economies. Future research could explore the role of additional variables, such as climate change and rural infrastructure, in influencing agricultural employment. By providing a deeper perspective on agricultural labor dynamics, this paper is a foundation for designing policies that support inclusive and sustainable development in transitional economies.

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