

Machines and Exports: Do They Complement or Counteract Agricultural Productivity?

Muhammed BENLİ¹

¹ Assoc. Prof., Bilecik Seyh Edebali University, Department of Economics, muhammed.benli@bilecik.edu.tr, ORCID: 0000-0001-6486-8739

Abstract: This study examines the impact of agricultural mechanization, food exports, per capita income, and human capital development on agricultural productivity. Utilizing panel data from 55 developing countries covering the period 2000–2019, the analysis employs the AMG and CCE-MG estimation techniques, accounting for heterogeneity and cross-sectional dependence. The findings reveal that agricultural mechanization, contrary to expectations, has a negative impact on productivity. This may be attributed to inadequate infrastructure, limited financial access, and smallholder farmers' difficulties in adopting new technologies. In contrast, per capita income positively influences agricultural productivity, indicating that economic growth facilitates the adoption of modern agricultural practices. Food exports also enhance productivity, though excessive reliance on external markets may introduce risks related to price volatility and food security. The effect of human capital (education) presents a more complex picture; while higher education levels are generally associated with increased efficiency, they may also drive the rural workforce to shift to non-agricultural sectors. This underscores the need for education systems to incorporate agricultural-specific skills and technological training. These findings highlight the necessity of a comprehensive policy framework to enhance agricultural productivity in developing economies.

Keywords: Agricultural Productivity, Agricultural Mechanization, Food Exports, AMG, CCE-MG

Jel Codes: Q16, Q17, C33

Makineler ve İhracat: Tarımsal Verimliliği Destekliyor mu, Engelliyor mu?

Öz: Bu çalışma, tarımsal mekanizasyon, gıda ihracatı, kişi başına düşen gelir ve beşeri sermaye gelişiminin tarımsal verimlilik üzerindeki etkilerini incelemektedir. 2000-2019 yıllarını kapsayan 55 gelişmekte olan ülkeye ait panel veriler kullanılarak, heterojenlik ve kesitler arası bağımlılığı dikkate alan AMG ve CCE-MG yöntemleri uygulanmıştır. Elde edilen bulgular, tarımsal mekanizasyonun verimlilik üzerinde beklenenin aksine negatif bir etkiye sahip olduğunu ortaya koymaktadır. Bu durum, altyapı eksiklikleri, finansmana erişim zorlukları ve küçük ölçekli çiftçilerin teknolojiye adaptasyonundaki yetersizliklerle açıklanabilir. Öte yandan, kişi başına düşen gelirin tarımsal verimliliği artırdığı görülmektedir; bu, ekonomik büyümenin modern tarımsal tekniklerin benimsenmesini teşvik ettiğini göstermektedir. Gıda ihracatının ise tarımsal verimliliği artırdığı tespit edilmiştir; ancak, dış pazarlara aşırı bağımlılığın fiyat dalgalanmalarına ve gıda güvenliği risklerine yol açabileceği unutulmamalıdır. Beşeri sermayenin (eğitim) etkisi ise karmaşık bir tablo sergilemektedir; genel eğitim seviyesinin artması kırsal iş gücünün tarım dışı sektörlerle kaymasına neden olabileceğinden, eğitimin tarım odaklı becerilerle desteklenmesi gerekmektedir. Bu bulgular, gelişmekte olan ülkelerde tarımsal verimliliği artırmak için çok yönlü bir politika çerçevesinin gerekli olduğunu göstermektedir.

Anahtar Kelimeler: Tarımsal Verimlilik, Tarımsal Mekanizasyon, Gıda İhracatı, AMG, CCE-MG

Jel Kodları: Q16, Q17, C33

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1. Introduction

Agricultural productivity is a crucial driver of economic development, poverty alleviation, and food security, particularly in developing countries where a significant portion of the labor force is engaged in agriculture (Timmer, 2009). Given the rising global food demand and the increasing pressure on natural resources, improving agricultural productivity has become a central policy concern for both national governments and international organizations (Fuglie, 2018). Despite substantial technological advancements, many developing economies continue to experience stagnation or only modest improvements in agricultural productivity, which has critical implications for rural livelihoods and economic transformation. This study seeks to examine key determinants of agricultural productivity in developing countries, with a specific focus on the roles of agricultural mechanization, food exports, per capita income, and human capital development.

Agricultural mechanization has long been recognized as a key factor driving productivity growth in the agricultural sector (Pingali, 2007). By reducing dependence on manual labor and improving efficiency in land cultivation and harvesting, mechanization has contributed to agricultural revolutions in many developed economies (Binswanger, 1986). However, its impact in developing countries remains ambiguous, as several constraints—such as limited financial access, inadequate infrastructure, and weak institutional support—hinder its effectiveness (Takeshima, 2017). In some cases, mechanization may even lead to unintended consequences, such as rural unemployment or increased economic disparities among farmers (Diao et al., 2010). Understanding how mechanization affects agricultural productivity in the context of developing economies is therefore critical for designing policies that maximize its benefits while mitigating potential drawbacks.

In addition to technological progress, international market integration plays a vital role in shaping agricultural productivity. Theoretically, greater participation in food exports can enhance agricultural efficiency by exposing producers to international competition, incentivizing technological adoption, and enabling economies of scale (Anderson & Martin, 2005). Empirical studies have found that export-led agricultural strategies contribute positively to productivity growth in various developing economies (Balassa, 1978; Dollar & Kraay, 2004). However, excessive reliance on food exports can also introduce risks, such as price volatility, trade policy uncertainties, and potential food security concerns for domestic markets (Swinnen & Squicciarini, 2012). This study aims to clarify the extent to which food exports contribute to agricultural productivity in developing countries and to assess whether export-driven growth strategies are sustainable in the long run.

Beyond technological and trade-related factors, economic growth and human capital development have been widely recognized as fundamental drivers of agricultural productivity. Rising per capita income fosters investment in modern farming techniques, irrigation infrastructure, and research and development (Gollin et al., 2002). However, economic development also accelerates the structural transformation of economies, shifting labor away from agriculture to industry and services (Timmer, 2009). While this transition is a natural process in economic development, its implications for agricultural productivity remain uncertain. Similarly, human capital accumulation—particularly through education—has been identified as a key determinant of agricultural efficiency, as educated farmers are more likely to adopt new technologies and optimize resource allocation (Schultz, 1964). Nonetheless, some studies suggest that higher education levels may lead to labor migration out of agriculture rather than increased productivity within the sector (Beine et al., 2008). This study seeks to explore these dynamics by empirically assessing how education influences agricultural productivity in developing economies.

The contribution of this research is twofold. First, it provides a comprehensive empirical analysis of the effects of mechanization, food exports, economic growth, and human capital development on agricultural productivity. The study focuses on the period

2000–2019, selected due to data availability constraints, and includes 55 developing countries identified based on their structural dependence on agriculture, their diverse agricultural trade profiles, and the availability of key variables for the analysis. By employing advanced panel data techniques, specifically the Augmented Mean Group (AMG) and Common Correlated Effects Mean Group (CCE-MG) estimators, this study accounts for heterogeneity and cross-sectional dependence (CSD), addressing key methodological challenges that are often overlooked in previous research. Second, this study offers policy-relevant insights into how developing countries can enhance agricultural productivity while ensuring sustainable economic transformation. Unlike previous studies that focus on isolated determinants, this research examines multiple interconnected factors within a unified analytical framework, thereby enriching the existing literature on agricultural development.

2. Literature Review

The determinants of agricultural productivity have been extensively explored in economic literature, with various studies highlighting the roles of technological progress, market integration, institutional quality, and human capital development. Among these, agricultural mechanization has long been regarded as a key driver of productivity growth, particularly in the context of historical agricultural transformations in developed countries. Pingali (2007) provides a global review of mechanization trends, focusing on the economic impact of labor-saving technologies. According to the study, mechanization contributes to productivity by reducing the reliance on manual labor, optimizing resource utilization, and enabling economies of scale. Similarly, Diao et al. (2010) use general equilibrium models and scenario analysis to explore the potential impact of mechanization on agricultural productivity in Sub-Saharan Africa and emphasize that mechanization can enhance labor productivity by facilitating shifts from subsistence farming to commercialized agricultural systems. However, in many developing countries, the adoption of mechanization is constrained by factors such as limited access to credit (Binswanger, 1986), inadequate infrastructure (Takeshima, 2017), and the absence of complementary investments in irrigation and extension services (Mottaleb, 2016).

While mechanization is widely acknowledged as a productivity-enhancing tool, its impact varies across regions and economic contexts. For instance, studies by Fuglie (2018) and Nin-Pratt & McBride (2014) suggest that in Sub-Saharan Africa and parts of South Asia, the benefits of mechanization have been less pronounced due to small farm sizes, fragmented land tenure systems, and weak rural financial institutions. Conversely, in countries such as China and Brazil, mechanization has played a central role in driving agricultural growth (De Monteiro Jales et al., 2006). A recent study by Toaha and Mondal (2023), utilizing ARDL models and long-run cointegration tests, examines how agricultural credit facilitates mechanization and, consequently, economic growth in Bangladesh, highlighting the critical role of access to finance in scaling agricultural technologies. These disparities highlight the importance of considering country-specific conditions when assessing the impact of mechanization on productivity.

In parallel, agricultural trade and food exports have gained increasing attention as potential catalysts for productivity improvements. According to Anderson & Martin (2005), participation in international markets can enhance efficiency by exposing domestic producers to competition, incentivizing technological adoption, and facilitating knowledge spillovers. Empirical studies such as those by Balassa (1978) and Dollar & Kraay (2004) provide evidence that export-led growth strategies contribute positively to overall economic development, including the agricultural sector. Chu et al. (2025) develop a Schumpeterian growth model with endogenous takeoff dynamics and complement it with cross-country panel data estimations to investigate the complex interactions between agricultural productivity, trade specialization, and industrialization in countries such as China, Japan, and the US. The empirical evidence emphasizes that agricultural productivity's relationship with economic growth varies with trade dependence: while

moderate integration fosters productivity, over-reliance on agricultural imports may hinder long-term growth. Additionally, Zeng et al. (2025) apply fixed effects models and Poisson Pseudo-Maximum Likelihood (PPML) estimators to assess how the depth of free trade agreements influences agricultural global value chain participation.

However, the relationship between food exports and agricultural productivity is complex. On the one hand, increased export orientation can drive investment in agricultural infrastructure and promote higher-value crop production (Foster & Rosenzweig, 2010). On the other hand, excessive reliance on food exports can introduce risks associated with price volatility and external demand shocks (Swinnen & Squicciarini, 2012). For instance, Sowrov (2024) employs OLS and fixed effects panel regression models to analyze the relationship between trade openness, tariffs, and economic growth in G-20 countries, emphasizing the importance of institutional quality. The study finds that trade openness positively influences economic growth, whereas higher tariff levels exert a negative impact, reinforcing the need for balanced trade strategies in agricultural policy.

The role of economic growth in driving agricultural productivity is also well-documented. Rising per capita income fosters increased investment in agricultural inputs, infrastructure, and research, which collectively enhance productivity (Gollin et al., 2002). Additionally, economic development often leads to structural transformation, shifting labor away from agriculture toward industry and services (Timmer, 2009). While this transition is a natural progression in development, it raises questions about the sustainability of agricultural productivity improvements in economies undergoing rapid industrialization.

Human capital, particularly education, has been widely recognized as a crucial factor influencing agricultural productivity. Schultz (1964) argues that education enhances farmers' ability to adopt and efficiently utilize new technologies, thereby improving productivity. Empirical studies by Foster & Rosenzweig (1996) and Asadullah & Rahman (2009) find a positive relationship between educational attainment and agricultural efficiency in various developing country contexts. However, other research suggests that the effect of education on productivity is conditional on the type of education provided. For example, McNamara et al. (1991) highlight that general education may not always translate into higher productivity unless it includes agricultural-specific knowledge and technical training. In some cases, higher education levels may even lead to a decline in agricultural productivity if they encourage skilled labor migration to non-agricultural sectors (Beine et al., 2008). Recent research by van Huyssteen et al. (2025) highlights the environmental trade-offs associated with agricultural trade in South Africa, revealing that imports require significantly more resources and generate higher emissions compared to exports, thereby questioning the sustainability of current trade practices.

Despite the extensive body of literature on the determinants of agricultural productivity, there remains a need for further empirical analysis that simultaneously considers the effects of mechanization, food exports, economic growth, and human capital development in a unified framework. This study contributes to the literature by employing advanced panel data techniques to examine these interrelationships in a sample of developing countries over the period 2000-2019. By addressing cross-sectional dependencies and heterogeneity, this research provides a more comprehensive understanding of the factors shaping agricultural productivity in developing economies.

3. Data

In this study, we examine the long-run effect of food exports and mechanization on agricultural productivity in developing countries. The analysis is based on annual data from 2000 to 2019, constrained by common data limitations across the model's variables. As a result, the study focuses on a sample of 55 developing countries, as listed in Table 1 below.

Table 1. List of Countries

Argentina	Colombia	Israel	Niger	South Africa
Benin	Costa Rica	Jordan	Oman	South Korea
Bolivia	Ecuador	Madagascar	Pakistan	Tanzania
Botswana	Egypt	Malaysia	Panama	Thailand
Brazil	El Salvador	Mauritania	Paraguay	Togo
Burkina Faso	Gabon	Mauritius	Peru	Tunisia
Burundi	Gambia	Mexico	Philippines	Türkiye
Cabo Verde	Guatemala	Morocco	Qatar	Uganda
Cameroon	Honduras	Mozambique	Rwanda	Uruguay
Chile	India	Namibia	Saudi Arabia	Viet Nam
China	Indonesia	Nicaragua	Senegal	Zambia

The selection of developing countries as the focus of this study is motivated by several key economic, structural, and institutional factors that distinguish them from advanced economies in the context of agricultural productivity and trade. Unlike developed nations, where agriculture accounts for a relatively small share of GDP and employment due to extensive industrialization and service sector expansion, many developing economies continue to rely heavily on agriculture as a primary driver of economic activity, employment, and food security (Timmer, 2009; Gollin, 2010). This dependence makes them particularly vulnerable to changes in agricultural trade dynamics and mechanization patterns, as well as broader economic transformations that influence sectoral productivity. Additionally, agricultural exports play a critical role in economic development by generating foreign exchange earnings, stimulating investment in rural areas, and facilitating technological spillovers from global markets (Anderson & Martin, 2005; Balassa, 1978). However, the extent to which food exports contribute to sustainable productivity growth remains uncertain, particularly in economies where mechanization, market integration, and institutional quality vary widely.

A crucial factor influencing agricultural productivity in developing countries is institutional and infrastructural constraints, which often moderate the impact of mechanization and trade expansion. Many of these nations face weak transportation networks, insufficient storage facilities, and fragmented land tenure systems, which hinder the efficient allocation of resources and the full realization of productivity gains from mechanization (Binswanger, 1986; Takeshima, 2017). Furthermore, access to financial services, particularly credit for smallholder farmers, remains a significant barrier to the adoption of advanced agricultural technologies (Fuglie, 2018). In some contexts, mechanization without complementary policies—such as training programs and access to affordable inputs—has resulted in labor displacement, increased production costs, and underutilization of machinery (Diao, Hazell, & Thurlow, 2010). Similarly, while food exports have the potential to enhance agricultural efficiency, their benefits may be offset by price volatility, trade restrictions, and supply chain inefficiencies (Swinnen & Squicciarini, 2012).

Moreover, the increasing role of global trade liberalization and regional trade agreements has significantly shaped agricultural trade patterns in developing countries. Over the past two decades, many developing nations have sought to diversify their agricultural exports and integrate into global value chains (Dollar & Kraay, 2004; Foster & Rosenzweig, 2010). However, while trade liberalization can create opportunities for growth, it may also expose countries to external shocks, such as global commodity price fluctuations and non-tariff trade barriers (Beine et al., 2008). Given these complexities, it is crucial to assess whether food exports serve as a viable long-term strategy for agricultural productivity enhancement or whether their effects are conditional on domestic policy frameworks and structural conditions. Understanding these interactions can provide valuable insights for policymakers, enabling them to design interventions that maximize the benefits of trade while mitigating associated risks, such as income volatility and food security concerns.

To empirically investigate these dynamics, this study employs an econometric model to examine the impact of food exports and mechanization on agricultural productivity in developing economies. The dependent variable is agriculture, forestry, and fishing value-added per worker (constant 2015 US\$), which serves as a proxy for agricultural productivity. The key independent variables include food exports as a percentage of total merchandise exports and farm machinery per unit of agricultural land, which capture the roles of trade and mechanization in shaping productivity. Additional control variables include GDP per capita (constant 2015 US\$) to account for the effects of structural transformation, and average years of schooling, which serves as a proxy for human capital development and reflects the role of education in improving agricultural efficiency.

To ensure robustness and comparability, all variables are transformed into natural logarithmic form, which facilitates elasticity-based interpretations and improves the normality of data distributions, reducing potential heteroskedasticity issues. Given the heterogeneous nature of developing countries and the likelihood of CSD in panel data, this study applies AMG and CCE-MG estimation techniques, which account for both country-specific heterogeneity and unobserved common factors affecting agricultural productivity. The summary statistics for the variables used in the analysis are presented in Table 2 and Table 3, offering an overview of the data characteristics and variation across the sample.

Table 2. Summary of variables

Target Variable	Proxy Variable	Symbol	Definition	Source
Agricultural Productivity	Agriculture, value added per worker	<i>AGRIPROD</i>	Agriculture, forestry, and fishing, value added per worker (constant 2015 US\$)	The World Bank (WB) – World Development Indicators (WDI)
Food Exports	Food exports (% of merchandise exports)	<i>FEXP</i>	Food exports (% of merchandise exports)	The WB – WDI
Economic Growth	Real GDP per capita	<i>GDPpc</i>	GDP per capita (constant 2015 US\$)	The WB – WDI
Agricultural Mechanization	Farm machinery per unit of agricultural land	<i>MACHINERY</i>	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
Education Level	Average years of schooling	<i>SCHOOL</i>	Average years of formal education for individuals aged 15-64.	Our World in Data

Table 3. Descriptive statistics

Variables	No. of obs.	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
<i>AGRIPROD</i>	1100	8.092	1.311	5.427	12.532	-1.298	6.154
<i>FEXP</i>	1100	2.687	1.461	-7.459	4.584	-2.190	10.471
<i>GDPpc</i>	1100	8.081	1.230	5.567	11.310	0.071	2.437
<i>MACHINERY</i>	1100	-2.218	2.049	-7.437	2.300	-0.394	2.993
<i>SCHOOL</i>	1100	1.778	0.512	-0.023	2.591	-1.195	4.069

Source: Author's calculations

4. Methodology

The empirical model used in this study is constructed based on the defined sample and data range and is specified as follows:

$$AGRIPROD_{it} = \beta_0 + \beta_2 FEXP_{it} + \beta_3 GDPpc_{it} + \beta_4 MACHINERY_{it} + \beta_5 SCHOOL_{it} + \varepsilon_{it} \quad (1)$$

where $i = 1, 2, 3, \dots, N$ denotes cross-sectional units (countries), $t = 1, 2, 3, \dots, T$ represents the time dimension, and ε_{it} is the error term. The selection of variables and the

theoretical framework of this study are informed by established literature on agricultural productivity. Specifically, the inclusion of agricultural mechanization is based on the works of Pingali (2007), Binswanger (1986), and Diao et al. (2010), which highlight both the potential benefits and constraints of mechanization in developing economies. The role of food exports is motivated by studies such as Anderson & Martin (2005), Balassa (1978), and Dollar & Kraay (2004), which emphasize the positive relationship between trade openness and agricultural efficiency. The inclusion of per capita income as a proxy for economic growth draws on Gollin et al. (2002) and Timmer (2009), who demonstrate that rising income levels foster investment and technological adoption in agriculture. Finally, the inclusion of human capital, measured by education, is grounded in the human capital theory of Schultz (1964) and supported by empirical evidence from Foster & Rosenzweig (1996) and Beine et al. (2008), which underline the importance of education for technology adoption, albeit with potential trade-offs in terms of labor migration.

This model framework facilitates a comprehensive examination of the relationship between food exports, mechanization, and agricultural productivity while accounting for key economic, technological, and human capital determinants that shape agricultural sector performance in developing economies.

Panel data models provide a robust framework for analyzing these relationships by incorporating both time dynamics and cross-country heterogeneity (Baltagi, 2008). However, ensuring unbiased and consistent estimates requires addressing key econometric concerns such as slope heterogeneity, CSD, stationarity, and cointegration (Pesaran, 2006). To ensure the validity of the estimation approach, we conduct a series of diagnostic tests before model estimation, allowing for the selection of the most appropriate methodology.

Given the diverse economic structures, agricultural policies, and trade dynamics across developing countries, it is crucial to assess whether slope coefficients vary across panel units. Standard panel estimation techniques often assume homogeneity, which may not hold when structural differences exist between economies (Pesaran & Yamagata, 2008). To address this, we employ the Delta test developed by Pesaran & Yamagata (2008), which evaluates whether slope coefficients are homogeneous across countries. If significant heterogeneity is detected, it justifies the use of heterogeneous estimators such as AMG and CCE-MG, which allow for country-specific variations in the effects of mechanization and food exports on agricultural productivity.

Due to the global nature of agricultural trade, mechanization diffusion, and external economic shocks, agricultural productivity in different countries may be correlated. Failing to account for CSD can lead to biased standard errors and inefficient estimates (Chudik & Pesaran, 2015). To detect CSD, we employ:

- The Breusch-Pagan (1980) Lagrange Multiplier (LM) test for CSD.
- The bias-adjusted LM test proposed by Pesaran et al. (2008), which corrects for over-rejection issues in large panels.
- The Pesaran (2004) CD test, which is robust to different panel sizes and is particularly effective when the number of cross-sectional units is large.

If CSD is present, traditional panel estimators such as Fixed Effects (FE) and Random Effects (RE) become unreliable, necessitating the use of CCE-MG and AMG estimators, which control for unobserved common factors affecting food exports, mechanization, and agricultural productivity.

In panel data analysis, non-stationary variables can lead to spurious regressions, making it essential to verify whether the time series properties of the variables support meaningful long-run relationships (Phillips & Perron, 1988). To address this, we employ:

- Cross-sectionally augmented Dickey-Fuller (CADF) test (Pesaran, 2007), which controls for CSD.
- Cross-sectionally augmented Im, Pesaran, and Shin (CIPS) test (Pesaran, 2007), an extension of the IPS (2003) test, which ensures that non-stationarity issues do not distort our findings.

These tests confirm whether all variables are integrated at the same order ($I(0)$ or $I(1)$), ensuring that a valid cointegration analysis can be performed in the next step.

Since agricultural productivity, mechanization, and food exports are expected to exhibit long-run equilibrium relationships, confirming cointegration is necessary. To do so, we apply:

- Westerlund (2005) error-correction-based cointegration test, which accommodates CSD in panel models.
- Pedroni (1999, 2004) cointegration tests, which determine whether a stable relationship exists among the variables.
- Kao (1999) residual-based cointegration test, an extension of the Engle-Granger approach for panel data.

The presence of cointegration justifies the use of long-run estimators such as AMG and CCE-MG, which effectively capture both short-run and long-run effects of mechanization and food exports on agricultural productivity.

Once cointegration is confirmed, we estimate the long-run relationships using:

- The AMG estimator by Eberhardt & Bond (2009), which allows for heterogeneous slope coefficients and corrects for unobserved common factors.
- The CCE-MG estimator by Pesaran (2006), which explicitly controls for CSD by including cross-sectional averages in the regression model.

Both estimators are designed for large heterogeneous panels with CSD, making them ideal for examining the interplay between agricultural mechanization, food exports, and productivity in developing countries.

By following this structured methodology, this study ensures that the empirical analysis accounts for heterogeneity, CSD, stationarity, and long-run relationships, thereby enhancing the robustness and interpretability of the findings.

5. Empirical Findings

The results of the Pesaran & Yamagata (2008) homogeneity test, presented in Table 4, provide critical insights into the structure of the panel data analyzed in this study. This test evaluates the assumption of slope homogeneity across cross-sectional units, which is a fundamental consideration in selecting the appropriate econometric methodology. The highly significant test statistics strongly reject the null hypothesis of slope homogeneity, indicating substantial differences in the estimated relationships across the countries in the panel.

These findings suggest that the impact of food exports and mechanization on agricultural productivity varies significantly across developing economies, likely due to structural differences in agricultural production systems, trade policies, technological adoption, and institutional frameworks. The rejection of slope homogeneity underscores the need for estimators that accommodate cross-country variations in the effects of mechanization and food exports rather than assuming a uniform relationship across all panel units.

The presence of heterogeneous slope coefficients implies that applying traditional panel estimators that assume a common slope for all cross-sectional units, such as FE and RE models, may introduce bias and lead to misleading conclusions (Pesaran & Yamagata, 2008). Specifically, such estimators would fail to account for country-specific variations in agricultural trade structures, mechanization levels, and policy environments, which are crucial determinants of agricultural productivity in developing economies.

To accurately capture the underlying economic relationships, this study employs heterogeneous panel estimators, namely the AMG estimator (Eberhardt & Bond, 2009) and the CCE-MG estimator (Pesaran, 2006). These methodologies explicitly accommodate heterogeneity by allowing country-specific slope coefficients, making them more suitable for examining the differential effects of food exports and mechanization on agricultural productivity. The AMG estimator corrects for unobserved common factors (Eberhardt &

Teal, 2011), while the CCE-MG estimator explicitly accounts for CSD (Pesaran, 2006), further enhancing the reliability of our findings.

The strong rejection of slope homogeneity provides robust empirical justification for employing heterogeneous panel estimation techniques. These methods allow for a more nuanced and accurate assessment of the trade-productivity and mechanization-productivity relationships, ensuring that policy implications derived from this study reflect the diverse economic realities of developing countries rather than being generalized under restrictive homogeneity assumptions.

Table 4. Pesaran & Yamagata (2008) homogeneity test

Test	Test Statistic
$\tilde{\Delta}$	25.392***
$\tilde{\Delta}_{adj}$	30.350***

Note: *** p<0.01

The highly significant rejection of the homogeneity assumption reinforces the necessity of adopting econometric techniques that accommodate country-specific variations in the impact of food exports and mechanization on agricultural productivity (Pesaran & Tosetti, 2011). Neglecting these structural differences could obscure critical cross-country variations, leading to biased estimates and misleading policy implications. The heterogeneous nature of developing economies suggests that agricultural productivity is influenced by country-specific trade policies, levels of technological adoption, institutional capacities, and infrastructure development, further justifying the use of AMG and CCE-MG estimators, which allow for differential impacts across panel units.

Beyond heterogeneity concerns, the results of the CSD tests, presented in Table 5 and Table 6, provide strong evidence that the panel dataset exhibits significant CSD. CSD arises when unobserved global and regional factors—such as international trade dynamics, macroeconomic shocks, climate variability, or financial market fluctuations—simultaneously affect multiple countries in the panel (Pesaran, 2006).

The results in Table 5 indicate that all CSD tests yield highly significant test statistics at conventional significance levels, confirming the presence of strong CSD across panel units. Specifically, the Breusch-Pagan LM test statistic and the bias-adjusted LM test statistic strongly reject the null hypothesis of cross-sectional independence, suggesting that food exports, mechanization, and agricultural productivity are influenced by interdependent global forces. Moreover, the Pesaran (2004) CD test further confirms the presence of interdependencies among panel units.

Furthermore, the Pesaran (2004) CD test results for individual variables, presented in Table 6, indicate that each variable in the model exhibits significant CSD, with test statistics exceeding conventional significance thresholds. Specifically, agricultural productivity, food exports, GDP per capita, mechanization, and schooling all display highly significant CSD.

These findings indicate that agricultural productivity, food exports, and other explanatory variables are significantly influenced by global and regional factors, such as trade liberalization, financial integration, technological diffusion, and macroeconomic volatility, which simultaneously shape agricultural and economic dynamics across multiple countries (Chudik & Pesaran, 2015). The existence of strong CSD further invalidates the use of traditional panel estimators such as FE or RE models, which assume independence across cross-sectional units. Instead, estimators that explicitly account for cross-sectional dependence, such as CCE-MG and AMG, provide more reliable and unbiased long-run estimates by controlling for the influence of unobserved common factors (Eberhardt & Bond, 2009).

Overall, the presence of both CSD and heterogeneity reinforces the suitability of employing AMG and CCE-MG estimators, which effectively capture the heterogeneous and interdependent nature of agricultural productivity in developing countries. These

results underscore the need for policy interventions that consider both global trade dynamics and country-specific structural factors, ensuring that mechanization and food export policies are tailored to the unique economic and institutional contexts of individual countries.

Table 5. Cross Sectional Dependency Tests

Test	Test Statistic
<i>LM</i>	2031***
<i>LM_{adj}</i>	11.55***
<i>LM_{CD}</i>	2.293**

Note: *** $p < 0.01$, ** $0.01 < p < 0.05$

Table 6. Cross sectional dependency test for variables (Pesaran CD test)

Variable	CD Test Statistic (p-değeri)
<i>AGRIPROD</i>	60.653***
<i>FEXP</i>	11.378***
<i>GDPpc</i>	114.34***
<i>MACHINERY</i>	5.137***
<i>SCHOOL</i>	145.335***

Note: *** $p < 0.01$

Given the strong presence of CSD, the use of first-generation panel unit root tests would be inappropriate, as these tests assume cross-sectional independence and could lead to misleading conclusions regarding the stationarity properties of the variables (Pesaran, 2007). Instead, second-generation unit root tests should be employed, as they explicitly account for cross-sectional interdependencies and provide more reliable inferences. To ensure robust stationarity testing, we employ both Pesaran's (2007) CIPS test and the CADF test, both of which control for common factors across panel units, making them more appropriate for heterogeneous panels with strong cross-sectional dependencies.

The results, presented in Table 7, indicate that all variables in the model are integrated of order one, $I(1)$. This confirms that all variables become stationary after first differencing, implying that they exhibit long-run stochastic trends. The finding that all variables are $I(1)$ has important econometric implications. Since the variables share a common order of integration, they may also share underlying stochastic trends, making it necessary to conduct cointegration analysis to determine whether a stable long-run equilibrium relationship exists among them (Kao, 1999; Pedroni, 2004). If cointegration is present, it would imply that despite short-term fluctuations, the variables move together over time, suggesting the existence of a long-run equilibrium relationship between agricultural productivity, mechanization, food exports, and other control variables.

Given the presence of long-run stochastic trends, employing long-run panel estimation techniques is justified. If cointegration is confirmed, methods such as the AMG and the CCE-MG estimators are appropriate, as they account for CSD and heterogeneity while estimating long-run coefficients. These methodologies provide robust long-term estimates that are not affected by short-term fluctuations, ensuring that the empirical approach properly reflects the dynamic properties of the data.

Overall, the results of the CADF and CIPS tests confirm that all variables in the model follow unit root processes and become stationary after first differencing, reinforcing the necessity of conducting cointegration analysis before proceeding with long-run estimation techniques. These findings validate the empirical approach taken in this study, ensuring that econometric techniques applied in subsequent analyses appropriately account for the dynamic nature of the data and provide reliable policy-relevant insights into the relationship between mechanization, food exports, and agricultural productivity in developing economies.

Table 7. CADF and CIPS unit root tests

Variables	CADF		CIPS	
	Level	First Difference	Level	First Difference
<i>AGRIPROD</i>	-2.325	-3.194***	-2.469	-4.209***
<i>FEXP</i>	-2.244	-3.430***	-2.375	-4.318***
<i>GDPpc</i>	-2.226	-2.641***	-1.961	-3.457***
<i>MACHINERY</i>	-2.069	-2.697***	-2.227	-4.014***
<i>SCHOOL</i>	-2.155	-2.579***	-1.622	-2.666**

Note: *** $p < 0.01$, ** $0.01 < p < 0.05$

Before estimating long-run relationships, we conduct panel cointegration tests to assess whether the variables in the model exhibit a stable equilibrium relationship over time. The presence of cointegration would indicate that, despite short-term fluctuations, mechanization, food exports, and agricultural productivity move together in the long run, justifying the application of long-run estimation techniques.

The results of the Westerlund (2005), Pedroni (1999, 2004), and Kao (1999) tests, presented in Table 8, provide strong evidence of cointegration among the variables. The significance of these panel cointegration tests validates the application of long-run estimation techniques that appropriately account for the equilibrium relationships among food exports, mechanization, and agricultural productivity. These findings provide robust empirical support for examining how trade and technology jointly influence agricultural performance in developing economies, reinforcing the relevance of long-term policy strategies aimed at balancing export growth, mechanization investments, and sectoral sustainability. Given that the variables exhibit long-run comovement, estimators such as the AMG and the CCE-MG estimators are particularly well-suited for this analysis. These methodologies explicitly address CSD and heterogeneity, ensuring that long-run relationships are accurately captured.

Table 8. Cointegration tests

Test	Test Statistics
Westerlund	
<i>Variance Ratio</i>	-2.079**
Pedroni	
<i>Modified Phillips – Perron t</i>	6.868***
<i>Phillips – Perron t</i>	-4.802***
<i>Augmented Dickey – Fuller t</i>	-4.891***
Kao	
<i>Modified Dickey – Fuller t</i>	2.721***
<i>Dickey – Fuller t</i>	2.395***
<i>Augmented Dickey – Fuller t</i>	3.752***
<i>Unadjusted Modified Dickey – Fuller t</i>	-0.058
<i>Unadjusted Dickey – Fuller t</i>	-0.164

Note: *** $p < 0.01$, ** $0.01 < p < 0.05$

Given the strong evidence of cointegration among agricultural productivity, mechanization, and food exports, employing estimation methods that explicitly account for long-run equilibrium relationships is necessary to obtain reliable and robust long-run coefficients. Traditional panel regression techniques, such as FE or RE models, are inappropriate in the presence of cointegration, as they fail to capture dynamic adjustments and long-term dependencies within the data. Instead, estimation techniques such as the AMG and the CCE-MG estimators are particularly well-suited for this analysis, as they explicitly address heterogeneity, CSD, and dynamic interactions in panel data settings.

The AMG estimator provides a flexible approach that accounts for unobserved heterogeneity across countries, making it highly suitable for modeling country-specific variations in the relationship between mechanization, food exports, and agricultural productivity. Unlike conventional pooled estimators, AMG allows all coefficients to vary across countries, ensuring that the estimated effects reflect structural differences in agricultural systems, trade policies, and technological adoption rates. This feature is

particularly valuable, as the impact of mechanization and trade on agricultural productivity is likely to be shaped by country-specific institutional, climatic, and technological conditions.

The CCE-MG estimator further enhances the robustness of long-run estimates by explicitly controlling for CSD, which arises when unobserved global shocks—such as climate variability, international trade fluctuations, or macroeconomic instability—simultaneously affect multiple countries in the panel (Chudik & Pesaran, 2015). By incorporating independent variables' cross-sectional averages, the CCE-MG estimator effectively controls for the influence of global common factors, thereby reducing omitted variable bias and producing more reliable estimates in the presence of strong interdependencies among panel units. This feature is particularly relevant in the context of agricultural trade and mechanization, as both factors are significantly shaped by global market dynamics, technological diffusion, and international policy frameworks.

The results are presented in Table 9. To ensure the robustness and stability of the estimates, we include all explanatory variables in the estimation models simultaneously, allowing for a comprehensive assessment of their joint effects on agricultural productivity.

This modeling strategy ensures that:

- All key explanatory variables are analyzed in a unified framework, capturing their simultaneous effects on agricultural productivity.
- Potential omitted variable bias is reduced, as the model incorporates key economic, technological, and human capital determinants.
- Multicollinearity is properly managed, ensuring that estimated coefficients reflect the distinct contributions of food exports, mechanization, and other controls.

By employing AMG and CCE-MG estimators in a fully specified econometric model, we provide statistically robust and economically meaningful insights into the long-run relationships between agricultural productivity, mechanization, and food exports in developing countries. The findings offer valuable guidance for policymakers seeking to design sustainable agricultural modernization policies while ensuring that trade strategies enhance, rather than hinder, productivity improvements in the sector.

Table 9. Panel cointegration coefficients estimation results

Dep. Var.: <i>AGRIPROD</i>	AMG		CCE	
Variables	Coeff.	Std. Error	Coeff.	Std. Error
<i>MACHINERY</i>	-0.298***	0.099	-0.353***	0.098
<i>GDPpc</i>	0.818***	0.164	0.787***	0.191
<i>FEXP</i>	0.052*	0.031	0.083**	0.043
<i>SCHOOL</i>	0.262	0.221	-0.962**	0.490

Note: *** $p < 0.01$, ** $0.01 < p < 0.05$, * $0.05 < p < 0.10$

The findings highlight that the factors influencing agricultural productivity can vary significantly across nations, emphasizing the necessity of policies tailored to country-specific conditions alongside broader agricultural development strategies.

One of the most striking findings is that agricultural mechanization, contrary to theoretical expectations, exhibits a statistically significant negative effect on agricultural productivity across the sampled developing countries. In theory, mechanization should enhance labor productivity by enabling higher output levels with reduced labor input. However, in many developing economies, the effectiveness of mechanization is contingent upon complementary factors such as infrastructure investment, farmer adaptation to new technologies, and access to affordable financing. Smallholder farmers often face constraints in acquiring and efficiently utilizing agricultural machinery, which can lead to productivity losses rather than gains. Moreover, improper use of mechanized equipment, inadequate training, and insufficient maintenance capabilities may result in operational inefficiencies that undermine potential benefits. Another plausible explanation is the labor displacement effect, where increased mechanization reduces the

demand for agricultural labor, potentially exacerbating rural unemployment and income disparities. In this context, mechanization policies should not be implemented in isolation but rather as part of a comprehensive rural development strategy that ensures adequate human capital development, financial support, and infrastructure improvements to maximize productivity gains.

Per capita income, as expected, exhibits a strong positive and statistically significant relationship with agricultural productivity. The link between economic growth and agricultural efficiency is well-established in the literature and is largely driven by improvements in infrastructure, increased investment, and technological progress. As income levels rise, greater capital investment in agriculture occurs, accelerating the adoption of modern farming techniques. Additionally, higher economic development fosters the expansion of non-agricultural sectors, which, in turn, enhances the overall economic ecosystem supporting agricultural production. Increased access to credit, improved financial markets, and enhanced supply chain logistics further contribute to boosting productivity. However, it is crucial to recognize that rising per capita income can also accelerate structural transformation, where labor and resources shift from agriculture to industry and services. While such shifts are a natural part of economic development, ensuring balanced sectoral transitions is essential to preventing negative spillover effects on food security and rural livelihoods.

Another key finding of this study is the positive and significant impact of food exports on agricultural productivity. This suggests that increased integration into global markets incentivizes farmers and agribusinesses to enhance efficiency, adopt advanced technologies, and optimize resource utilization. Export-oriented agriculture fosters market-driven innovation, as producers must meet international quality and efficiency standards, leading to productivity improvements. Furthermore, participation in global markets enables agricultural enterprises to achieve economies of scale, lowering production costs and enhancing competitiveness. However, while export-oriented agricultural growth presents significant opportunities, it also entails potential risks and challenges. Over-reliance on food exports can expose domestic agricultural sectors to external shocks, such as fluctuations in global demand, trade policy changes, and price volatility. Moreover, excessive focus on export markets may create domestic food security concerns, particularly if agricultural production becomes overly concentrated on cash crops rather than staple food crops. Therefore, policies aimed at boosting food exports should be carefully designed to balance international competitiveness with domestic agricultural sustainability and food availability.

The impact of education on agricultural productivity presents mixed results, varying across the estimation models. In the AMG model, the effect of education is positive but statistically insignificant, whereas in the CCE-MG model, the effect is statistically significantly negative. These contrasting results indicate that the relationship between education and agricultural productivity is context-dependent and may not always be direct. One possible explanation is that higher education levels encourage labor migration from agriculture to industry and services, reducing the available workforce for farming activities. As rural populations become more educated, younger generations may opt for employment opportunities in non-agricultural sectors, potentially leading to labor shortages in the agricultural sector. Another possible reason is the misalignment between formal education systems and agricultural skill development. In many developing countries, education curricula do not sufficiently equip individuals with the technical and managerial skills required to enhance productivity in modern agriculture. If education policies fail to integrate agricultural training and technological know-how, their impact on productivity may remain limited or even negative in the short term. This highlights the importance of agriculture-specific educational reforms, such as vocational training programs, farmer extension services, and knowledge transfer initiatives to bridge the gap between education and practical agricultural improvements.

Taken together, the findings of this study underscore the need for multidimensional and integrated agricultural policies to enhance productivity in developing countries. Agricultural mechanization alone is not sufficient to drive productivity growth; it must be accompanied by investment in human capital, rural infrastructure, and financial accessibility to ensure effective technology adoption. While economic growth contributes positively to agricultural efficiency, structural changes must be managed carefully to avoid unintended consequences such as labor displacement and rural decline. The positive impact of food exports on productivity highlights the importance of integrating agriculture into global trade networks, but such strategies must be balanced with domestic food security priorities to ensure sustainable growth. Finally, education policies should be tailored to equip agricultural workers with relevant skills, fostering a knowledge-based approach to agricultural development. These findings provide valuable insights for policymakers seeking to promote sustainable and inclusive agricultural transformation in developing economies.

6. Conclusion and Discussion

This study has examined the determinants of agricultural productivity in developing countries, focusing on the roles of agricultural mechanization, food exports, per capita income, and human capital development. By employing the AMG and CCE-MG estimation techniques on panel data covering 55 developing countries from 2000 to 2019, the analysis has provided new empirical insights into the factors that shape agricultural productivity. The findings reveal complex and sometimes counterintuitive relationships between these variables, underscoring the need for a nuanced approach to agricultural policy in developing economies.

One of the most striking results of this study is the negative impact of agricultural mechanization on productivity. While mechanization has historically been a key driver of agricultural transformation in developed economies, its effects in developing countries appear to be less straightforward. The results suggest that without adequate infrastructure, financial access, and technical expertise, the potential benefits of mechanization may not materialize. In some cases, mechanization may even lead to reduced productivity due to labor displacement, inefficient technology use, and increased financial burdens on smallholder farmers. These findings highlight the importance of accompanying mechanization policies with complementary investments in infrastructure, farmer training, and institutional support to ensure that mechanization translates into genuine productivity gains.

The study also finds that per capita income is a strong and consistent driver of agricultural productivity. Higher income levels facilitate investments in modern farming technologies, irrigation, and research and development, all of which contribute to improved productivity. However, as economies grow, labor tends to shift away from agriculture toward industry and services, raising concerns about the long-term sustainability of agricultural productivity improvements. This suggests that policies aimed at boosting agricultural productivity should not only focus on increasing income levels but also on ensuring that agricultural transformation occurs in a way that maintains sectoral competitiveness and resilience.

Another key finding is that food exports have a positive and significant effect on agricultural productivity. This supports the view that greater participation in international markets encourages efficiency, technology adoption, and specialization in high-value agricultural production. However, the potential risks of export-driven growth—such as exposure to global price volatility and threats to domestic food security—should not be overlooked. To mitigate these risks, governments should implement strategies that balance export growth with domestic food security considerations, ensuring that increased trade does not come at the expense of vulnerable populations.

The role of education in agricultural productivity presents a more complex picture. While theoretical expectations suggest that human capital development should enhance productivity, this study finds mixed evidence regarding its impact. In one model, education appears to have a positive but statistically insignificant effect, while in another, it has a significant negative effect. This suggests that general education alone may not be sufficient to drive productivity gains in agriculture; rather, its impact depends on the relevance of education to agricultural practices. If education primarily leads to labor migration from agriculture to non-agricultural sectors, its direct contribution to agricultural productivity may be limited. This underscores the need for agriculture-specific educational programs, vocational training, and extension services that equip farmers with the skills necessary to adopt and utilize modern agricultural technologies effectively.

These findings are consistent with prior studies in the field. The negative impact of mechanization echoes the concerns raised by Diao et al. (2010), who emphasize that without adequate institutional support and infrastructure, mechanization may lead to productivity stagnation or even decline in developing countries. The positive effect of food exports on agricultural productivity aligns with the findings of Balassa (1978), Dollar & Kraay (2004), and Zeng et al. (2025), who argue that trade openness facilitates technological diffusion and efficiency gains in the agricultural sector. The mixed effects of education resonate with the insights of Schultz (1964) and Beine et al. (2008), highlighting that while education can enhance productivity, it may also drive labor out of agriculture, especially in the absence of sector-specific training.

The findings of this study have important policy implications for developing countries seeking to enhance agricultural productivity while ensuring long-term economic sustainability. First, mechanization policies should be designed with a holistic approach that includes investments in complementary infrastructure, financial mechanisms to support smallholder farmers, and technical training to ensure proper use of agricultural machinery. Without such supporting measures, mechanization alone may fail to deliver its intended productivity benefits.

Second, economic growth strategies should integrate agriculture as a central component of national development plans. While structural transformation is inevitable, ensuring that agriculture remains competitive and productive requires investments in modern technologies, improved access to credit, and policies that facilitate the integration of agriculture into higher-value supply chains.

Third, trade policies should be crafted in a way that promotes both international competitiveness and domestic food security. While food exports contribute positively to agricultural productivity, excessive dependence on global markets can expose developing economies to external shocks. Governments should therefore implement safety nets, strategic reserves, and diversified production policies to mitigate risks associated with export-oriented agriculture.

Finally, education policies should be reformed to better align with the needs of the agricultural sector. General education may not always translate into higher agricultural productivity unless it includes specific agricultural training, technology adoption programs, and knowledge transfer mechanisms. Strengthening agricultural extension services and incorporating agricultural innovation into educational curricula can help bridge this gap.

While this study provides important insights into the determinants of agricultural productivity, several areas warrant further research. First, future studies could explore the heterogeneous effects of mechanization across different types of farms, distinguishing between large-scale commercial farms and smallholder farms. Second, further research is needed to investigate the long-term dynamics of food exports and their impact on domestic food security, particularly in regions vulnerable to trade shocks. Third, more granular data on agricultural education and skill development could help clarify the mechanisms through which human capital affects productivity. Finally, future studies

could extend this analysis by incorporating climate change variables to assess how environmental factors interact with mechanization, trade, and education in shaping agricultural productivity outcomes.

In conclusion, this study underscores the multifaceted nature of agricultural productivity in developing economies and the need for an integrated policy approach that considers technological, economic, and human capital factors. Mechanization, while promising, requires supportive infrastructure and institutional frameworks to be effective. Economic growth fosters agricultural transformation, but its effects must be managed to ensure sustained productivity improvements. Food exports drive efficiency, yet they must be balanced with domestic food security priorities. Finally, education policies should be tailored to equip farmers with the skills necessary for modern agricultural production. By addressing these interrelated factors in a holistic manner, policymakers can foster a more resilient, productive, and sustainable agricultural sector in developing economies.

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