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Examining Foreign Direct Investment effects on agricultural productivity in Sub-Saharan African economies

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A B S T R A C T

Spillover effects of Foreign Direct Investments (FDI) in developing countries have been theoretically linked to productivity enhancement through knowledge transfer. In Sub-Saharan Africa, where agricultural productivity remains persistently low, these potential spillovers could be critical for poverty alleviation and economic structural transformation. This study provides a novel empirical investigation of FDI inflows to agriculture in Sub-Saharan African countries, examining their impact on agricultural total factor productivity (TFP), as well as labor and land productivity. Leveraging a unique dataset compiled from official statistical sources, the research measures FDI in monetary terms—an approach that provides methodological advantages over traditional area-based investment measures. Employing a fixed effects framework and addressing potential endogeneity through a System Generalized Method of Moments (System GMM) approach, the analysis reveals complex findings. While the empirical results demonstrate statistically significant positive effects of FDI on total factor productivity, impacts on land and labor productivity remain insignificant. These findings suggest limited technology transfers and underscore the necessity for context-specific policy interventions, emphasizing that foreign investments are not universally beneficial and require careful, targeted evaluation.

1. Introduction

Foreign Direct Investment (FDI) in agriculture has reached up to around a quarter of total FDI inflows in some Sub-Saharan African countries. For example, Kenya received 28 % of its total yearly FDI in the agricultural sector in 2009 and 18 % in 2019 (FAO, 2024). High shares and absolute figures of agricultural FDI were especially recorded in many countries in the region in the early 2000s. FDI has been shown outside of agriculture to impact low-income host countries' industries by creating spillover effects that can improve productivity (Abebe et al., 2022). However, in the overall economy and agriculture, the empirical evidence is not conclusive (Demena and van Bergeijk, 2017). In Sub-Saharan Africa (SSA) and its agricultural sector, where productivity is notably low, the potential benefits of FDI for productivity are exceptionally high. Therefore, many governments strive to attract significant levels of foreign investment. Appropriate investments, including foreign investments in agriculture, could aid food security and may reduce the number of people at risk of hunger to below 5 %, at least in Western and Southern Africa (Mason-D'Croz et al., 2019). On the investors' side, agriculture is one of the critical sectors for foreign investments because of favorable agroecological conditions and abundant water resources in various locations across SSA (Dell'Angelo et al., 2018; Hirsch et al., 2020; Müller et al., 2021). Expanding local markets for agricultural products supported by growing populations and economies provide revenue opportunities beyond exporting. Despite growing interest in FDI's role in developing economies, empirical evidence on sectoral FDI impacts in Sub-Saharan Africa remains

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severely limited due to persistent data constraints. This study addresses this gap by constructing a novel dataset of agricultural FDI inflows for 22 SSA countries over 21 years, representing a significant advancement in data availability for this under-researched region.

This paper presents an analysis that, to the best of my knowledge, is the first investigation of the FDI-productivity nexus in agriculture at the country level in Sub-Saharan Africa. In contrast to previous studies, I use a more detailed dataset constructed for this study from official reports of international organizations, central banks, national statistical institutes and investment promotion agencies. In the past, the lack of sufficient panel data was a main restricting factor for analyzing the sectoral productivity of FDI in SSA. The novel dataset collected for this study covers 22 countries over the period 2000 to 2020. I study from a macroeconomic sectoral perspective whether, at the country level, higher levels of FDI enhance productivity. Recent evidence points in this direction with studies finding increased agricultural production in countries with high levels of foreign investment in land (Ben Slimane et al., 2016; Kinda et al., 2022; Müller et al., 2021; Santangelo, 2018) or FDI inflows into the entire economy (Ding et al., 2021; Nugroho et al., 2021). However, most of these studies also find some increases in cultivated land in countries with significant foreign investments in land, questioning whether additional production is caused by intensification, meaning increased productivity, or by the expansion of land under constant productivity. I investigate these channels using measures of productivity, as well as land and labour, as outcome variables in a regression framework.

Reverse causality, where higher productivity leads to higher investments, could play a role in the interplay of FDI and agricultural productivity. Investment decisions of multinationals are often driven by favorable agroecological conditions, which are prerequisites for high agricultural yields. To address this, I use a Generalized Method of Moments (GMM) approach in which lagged variables are used as instruments to account for reverse causality. Total Factor Productivity is used as a measure of productivity in the main specifications. I explicitly test whether the positive relationship between FDI and TFP found in developing countries over all sectors (Iamsiraroj and Ulubaşoğlu, 2015; Li and Tanna, 2019; Makiela and Ouattara, 2018) also holds for the agricultural sector. A global study, for example, found no significant effects of FDI on TFP in any sector other than manufacturing (Demir and Duan, 2018). To examine underlying dynamics, I also estimate regressions with land and labor productivity as dependent variables. Using these alternative measures also at least partly addresses concerns arising from the fact that TFP itself is an estimated quantity.

Potential positive spillovers can arise from technology transfers from foreign to local firms, from better access to input and output markets, and other supporting factors such as better access to credit or outgrower contracts offered by foreign investors (Deininger and Byerlee, 2011). Conversely, agricultural producers in SSA can be adversely impacted by foreign investments if investors secure rights to the most productive land, water sources, agricultural laborers, or market shares in essential segments for local producers.

The results presented here indicate that in some settings, technology could improve due to foreign investments, as evidenced by the significant effects of FDI on TFP in SSA agriculture. However, the results are heterogeneous, and the coefficients for the influence of FDI on land and labor productivity are insignificant. The main innovations of this paper thus lie in its novel data and the first-time application of a country-level regression framework to FDI and agricultural productivity in SSA but must be contrasted with micro-level literature for researchers and policymakers to gain insights into which FDI is beneficial for which type of location.

The paper is structured as follows: section 0 discusses related empirical literature and the direction and interplay of spillover channels. Section 3 outlines a conceptual model and the regression methodology. Section 4 provides details about the novel dataset on FDI inflows in SSA constructed for this study along with productivity data. Section 5 presents the empirical results of the regression analysis, including robustness checks. Section 6 examines the potentials and drawbacks of the data used here and links the empirical results to the hypothesis for spillover channels outlined in Section 2.

2. Potential spillover channels

Positive and negative influences of FDI on productivity are theoretically and empirically feasible. I discuss here the theoretical channels through which the two variables are linked and connect them to published empirical studies. Previous studies have focused on different aspects of the effects of FDI on African agriculture. The studies included here fall into two broad fields: First, macroeconomic studies at the country level, examining the effects of FDI on levels of agricultural production and food security. The second field is microeconomic studies at the (smallholder) farmer level, investigating productivity and other effects of foreign land acquisitions in single SSA countries. These studies usually link smallholders and foreign-owned large farms based on geographical or other measures of proximity. To improve upon these studies, there is a need to either simultaneously collect data on all types of farms, large and small (Deininger et al., 2022), or use figures aggregated at the country level, as I propose in this study. In this section, I lay out three crucial channels through which FDI can influence productivity and relate them to both types of studies.

2.1. Technology transfers

A central argument for countries to host FDI is the theoretical potential for knowledge spillovers. These technology transfers from foreign to local businesses and farmers could raise productivity. In all sectors of the economies of developing countries, some recent evidence suggests that beyond overall output growth, FDI inflows are also positively associated with productivity growth. This is especially true in settings with high institutional quality, which could support technology transfers (Li and Tanna, 2019).

In agriculture, new technologies introduced by foreign investors in SSA could include plant breeding techniques, plant spacing, irrigation techniques, and many others. Likely, employees on agricultural estates set up by foreign investors, especially outgrowers, whom investors contract to grow specific crops, benefit most from these potential channels (Herrmann, 2017; Osabuohien et al., 2019). When these groups obtain knowledge of agricultural techniques from multinationals, productivity can rise. However, recent literature does not clearly indicate whether this is the case. Thus, the expected effect of FDI on productivity through the knowledge spillover channel is either positive or equal to zero.

2.2. Market access

Infrastructure built or infrastructure improvements catalyzed by the presence of large investors can benefit local farmers in SSA. Roads, for example, enhance access to both input and output markets and can substantially improve smallholder productivity (Gebresilasse, 2023). Essential aspects of infrastructure are improved access to high-quality inputs such as fertilizer and better functioning of both input and output markets, thereby offering better prices for farmers (de Janvry and Sadoulet, 2020).

Foreign investors in SSA agriculture tend to choose locations with abundant land and labor. At the same time, infrastructure capacity is also generally low in these areas (Richetta, 2022)Since low-quality infrastructure is often associated with low productivity, there is potential for investments to upgrade productivity through infrastructure enhancements. Thus, the expected sign of the effects of the infrastructure development and market access channels of FDI on agricultural productivity is positive.

2.3. Resource availability

Natural resources, including land and water, are essential inputs for agricultural production. Investors choose their locations according to the availability of highly productive land and water resources (Dell'Angelo et al., 2018; Hirsch et al., 2020; Lay and Nolte, 2017). For water, it has also been shown that foreign investors tend to seek areas with good access to surface and groundwater. Through their preference for irrigated and water-intensive crops, foreign investors tend to contribute to water scarcity (Chiarelli et al., 2022; Rulli et al., 2013). Water scarcity, in turn, is likely to reduce the productivity of neighboring farmers. Generally, when foreign investors secure the most productive lands or use water in ways that impede local farmers' irrigation potential, the productivity of those farmers is likely to decrease.

A further aspect concerns the labor market. New investors may hire laborers who were previously subsistence or locally-employed farmers because first, they are trained in or have substantial experience executing tasks on farms. Second, subsistence farmers in SSA are commonly in remote areas and have few other income-generating activities available to them. If, through being employed by foreign investors, however, these farmers shift away from cultivating their own fields at least partially, the productivity of local farmers reduces. While micro-level evidence from Ethiopia suggests that the labor generation of foreign investors is only marginal (Ali et al., 2019), certain crops and other factors could play a role in the number of jobs created (Yimam et al., 2022). Therefore, the expected sign of FDI's effects on agricultural productivity through the resource and labor market channels is negative.

3. Methods

I discuss here the theoretical connection between productivity and FDI and the econometric methods used to estimate their relationship.

3.1. Conceptual model

In my main specification, I use TFP in agriculture as an indicator of productivity. This is determined by many factors such as land used for production, and capital intensity, including the number of tractors or employed workers (K. O. Fuglie, 2018). The advantage of using a pre-calculated TFP measure from an available dataset is that the data and underlying methods are well established and tested and leverage a wealth of available quality-checked data sources. Some caution must be employed though when interpreting the result given the fact that the TFP estimation method can in some cases influence the estimated productivity levels (Bournakis and Mallick, 2018).The two main components, land and labor, are essential for agricultural productivity. This is particularly important in SSA, where smallholder farmers who rarely use machines account for large shares of agriculture. Therefore, beyond TFP, land and labor productivity are essential productivity measures.

A simple model underlying TFP in agriculture can be derived from adapting the neoclassical growth model to the sectoral level. This means applying the Cobb-Douglas production function of the Solow model to the case of a single sector – the primary sector.

$$Y_i = A_i K_i^{\alpha} L_i^{1-\alpha}$$

Where Y_i is output in country i, A_i is TFP, K_i is capital and L_i is labor. This term can be reformulated to express TFP in terms of the inputs, which will be the basis for the regression framework in section 3. Following (Bournakis and Mallick, 2018), I acknowledge that TFP estimation methods can significantly influence productivity measurements. However, given data constraints in SSA, I rely on established pre-calculated TFP measures from USDA-ERS, which provide consistent cross-country comparisons despite potential limitations in capturing firm-level heterogeneity.

While the TFP analysis aims to investigate the potential influences of FDI on technological progress, two additional sets of productivity measures can be used to investigate further the interplay between FDI and output: labor and land productivity. For these, a Cobb-Douglas function can be rewritten to output per capita or per unit of land. For example, dividing output by labor force yields the intensive form:

$$y = Ak^{\alpha}$$

Where $y = \frac{Y}{L}$ is output per worker and analogously k is capital per worker. This equation can similarly be rewritten to express output per unit of capital to obtain an expression for Y/K dependent on TFP, levels of capital and labor and the factor share α. Taking the simplifying assumption that capital in SSA's agricultural sector is composed only of (or at least proportional to) the quantity of land used for agricultural purposes, it can be interpreted as land. The left-hand side of the resulting equation will thus be the value of agricultural output per unit of cropland, which is an essential measure of agricultural productivity as it closely corresponds to yields, calculated as output weight per unit of land.

While the growth of output per laborer is a standard measure of the growth of a sector, output per hectare is a standard measure of agricultural productivity. Both can be augmented by multiple factors discussed in the following subsections and the description of the setup of the regression model.

3.2. Model specification and estimation

The main empirical model is oriented along the lines of a neoclassical production function, as outlined above in section 3.1. When imposing a standard assumption of fixed capital shares, TFP can be expressed as for example by (Li and Tanna, 2019; Makiela and Ouattara, 2018) in a regression of the form:

$$TFP_{i,t} = \beta_0 TFP_{i,t-1} + \beta_1 FDI_{i,t} + \beta_2 X_{i,t} + \mu_i + \varepsilon_{i,t}$$

Where $TFP_{i,t}$ is the yearly Total Factor Productivity in agriculture in country i in year t, one-year lags in the autoregressive setup are included by $TFP_{i,t-1}$, $FDI_{i,t}$ are FDI in agriculture in country i in year t at constant prices, $X_{i,t}$ are a set of control variables and μ_i and $\varepsilon_{i,t}$ are country-specific and country-year-specific iid error terms. In a first step, the regression above is estimated in a fixed effects autoregressive model as denoted and with robust standard errors. This, however, is likely to be biased, given endogeneity concerns.

Estimating the regression within an autoregressive ordinary least squares (OLS) framework is vulnerable to potential reverse causality. This susceptibility arises from the bidirectional relationship between FDI and productivity, as investments are likely to fluctuate in response to the initial levels of productivity in a host country. For example, studies have found that agricultural FDI is often located in areas with superior agroecological conditions and abundant land (Lay and Nolte, 2017; Mazzocchi et al., 2018; Tulone et al., 2022) or access to water (Chiarelli et al., 2022; Dell'Angelo et al., 2018; Hirsch et al., 2020). Thus FDI targets low-productivity areas, but in turn, it exerts a considerable impact on productivity.

I employ an instrumental variable technique to address the challenge of reverse causality. I use a System Generalized Method of Moments (GMM) estimator, which uses lags of dependent variables as instruments to account for potential endogeneity. The system GMM estimator proposed by (Blundell and Bond, 1998) can estimate dynamic panel data models, including lagged dependent variables as regressors, by using moment conditions that use moments not only in first differences but also in levels. Blundell & Bond find that this estimator is particularly well suited for panels with short time spans. In addition to more standard instrumental variable (IV) estimators, System GMM also accounts not only for endogeneity in the main explanatory variable but also in additional control variables. This is relevant since several control variables could be endogenous in the setup at hand. For example, many countries in SSA have high shares of the primary sector's Gross Value Added in their Gross Domestic Product (GDP). Therefore, higher productivity can be linked to higher GDP in such instances. While advanced techniques for addressing endogeneity in FDI-productivity relationships exist (Bournakis and Tsionas, 2022), their implementation requires firm-level panel data with detailed information on business relationships. In the absence of such data for SSA agriculture, I employ System GMM as the most robust available alternative for addressing simultaneity bias at the country level.

The two-step System GMM framework is estimated with robust standard errors corrected for small sample bias (Windmeijer, 2005). To avoid the problem of proliferation of instruments, meaning in this case, more instruments than countries in the panel, the instruments are collapsed, and lags are included as instruments up to order four. Finally, I use orthogonal deviations, which is standard practice for panels with gaps, to maximize sample size (Roodman, 2009).

To further examine potential connections between FDI inflows and productivity, I also use output per unit of labor and per unit of land as dependent variables in the regression framework. To do so, I replace $TFP_{i,t}$ and $TFP_{i,t-1}$ with the corresponding expressions for the value of agricultural output in 1000 US$ per 1000 workers and the value of agricultural output per 1000 ha of agricultural land. If the value of output per hectare increases, it is of interest whether this is because of changes in land used for agriculture, because of changes in output growth, or both. This is relevant since productivity enhancements could help decrease the resource intensity of agricultural production if land was spared to obtain similar output levels. To investigate this in a further step of the analysis, I also use absolute output and land as dependent variables in the regression model.

4. Data

The novel dataset on FDI in agriculture in SSA collectected for this purpose is a major innovation of this study. This section summarizes the FDI dataset and its assembly process and then proceeds to provide information on data for the control variables employed in the regression framework.

4.1. A new data set for measuring agricultural FDI

The data set compiled for this study differs from previous macro-economic studies because it relies on official statistics supplied by governments, official bodies, or international organizations. Most preceding studies (e.g. Kinda et al., 2022; Mechiche-Alami et al., 2021; Santangelo, 2018; Tulone et al., 2022) use publicly reported data collected by researchers of the Land Matrix (LM) project. A single example using similar administrative data as collected here addresses the effects of sectoral FDI on agricultural production, not productivity, and only includes few African countries (Ben Slimane et al., 2016). It is unclear to what extent this previous study's results can be used since it pools poor and wealthy countries, which is inappropriate for studying FDI effects (Blonigen and Wang, 2005).

The Land Matrix project relies on media and other local reports on planned or implemented foreign land acquisitions. The project is a research effort coordinated by the International Land Coalition and multiple research organizations and universities. Scholarly arguments have been put forward that media and locally collected reports significantly overstate investments in contrast to data available form official registers (Ali et al., 2017). Common problems include non-operational or repurposed investment sites not accurately captured. Official statistics used in this paper instead measure FDI as the yearly inflows of capital used to purchase land and invest in the agricultural sector in general. Invested amounts are only captured for a restricted number of records of the Land Matrix, which is among the reasons why studies using LM data measure FDI by the land sizes of investments in hectares. Measuring FDI in monetary values includes additional information on the amount of capital used for production. Thus, these data could be more strongly correlated with agricultural productivity if, for example, in one country, investors purchase significantly more capital-intensive machinery to use on their fields than in another.

Accumulated FDI stocks could be better suited than inflows to research the productivity effects of FDI, because they could capture the effects of FDI, which might take multiple years to materialize. However, this data is rarely available. I address this issue in two ways: First, I lag FDI inflows by one year in the analytical framework presented here to allow for spillover effects to occur. Second, the GMM is some remedy to this problem because it includes FDI lags. Additionally, to account for changes in prices over time I use country-year-specific Consumer Price Indices (CPI) to transform all FDI inflows into constant 2015 US dollars.

A high investment could also mean investment into a more capital- or labor-intensive crop. If crops require higher investments but are still profitable for the investor, revenues per hectare must also be higher, owing to either high yields or high prices per unit of output. In this setting with high-value crops, investments with small land sizes could still lead to significant spillovers in terms of the value of production if the host economy can profit from foreign technology for these crops. When measuring FDI with land sizes, these types of investments are not adequately reflected. On the other hand, land sizes contracted by foreign investors could also be an inadequate measure of FDI to study its effects on productivity if only fractions of the land under contract are used for agricultural production or capital investment in this land is low for other reasons. The substantial shares of abandoned and failing projects in the Land Matrix database are the first indicator of this. Projects, for example, regularly fail when there is little involvement of local actors and stakeholders (Nolte, 2020).

The data set was compiled using a set algorithm. First, data on FDI in the primary sector was obtained from the Food and Agricultural Organization's Statistical Office (FAOSTAT). If no data was available, missing values were filled consecutively with data from the Common Market for Eastern and Southern Africa (COMESA) statistics, and other secondary data from the countries' institutions. The search at the country level was conducted by searching and filling in publicly available data from 1) National Banks, 2) national statistical institutes, and 3) investment promotion agencies (IPA). Data sources, the number of observations, and the countries covered by each source are displayed in Table 1. All data is for FDI in the primary sector and generally uses the Balance of Payments methodology defined by the International Monetary Fund. The full data set is an unbalanced panel spanning from 2000 to 2020 for 22 Sub-Saharan countries.[1] A small fraction of records exhibit negative values owing to either divestment of capital or correction of records. Western African countries Benin, Burkina Faso, Mali, and Niger are reported by their Banque Centrale des Etats de l'Afrique du Ouest (BCEAO) to exhibit zero flows in all years covered in their statistics. While the Land Matrix shows some investment in these countries, the implementation status in LM data is unclear, making the BCEAO numbers feasible. The reliability of the data provided by the data sources on FDI inflows is potentially higher than that of previous studies. The advantage of the data is that it is thoroughly cross-checked by national entities compiling the data according to IMF standards and, in most cases, by international organizations, including FAO and COMESA.

A simple comparison between data from official statistics and the Land Matrix is displayed in Fig. 1. While there is some connection between invested amounts captured in the FDI dataset and contracted areas from the LM, outliers drive the overall image. The LM relies on a low number of 105 observations for which FDI data was available, and the LM recorded any deals. The corresponding Pearson's correlation coefficient is low at 0.065, and a t-test rejects correlation between the monetary flows and area-based measures of foreign investment in the SSA agricultural sector. The discrepancies could stem from any of the reasons discussed above, including definitional aspects as well as the incompleteness of news reports used to compile the LM statistics.

The assembly of this dataset represents a crucial first step toward enabling more sophisticated analyses of sectoral FDI impacts in SSA. As data collection efforts expand to cover other sectors and firm-level information becomes available, future research can implement more advanced methodologies, including the endogenous spillovers framework proposed by Bournakis and Tsionas (2022).

[1] The dataset includes the following countries: Benin, Burkina Faso, Burundi, Congo - Kinshasa, Côte d'Ivoire, Ghana, Guinea-Bissau, Kenya, Madagascar, Malawi, Mali, Mauritius, Mozambique, Niger, Nigeria, Rwanda, Senegal, Sudan, Tanzania, Uganda, Zambia, Zimbabwe. A detailed table of data sources and available years for each country is provided in the appendix.

Table 1
Data sources for FDI inflow database. Detailed references are provided in the appendix.

source	n	# of countries
Food and Agricultural Organization Statistical Office (FAOSTAT) FDI Statistics	156	12
Banque Centrale des Etats de l'Afrique d'Ouest (BCEAO) Balances des Paiments	53	7
Agence Nationale pour la Promotion des Investissements (ANAPI) Democratic Republic of Congo [via US Department Of State Investment Climate Reports 2010,2014]	8	1
Ghana Investment Promotion Centre (GIPC) Quarterly Investment Reports, FAO (Trends and impacts of foreign investment in developing country agriculture p 192)	8	1
Zimbabwe Investment Authority (Annual Reports, 2009–2015)	7	1
Senegal Agence Nationale chargée de la Promotion de l'Investissement et des Grands Travaux (APIX)	6	1
Sudan Ministry of Investment official statistics	6	1
Burundi Investment Promotion Agency official statistics	5	1
Common Market for Eastern and Southern Afica (COMESA) Statistical Office	5	2
Agence Nationale pour la Promotion des Investissements (ANAPI) DRC, Rapport Annuel 2015–2016	2	1
Banque National de Madagascar (Enquete sur les IDE et IPF, 2001,2005,2012,2013,2015)	2	1
Nigeria Investment Promotion Comission - FDI Statistics 1999–2005, Annual Report 2006–2008	2	1
National Statistical Office of Malawi (Malawi Foreign Private Capital report 2009, 2011, 2017)	1	1
Schuepbach (2014)	1	1

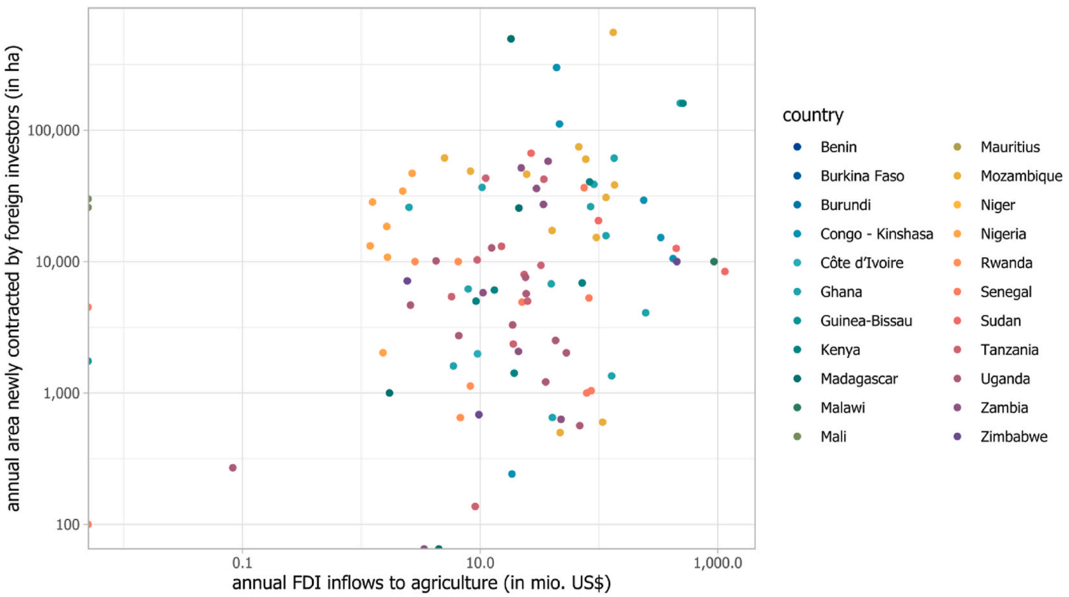

Fig. 1. Comparison of yearly FDI inflows in monetary terms from official statistics to contracted area by foreign investors in SSA per year from Land Matrix data. Each dot represents a country-year observation in the panel data. Both scales are logarithmic.

The current data limitations underscore the critical need for enhanced statistical capacity in SSA countries. Investment in comprehensive firm-level surveys and sectoral FDI tracking systems would enable researchers to apply cutting-edge methodologies and provide more nuanced policy guidance.Productivity and control variable data.

4.2. Productivity and control variable data

Total Factor Productivity is used as dependent variable in the form of a TFP index, which is computed as the weighted mean of productivity of all agricultural inputs (K. Fuglie, 2015). An updated dataset on agricultural TFP using Fuglie's methodology was obtained from the United States Department of Agriculture's Economic Research Service (USDA-ERS). This dataset also contains control variables and variables used for alternative productivity measures in this paper. Primarily, these variables were sourced from the United Nations Food and Agricultural Organization's statistical office (FAOSTAT). Additional variables obtained from the USDA-ERS dataset are land for agricultural production in hectares, the value of agricultural output in constant 2015 US$, and persons employed in agriculture. All dependent variables are modeled quantities, not observed data from surveys or national statistics. TFP estimation is described above. Labor variables were sourced by the compilers of TFP statistics from the International Labour Organization's Department of Statistics who estimate employment in agriculture using a regression-based approach, and land is measured as rainfed-equivalent total harvested area for all crops with raw data compiled from national statistics by FAOSTAT and adjusted for land quality, including irrigation status by USDA-ERS.

Control variables included in the vector $X_{i,t}$ include trade openness which is defined as the ratio of exports and imports to GDP. Data on countries' Gross Domestic Product (GDP) at constant 2015 prices per capita from the World Bank's World Development Indicators (WDI) is included to account for the fact that larger and richer economies could have generally higher productivity in any sector. Differences in weather conditions across countries are accounted for by including country-level averages of yearly levels of precipitation published by the Climatic Research Unit of the University of East Anglia (Harris et al., 2020). Two controls for sources of finance are included: First, the amount of remittances received as a share of GDP for which data is sourced from WDI, second the inflows of official development assistance (ODA) to agriculture as shares of agricultural gross value added, which is obtained from FAOSTAT. Through the additionally available capital available to farms and agricultural development, both monetary inflows could in theory contribute to higher levels of production and productivity. To control for different levels of education, I include mean years of schooling of a country's adult population (UNDP, 2022). The political stability percentile rank from the Worldwide Governance Indicators published by the Brookings Institution and the World Bank (Kaufmann and Kraay, 2023) is included to account for differences in institutional frameworks laying the ground for productive business operations in agriculture.

The reliance on country-level aggregates, while necessary given data constraints, prevents me from capturing within-country heterogeneity in FDI impacts. This limitation is particularly relevant when considering that FDI effects may vary substantially across regions, firm sizes, and crop types within countries.

5. Results

Results from the FE and System GMM regressions are presented here in the following order: First, I discuss the main results for TFP, then those for output per units of labor and land and the components thereof, and lastly, I conduct robustness checks by excluding different sets of observations from the dataset. A discussion and links to theoretical channels and the state of literature follow in the discussion section (section 6). My empirical approach, while constrained by data availability, provides the first systematic evidence on agricultural FDI-productivity relationships in SSA using official statistics. These baseline estimates can inform future research as data infrastructure improves.

5.1. Regression results

The first variable used in the regressions to measure changes in productivity is TFP. Results for FE and System GMM estimations are displayed in Table 2. For all model variants, I start with a baseline model that only includes the lagged dependent variable and FDI on the right-hand side of the regression equation. I then add control variables *precipitation, ODA in agriculture, remittances, education* measured by years of schooling and *political stability* rank. First, I estimate all models using a fixed effects framework, which accounts for unobservable country characteristics (for example columns 1 and 2 in Table 2). This model does not have the potential weakness of too many instruments that can arise in System GMM models. However, it is likely to suffer from endogeneity concerns. Hence, I also estimate corresponding models addressing endogeneity using System GMM, which is similar to FE because of the first differences built.

TFP is estimated to be significantly positively influenced by FDI in the FE estimations and when accounting for reverse causality,

Table 2
Regression results with TFP index as dependent variable.

	(1)	(2)	(3)	(4)
	FE	FE	Sys.GMM	Sys.GMM
Lag TFP	0.695***	0.665***	−0.260	1.602***
	(0.0604)	(0.0639)	(0.634)	(0.517)
FDI (million US$), 1-year lag	0.00628	0.00612*	0.0260	0.210**
	(0.00370)	(0.00343)	(0.0714)	(0.0956)
ODA agriculture (percent of ag. GVA)		−5.386		−108.2
		(4.697)		(67.10)
Remittance inflows (% of GDP)		0.806*		−4.908**
		(0.399)		(2.369)
Precipitation (% deviation from mean)		0.0228		0.284***
		(0.0386)		(0.0853)
Mean years of schooling		−0.466		−3.506
		(1.658)		(4.916)
Political stability rank (0–100)		0.00688		0.514**
		(0.0608)		(0.210)
Observations	230	224	230	224
No. of instruments			26	34
No. of countries	22	22	22	22
AR2 (p-value)			0.660	0.629
Hansen-J (p-value)			0.963	1

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

meaning when using System GMM. The estimated effect of FDI on TFP is small at 0.2 TFP index points per million USD of FDI inflow (Table 2 column 4) but positive and significant at the 5 % level. For System GMM estimations, several statistical tests are necessary to ensure the underlying assumptions hold. First, I test for auto-correlation in the second-order residuals. This can be rejected at the five percent level (columns 3 and 4). The Hansen test for overidentifying restrictions does not reject instrument validity. Finally, collapsing instruments and limiting instruments to lags up to three periods, as discussed in the methods section, ensures that the number of instruments remains below the number of countries.

The second measure of productivity in agriculture employed is the value of output per worker. If this measure increases, countries' agricultural sectors can benefit from either increased income from the agricultural sector or can induce structural transformation of their economies. The regression results in Table 3 show no statistically significant effects of FDI on value added per worker. This holds under all FE (columns 1 and 2) and System GMM (column 4) specifications, while relevant test statistics render GMM reliable since required assumptions hold. In the GMM estimation in column 4 and some of the variants presented at later stages, the model cannot accommodate ODA as a control. At a later stage, I also test whether absolute values of output increase or decrease with additional FDI inflows. In case of an increase, an explanation for the insignificant increase in the relative per worker term could be variation in labor intensities. Table 4, however, shows no signs of such increases in the value of output. Therefore, I do not investigate this channel further.

Similar to labor productivity, coefficients are insignificant for land productivity measured by value of output per hectare of agricultural land in my preferred specification accounting for controls and endogeneity (Table 4, column 4). While in the Fixed Effects model with controls in columns 1 and 2 of Tables 4 and I find a positive and significant effect of FDI on this productivity measure which corresponds to agricultural yields, System GMM estimations instrumenting with lags to tackle endogeneity concerns show no significant effects. Not all assumptions required for System GMM estimation hold in this last specification, however, as evidenced by the p-values for the required tests and the instrument count. In columns 5 and 6, I report the regression results for the components of land productivity.

5.2. Robustness checks

The FDI data exhibits certain features, including outliers and zero values, that could drive the results obtained. In particular, specific observations and country characteristics could be influencing the results. A first check is conducted in Table 5 in columns 1–2 where the TFP System GMM regressions are repeated without the observations for Mauritius since its productivity levels are outliers in the sample, partly due to its unique role in the sample as the only small-island economy. The sample size is only reduced by 19 observations in this case. The estimates still correspond to those obtained in the main specifications but statistical significance for the DI effects is lower. Thus, the particular characteristics of Mauritius are relatively unlikely to bias the observed effects.

A second set of robustness checks (columns 3 and 4) drops observations with zero inflows recorded by the central bank for West African francophone countries (BCEAO) discussed in section 0. The magnitude of effects estimated in the reduced sample does not correspond to those estimated using the full sample thereby questioning the obtained positive effects from the main specification. Reducing the already small sample size by twenty percent limits the importance of this robustness check. It is, however, an indication

Table 3
Regression results with labor productivity measured by value of output in 1000 US$ at constant 2015 prices per agricultural worker as dependent variable.

	(1)	(2)	(3)	(4)
	FE	FE	Sys.GMM	Sys.GMM
Lag labor prod.	0.895***	0.819***	0.704**	1.068***
	(0.0297)	(0.0581)	(0.327)	(0.352)
FDI (million US$), 1-year lag	−0.00740	−0.00723	−3.557*	6.818
	(0.0572)	(0.0638)	(2.105)	(10.71)
ODA agriculture (percent of ag. GVA)		5.364		0
		(123.4)		(.)
Remittance inflows (% of GDP)		13.31		182.0
		(9.610)		(236.5)
Precipitation (% deviation from mean)		−0.405		15.55
		(1.525)		(23.72)
Mean years of schooling		241.9		102.4
		(146.0)		(153.2)
Political stability rank (0–100)		0.860		19.85
		(1.006)		(24.71)
Observations	230	224	230	224
No. of instruments			26	34
No. of countries	22	22	22	22
AR2 (p-value)			.	0.481
Hansen-J (p-value)			0.931	1

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table 4
Regression results with land productivity measured by value of output in US$ per hectare and its components as dependent variables.

	(1)	(2)	(3)	(4)
	FE	FE	Sys.GMM	Sys.GMM
Lag land prod.	0.554***	0.467***	1.413***	1.052***
	(0.0536)	(0.0855)	(0.174)	(0.114)
FDI (million US$), 1-year lag	0.153**	0.141**	−2.562*	0.121
	(0.0659)	(0.0633)	(1.437)	(0.587)
ODA agriculture (percent of ag. GVA)		−24.76		−1285.6
		(58.93)		(1354.5)
Remittance inflows (% of GDP)		10.22*		−82.78
		(5.086)		(77.55)
Precipitation (% deviation from mean)		−0.491		−0.581
		(0.671)		(1.631)
Mean years of schooling		59.03		19.17
		(60.12)		(18.51)
Political stability rank (0–100)		−1.034		4.070
		(0.951)		(4.936)
Observations	230	224	230	224
No. of instruments			26	34
No. of countries	22	22	22	22
AR2 (p-value)			0.300	0.0450
Hansen-J (p-value)			1.000	1

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

Table 5
Regression results for robustness checks on subsets of the panel with TFP in percentage points as dependent variable.

	(1)	(2)	(3)	(4)
	FE w/o Mauritius	GMM w/o Mauritius	FE w/o zero flows	GMM w/o zero flows
Lag TFP	0.678***	0.379	0.645***	1.110***
	(0.0654)	(0.260)	(0.0709)	(0.150)
FDI (million US$), 1-year lag	0.00666*	0.158	0.00619*	−0.0275
	(0.00349)	(0.0989)	(0.00315)	(0.0352)
ODA agriculture (percent of ag. GVA)	−5.588	0	−6.846	0
	(4.840)	(.)	(5.556)	(.)
Remittance inflows (% of GDP)	0.737*	−3.625*	0.918*	−2.284
	(0.411)	(2.052)	(0.460)	(1.545)
Precipitation (% deviation from mean)	0.0388	0.765***	0.000521	0.131*
	(0.0474)	(0.271)	(0.0416)	(0.0798)
Mean years of schooling	−2.793	14.90**	0.109	1.006
	(3.197)	(6.759)	(1.547)	(1.302)
Political stability rank (0–100)	0.00622	0.827**	−0.0385	−0.00204
	(0.0656)	(0.354)	(0.0691)	(0.108)
Observations	211	211	185	185
No. of instruments		37		34
No. of countries	21	21	18	18
AR2 (p-value)		0.669		0.535
Hansen-J (p-value)		1		1

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

that observations with no FDI inflows might somewhat drive results with TFP as dependent variable estimated in the baseline TFP regressions.

A further set of robustness checks uses relative levels of FDI in the agricultural sector by substituting the FDI independent variable in the regressions with the ratio of agricultural FDI to Value Added in agriculture. The results remain largely unchanged and confirm the main results of the main estimations. For conciseness I present the results of these estimations in the appendix.

6. Discussion

Previous research on the effects of FDI on productivity in SSA or developing countries was limited to the overall economy. Using a newly constructed dataset, I here analyze these effects in the primary sector. In this sector, some research has been conducted using Land Matrix data to estimate FDI effects on absolute production. The discussion in the preceding data section shows several unique advantages of using national statistics in analyzing FDI instead of LM data. Therefore, this study presents an important first step in analyzing sectoral impacts of FDI in SSA. Future research needs to collect and leverage data from all sectors, preferably at firm-level to be able to analyze cross-sectoral effects and apply advanced methods for endogenous spillovers (Bournakis and Tsionas, 2022). To increase the reliability of the estimates obtained here, it will be critical to increase the sample size. This increase and the expansion to other sectors can mainly be achieved by statistical capacity building and sufficient funding for data collection in SSA countries.

The empirical results using a new dataset suggest a small but positive association between FDI and Total Factor Productivity in the agricultural sector. This is in line with the results obtained for the effects of FDI on TFP obtained for all sectors in developing countries in previous studies (Li and Tanna, 2019). Contrasting insignificant effects were found for the overall economy of SSA (Kariuki and Kabaru, 2022) or negative effects (Herzer and Donaubauer, 2018). The effects I find are only statistically significant in a System GMM framework that controls for endogeneity in the FDI-TFP nexus, where countries with higher productivity could receive more FDI than those with low productivity levels.

Changes in TFP need not necessarily be related to land or labor productivity if these quantities are measured as the value of output per laborer or per unit of land. Changes in factor shares (α) could be relevant, and therefore, situations in which these quantities remain largely unchanged while TFP increases are possible. The empirical results suggest this is the case in the sample of SSA countries studied. Labor and land productivity are, however, still essential measures of spillovers. When less labor or land needs to be used to produce agricultural output, this frees up resources to be used in other sectors. This can be an important trigger of structural transformation in African economies. While overall, FDI might not be effective for catalyzing these transformational processes (Gui-Diby and Renard, 2015), agricultural investments could be. A problem with this approach to structural transformation is likely caused in several SSA countries by resource-seeking FDI, which extract rents from land in industries such as agriculture or mining. These can cause shifts of capital away from manufacturing or even services and cause deindustrialization (Wako, 2021).

Capital and water-intensive investments such as horticulture are likely to create jobs, especially when compared to less labor-intensive crops (Yimam et al., 2022). Similarly, contract farming somewhat increases labor demand in developing countries (Meemken and Bellemare, 2020), but it is unclear whether, in the case of FDI, this is because of upgrading in the extensive or intensive margin. It has been observed that foreign investments crowd out local employment in agriculture, leading to somewhat lower overall employment in the sector (Nolte and Ostermeier, 2017). However, given the relatively small size of the effect and the sizes of investments compared to the entire sector, the employment reduction could simply be not large enough to significantly influence the employment numbers relevant for the indicator I use here. Since a general trend toward higher labor intensity by either reduced labor on similar land or higher increases in land than in labor are not observed, the positive TFP associations of FDI are likely to produce only few benefits in terms of labor productivity upgrading for host countries of foreign investments.

The regressions included here do not find any significant effects of FDI on values of output per hectare in the agricultural sector. The two components of the fraction in the dependent variable are also used as indicators in two separate regressions. Here, I find that FDI inflows are associated with neither of them. Whether international land acquisitions crowd in or out local farmers depends on the investment's characteristics and success (Williams et al., 2021). The result of the analysis in this paper hints towards a dynamic where both changes in the value of output and agricultural land increase and decrease independently of the level of foreign investments a country receives. TFP growth has been found to rarely be associated with an expansion of cropland (Villoria, 2019). These dynamics can partly explain the lack of significant changes in land.

Three important channels for potential spillovers are discussed in section 0: technology transfers, market access, and resource availability. At the country level, increased yields or value of output in proximity to agricultural estates or large-scale land acquisitions have been observed in several cases (Glover and Jones, 2019; Joseph et al., 2023; Lay et al., 2020; Sullivan et al., 2022) but usually with many limitations and only in closest proximity to investment sites. Other studies found little significant effects (e.g. Ali et al., 2019). The results found in this paper indicate that some technology transfers are likely since TFP is a measure of technology. The mixed results from micro-level studies and the lack of significant effects on other measures of productivity can be connected to differences in data discussed in section 0 and to heterogeneous effects across different types of investments, such as different characteristics of crops or host countries. Research and development (R&D) significantly positively affects agricultural TFP in Africa (Alene, 2010). One way of increasing the productivity impacts of agricultural investments through knowledge and the transfer thereof can thus be future increases in R&D spending.

The estimates in the empirical section of this paper cannot substantiate the channels of access to input and output markets. Even though some past evidence points towards higher use of modern inputs, for example, improved seeds, fertilizer, and pesticides by farmers close to newly established large-scale farms in Mozambique (Deininger and Xia, 2016), it is unclear to which extent these results are transferable to the entire Sub-Saharan sub-continent. Given the lack of statistically significant effects of FDI on value of output in a country, the input market channel might not play a substantial role. A similar argument can be made for output markets.

Resource availability likely also influences yields and, consequently the value of output per hectare. Abundant land and water resources could be one such case. Since there is no evidence for an association of FDI with a higher value of output, this channel is unlikely.

Food security is among the most direct and important implications of agricultural production and productivity. The impact of FDI on food security and its connection with productivity depends on a multitude of factors. When productivity gains are used for land-sparing purposes, meaning producing similar quantities but on less land or with less labor or capital, production and food security will likely not increase. However, the volatility of food availability, which is often lower in irrigated, capital-intensive agriculture, also plays a role in food security. Through this channel, food security might somewhat increase. Target markets are critical for food security ramifications of foreign investments in the primary sector. Because FDI in developing countries mainly target export markets or at least reinforce existing structures focusing on exports (Sahoo and Dash, 2022), the probability of decreasing food security is high. This is often the case in SSA, where production targets local food markets only in exceptional investment sites (Mechiche-Alami et al., 2021). Thus, even if productivity increases through FDI in agriculture, it is advisable to complement them with policies ensuring food security for local populations. However, the impacts of trade on TFP are not homogeneous. Trade within Africa is associated with higher agricultural TFP growth than trade with economies outside of the continent (Sunge and Ngepah, 2020). Hence, policies regulating or promoting FDI in agriculture should consider these differential effects of investor intentions.

This study's findings should be interpreted considering the methodological constraints imposed by data limitations. While I cannot endogenize spillovers as in Bournakis and Tsionas (2022), my approach captures the net effect of FDI on agricultural productivity at the macro level, providing valuable insights for policymakers despite these limitations. As statistical capacity improves in SSA, several research avenues will become feasible: (i) implementing endogenous spillovers frameworks to obtain unbiased estimates of FDI impacts; (ii) conducting cross-sectoral analyses to identify industries with superior absorptive capacity; (iii) examining firm-level heterogeneity in FDI responses; and (iv) analyzing spatial spillovers using geo-referenced data.

7. Conclusion

FDI inflows into SSA could theoretically be associated with higher productivity in SSA, particularly in the agricultural sector. Using a newly collected dataset measuring monetary inflows instead of contracted land and controlling for potential endogeneity, I find some evidence to support the hypothesis of a slight increase in total factor productivity associated with inflows of foreign direct investments. I do not find any statistically significant effects for alternative productivity specifications, namely land and labor productivity. Neither is there support for the notion that production or agricultural land might expand when more foreign capital supplied by multinational enterprises in the form of FDI flows into the SSA agricultural sector. The results confirm previous findings of microeconomic studies, which show only limited evidence for any positive effects of foreign agricultural investors on local productivity. In the cases where these productivity spillovers occur, they are likely to occur via knowledge spillovers but only to a subset of local populations who are either employed by or contracted by foreign-owned farming businesses.

Using national statistics and other official sources, including international organizations and central banks, comes with the advantage of being able to measure the capital intensity of investments more accurately as opposed to area-based measures. This is an essential advancement of this study over some previous studies. However, the results presented here could be extended with additional data on FDI inflows for more countries and years. Among the most important future avenues for the extension of the study with additional data is an analysis of mediating factors and the absorptive capacity of countries for productivity growth induced by FDI. Research on the FDI-TFP nexus in rich countries for example, suggests that lower entry and trade barriers in upstream industries of the main FDI targets can catalyze positive productivity impacts (Papaioannou and Dimelis, 2019). Results on absorptive capacity are mixed. The few indications for positive associations of FDI and TFP found here suggest that not all countries and farmers are likely to benefit from FDI in agriculture. In developing countries such as those in SSA studied here, the substantial discrepancies between investor and host technologies could be a reason for this lack of spillovers. For example, Ashraf et al. (2016) found that in all sectors of developing countries, productivity increases only materialize if technologies in host countries do not lag too far behind the technological frontier.

A further important line of research for FDI in agriculture in SSA is the assessment of the impacts of similar investments along the entire agri-food value chain. Many actors, from input suppliers and manufacturers trading with seed, fertilizers, and other inputs to food processors and many different parts of agri-food value chains, are targeted by multinational enterprises. These vertical linkages are understudied but important (Scoppola, 2021). An additional potential extension of this study is to account for spatial autocorrelation for example in a model similar to the spatial Durbin model used by Tientao et al. (2016).

TFP growth is, on average, substantially slower in SSA than in other regions of the world. Additionally, climate change further reduces TFP growth (Ortiz-Bobea et al., 2021). Leveraging investments by smallholders, but potentially also by well-linked foreign investors, could be a way for countries in SSA to increase productivity in general and in terms of climate change adaptation. However, evidence for positive associations of FDI with productivity in the context of African agriculture remains moderate. Besides the intention of investors and their local linkages, the size of the farms built up by foreign investors plays a role in the spillovers they create. For example, medium-scale farms are often associated with spillovers to smallholders, while the spillover effect of large-scale farms is ambiguous (Jayne et al., 2021). Thus, only a narrow set of well-planned and implemented FDI could help boost productivity. These effects are primarily at the local scale and often insufficient to lift productivity in the entire sector of a whole country.

The policy implications of this study are relevant in two dimensions. On the one hand, it is essential to finance and support statistical capacity building to measure sectoral FDI inflows more accurately. This will enable countries, institutions, and researchers to study their implications and determinants in more detail, including the heterogeneous effects of FDI on host countries and absorptive capacity. Moreover, including additional sectors in FDI data collection will allow for analyzing the interconnections between sectors and the differential effects in industry and services as compared to agriculture. On the other hand, the analysis conducted here cannot be seen as a strong argument to solely rely on FDI in the agricultural sector to boost its productivity. A diverse set of measures, where only hand-picked well prepared and executed foreign investments which benefit local farmers and communities are implemented, seems more appropriate to reach this goal.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

Variable definitions

Table 6
Definitions of variables and data sources

variable	definition	unit	source
TFP growth	year-to-year growth rate of Total Factor Productivity	percent	Fuglie (2015)
FDI inflows	yearly inflows of FDI to the primary sector lagged by one year	million US dollars, 2015 prices	see detailed FDI table
Precipitation	average rainfall in country	mm annually	Climatic Research Unit of the University of East Anglia (Harris et al., 2020)
GDP per capita	Gross Domestic Product per capita	US dollars, 2015 prices	World Development Indicators (WDI)
openness	trade as percent of GDP	percent	World Development Indicators (WDI)
ODA agriculture	Official Development Assistance for agriculture as share of Gross Value Added in agriculture	percent	FAOSTAT
Remittance inflows	Remittance inflows in percent of GDP	percent	World Development Indicators (WDI)
Mean years of schooling	Average years of school attendance of working age population	years	UNDP (2022)
Political stability	Rank of political stability	rank (0–100)	Brookings Institution and World Bank (Kaufmann and Kraay, 2023)
Agricultural output	Quantity of total agricultural output	thousands US dollars, 2015 prices	Fuglie (2015)
Labor productivity	Output per number of persons economically active in agriculture	US dollars per persons	Fuglie (2015)
Land productivity	Output per rainfed-cropland-equivalents	US dollars per hectare	Fuglie (2015)
FDI share	FDI inflows divided by GDP	percent	see FDI and GDP above

FDI database details

Table 7
Summary statistics of Foreign Direct Investment inflows to the agricultural sector in million US dollars at 2015 prices.

country	min	mean	median	max	n	first year	last year
Benin	0	0	0	0	9	2010	2019
Burkina Faso	0	0	0	0	8	2012	2019
Burundi	35	2196	2093	4937	5	2010	2014
Congo - Kinshasa	0	11836	4524	42021	10	2006	2016
Côte d'Ivoire	0	359	214	951	8	2012	2019
Ghana	91	734	2195	48284	20	2001	2020
Guinea-Bissau	0	237	1	1466	8	2012	2019
Kenya	−2612	5533	1317	50853	13	2007	2019
Madagascar	−1862	75	533	2117	12	2000	2014
Malawi	−8794	11877	705	92989	8	2002	2017
Mali	0	0	0	0	8	2012	2019
Mauritius	3	478	99	2137	16	2001	2020
Mozambique	−87	6019	577	13515	20	2001	2020
Niger	0	0	0	0	8	2012	2019
Nigeria	77	497	165	5149	16	2000	2015
Rwanda	189	1297	982	3883	13	2008	2020
Senegal	0	352	2126	8599	14	2003	2019
Sudan	2683	30769	9826	114756	6	2000	2005
Tanzania	−1649	2226	1624	10818	18	2000	2017
Uganda	8	2898	2439	7478	21	2000	2020
Zambia	−13084	1092	2158	6284	14	2007	2020
Zimbabwe	223	7187	976	45168	7	2009	2015

Table 8
FDI inflow data sources and available years

country	source	years
Benin	Banque Centrale des Etats de l'Afrique d'Ouest	2010, 2012–2019

(*continued on next page*)

Table 8 (*continued*)

country	source	years
Burkina Faso	Banque Centrale des Etats de l'Afrique d'Ouest	2012–2019
Burundi	Burundi Investment Promotion Agency (http://www.investburundi.bi/index.php/a-propos-de-l-api1/api-en-chiffres)	2010–2014
Congo - Kinshasa	ANAPI (IPA in DRC) [via US Dep. Of State Investment Climate Reports 2010,2014]	2006–2013
Congo - Kinshasa	ANAPI, Rapport Annuel 2015–2016	2015–2016
Côte d'Ivoire	Banque Centrale des Etats de l'Afrique d'Ouest	2012, 2015, 2018, 2019
Côte d'Ivoire	FAO (Food and Agricultural Organization Statistical Office (FAOSTAT, 2024)	2013, 2014, 2016, 2017
Ghana	FAO	2009–2020
Ghana	GIPC Ghana (Quarterly Investment Reports), FAO (Trends and impacts of foreign investment in developing country agriculture p 192)	2001–2008
Guinea-Bissau	Banque Centrale des Etats de l'Afrique d'Ouest	2012–2019
Kenya	FAO	2007–2019
Madagascar	Banque National de Madagascar (Enquete sur les IDE et IPF, 2001,2005,2012,2013,2015)	2000, 2001
Madagascar	FAO	2005–2014
Malawi	COMESA	2011, 2012
Malawi	FAO	2002–2004, 2008, 2010
Malawi	National Statistical Office of Malawi (Malawi Foreign Private Capital report 2009, 2011, 2017)	2017
Mali	Banque Centrale des Etats de l'Afrique d'Ouest	2012–2019
Mauritius	FAO	2001, 2004–2008, 2011–2020
Mozambique	FAO	2001–2020
Niger	Banque Centrale des Etats de l'Afrique d'Ouest	2012–2019
Nigeria	FAO	2002–2015
Nigeria	Nigeria Investment Promotion Comission - FDI Statistics 1999–2005, Annual Report 2006–2008 (http://www.nipc.gov.ng/important%20document/FDI%20Data.doc)	2000, 2001
Rwanda	FAO	2008–2020
Senegal	APIX (in http://www.fao.org/docrep/017/i3112e/i3112e.pdf)	2003–2005, 2007–2009
Senegal	Banque Centrale des Etats de l'Afrique d'Ouest	2012–2019
Sudan	Sudan Ministry of Investment (http://www.sudaninvest.org/English/Foreign_Investments.htm)	2000–2005
Tanzania	FAO	2000, 2001–2017
Uganda	COMESA	2001, 2003, 2004
Uganda	FAO	2000, 2002, 2005–2020
Zambia	FAO	2007, 2009–2020
Zambia	Schuepbach (2014) (in https://www.ethz.ch/content/dam/ethz/special-interest/gess/nadel-dam/documents/research/eth-47518-02_Schuepbach_Dissertation.pdf)	2008
Zimbabwe	Zimbabwe Investment Authority (Annual Reports, 2009–2015)	2009–2015

Alternative regressions using FDI shares as independent variable

	(1)	(2)	(3)	(4)
	FE	FE	Sys.GMM	Sys.GMM
Lag TFP	0.697***	0.666***	1.850	0.911***
	(0.0602)	(0.0633)	(.)	(0.313)
FDI share, 1-year lag	0.172*	0.178**	−12.64	1.370
	(0.0933)	(0.0834)	(.)	(2.111)
ODA agriculture (percent of ag. GVA)		−5.338		0
		(4.873)		(.)
Remittance inflows (% of GDP)		0.823**		2.396*
		(0.394)		(1.419)
Precipitation (% deviation from mean)		0.0204		0.243**
		(0.0399)		(0.109)
Mean years of schooling		−0.402		2.442
		(1.647)		(2.806)
Political stability rank (0–100)		0.00924		0.233*
		(0.0612)		(0.123)
Observations	230	224	230	224
No. of instruments			26	34
No. of countries	22	22	22	22
AR2 (p-value)			.	0.0766
Hansen-J (p-value)			0.953	1

Standard errors in parentheses.
*p < 0.10, **p < 0.05, ***p < 0.01.

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While the database collected for this study contained further sources, only these sources remained after data cleaning. Cleaning consisted of dropping all countries and years with insufficient numbers of observations as described in detail in the methodology section in the main text.

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