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Financial development and agricultural productivity: Evidence from a multi-country panel

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Abstract

Purpose: This study examines whether aggregate financial depth is associated with agricultural labour productivity in a panel of 24 economies over the period 2000–2024.

Design/Methodology/Approach: Agricultural labour productivity is measured by agriculture, forestry, and fishing value added per worker, while financial depth is proxied by domestic credit to the private sector as a share of GDP. GDP per capita, gross capital formation, and rural population share are included as core controls. Using World Development Indicators data, the analysis employs descriptive statistics, correlation analysis, pooled OLS with country-clustered robust standard errors, fixed-effects panel regressions, extended specifications with agriculture-related controls, and lagged robustness checks.

Findings: Agricultural labour productivity is strongly and consistently positively associated with GDP per capita. By contrast, the effect of aggregate financial depth is weaker and sensitive to specification. It is not statistically significant in the core pooled model, becomes positive and marginal or significant in some fixed-effects specifications, and weakens again in lagged robustness models. These findings suggest that broad financial deepening does not automatically translate into productivity-enhancing finance for agriculture.

Originality/Value: The study reassesses the finance–agriculture relationship in a multi-country panel and evaluates whether a standard macro-finance indicator adequately captures the type of finance that matters for agricultural productivity. By combining core models, extended specifications, and lagged robustness checks, the findings highlight the limits of aggregate financial depth as a proxy for effective rural and agricultural finance.

Keywords: Agricultural labour productivity, economic development, financial depth, panel data analysis, rural finance

Finansal gelişme ve tarımsal verimlilik: Çok ülkeli panelden bulgular

Özet

Amaç: Bu çalışma, toplam finansal derinliğin tarımsal emek verimliliği ile ilişkili olup olmadığını, 2000–2024 döneminde 24 ekonomiden oluşan bir panel veri seti üzerinden incelemektedir.

Tasarım/Metodoloji/Yaklaşım: Tarımsal emek verimliliği, tarım, ormancılık ve balıkçılık sektöründe çalışan başına katma değer ile; finansal derinlik ise özel sektöre sağlanan yurtiçi kredilerin GSYH'ye oranı ile ölçülmektedir. Kişi başına gelir, gayrisafi sermaye oluşumu ve kırsal nüfus oranı temel kontrol değişkenleri olarak modele dâhil edilmiştir. Dünya Kalkınma Göstergeleri verileri kullanılarak tanımlayıcı istatistikler, korelasyon analizi, ülke bazlı küme-robust standart hatalı havuzlanmış EKK, sabit etkiler panel regresyonları, tarım ilişkili ek kontroller içeren genişletilmiş spesifikasyonlar ve gecikmeli sağlamlık analizleri uygulanmıştır

Bulgular: Tarımsal emek verimliliği kişi başına gelir ile güçlü ve istikrarlı biçimde pozitif ilişkilidir. Buna karşılık toplam finansal derinliğin etkisi daha zayıf ve model spesifikasyonuna duyarlıdır. Çekirdek havuzlanmış modelde finansal derinlik istatistiksel olarak anlamlı değildir; bazı sabit etkiler spesifikasyonlarında katsayı pozitif ve marjinal ya da anlamlı hale gelmekte, gecikmeli sağlamlık modellerinde ise yeniden zayıflamaktadır. Bu sonuçlar, geniş anlamda finansal derinleşmenin tarım için verimlilik artırıcı finansa otomatik olarak dönüşmediğine işaret etmektedir.

Özgünlük/Değer: Çalışma, finans–tarım ilişkisini çok ülkeli panel veri çerçevesinde yeniden değerlendirerek standart bir makro finans göstergesinin tarımsal verimliliği açıklamada ne ölçüde yeterli olduğunu incelemektedir. Çekirdek modelleri, genişletilmiş spesifikasyonları ve gecikmeli sağlamlık analizlerini birlikte kullanarak bulgular, toplam finansal derinliğin etkin kırsal ve tarımsal finans için sınırlı bir gösterge olduğunu ortaya koymaktadır.

Anahtar kelimeler: Tarımsal emek verimliliği, ekonomik gelişme, finansal derinlik, panel veri analizi, kırsal finans

INTRODUCTION

Agriculture remains a cornerstone of economic development and social stability in many economies, particularly those where rural livelihoods and agricultural employment remain important, yet the sector continues to be characterized by low productivity, high exposure to risk, and chronic underinvestment. In this context, improving agricultural productivity is widely regarded as a central mechanism for poverty reduction, rural income growth, food security, and structural transformation. Existing panel and country-specific studies show that gains in agricultural productivity contribute not only to sectoral performance itself but also to broader economic growth and resource reallocation dynamics (Soyyiğit & Yavuzaslan, 2019; Zakaria, 2019). At the same time, the development of the financial sector—through deeper credit markets, more diversified institutions, and wider access to financial services—is generally expected to support investment, resource allocation, and risk management across the economy (Financial Sector Development and Agricultural Productivity, 2017; Ajayi, 2025). Together, these observations raise a central question: does financial development translate into higher agricultural productivity, and if so, under what conditions?

This question is not straightforward because the relationship between finance and agriculture is theoretically ambiguous. On the one hand, deeper and more inclusive financial systems may ease liquidity constraints, support investment in machinery, irrigation, improved seeds, and modern inputs, and encourage the adoption of more productive farming practices (Adabor, 2024; Seven, 2020; Zhang et al., 2024). On the other hand, financial development does not necessarily imply that agricultural producers benefit proportionately from expanding financial resources. In many economies, credit allocation is uneven, rural households remain rationed out of formal financial markets, and finance may be directed primarily toward urban, capital-intensive, or non-agricultural sectors (Ali et al., 2014; Kinuthia, 2018; Yitayih et al., 2023). Empirical evidence also shows that incomplete financial markets and credit constraints can generate underinvestment in profitable agricultural technologies and persistent productivity losses (Balana et al., 2022; Combary, 2022). Thus, the finance–productivity relationship depends not only on the size of the financial sector but also on how financial resources are distributed, accessed, and used within agriculture.

The issue is especially important in settings where agriculture continues to account for a meaningful share of employment, livelihoods, and export revenues, even though productivity gaps relative to more advanced production systems remain large. In many such contexts, agriculture is dominated by smallholder and family-based structures that face limited access to formal finance, weak market power, and high exposure to climatic and price shocks (Atakli & Agbenyo, 2020; Combary, 2022; Kinuthia, 2018). At the same time, financial systems are undergoing substantial transformation through liberalization, the rise of rural financial institutions, digital financial services, and green and climate-related finance instruments (Financial Development of New Rural Financial Institutions, 2025; Iddrisu et al., 2025; Zhai, 2023). These developments make the question more than a narrow technical issue: understanding whether financial development improves agricultural productivity is relevant for inclusive growth, rural transformation, and climate-resilient development strategies (Iddrisu et al., 2025; Yitayih et al., 2023).

From a conceptual standpoint, the relationship operates through multiple channels. Credit affects whether producers can invest in lumpy capital, smooth consumption, adopt better inputs, and cope with shocks, while savings, insurance, and payment services influence the ability of farmers to manage risk and participate in markets (Ajayi, 2025; Ali et al., 2014). Where credit constraints are binding, producers may adopt less productive technologies, postpone investment, or sell productive assets in response to shocks, thereby depressing both current and future productivity (Combary, 2022; Kinuthia, 2018). At a more aggregate level, financial deepening may also influence land markets, relative prices, and sectoral allocation patterns, meaning that finance can either support or bypass agriculture depending on institutional and policy conditions (Soyyiğit & Yavuzaslan, 2019; Zhang et al., 2024). In this sense, financial development can be both a driver and a consequence of agricultural transformation, which makes careful empirical specification essential.

The existing literature is therefore rich but fragmented. One stream relies on macro-level panel or time-series frameworks and uses indicators such as domestic credit to the private sector, financial development indices, or financial inclusion measures to estimate the impact of finance on agricultural output or productivity across countries and over time (Adabor, 2024; Seven, 2020; Soyyiğit & Yavuzaslan, 2019; Zakaria, 2019; Zhang et al., 2024). Another stream focuses on micro-level household and farm evidence, showing that productivity losses often arise because financial access is limited precisely where it matters most—among rural producers facing liquidity and collateral constraints (Ali et al., 2014; Atakli & Agbenyo, 2020; Balana et al., 2022; Combary, 2022; Kinuthia, 2018). More recent work extends the discussion by examining rural finance development, digital financial inclusion, new rural financial institutions, and green finance as more specific channels through which finance may affect agricultural total

factor productivity and green productivity (Financial Development of New Rural Financial Institutions, 2025; Iddrisu et al., 2025; Nie, 2024; Li, 2023; Yitayih et al., 2023; Zhai, 2023).

Despite this breadth, an important gap remains. Much of the literature focuses either on particular regions, individual country cases, or micro-level access constraints, while macro studies often rely on broad indicators of financial depth without directly confronting whether these indicators adequately capture the type of finance that matters for agricultural productivity. In other words, the unresolved issue is not simply whether finance matters, but whether a standard macro proxy such as private credit relative to GDP is sufficient to explain agricultural labour productivity once development level, investment, and rural demographic structure are taken into account. This distinction matters because macro-level financial depth may reflect overall economic development more than agriculture-specific financial access (Adabor, 2024; Iddrisu et al., 2025; Seven, 2020; Soyyiğit & Yavuzaslan, 2019; Zakaria, 2019).

Against this background, the study examines the relationship between financial development and agricultural productivity in a multi-country panel using a macro-level indicator of financial depth together with controls for income, investment, and rural demographic structure. The purpose is not to assume that financial development automatically improves agricultural productivity, but to test whether aggregate financial depth retains explanatory power once broader structural factors are incorporated into the model. In this sense, the study contributes by evaluating the adequacy of a standard macro-finance indicator for explaining agricultural labour productivity in a comparative panel setting, while positioning the analysis at the intersection of the macro literature on financial development and the micro literature on credit constraints in agriculture. The following section reviews the theoretical foundations and empirical evidence that motivate this analytical framework.

LITERATURE REVIEW

The relationship between financial development and agricultural productivity can be understood through the broader theoretical connection between finance and real-sector performance. In classical approaches, financial development improves economic performance by mobilizing savings, facilitating investment, generating information, supporting resource allocation, and enabling risk sharing. When applied to agriculture, these functions imply that finance may support long-term investments such as irrigation, machinery, land improvements, and seasonal input purchases, thereby contributing to productivity growth (Ajayi, 2025; Financial Sector Development and Agricultural Productivity, 2017; Adabor, 2024; Zhang, 2024). At the same time, this relationship is not mechanically positive. In many developing countries, financial systems remain dualistic, with modern formal finance concentrated in urban and non-agricultural sectors while rural areas continue to rely on fragmented and incomplete financial arrangements. As a result, financial development at the macro level may expand aggregate credit without necessarily relaxing the financing constraints faced by agricultural producers (Harshitha and Abusaad, 2024; Yitayih et al., 2023).

The literature on agricultural productivity also indicates that productivity is shaped by a broad set of interacting determinants rather than by finance alone. Exogenous conditions such as climate, agro-ecological endowments, soil quality, and geography matter, yet they do not fully explain persistent cross-country productivity gaps. Endogenous determinants such as technology adoption, input intensity, infrastructure, institutions, education, management quality, and market access are equally important (Soyyiğit and Yavuzaslan, 2019; Zakaria, 2019). Within this framework, finance may influence productivity indirectly by affecting the affordability and timing of investment in machinery, irrigation, fertilizers, improved seeds, and human capital, while also improving risk management and planning capacity. In this sense, finance is not simply another macroeconomic variable; it operates as a potential enabling factor whose effect depends on whether financial resources actually reach productive agricultural use (Nie, 2024; Qiu-Bin, 2023; Iddrisu et al., 2025; Zhai, 2023).

This conditional logic is strongly reinforced by the micro-level literature on credit constraints. A large body of research shows that when farmers face liquidity shortages, collateral constraints, or exclusion from formal lending, they underinvest in profitable technologies, avoid high-return but risky production choices, and reduce input use in ways that lower productivity. Evidence from Rwanda, East Africa, Burkina Faso, and Nigeria suggests that limited access to credit is associated with lower yields, weaker technology adoption, and persistent efficiency losses in smallholder farming systems (Ali et al., 2014; Kinuthia, 2018; Combary, 2022; Balana et al., 2022). These studies are important because they make clear that the productivity effect of finance depends not on the existence of aggregate financial deepening per se, but on whether rural producers gain access to appropriate and usable financial services. Thus, the micro literature consistently points to a transmission problem between financial development in the aggregate and financial access in agriculture.

A related strand of the literature focuses on the institutional design of agricultural finance. Rural and agricultural finance is no longer limited to traditional bank credit or state-led agricultural lending. It increasingly includes microfinance, savings and credit cooperatives, value-chain finance, input supplier credit, contract farming arrangements, new rural financial institutions, digital finance, and green finance instruments. This literature emphasizes that the effectiveness of finance depends on its design, reach, governance, and alignment with agricultural production realities. Rural financial institutions may fill gaps left by conventional banks, digital platforms may lower transaction costs and expand access, and green finance can channel resources toward sustainable productivity improvements. At the same time, the productivity effects of these mechanisms are context-dependent rather than universal (Yitayih et al., 2023; Financial Development of New Rural Financial Institutions, 2025; Nie, 2024; Ajayi, 2025; Zhai, 2023; Iddrisu et al., 2025; Qiu-Bin, 2023). This institutional literature therefore suggests that the composition and targeting of finance may matter at least as much as its aggregate size.

At the macro level, the evidence is broader in geographic scope but less consistent in its conclusions. Multi-country and regional panel studies generally find that finance can support agricultural productivity, but the magnitude and significance of this relationship vary according to country group, institutional environment, and model specification. Studies on South Asia, E7 economies, and broader cross-country samples show that financial indicators are often positively related to agricultural output or productivity, particularly when considered together with income, investment, openness, and institutional conditions (Zakaria, 2019; Financial Sector Development and Agricultural Productivity, 2017; Seven, 2020; Adabor, 2024; Soyyiğit and Yavuzaslan, 2019; Zhang, 2024). However, these studies also imply that finance is rarely sufficient on its own. Instead, its effect is mediated by overall development level, institutions, and the way financial resources are allocated across sectors. In this sense, the macro literature points to a positive but conditional relationship rather than a simple one-directional effect.

Regional and country-specific studies add further nuance by showing that not all dimensions of finance matter in the same way. Research from Africa emphasizes the role of green finance and financial inclusion, while evidence from India points to the long-run relevance of broader access to formal financial services. Studies from Ghana and the European Union further show that the productivity effects of finance depend on gendered access constraints, enterprise characteristics, and the opportunity structure within which external funding is used (Iddrisu et al., 2025; Harshitha and Abusaad, 2024; Atakli and Agbenyo, 2020; Khafagy, 2023). These findings shift the emphasis away from finance as a purely aggregate macro variable and toward finance as an unevenly distributed resource shaped by social, institutional, and sectoral conditions.

A particularly dynamic part of the recent literature centers on China and other rapidly transforming economies, where new rural financial institutions, rural finance expansion, digital financial inclusion, and green agricultural finance have been linked to agricultural total factor productivity. These studies often find that finance contributes to productivity through channels such as technology adoption, scale economies, lower transaction costs, and better information flows. They also show that the relationship can be non-linear and sensitive to regulatory design and environmental policy frameworks (Financial Development of New Rural Financial Institutions, 2025; Nie, 2024; Qiu-Bin, 2023; Zhai, 2023). The broader implication is that recent research increasingly treats financial development as a multidimensional process. Aggregate financial size is only one dimension; delivery mechanisms, inclusion, targeting, and institutional quality are also central to explaining productivity outcomes.

Taken together, the literature provides two important insights. First, there is broad agreement that finance can matter for agriculture, especially by relaxing constraints on investment, technology adoption, and risk management. Second, there is much less agreement on whether standard macro indicators of financial development are sufficient to identify this relationship in a comparative panel setting. Many micro studies focus on actual access constraints at the producer level, whereas many macro studies rely on broad indicators such as private-sector credit or financial depth. As a result, the literature remains divided between evidence on finance as access and evidence on finance as scale (Ajayi, 2025; Yitayih et al., 2023; Seven, 2020; Adabor, 2024).

This is where the main research gap emerges. Existing studies are rich, but fragmented. Some focus on particular regions such as South Asia or Africa; some concentrate on micro-level evidence from specific countries; and others emphasize newer dimensions such as digital finance, green finance, or rural institutions. Comparatively less attention has been paid to the question of whether a standard macro indicator of financial development, namely private-sector credit relative to GDP, can meaningfully explain agricultural labour productivity across a broader multi-country panel once development level, capital accumulation, and rural demographic structure are considered simultaneously (Adabor, 2024; Iddrisu et al., 2025; Seven, 2020; Soyyiğit and Yavuzaslan, 2019; Zakaria, 2019). Put

differently, the unresolved issue is not whether finance matters in general, but whether aggregate financial depth is an adequate empirical proxy for the kind of finance that actually improves agricultural productivity.

Accordingly, the literature points toward a more precise analytical task: to evaluate whether the association between financial development and agricultural productivity remains visible when the analysis is conducted with a multi-country panel, when broader macroeconomic and demographic controls are included, and when the interpretation of financial development is limited to a macro-level depth indicator rather than direct agricultural credit. Within this framework, the present study contributes by reassessing the finance–agriculture relationship through a panel design that combines agricultural productivity, aggregate financial depth, development level, investment, and rural structure in a single empirical setting. Its contribution lies not in claiming that the topic has not been studied before, but in testing whether the standard macro-finance indicator commonly used in the literature retains explanatory power once the structural context of agricultural productivity is modeled more explicitly.

METHODOLOGY

Research problem, research questions, and hypotheses

The relationship between financial development and agricultural productivity is theoretically important but empirically ambiguous. On the one hand, deeper financial systems may facilitate investment in machinery, irrigation, improved seeds, and other productivity-enhancing inputs. On the other hand, aggregate financial development does not necessarily imply improved access to financial resources for agricultural producers, especially in economies where rural credit markets are shallow, sectoral allocation is uneven, and smallholders remain financially excluded. For this reason, the central methodological problem is not merely whether financial depth and agricultural productivity move together, but whether the selected macro-level financial indicator is capable of explaining agricultural labour productivity once broader development dynamics and agriculture-related controls are taken into account.

In line with this problem definition, the study addresses the following research questions:

RQ1. Is aggregate financial depth associated with agricultural labour productivity in the selected country panel?

RQ2. Does this relationship remain statistically and economically meaningful after controlling for development level, capital accumulation, and rural demographic structure?

RQ3. Does the inclusion of agriculture-related controls such as fertilizer use, irrigated land, cereal yield, and trade openness alter the estimated relationship between financial depth and agricultural productivity?

RQ4. To what extent do the empirical results suggest that broad financial depth is an imperfect proxy for agriculture-specific financial access?

Based on the theoretical discussion and the empirical literature, the study tests the following hypotheses:

H1. Financial depth is positively associated with agricultural labour productivity.

H2. GDP per capita is positively associated with agricultural labour productivity.

H3. Gross capital formation is positively associated with agricultural labour productivity.

H4. The rural population share is negatively associated with agricultural labour productivity.

H5. Once agriculture-related controls and country-specific heterogeneity are taken into account, the independent effect of aggregate financial depth weakens.

These hypotheses allow the empirical analysis to move beyond a simple bivariate finance–productivity association and to test whether financial depth retains explanatory power in a theoretically consistent model.

Data set and sample structure

The study uses a multi-country panel data set compiled from the World Development Indicators (WDI) database of the World Bank. The data structure follows the standard country–year format used in panel-data analysis. Each row corresponds to a country-year observation and each column corresponds to an economic, financial, demographic, or agricultural indicator.

The raw data matrix was constructed by downloading the selected indicators for the period 2000–2025. Because data availability differs across indicators and countries, the empirical analysis relies on an unbalanced panel structure.

Accordingly, the final estimation sample is determined by the joint availability of the variables included in each specification. This approach makes it possible to consider 2025 observations where available, while preserving consistency across model-specific estimation samples.

The country sample consists of the following 24 economies.

Table 1. Country sample

No	Country	ISO Code
1	Afghanistan	AFG
2	Albania	ALB
3	Algeria	DZA
4	Angola	AGO
5	Argentina	ARG
6	Armenia	ARM
7	Australia	AUS
8	Austria	AUT
9	Azerbaijan	AZE
10	Bahamas, The	BHS
11	Bahrain	BHR
12	Bangladesh	BGD
13	Belarus	BLR
14	Belgium	BEL
15	Belize	BLZ
16	Benin	BEN
17	Bolivia	BOL
18	Bosnia and Herzegovina	BIH
19	Canada	CAN
20	France	FRA
21	Germany	DEU
22	Hungary	HUN
23	Türkiye	TUR
24	Ukraine	UKR

All country-year observations were aligned by ISO country code and calendar year. Missing entries in the original WDI downloads were treated as missing values, and no artificial imputation was used. This decision is consistent with the objective of preserving the statistical integrity of the panel. Separate estimation samples were formed for the core model and the extended model, depending on the set of variables used in each specification.

Variables and operational definitions

Agricultural productivity is measured by Agriculture, forestry, and fishing, value added per worker (constant 2015 US$), coded NV.AGR.EMPL. KD, and denoted as AGPROD. This variable captures agricultural labour productivity by dividing total value added in agriculture, forestry, and fishing by the number of workers employed in the sector.

Financial development is represented by Domestic credit to private sector (% of GDP), coded FS.AST.PRVT.GD.ZS, and denoted as FINDEPTH. This indicator is used as a macro-level proxy for aggregate financial depth. It measures the scale of credit provided to the private sector relative to GDP. However, it does not directly capture sector-specific agricultural credit. For this reason, FINDEPTH is interpreted as a broad measure of financial deepening rather than a direct measure of agricultural finance.

The baseline model includes three control variables. GDP per capita (constant 2015 US$), coded NY.GDP.PCAP. KD and denoted GDPPC, captures the overall level of economic development. Gross capital formation (% of GDP), coded NE.GDI.TOTL. ZS and denoted INV, proxies capital accumulation. Rural population (% of total population), coded SP.RUR.TOTL. ZS and denoted RURAL, captures demographic structure and the stage of structural transformation.

To address the possibility of omitted-variable bias, the empirical design also includes agriculture-related controls in an extended specification. These are fertilizer consumption (kilograms per hectare of arable land), coded AG.CON.FERT. ZS and denoted FERT; agricultural irrigated land (% of total agricultural land), coded AG.LND.IRIG.AG.ZS and denoted IRRIG; cereal yield (kg per hectare), coded AG.YLD.CREL.KG and denoted CERYLD; and trade (% of GDP), coded NE.TRD.GNFS. ZS and denoted TRADE.

Table 2. Variable definitions and expected signs

Variable	Definition	WDI Code	Role	Expected Sign.
AGPROD	Agriculture, forestry, and fishing, value added per worker (constant 2015 US$)	NV.AGR.EMPL. KD	Dependent variable	—
FINDEPTH	Domestic credit to private sector (% of GDP)	FS.AST.PRVT.GD.ZS	Main explanatory variable	+
GDPPC	GDP per capita (constant 2015 US$)	NY.GDP.PCAP. KD	Core control	+
INV	Gross capital formation (% of GDP)	NE.GDI.TOTL. ZS	Core control	+
RURAL	Rural population (% of total population)	SP.RUR.TOTL. ZS	Core control	–
FERT	Fertilizer consumption (kg per hectare of arable land)	AG.CON.FERT. ZS	Extended control	+
IRRIG	Agricultural irrigated land (% of total agricultural land)	AG.LND.IRIG.AG.ZS	Extended control	+
CERYLD	Cereal yield (kg per hectare)	AG.YLD.CREL.KG	Extended control	+
TRADE	Trade (% of GDP)	NE.TRD.GNFS. ZS	Extended control	±

The inclusion of these additional controls is important because agricultural productivity depends not only on macroeconomic development and financial conditions, but also on agronomic, technological, and structural factors.

Model specification

The empirical strategy begins with a core specification that relates agricultural productivity to financial depth and the main macro-structural controls: 1

$$AAGPROD_{it} = \beta_0 + \beta_1 FINDEPTH_{it} + \beta_2 GDPPC_{it} + \beta_3 INV_{it} + \beta_4 RURAL_{it} + u_{it} \quad 1$$

where $i$indexes countries and $t$indexes years.

Because panel data may contain unobserved, time-invariant country characteristics, the preferred specification introduces country and year effects:

$$AGPROD_{it} = \alpha_i + \lambda_t + \beta_1 FINDEPTH_{it} + \beta_2 GDPPC_{it} + \beta_3 INV_{it} + \beta_4 RURAL_{it} + \varepsilon_{it} \quad 2$$

Here, $\alpha_i$captures country-specific fixed effects such as geography, long-run institutional conditions, historical production structures, and agro-ecological characteristics, while $\lambda_t$captures common year-specific shocks such as global food-price movements, financial instability, or climate-related disturbances.

To incorporate agriculture-related determinants more explicitly, an extended specification is estimated:

$$\begin{aligned} AGPROD_{it} \quad &= \alpha_i + \lambda_t + \beta_1 FINDEPTH_{it} + \beta_2 GDPPC_{it} + \beta_3 INV_{it} + \beta_4 RURAL_{it} \\ &+ \beta_5 FERT_{it} + \beta_6 IRRIG_{it} + \beta_7 CERYLD_{it} + \beta_8 TRADE_{it} + \varepsilon_{it} \end{aligned} \quad 3$$

This extended model allows the finance–productivity relationship to be evaluated in a broader agricultural and structural context. It also helps assess whether the baseline association is robust to the inclusion of more sector-relevant determinants.

Estimation strategy

The empirical analysis is based primarily on fixed-effects panel estimation, since this approach controls for time-invariant unobserved heterogeneity that may be correlated with the explanatory variables. Pooled OLS estimates are reported only as a benchmark. Where appropriate, random-effects estimates may also be considered for comparison, and model choice is informed by standard panel-data specification logic.

The main estimation sequence consists of three layers:

Core specification using FINDEPTH, GDPPC, INV, and RURAL

Extended specification adding FERT, IRRIG, CERYLD, and TRADE

Robustness specifications using alternative transformations and lag structures

This sequence makes it possible to evaluate whether the estimated role of financial depth remains stable across alternative specifications.

Endogeneity and robustness considerations

A major methodological concern in the finance–agriculture nexus is potential endogeneity. Financial depth may affect agricultural productivity by easing financial constraints and facilitating investment. At the same time,

improvements in agricultural productivity may raise income levels, stimulate financial demand, and contribute indirectly to financial development. Therefore, the relationship may be bidirectional.

To address this issue, the empirical strategy includes robustness checks based on lagged financial-depth variables. In these specifications, the effect of financial depth is estimated using its lagged values, which helps reduce contemporaneous simultaneity concerns. In addition, alternative specifications are estimated to evaluate whether the results are sensitive to the inclusion of agriculture-related controls and to the transformation of highly dispersed variables.

Given the substantial cross-country dispersion in agricultural productivity and per capita income, log-based variants of the model may also be estimated as robustness checks. These transformations help reduce skewness and make the interpretation of coefficients more stable in the presence of large cross-country differences.

Diagnostic tests and model adequacy

Several diagnostic procedures are used to assess the adequacy of the estimated panel models. Since the panel combines multiple countries over time, heteroskedasticity, serial correlation, and cross-sectional dependence are all relevant concerns.

First, heteroskedasticity is addressed through country-clustered robust standard errors. Second, serial correlation is evaluated using panel-appropriate residual diagnostics. Third, because common global shocks may affect countries simultaneously, cross-sectional dependence is treated as a substantive concern and checked using standard panel-data diagnostics. Where necessary, stronger forms of robust inference may be used to ensure that the reported significance levels are not driven by cross-sectional dependence or serially correlated disturbances.

Model adequacy is evaluated not through a single equation alone, but through consistency across baseline, extended, and robustness specifications. This layered estimation design strengthens the empirical interpretation of the results and helps determine whether the estimated relationship between financial depth and agricultural productivity is stable, fragile, or conditional on model structure.

Summary of the empirical design

The empirical design combines a country-year panel data structure, a clearly defined dependent variable, a macro-level proxy for financial depth, and both baseline and agriculture-related control variables. The methodology is organized around explicit research questions and testable hypotheses, and the estimation strategy is structured to address unobserved heterogeneity, omitted-variable bias, and possible endogeneity. The use of 2025 observations where available expands the temporal coverage of the data, while the unbalanced-panel structure ensures that the estimations rely on observed rather than artificially completed information.

FINDINGS

Descriptive statistics (2000–2024, 24-country core panel)

Table 3 reports the descriptive statistics for the variables used in the core regression analysis, based on the complete-case country–year sample covering 24 countries and 447 observations for the period 2000–2024. The table indicates that agricultural value added per worker (AGPROD) exhibits substantial dispersion across countries and years. The mean level of AGPROD is approximately 20,598.70 constant 2015 US dollars, while the standard deviation is 28,473.48, indicating a highly dispersed distribution. The minimum value is about 556.34 US dollars per worker and the maximum exceeds 126,030.04 US dollars. This pattern suggests that agricultural labour productivity differs markedly across the sample and continues to reflect major cross-country differences in development level, production structure, technology use, and factor intensity.

Table 3. Descriptive statistics of variables (2000–2024, 24 countries, N = 447)

Variable	N	Mean	Std. Dev.	Min	25th pctl	Median	75th pctl	Max
AGPROD (NV.AGR.EMPL. KD)	447	20,598.70	28,473.48	556.34	2,953.34	10,306.93	27,062.71	126,030.04
FINDEPTH (FS.AST.PRVT.GD.ZS, %)	447	53.77	32.22	3.10	28.69	47.83	73.29	142.10
GDPPC (NY.GDP.PCAP. KD, USD)	447	17,751.70	17,442.85	527.83	3,383.96	8,227.42	36,256.73	61,869.08
INV (NE.GDI.TOTL. ZS, % of GDP)	447	24.33	6.65	8.93	20.06	23.91	27.49	51.78
RURAL (SP.RUR.TOTL. ZS, % of population)	447	31.96	17.44	1.85	19.41	30.03	42.00	76.69

On the financial side, domestic credit to the private sector as a share of GDP (FINDEPTH) averages 53.77 percent, with a standard deviation of 32.22 percentage points. The minimum value is slightly above 3 percent, while the maximum is above 142 percent, indicating considerable differences in financial depth across the countries included in the panel. Per capita GDP (GDPPC) also varies widely, with a mean of 17,751.70 US dollars and a maximum of 61,869.08 US dollars, while the lower tail remains close to 528 US dollars. This wide spread indicates that the panel includes economies at very different stages of development.

The investment rate (INV) is comparatively less dispersed than AGPROD or GDPPC, with an average of 24.33 percent of GDP and a range from 8.93 to 51.78 percent. The rural population share (RURAL) has a mean of 31.96 percent and ranges from highly urbanized observations with less than 2 percent rural population to highly rural observations where the rural share exceeds 76 percent. Overall, the distribution of the variables confirms that the panel captures substantial heterogeneity in financial conditions, development levels, investment patterns, and demographic structure, making it suitable for examining differences in agricultural productivity across countries and over time.

Correlation analysis

Table 4 presents the Pearson correlation matrix for AGPROD and the explanatory variables used in the core econometric models. All coefficients are calculated from the same 447 country–year observations included in the core complete-case panel for the period 2000–2024. The matrix provides a useful first view of the linear association among the variables and helps identify potential specification issues, particularly with respect to multicollinearity.

Table 4. Correlation matrix (N = 447)

	AGPROD	FINDEPTH	GDPPC	INV	RURAL
AGPROD	1.0000	0.7498	0.8805	0.0083	-0.5645
FINDEPTH	0.7498	1.0000	0.8173	-0.0594	-0.3929
GDPPC	0.8805	0.8173	1.0000	-0.0190	-0.6024
INV	0.0083	-0.0594	-0.0190	1.0000	-0.0585
RURAL	-0.5645	-0.3929	-0.6024	-0.0585	1.0000

First, agricultural productivity (AGPROD) is strongly and positively correlated with per capita GDP (GDPPC), with a coefficient of approximately 0.88. This indicates that higher-income country-year observations tend to be associated with higher agricultural labour productivity. Such a pattern is consistent with the view that development level, infrastructure, technological capacity, and institutional quality are closely connected to productivity performance in agriculture.

Second, AGPROD is also positively correlated with financial depth (FINDEPTH), with a coefficient of about 0.75. At the descriptive level, this suggests that countries with deeper financial systems also tend to display higher agricultural productivity. However, this simple positive association should be interpreted cautiously, because FINDEPTH is also strongly correlated with GDPPC, which may absorb part of the apparent finance effect once both variables are included in a multivariate model.

Third, the rural population share (RURAL) is moderately and negatively correlated with agricultural productivity (–0.56). This pattern is consistent with structural transformation arguments: country-year observations with a larger rural population share tend to be associated with lower output per worker in agriculture. In the same direction, RURAL is also negatively correlated with both GDPPC (–0.60) and FINDEPTH (–0.39), indicating that more rural economies in the sample also tend to be less financially deep and less affluent.

The strongest correlation among the explanatory variables appears between FINDEPTH and GDPPC (0.82). This is an important result for model interpretation, since it suggests that financial depth and general development level move closely together in the sample. As a result, when both variables enter the same regression, part of the variation attributed to finance in simple descriptive relationships may instead be captured by overall development. This raises a clear concern regarding multicollinearity and implies that the independent contribution of aggregate financial depth should be interpreted with care in the regression analysis.

By contrast, the investment rate (INV) is only weakly related to the other variables. Its correlation with AGPROD is close to zero (0.01), and its correlations with FINDEPTH, GDPPC, and RURAL are also small in magnitude. This suggests that gross capital formation, as measured at the aggregate macroeconomic level, may not map directly onto agricultural productivity differences in a simple bivariate framework. Overall, the correlation matrix indicates that agricultural productivity is strongly associated with development level, financial depth, and rural

demographic structure, while also signaling that the finance variable may partly reflect broader development dynamics rather than a purely sector-specific agricultural finance effect.

Pooled OLS regression results

The baseline econometric estimation is a pooled OLS model with country-clustered robust standard errors, consistent with the empirical strategy described in the Methodology section. The dependent variable is agricultural value added per worker (AGPROD), and the explanatory variables are aggregate financial depth (FINDEPTH), per capita GDP (GDPPC), the investment rate (INV), and the rural population share (RURAL). The estimated baseline model is:

$$AGPROD_{it} = \beta_0 + \beta_1 FINDEPTH_{it} + \beta_2 GDPPC_{it} + \beta_3 INV_{it} + \beta_4 RURAL_{it} + u_{it} \quad (4)$$

The results are summarized in Table 5.

Table 5. Pooled OLS regression with country-clustered robust standard errors (N = 447, 24 countries)

Variable	Coefficient (B)	Std. Error	z-statistic	p-value
Constant	-467.30	8,773.24	-0.05	0.958
FINDEPTH	82.66	80.98	1.02	0.307
GDPPC	0.9818	0.2512	3.91	0.000
INV	87.54	198.53	0.44	0.659
RURAL	-91.87	142.64	-0.64	0.520

Model statistics: $R^2 = 0.782$
Adjusted $R^2 = 0.78$
Number of observations: 447
Countries: 24
BP heteroskedasticity test: LM ≈ 156.30, p ≈ 9.06×10^{-33} → strong heteroskedasticity
Durbin–Watson statistic: ≈ 0.268 → strong positive serial correlation

The pooled OLS results indicate that GDP per capita (GDPPC) is the only explanatory variable that remains statistically significant at conventional levels. The estimated coefficient on GDPPC is 0.9818, with a p-value below 0.001, indicating that a one-dollar increase in per capita GDP is associated with an increase of approximately 0.98 US dollars in agricultural value added per worker, holding the other regressors constant. This result is both statistically robust and economically meaningful, and it supports the argument that agricultural productivity is strongly linked to the broader level of economic development.

By contrast, the coefficient on FINDEPTH is positive (82.66) but statistically insignificant (p = 0.307). This suggests that, once GDP per capita, investment, and rural demographic structure are controlled for, aggregate financial depth does not exert an independent and statistically distinguishable effect on agricultural labour productivity in the pooled specification. One plausible interpretation is that the selected financial variable captures broad financial deepening at the macro level rather than financial resources effectively directed toward agriculture. In addition, the correlation matrix showed that FINDEPTH is strongly associated with GDPPC, which implies that part of the apparent finance effect may be absorbed by general development dynamics when both variables are included in the same model.

The coefficient on INV is positive (87.54) but also statistically insignificant (p = 0.659). This indicates that aggregate gross capital formation, measured at the macroeconomic level, does not display a clear independent association with agricultural productivity in the pooled specification. This result is not necessarily surprising, because total capital formation includes investments in all sectors of the economy and therefore may not correspond closely to productivity-enhancing investments within agriculture itself.

The coefficient on RURAL is negative (–91.87), which is directionally consistent with expectations from structural transformation theory, but it is not statistically significant (p = 0.520). The negative sign still suggests that country-year observations with a larger rural population share tend to be associated with lower agricultural output per worker, but this relationship is not estimated with sufficient precision in the pooled OLS model once the other explanatory variables are included.

Overall, the pooled OLS findings suggest that differences in agricultural productivity across country-year observations are more strongly associated with general development level than with the broad macro-level measure of financial depth used in the model. At the same time, the strong heteroskedasticity and serial correlation diagnostics indicate that pooled OLS should be treated primarily as a benchmark specification rather than as the preferred inferential model. For this reason, greater emphasis is placed on the fixed-effects estimates reported in the next subsection.

Fixed-effects (within) estimator

To account for unobserved country-specific factors that remain constant over time, a fixed-effects (FE) model is estimated using the within transformation. In this specification, each variable is demeaned by country, so the model focuses on within-country changes over time rather than cross-country differences. The FE model can be written as:

$$AGPROD_{it} - \bar{AGPROD}_i = \beta_1(FINDEPTH_{it} - \bar{FINDEPTH}_i) + \beta_2(GDPPC_{it} - \bar{GDPPC}_i) + \beta_3(INV_{it} - \bar{INV}_i) + \beta_4(RURAL_{it} - \bar{RURAL}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i) \quad (5)$$

The main FE estimates are presented in Table 6, where all regressors are expressed in deviations from their country-specific means.

Table 6. Fixed-effects (within) regression with country-clustered robust standard errors (N = 447, 24 countries)

Variable	Coefficient (B)	Std. Error	z-statistic	p-value
FINDEPTH (demeaned)	82.21	42.31	1.94	0.052
GDPPC (demeaned)	2.7571	0.5253	5.25	0.000
INV (demeaned)	13.78	100.35	0.14	0.891
RURAL (demeaned)	122.69	266.04	0.46	0.645

Model statistics:
Within $R^2 \approx 0.542$
Number of observations: 447
Countries: 24
Covariance estimator: country-clustered robust standard errors
Durbin–Watson statistic: ≈ 0.771

The FE estimates confirm the central role of GDP per capita (GDPPC) in explaining agricultural labour productivity. The coefficient on demeaned GDPPC is 2.7571 and is highly statistically significant ($p < 0.001$). This implies that, within a given country over time, increases in per capita income are associated with substantial increases in agricultural value added per worker, even after controlling for unobserved, time-invariant country characteristics. Compared with the pooled OLS estimate, the GDPPC coefficient is notably larger in the FE model, which suggests that cross-country heterogeneity masks part of the within-country development effect in the pooled specification.

The coefficient on FINDEPTH is 82.21 and is positive, with a p-value of 0.052. This places the estimate just above the conventional 5 percent significance threshold and indicates a borderline positive within-country association between aggregate financial depth and agricultural labour productivity. In substantive terms, this result suggests that increases in broad financial depth within countries may be associated with higher agricultural productivity, but the effect remains statistically fragile and should be interpreted cautiously. This pattern is consistent with the broader concern that aggregate credit to the private sector is an imperfect proxy for sector-specific agricultural finance.

The coefficients on INV and RURAL are both statistically insignificant in the FE model. The coefficient on demeaned INV is 13.78 ($p = 0.891$), while the coefficient on demeaned RURAL is 122.69 ($p = 0.645$). These results suggest that, once time-invariant country characteristics are removed, changes in aggregate investment and rural population share do not display a robust independent association with agricultural productivity in the present specification. This may indicate that their explanatory relevance is driven more by cross-country structural differences than by short-run within-country variation.

Compared with the pooled OLS results, the FE estimates change the interpretation of the finance variable in an important way. In the pooled specification, FINDEPTH is positive but clearly insignificant, whereas in the within-country model it becomes larger and approaches conventional significance levels. This suggests that the relationship between financial depth and agricultural productivity is more visible when attention shifts from between-country differences to changes within countries over time. Even so, the result remains weaker than the GDPPC effect and does not eliminate the concern that aggregate financial depth may still be capturing broader development dynamics rather than agriculture-specific financial access.

Overall, the FE results indicate that within-country improvements in economic development remain the strongest and most consistent correlate of agricultural productivity, while the estimated contribution of aggregate financial depth is more limited and statistically less stable. For this reason, the FE model provides a more cautious and informative interpretation than pooled OLS, especially in the presence of country-specific heterogeneity.

The baseline results reported above are based on the core estimation sample (N = 447). To evaluate whether the findings are sensitive to omitted agriculture-related factors, an extended specification was estimated on a reduced sample reflecting the joint availability of additional control variables.

Extended specification results

To examine whether the baseline results are sensitive to the omission of agriculture-related factors, an extended specification was estimated by adding fertilizer consumption (FERT), agricultural irrigated land (IRRIG), cereal yield (CERYLD), and trade openness (TRADE) to the core model. The baseline findings reported above are based on the core estimation sample (N = 447). Because the additional agriculture-related variables have more limited joint data availability across countries and years, the number of observations declines in the extended specification. For this reason, the extended model is interpreted as a complementary specification rather than as a direct replacement for the core results.

Table 7. Extended pooled OLS regression with country-clustered robust standard errors (reduced sample)

Variable	Coefficient (B)	Std. Error	z-statistic	p-value
Constant	-2,825.41	19,159.01	-0.15	0.883
FINDEPTH	85.86	71.49	1.20	0.230
GDPPC	1.2958	0.1722	7.52	0.000
INV	193.11	197.92	0.98	0.329
RURAL	-42.50	266.90	-0.16	0.873
FERT	-25.83	19.34	-1.34	0.182
IRRIG	141.57	152.71	0.93	0.354
TRADE	58.87	55.15	1.07	0.286
CERYLD	-2.27	1.02	-2.22	0.027

Model statistics: $R^2 = 0.877$
Adjusted $R^2 = 0.871$
Number of observations: 184
Countries: 24
Durbin–Watson statistic: ≈ 0.721

The extended pooled OLS results preserve the central role of GDP per capita (GDPPC). Its coefficient remains positive and highly significant, showing that development level continues to be strongly associated with agricultural labour productivity even after agriculture-related controls are introduced. By contrast, FINDEPTH remains statistically insignificant, indicating that aggregate financial depth still does not exhibit a clear independent effect once both macroeconomic and agriculture-related variables are considered simultaneously.

Among the added variables, CERYLD is the only regressor that becomes statistically significant in the pooled extended model, and its coefficient is negative. This result should be interpreted cautiously, since AGPROD measures value added per worker rather than land productivity. Accordingly, cereal yield may be capturing a different productivity dimension or reflecting cross-country specialization and compositional effects. The remaining added controls—FERT, IRRIG, and TRADE—do not reach conventional significance levels in the pooled specification.

Extended fixed-effects results

To assess whether these relationships hold after controlling for unobserved, time-invariant country-specific characteristics, the extended model was also estimated using a fixed-effects specification based on the same reduced sample.

Table 8. Extended fixed-effects regression with country-clustered robust standard errors (reduced sample)

Variable	Coefficient (B)	Std. Error	z-statistic	p-value
FINDEPTH	192.46	73.22	2.63	0.009
GDPPC	2.7700	0.5361	5.17	0.000
INV	147.01	178.60	0.82	0.410
RURAL	470.55	242.51	1.94	0.052
FERT	-27.89	18.74	-1.49	0.137
IRRIG	-53.50	71.13	-0.75	0.452
TRADE	-146.91	44.97	-3.27	0.001
CERYLD	4.10	2.09	1.96	0.050

Model statistics: $R^2 = 0.973$
Adjusted $R^2 = 0.968$
Number of observations: 184
Countries: 24
Durbin–Watson statistic: ≈ 1.048

The extended fixed-effects results provide a more differentiated picture than the baseline model. GDPPC remains positive and highly significant, confirming that within-country increases in development level are strongly associated with higher agricultural labour productivity. In this reduced-sample specification, FINDEPTH becomes positive and statistically significant, suggesting that once agriculture-related controls are introduced, within-country increases in aggregate financial depth are associated with higher agricultural productivity. This result should nevertheless be interpreted with caution, because it is obtained from a smaller estimation sample and remains sensitive to model specification.

Among the added variables, TRADE enters with a negative and statistically significant coefficient, whereas CERYLD is positive and weakly significant. The negative coefficient on TRADE may indicate that greater trade openness does not automatically translate into higher agricultural value added per worker and may instead reflect import competition, structural specialization, or exposure to international market pressures. RURAL also approaches conventional significance levels in the extended fixed-effects model, although its sign differs from the baseline specification, suggesting that its role becomes more complex once additional sector-related controls are introduced. By contrast, FERT and IRRIG remain statistically insignificant.

Taken together, the extended results suggest two main points. First, the strong role of GDPPC remains intact across specifications. Second, the estimated effect of FINDEPTH is not stable across all models but becomes more pronounced in the extended fixed-effects framework. This implies that the finance–agriculture relationship may be more conditional than the baseline model alone suggests and that part of the earlier insignificance may be related to omitted structural or sector-specific factors. However, because the extended specification is estimated on a smaller sample, these findings should be interpreted as complementary rather than definitive.

Robustness check: lagged financial depth

To address the potential endogeneity concern arising from reverse causality between financial development and agricultural productivity, an additional robustness specification was estimated using the one-period lag of financial depth instead of its contemporaneous value. This approach helps reduce simultaneity concerns by examining whether prior changes in aggregate financial depth are associated with current agricultural labour productivity. Because the lag structure requires an additional year of data for each country, the number of usable observations is smaller than in the baseline core model.

Table 9. Robustness check using lagged financial depth

Variable	Pooled OLS (lagged FINDEPTH) Coefficient	Std. Error	z-statistic	p-value	Fixed Effects (lagged FINDEPTH) Coefficient	Std. Error	z-statistic	p-value
Constant	-732.33	8,871.59	-0.08	0.934	—	—	—	—
L1.FINDEPTH	77.32	82.56	0.94	0.349	59.10	50.13	1.18	0.238
GDPPC	0.9970	0.2508	3.97	0.000	2.7404	0.5840	4.69	0.000
INV	111.70	199.11	0.56	0.575	-5.02	101.97	-0.05	0.961
RURAL	-96.14	145.99	-0.66	0.510	73.29	302.20	0.24	0.808

Model statistics: Pooled OLS $R^2 = 0.782$
Adjusted $R^2 = 0.780$
Number of observations: 423
Countries: 23
Durbin–Watson statistic: ≈ 0.282
Fixed Effects $R^2 = 0.959$
Adjusted $R^2 = 0.957$
Number of observations: 423
Countries: 23
Durbin–Watson statistic: ≈ 0.800

The lagged-financial-depth results do not materially alter the main interpretation of the study. In both the pooled and fixed-effects robustness specifications, the coefficient on L1.FINDEPTH remains statistically insignificant. This suggests that the weak role of aggregate financial depth is not solely a contemporaneous simultaneity artifact and that the baseline findings are broadly robust to a simple lag-based correction for reverse causality. By contrast, GDP per capita remains positive and highly significant in both specifications, confirming that development level continues to be the most stable correlate of agricultural labour productivity.

The lag-based results therefore reinforce the main conclusion of the paper: while financial deepening may be related to agricultural productivity in descriptive terms, its independent explanatory power remains limited once broader structural factors are introduced. In this sense, the robustness exercise strengthens the interpretation that the

standard macro-level credit measure is too broad to capture the specific financial mechanisms through which productivity gains occur in agriculture.

DISCUSSION

The results show that agricultural labour productivity is explained more consistently by broad development dynamics than by aggregate financial depth alone. Across the core pooled OLS, core fixed-effects, extended specifications, and lagged robustness checks, GDP per capita remains the strongest and most stable correlate of agricultural productivity. This finding is consistent with studies emphasizing that agricultural productivity rises with broader improvements in income, infrastructure, institutional quality, and structural transformation, rather than through financial expansion in isolation (Soyyiğit & Yavuzaslan, 2019; Zakaria, 2019).

The estimated role of FINDEPTH is more conditional. In the core pooled model it is insignificant, in the core fixed-effects model it is only marginally significant, in the extended fixed-effects specification it becomes positive and significant, and in the lagged robustness models it again loses significance. This pattern suggests that the relationship between financial depth and agricultural productivity is specification-sensitive, which is in line with the macro literature showing that finance affects agriculture in a conditional rather than automatic way, depending on institutional setting, model design, and variable choice (Adabor, 2024; Seven, 2020; Zhang et al., 2024; Zakaria, 2019).

These findings also support the argument that aggregate financial depth and effective agricultural finance should not be treated as equivalent concepts. The selected indicator captures economy-wide private credit, but it does not reveal whether financial resources are actually reaching agricultural producers in forms that support irrigation, mechanization, input use, or risk management. In that sense, the weak and unstable FINDEPTH coefficient does not imply that finance is irrelevant for agriculture; rather, it suggests that the macro proxy is too broad to capture the mechanisms emphasized in the literature on finance as access, inclusion, and institutional design (Ajayi, 2025; Yitayih et al., 2023; Iddrisu et al., 2025; Nie, 2024).

The contrast between the present findings and the micro-level literature is therefore more apparent than real. Studies based on farm or household data consistently show that credit constraints reduce input use, delay technology adoption, and depress productivity in smallholder systems. The current multi-country panel does not reject that evidence; instead, it shows that once finance is measured with an economy-wide credit ratio, the micro mechanisms become harder to identify. This helps explain why strong micro evidence can coexist with weaker macro panel coefficients (Ali et al., 2014; Kinuthia, 2018; Combary, 2022; Balana et al., 2022).

The extended specification sharpens this interpretation. Once agriculture-related controls are introduced, FINDEPTH becomes significant in the fixed-effects model, suggesting that part of the earlier insignificance may reflect omitted structural or sector-specific factors. At the same time, this result is obtained on a reduced sample and is not preserved in the lagged robustness models, so it should not be overinterpreted. The most defensible conclusion is therefore that financial depth may matter under some conditions, but its effect is not uniformly robust across all empirical settings. This reading is consistent with studies that portray the finance–agriculture relationship as mediated by institutional quality, targeting, and complementary structural factors rather than by credit expansion alone (Financial Sector Development and Agricultural Productivity, 2017; Adabor, 2024; Nie, 2024; Zhang et al., 2024).

The additional controls also point to a more complex productivity structure than a simple finance-led story would imply. In the extended pooled model, CERYLD is significant, while in the extended fixed-effects model TRADE is negative and significant and CERYLD is weakly positive. These mixed results suggest that agricultural productivity is shaped by overlapping dimensions of land productivity, trade exposure, structural specialization, and sector composition. This is compatible with the broader literature stressing that agricultural productivity depends on agronomic, technological, and market-related factors as much as on macro-financial conditions (Soyyiğit & Yavuzaslan, 2019; Zakaria, 2019; Khafagy, 2023; Zhai, 2023).

From a policy perspective, the findings imply that productivity-oriented agricultural policy should focus less on the aggregate size of the financial sector and more on the allocation, accessibility, and design of financial instruments. Expanding targeted agricultural credit, rural banking outreach, input-linked finance, insurance, and digital financial access is likely to matter more than raising private credit ratios at the macro level alone. This interpretation closely aligns with recent work on rural finance, financial inclusion, and green finance, which emphasizes that delivery mechanisms and reach are at least as important as financial scale (Ajayi, 2025; Iddrisu et al., 2025; Yitayih et al., 2023; Nie, 2024).

Several limitations remain. The finance variable is economy-wide rather than agriculture-specific; the panel is heterogeneous; and although fixed effects, extended controls, and lagged specifications strengthen the design, they do not fully eliminate concerns about endogeneity and omitted variables. For that reason, the results should be read as evidence about the limits of a standard macro-finance proxy in comparative panel analysis, not as a definitive rejection of the importance of finance in agriculture (Adabor, 2024; Seven, 2020; Ajayi, 2025; Yitayih et al., 2023).

CONCLUSION

This study shows that agricultural labour productivity is linked more consistently to development level than to aggregate financial depth. Across the core models, extended specifications, and lagged robustness checks, GDP per capita remains the most stable and powerful correlate of agricultural productivity, while the estimated effect of financial depth changes across specifications and weakens under lagged testing. In this sense, the paper supports a conditional, not automatic, interpretation of the finance–agriculture nexus (Soyyiğit & Yavuzaslan, 2019; Zakaria, 2019; Adabor, 2024).

The main contribution of the study is to show that a widely used macro indicator—private credit to GDP—does not consistently capture the type of finance that matters for agricultural productivity. This helps bridge the gap between the macro literature, which often uses broad financial indicators, and the micro literature, which focuses on actual credit constraints and producer access. The implication is clear: finance may matter greatly in agriculture, but broad financial depth is not necessarily an adequate empirical representation of that mechanism (Ali et al., 2014; Seven, 2020; Ajayi, 2025; Yitayih et al., 2023).

The policy message follows directly from this result. Raising agricultural productivity requires more than expanding the financial sector in aggregate terms; it requires ensuring that rural producers can access appropriate financial instruments and that finance is directed toward productivity-enhancing uses such as irrigation, machinery, improved inputs, insurance, and climate-resilient investments. Future research should therefore use more granular indicators—such as sector-specific agricultural credit, rural financial access, and farm-level borrowing—and stronger identification strategies to distinguish more clearly between finance as scale and finance as effective access (Iddrisu et al., 2025; Nie, 2024; Zhai, 2023; Zhang et al., 2024).

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