FARM PRODUCTIVITY AND COMMERCIAL AGRICULTURE: EVIDENCE FROM A STOCHASTIC FRONTIER ANALYSIS IN SIX SUB-SAHARAN AFRICAN COUNTRIES

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ABSTRACT

Agricultural productivity in Sub-Saharan Africa remains low relative to other developing regions, with substantial dispersion across and within countries. While much of the literature emphasizes technological gaps and factor misallocation, less attention has been paid to how market integration affects farms' ability to use existing technologies effectively. This paper examines whether farm-level commercialization and local intermediary density are associated with improvements in technical efficiency—that is, the extent to which producers operate close to their production frontier given available inputs. Using harmonized farm household data from six Sub-Saharan African countries and a True Random Effects stochastic frontier model, we estimate country-specific production technologies and recover farm-level efficiency scores. We then model inefficiency as a function of commercialization, trader density, MSME engagement, and household and contextual characteristics. The results reveal substantial dispersion in performance, indicating considerable unrealized productive potential under current technologies. Participation in output markets is consistently associated with operating closer to the frontier across countries. Denser local trader networks are also linked to improved performance in several settings, though effects vary by institutional context. Quantile regressions show that commercialization is most strongly associated with improvements among farms operating farthest from the frontier, suggesting catch-up dynamics rather than uniform productivity shifts. These findings highlight the role of rural market systems—not only technological upgrading—in shaping agricultural productivity. Policies that deepen market integration and strengthen intermediary networks may yield substantial gains by enabling producers to operate closer to their existing productive potential.

Keywords: Agricultural productivity; Technical efficiency; Market integration; Commercialization; Hidden middle; Stochastic frontier analysis; Sub-Saharan Africa.

JEL Classification: Q12, Q13, O13, D24

RESUMEN EJECUTIVO

La productividad agrícola en el África subsahariana sigue siendo baja en comparación con otras regiones en desarrollo, con una dispersión considerable entre los países y dentro de ellos. Si bien gran parte de la bibliografía hace hincapié en las brechas tecnológicas y la mala asignación de los factores, se ha prestado menos atención a cómo la integración de los mercados afecta a la capacidad de las explotaciones agrícolas para utilizar eficazmente las tecnologías existentes. En este documento se examina si la comercialización a nivel de las explotaciones agrícolas y la densidad de intermediarios locales están relacionadas con mejoras en la eficiencia técnica, es decir, con la medida en que los productores operan cerca de su frontera de producción, dados los insumos disponibles. Utilizando datos armonizados de hogares agrícolas de seis países del África subsahariana y un modelo de frontera estocástica de efectos aleatorios verdaderos, estimamos las tecnologías de producción específicas de cada país y recuperamos las puntuaciones de eficiencia a nivel de las explotaciones agrícolas. A continuación, modelamos la ineficiencia como una función de la comercialización, la densidad de comerciantes, la participación de las micro, pequeñas y medianas empresas (MIPYME) y las características de los hogares y del contexto. Los resultados revelan una dispersión considerable en el rendimiento, lo que indica un potencial productivo considerable no realizado con las tecnologías actuales. La participación en los mercados de producción se asocia sistemáticamente con una actividad más cercana a la frontera en todos los países. Las redes de comerciantes locales más densas también están relacionadas con un mejor rendimiento en varios entornos, aunque los efectos varían según el contexto institucional. Las regresiones cuantílicas muestran que la comercialización está más fuertemente asociada con las mejoras entre las explotaciones agrícolas que operan más lejos de la frontera, lo que sugiere una dinámica de recuperación en lugar de cambios uniformes en la productividad. Estos resultados ponen de relieve el papel de los sistemas de mercados rurales —y no solo la mejora tecnológica— en la configuración de la productividad agrícola. Las políticas que profundizan la integración de los mercados y fortalecen las redes de intermediarios pueden generar ganancias sustanciales al permitir a los productores operar más cerca de su potencial productivo existente.

Palabras clave: Productividad agrícola; Eficiencia técnica; Integración de mercados; Comercialización; Clase media oculta; Análisis de frontera estocástica; África subsahariana.

Clasificación JEL: Q12, Q13, O13, D24

1. INTRODUCTION

Agricultural productivity growth remains a central development challenge in Sub-Saharan Africa (SSA), with implications extending beyond farm incomes to food security, structural transformation, and environmental sustainability. Rapid population growth, urbanization, and dietary change continue to raise demand for food, yet agricultural output growth in many SSA countries has relied heavily on factor expansion rather than sustained gains in total factor productivity (TFP). As documented by international productivity accounts, the region continues to lag behind Asia and Latin America in both land and labor productivity, and substantial gaps persist across and within countries. Understanding the sources of these productivity gaps is therefore critical for designing effective policy interventions.

A growing body of research highlights the role of misallocation and inefficiency in explaining persistent productivity dispersion. Even under similar technologies, farms may produce very different output levels because they operate at varying distances from the production frontier. These differences reflect not only factor endowments, but also managerial capacity, information constraints, liquidity limitations, and coordination failures. In smallholder agricultural systems, where input and output markets are often incomplete or thin, such frictions can generate large efficiency losses. Improving productivity may therefore require not only technological upgrading, but also enabling producers to use existing technologies more effectively.

One potential channel through which this may occur is market integration. Participation in output markets exposes farmers to price signals, quality requirements, and competitive pressures that can discipline input use and production decisions. Interaction with traders and intermediaries may improve information flows, facilitate access to inputs and services, and reduce uncertainty regarding marketing outlets. In this sense, markets may influence productivity not only by shifting the technological frontier, but also by reducing technical inefficiency—allowing producers to move closer to the frontier under existing technologies.

Recent work on agrifood system transformation further emphasizes the importance of midstream actors—the so-called "hidden middle"—in shaping rural production incentives (Reardon, 2015). Across many African countries, micro, small, and medium-sized enterprises (MSMEs) engaged in aggregation, processing, storage, and wholesale trade increasingly mediate the link between farms and consumers. These intermediaries reduce spatial and temporal transaction costs, coordinate supply chains, and often bundle complementary services such as input provision and information. While a growing literature links these midstream segments to welfare, commercialization, and structural transformation (Reardon et al., 2019; Trivelli et al., 2026), much less is known about whether—and through which mechanisms—their presence translates into higher on-farm productivity.

This paper examines how farm-level commercialization and local market structure relate to agricultural productivity through the channel of technical efficiency. Rather than treating commercialization as a binary outcome or focusing solely on yields or revenues, we analyze how different dimensions of market integration—direct market participation and exposure to local

intermediary networks—are associated with farms' distance from the production frontier. By focusing explicitly on technical efficiency, we isolate a central and policy-relevant component of productivity that reflects how effectively farmers combine inputs under prevailing technologies.
We use harmonized farm household data from six Sub-Saharan African countries—Ethiopia, Ghana, Malawi, Nigeria, Tanzania, and Uganda—combined with spatial measures of local market conditions. Employing a True Random Effects stochastic frontier framework, we estimate country-specific production technologies and recover farm-level technical efficiency while disentangling inefficiency from time-invariant heterogeneity. We then model inefficiency as a function of commercialization, trader density, MSME engagement, and household and contextual characteristics. To explore heterogeneity, we complement the frontier analysis with quantile regressions of efficiency scores.

Our contribution is threefold. First, we provide new cross-country evidence on the distribution and determinants of technical efficiency in African smallholder agriculture. Second, we explicitly connect the misallocation and inefficiency literature with the emerging literature on the hidden middle by linking efficiency outcomes to local intermediary density and market thickness. Third, we document strong distributional heterogeneity: commercialization is most strongly associated with efficiency improvements among farms operating furthest from the frontier, suggesting "catch-up" dynamics rather than uniform productivity shifts.

The findings indicate that deeper market integration—particularly in contexts characterized by thicker and more competitive intermediary networks—is associated with lower technical inefficiency. However, these gains are uneven across countries and across the efficiency distribution, underscoring the importance of institutional context and complementary capabilities. Collectively, the results suggest that strengthening rural market systems may generate substantial productivity gains not only through technological change, but also by enabling farms to operate closer to their existing productive potential.

2. LITERATURE REVIEW

2.1 Productivity and Misallocation in Agriculture

Large cross-country differences in income and output per capita are now widely understood to reflect differences in total factor productivity (TFP) rather than factor accumulation alone. A central insight of the modern misallocation literature is that aggregate productivity depends not only on the technological frontier but also on how efficiently factors of production are allocated across heterogeneous production units (Restuccia & Rogerson, 2013). When land, labor, or capital are misallocated, aggregate output falls below its potential even if frontier technologies are available.

In influential work, Hsieh and Klenow (2009) demonstrate that distortions in factor markets can generate large productivity losses by preventing high-productivity firms from expanding and low-productivity firms from contracting. Although their empirical application focuses on manufacturing, the conceptual framework has been extended to agriculture, where heterogeneity across producers is often even more pronounced. Restuccia and Rogerson (2013) emphasize that distortions in factor allocation can account for substantial TFP gaps across countries, while Ghatak and Mookherjee (2025) stress that many such distortions arise from market failures—such as asymmetric information, missing markets, transaction costs, and limited state capacity—rather than policy barriers alone.

A growing body of work applies this perspective directly to agricultural settings. Adamopoulos and Restuccia (2014) argue that cross-country differences in productivity reflect barriers to factor reallocation and scale adjustment. Using panel data from China, Adamopoulos, Brandt, Leight, and Restuccia (2022) document substantial within-village misallocation of land and capital linked to land institutions and local market frictions, operating through both resource allocation (across farms) and selection (who remains in agriculture). Evidence for Malawi suggests that reallocating land and capital toward more productive farmers could increase agricultural output by a factor of 1.7 to 2.8 (Chen, Restuccia, & Santaeulàlia-Llopis, 2023). Similar findings from India and Vietnam point to the importance of land-market barriers, state-level institutional differences, and land-use restrictions in generating persistent productivity gaps (Kien Le, 2020; Bolhuis, Rachapalli, & Restuccia, forthcoming).

Misallocation operates through two related margins. The first is across-farm allocation: whether inputs flow to the most productive producers. The second is within-farm performance: how effectively farmers transform given inputs into output relative to the production frontier. While the macro misallocation literature focuses primarily on the first margin, micro-level evidence consistently documents large dispersion in farm efficiency, particularly in Sub-Saharan Africa. Gollin and Udry (2021) show that farm-level productivity dispersion in African agriculture remains large even after accounting for observed inputs, environmental conditions, and measurement error. Related stochastic frontier evidence similarly finds that many farmers operate well below estimated production frontiers in countries such as Ghana, Ethiopia, and Uganda (e.g., Agazhi, Mada, & Alemu, 2025; Asravor et al., 2023; Morando, 2022), implying substantial scope for gains within existing technologies.

Despite the prominence of market frictions in explanations of misallocation, relatively little empirical work links market integration and local market structure to within-farm efficiency in agriculture. Most studies quantify aggregate productivity losses under counterfactual reallocation scenarios, while fewer examine whether better market functioning helps farmers move closer to the frontier. This distinction matters for policy: reallocating land or consolidating farms differs fundamentally from interventions that reduce transaction costs, improve information flows, deepen markets, or strengthen rural exchange systems.

This paper contributes to this gap by examining whether market integration—captured through farm-level commercialization and the density of local intermediaries—is associated with lower technical inefficiency among smallholder farms in Sub-Saharan Africa. Rather than focusing only on scale or reallocation, we test whether improved market connectivity helps producers operate closer to the existing frontier, thereby bridging the macro misallocation literature with micro-level stochastic frontier evidence.

2.2 Market Access, Participation, and Agricultural Productivity

A complementary literature examines how access to—and participation in—output markets shapes agricultural performance. The central premise is that when transaction costs are high and exchange is unreliable, farmers face muted price signals, greater marketing risk, and lower expected returns to investment. Even when improved technologies are available, weak market integration can therefore depress productivity.

This literature identifies three interrelated mechanisms through which market access and participation affect agricultural outcomes: reducing transaction and marketing costs, strengthening price incentives and information flows, and mitigating risk and coordination failures that constrain investment.

Early agricultural household models emphasize that production decisions are shaped by missing or imperfect markets. When labor, food, or credit markets fail, households prioritize subsistence needs over market-oriented production (de Janvry, Fafchamps, & Sadoulet, 1991). Subsequent work formalized how fixed and proportional transaction costs segment households into net sellers, net buyers, or nonparticipants (Goetz, 1992; Key, Sadoulet, & de Janvry, 2000). High fixed marketing costs can rationally deter participation even when output prices rise, dampening supply response and weakening incentives to invest in productivity-enhancing inputs. Empirical evidence supports this logic. Suri (2011) shows that technology adoption decisions among Kenyan farmers are well explained by heterogeneous net benefits driven in part by transaction costs. Barrett (2008) argues that market participation both reflects and shapes broader development conditions: households with limited assets and poor infrastructure may remain in semi-subsistence equilibria, unable to exploit market opportunities. In such contexts, price reforms alone are insufficient; reductions in transaction costs and improvements in infrastructure and complementary services are necessary for farmers to respond to incentives. Experimental evidence similarly shows that relatively small frictions in financing, timing, and market access can significantly affect input adoption and farm performance (Duflo, Kremer, & Robinson, 2011). Collectively, this strand of research suggests that commercialization is constrained not only by preferences but by the feasibility and cost of exchange. When those constraints are relaxed, incentives to intensify production and adopt improved technologies increase.

A second body of work highlights how reductions in trade and commercialization costs reshape production incentives. In general equilibrium settings, improved connectivity expands effective market size, strengthens price transmission, and raises returns to specialization and investment. Donaldson and Hornbeck (2016), for example, show that railroad expansion in the United States substantially increased agricultural land values, illustrating how lower trade costs can transform agricultural outcomes. In low-income contexts, high transport costs and weak connectivity depress farm-gate prices, raise input costs, and reduce the profitability of commercialization (Fafchamps & Vargas Hill, 2005; Stifel & Minten, 2017). Empirical studies of rural infrastructure reinforce this link. Improvements in road networks have been associated with higher agricultural incomes, increased commercialization, and expanded local economic activity (Jacoby, 2000; Asher & Novosad, 2020). In Sub-Saharan Africa, remoteness is strongly correlated with lower productivity and weaker engagement in output markets (Stifel & Minten, 2008). These findings suggest that improved market access affects productivity not only through scale or reallocation effects, but by increasing expected returns to effort, input use, and specialization.

Market participation also influences productivity through information flows, risk reduction, and coordination. When farmers produce for markets rather than subsistence alone, they face stronger incentives to adopt yield-enhancing technologies and improve quality (von Braun, 1995; Barrett, 2008). ICT-based market information services in Kenya have been shown to increase input use and labor productivity (Ogutu, Okello, & Otieno, 2014), while access to markets that reward quality with price premia induces productivity and income gains (Bold et al., 2022). Credible price signals and quality incentives can therefore stimulate upgrading. More structured market arrangements may reinforce these effects. Contract farming can reduce risk and uncertainty, facilitate access to inputs or credit, and promote technology transfer (Barrett et al., 2012; Ton et al., 2018). Similarly, collective marketing arrangements can reduce transaction costs and improve information flows, sometimes fostering innovation adoption and higher incomes (Fischer & Qaim, 2012). However, impacts vary across contexts and depend on institutional conditions.

A broader welfare literature further links improved market access to higher incomes and improved food security (Usman & Haile, 2022), while expanding value chains can create income opportunities beyond the farm (Vos & Cattaneo, 2021). Recent work on rural Africa emphasizes that better integration into food markets can expand opportunities for small-scale producers and rural enterprises, with implications for inclusive growth (Trivelli et al., 2026). Yet commercialization does not automatically generate welfare gains: evidence from Kenya shows that higher commercialization can coexist with persistent food insecurity when structural constraints remain binding (Mutea et al., 2025). This underscores that market participation interacts with asset endowments and institutional quality in shaping outcomes.

Overall, the literature suggests that market access enhances agricultural productivity by lowering transaction costs, strengthening price incentives, improving information flows, and reducing risk and coordination failures. However, most empirical studies evaluate reduced-form outcomes—such as yields, sales, or incomes—without distinguishing between technological change, reallocation across farms, and movements toward the existing production frontier. As discussed in the previous section, substantial productivity dispersion persists even within similar agroecological environments. Whether deeper market integration helps farmers operate closer to the frontier—by improving input timing, managerial practices, and effort—remains comparatively underexplored. This gap motivates our empirical focus. By examining farm-level market participation and local market integration as correlates of technical efficiency, we connect the incentive and transaction-cost mechanisms outlined here with the misallocation and inefficiency framework discussed earlier. The next subsection turns to rural market organization—particularly the role of intermediaries and the "Hidden Middle"—to explore how local market structure may condition these relationships.

2.3 The Hidden Middle and Food System Transformation

While the previous sections emphasize misallocation, farm efficiency, and market participation, a growing literature argues that agricultural transformation increasingly depends on what happens beyond the farm gate. In many low- and middle-income countries, agrifood systems have expanded rapidly due to urbanization, income growth, dietary change, and technological shifts. A key feature of this transformation has been the rise of thousands of micro, small, and medium enterprises (MSMEs) operating in processing, logistics, aggregation, storage, and wholesale distribution. These midstream and downstream segments—often referred to as the "Hidden Middle"—play a central but historically underappreciated role in shaping agricultural productivity and inclusion (Reardon, 2015; Reardon, Liverpool-Tasie, & Minten, 2021; Liverpool-Tasie et al., 2021).

Early development narratives emphasized either smallholders or large-scale agribusiness firms. In contrast, the Hidden Middle literature shows that much of food system transformation occurs through decentralized, labor-intensive enterprises that connect farmers to markets. These actors reduce spatial and temporal transaction costs, aggregate output, enforce quality standards, facilitate storage and processing, and often provide complementary services such as input supply, credit, and market information (Reardon et al., 2014; Reardon & Timmer, 2012). By coordinating exchange and lowering the costs of compliance and commercialization, they influence both the incentives and the feasibility of market participation.

This meso-level perspective complements the transaction cost mechanisms discussed in Section 2.2. Whereas agricultural household models treat marketing frictions abstractly, the Hidden Middle literature identifies the organizational and infrastructural actors through which those frictions are mediated. Intermediaries influence farm-level outcomes by stabilizing demand, transmitting price signals, enabling quality differentiation, and bundling services such as finance and logistics. In doing so, they shape not only commercialization rates but potentially farmers' productivity and efficiency.

A growing empirical literature documents the expansion and dynamism of these midstream segments across Africa and Asia. Reardon et al. (2021) show that private wholesalers, processors, and logistics firms have grown rapidly in several African countries and now account for a substantial share of food distribution. Minten and coauthors document similar patterns in Madagascar and other settings, where investments in cold chains, transport, and wholesale markets have altered value chain structures and reduced marketing margins (Minten et al., 2009; Minten et al., 2016). Liverpool-Tasie et al. (2021) show that the modernization of agrifood systems is often driven by MSMEs rather than large firms, particularly in staple food markets. These changes can reduce marketing margins, improve quality consistency, and increase farmer access to urban demand.

Recent syntheses also underscore both the policy relevance of the Hidden Middle and the limitations of the current evidence base. Espinoza, Trivelli, and Fuica (2025a) document strong convergence in the literature around "bundled" policy approaches that combine finance and risk-management instruments with investments in logistics, processing infrastructure, food-safety systems, and coordination platforms. The underlying logic is that competitiveness and inclusion depend on reducing the costs of investing, complying, and coordinating along value chains—costs that often constrain small-scale producers and smaller firms. At the same time, a companion evidence review (Espinoza, Trivelli, & Fuica, 2025b) shows that relatively few rigorous impact evaluations explicitly target the midstream segment, and many focus on contract farming mechanisms that bypass intermediaries rather than strengthening them. This gap limits our understanding of how improvements in local market structure translate into productivity gains at the farm level.

A Importantly, the structure of midstream markets varies widely across contexts. In some areas, dense networks of traders and processors generate competition and facilitate price transmission; in others, thin or concentrated markets limit bargaining power and service provision (Fafchamps & Vargas Hill, 2005; Barrett, 2008). Emerging evidence further suggests that agrifood transformation is territorially embedded. Participation in commercial agriculture and MSMEs is associated with improved welfare outcomes, particularly in areas characterized by stronger agrifood dynamism and interconnectivity, with some spillover benefits to nonparticipants (Trivelli et al., 2026). Complementary research shows that commercialization decisions are socially embedded, with peer effects influencing input adoption and output market participation, especially in early stages of diffusion (Dzanku, Liverpool-Tasie, & Reardon, 2026). Together, these findings indicate that market integration unfolds within structured local ecosystems rather than homogeneous market environments.

Despite this growing recognition, the Hidden Middle remains under-integrated into empirical analyses of farm-level productivity. Much of the misallocation literature abstracts from local market structure, while studies of commercialization often treat markets as homogeneous environments. Yet if intermediaries reduce coordination failures, stabilize output demand, and facilitate access to inputs and services, their presence may influence how effectively farmers combine inputs and approach the production frontier.

This perspective suggests that the structure and density of midstream actors constitute a meso-level mechanism linking market development to productivity performance. By shaping local market thickness, competition, and service provision, the Hidden Middle may condition both the incentives to invest and the capacity to operate efficiently. This paper contributes to this agenda by linking farm-level efficiency estimates with measures of commercialization and local intermediary density across multiple African countries. In doing so, we move beyond viewing markets as exogenous backdrops and instead analyze how the organization of rural agrifood systems—the Hidden Middle—may function as a structural channel connecting market integration to farm-level performance.

3. PRODUCTIVITY TRENDS: REGIONAL AND COUNTRY BACKGROUND

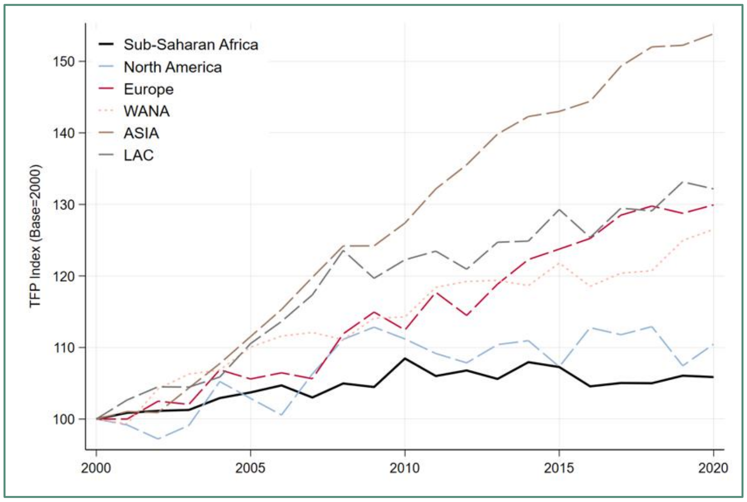
To situate the farm-level analysis within broader structural patterns, this section provides a descriptive overview of agricultural productivity trends using the USDA Economic Research Service's International Agricultural Productivity (IAP) database. The IAP dataset offers internationally comparable time series beginning in 1961 and constructed from FAO, ILO, national statistics, and related sources. Agricultural output aggregates 189 crop and livestock commodities valued at constant 2004–06 international prices, allowing consistent cross-country comparisons over time.

Labor productivity is measured as agricultural output per 1,000 economically active persons in agriculture, while land productivity is defined as output per hectare of agricultural land (expressed in rainfed cropland equivalents). Total factor productivity (TFP) is calculated as the ratio of aggregate output to a cost-share–weighted bundle of inputs—including land, labor, capital, fertilizers, and feed—and therefore captures output growth net of input accumulation.
This macro evidence provides important context for the micro-level analysis that follows. In particular, it highlights persistent productivity gaps across regions and countries, but does not reveal whether these gaps reflect differences in technology, efficiency, or both—a distinction that motivates the empirical framework developed later in the paper.

3.1. Regional productivity patterns

Figure 1 presents agricultural TFP growth since 2000 across major world regions. Sub-Saharan Africa exhibits markedly slower productivity growth relative to Asia and Latin America. While Asia and Latin America experienced sustained increases in TFP, Sub-Saharan Africa's index remains close to its base-year level, indicating limited structural transformation in agricultural production. Europe and North America display steadier growth from already high productivity baselines.

Figure 1: Agricultural Total Factor Productivity Growth by World Region



Notes: Sourced by the international agricultural productivity dataset (USDA, ERS).

Table 1 complements this picture by reporting average land and labor productivity for three subperiods (2000–2008, 2009–2015, and 2016–2021). Sub-Saharan Africa lags behind in both dimensions. Average land productivity in the region is less than half that of Latin America and Asia. Labor productivity gaps are also substantial: output per agricultural worker in Sub-Saharan Africa is roughly half that of Asia and a fraction of that observed in Latin America. These disparities underscore both the relatively slow pace of productivity growth in Sub-Saharan Africa and the large structural differences in factor intensity and technological development across world regions.

Table 1: Average land and labor productivity, by World Region and Period

	Average Land Productivity			Average Labor Productivity		
Region	**(2000-2008)**	**(2009-2015)**	**(2016-2021)**	**(2000-2008)**	**(2009-2015)**	**(2016-2021)**
Sub-Saharan Africa	865	947	973	1,109	1,274	1,396
North America	1,215	1,396	1,528	135,361	153,308	155,222
Europe	1,357	1,461	1,582	16,842	22,633	28,397
WANA	919	1,085	1,187	4,905	6,110	7,001
ASIA	1,917	2,385	2,661	1,778	2,627	3,485
LAC	1,862	2,161	2,533	8,638	11,016	12,898
Total	**1,269**	**1,463**	**1,620**	**37,693**	**44,881**	**47,172**

Notes: Sourced by the international agricultural productivity dataset (USDA, ERS).

3.2. Country-level trends in six Sub-Saharan African economies

Substantial variation also exists within Sub-Saharan Africa. Table 2 reports average land and labor productivity for the six countries analyzed in this study. Ghana stands out with consistently high land and labor productivity levels across all subperiods. Ethiopia shows steady improvements in both measures, particularly after 2008. Malawi and Tanzania remain at the lower end of the distribution, while Nigeria exhibits relatively stronger labor productivity than land productivity. Uganda presents a mixed picture: land productivity remains relatively high compared to the regional average, but labor productivity declines in later years.

Table 2: Average land and labor productivity in six SSA countries, by period

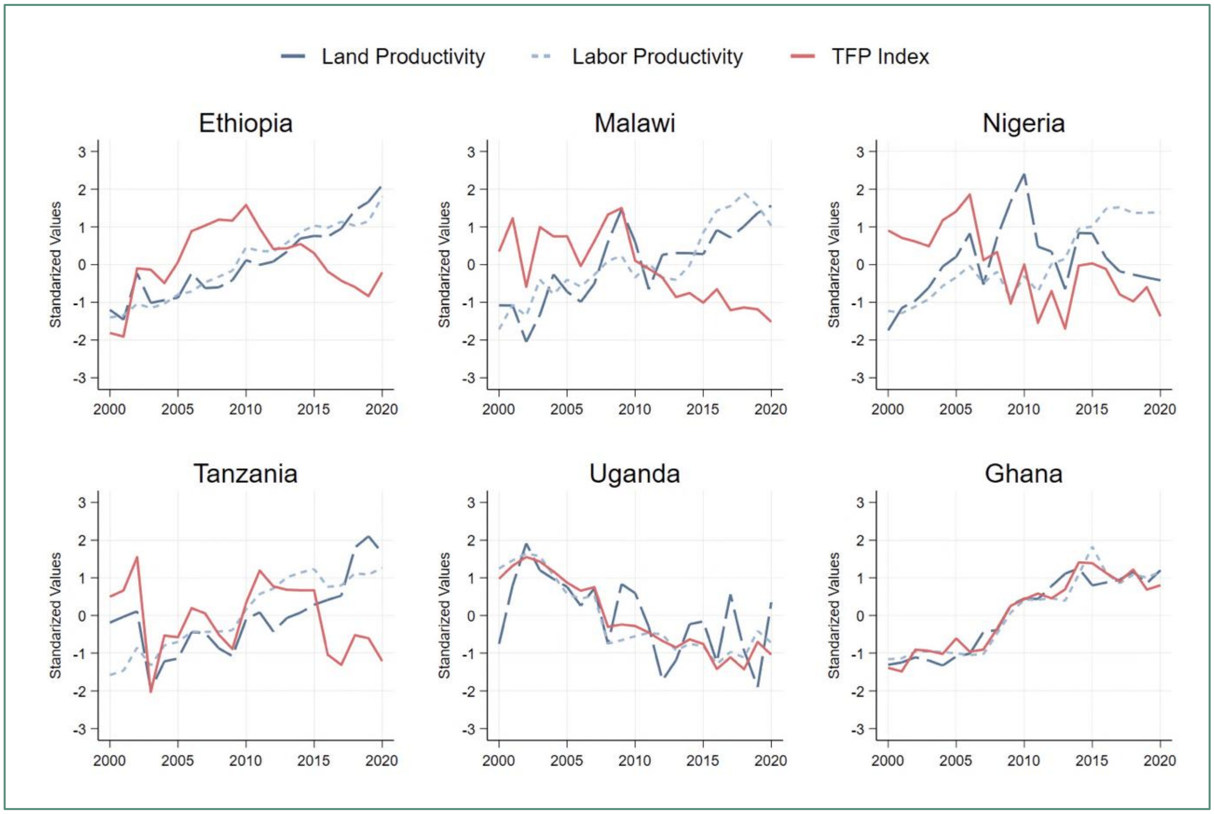
	Average Land Productivity			Average Labor Productivity		
Country	**(2000-2008)**	**(2009-2015)**	**(2016-2021)**	**(2000-2008)**	**(2009-2015)**	**(2016-2021)**
Ethiopia	753	909	1,101	381	502	573
Malawi	585	684	733	1,220	1,356	1,714
Nigeria	951	1,025	971	2,110	2,329	2,926
Tanzania	782	823	954	622	867	954
Uganda	1,296	1,264	1,256	1,347	985	926
Ghana	1,149	1,457	1,503	1,599	2,303	2,646
Average SSA	**865**	**947**	**973**	**1,109**	**1,274**	**1,396**

Notes: Sourced by the international agricultural productivity dataset (USDA, ERS).

Figure 2 illustrates the dynamic evolution of land productivity, labor productivity, and TFP (standardized) over 2000–2020. Ethiopia and Ghana display sustained upward trends across most indicators, though Ghana's trajectory is more stable. Malawi experiences gains in factor productivity but declining TFP in recent years. Nigeria and Tanzania exhibit considerable volatility, reflecting structural constraints and exposure to macroeconomic and climatic shocks. Uganda shows early gains followed by stagnation or decline in TFP.

Figure 2 illustrates the dynamics of land productivity, labor productivity, and TFP (standardized) for the six countries over 2000–2020. Ethiopia and Ghana display upward trends across all three measures, though Ghana's productivity gains are steadier. Malawi shows improvements in land and labor productivity but a declining TFP trajectory since the early 2010s. Nigeria and Tanzania reveal high volatility in productivity indicators, reflecting both structural constraints and exposure to shocks. Uganda experienced some early gains but has shown stagnation or decline in recent years.

Figure 2: Trends in productivity, six SSA countries



Notes: Sourced by the international agricultural productivity dataset (USDA, ERS).

Taken together, these patterns reveal two central features of agricultural performance in the region. First, Sub-Saharan Africa as a whole continues to lag behind other regions in both factor productivity and TFP growth. Second, performance varies considerably across countries, even within similar agroecological contexts.

However, aggregate productivity measures do not reveal the underlying mechanisms driving these differences. Are observed gaps primarily the result of technological differences across countries, or do they reflect variation in how efficiently farmers use available inputs? The farm-level stochastic frontier analysis developed below addresses this question directly by decomposing productivity into technological and efficiency components and examining how market participation and local market structure relate to technical efficiency.

4. METHODOLOGY

This section outlines the empirical framework used to examine how market integration relates to farm productivity through the channel of technical efficiency. Rather than attributing productivity differences solely to variations in production technology or factor endowments, our approach explicitly distinguishes between the production frontier—capturing the maximum attainable output given inputs—and the degree to which farms operate relative to that frontier. This distinction is central to our analysis. Market participation and local market structure may affect productivity not only by shifting the frontier (through technological upgrading), but also by enabling farmers to use existing inputs more effectively. To isolate this efficiency channel, we employ a stochastic frontier framework that decomposes deviations from potential output into random shocks and technical inefficiency, allowing inefficiency to be modeled as a function of farm-level and local market characteristics.

4.1 Agricultural Productivity and Efficiency: Conceptual Background

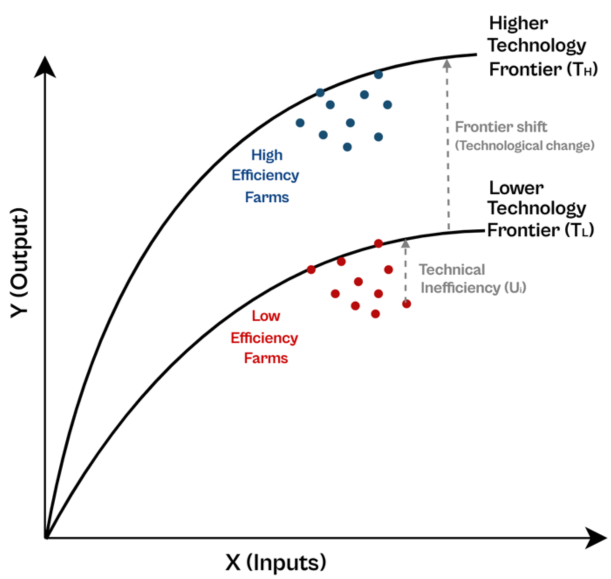
Agricultural productivity is commonly defined as the ratio of output to inputs, with total factor productivity (TFP) capturing the portion of output not explained by observable input accumulation (Solow, 1957). In empirical applications, productivity differences may arise from two conceptually distinct sources: shifts in the production frontier — reflecting technological change or structural differences in production technology — and variation in technical efficiency, which captures the extent to which producers operate below that frontier (Aigner, Lovell, and Schmidt, 1977).

Technological change corresponds to outward shifts of the production frontier, typically driven by the adoption of improved seed varieties, irrigation systems, mechanization, or other innovations that expand the feasible production set. Technical efficiency, by contrast, reflects how effectively farmers combine existing inputs given prevailing technologies. Even under identical technologies and factor endowments, farms may produce different output levels due to managerial capacity, imperfect information, liquidity constraints, coordination failures, or transaction costs. The distinction between frontier shifts and efficiency improvements has been central to the productivity and frontier literature (Kumbhakar and Lovell, 2000).

This distinction is particularly relevant in smallholder agricultural systems, where producers operate under heterogeneous market conditions and face varying access to information, inputs, credit, and output markets. In such settings, productivity gaps may reflect not only technological constraints but also differences in how efficiently available technologies are utilized. A growing body of work in development economics emphasizes that dispersion in productivity is often driven by misallocation and inefficiency rather than purely by technological gaps (e.g., Adamopoulos, Brandt, Leight, and Restuccia, 2022). This perspective suggests that improving productivity does not necessarily require shifting the production frontier; it may also involve enabling producers to move closer to it.

Figure 3 provides a conceptual illustration of this distinction. The lower curve represents a lower-technology frontier, while the upper curve represents a higher-technology frontier. A vertical shift from the lower to the upper frontier captures technological progress — an outward expansion of the feasible production set for any given level of inputs. By contrast, the vertical distance between a farm's observed output and the relevant frontier represents technical inefficiency. Farms operating below the frontier can increase output without changing input quantities by improving managerial performance, input allocation, or access to complementary services. In this sense, productivity gains may occur either through frontier shifts (technological upgrading) or through reductions in inefficiency that allow farms to "catch up" to the existing frontier.

Figure 3. Productivity and Technical Efficiency: Conceptual Illustration



The distinction between these channels is central to this study. While technological upgrading remains critical for long-run agricultural transformation, we focus on the second mechanism: whether and how market integration is associated with reductions in technical inefficiency. Market participation and the presence of local intermediaries may influence productivity not only by facilitating access to new technologies, but also by improving information flows, reducing transaction costs, stabilizing input and output markets, and strengthening incentives—mechanisms that enable producers to use existing technologies more effectively. The empirical framework developed below is designed to isolate and quantify this efficiency component of productivity variation.

4.2 The Stochastic Production Frontier Model

Stochastic frontier analysis (SFA) provides a framework for estimating a production frontier that reflects the current state of technology while allowing deviations from the frontier to arise from both random shocks and inefficiency. Following Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), output deviations are decomposed into a symmetric noise component and a non-negative inefficiency term. This distinction is particularly important in agricultural settings, where weather variability, measurement error, and other exogenous shocks may affect observed output.

Let output of farm i in country c and year t be denoted by Y_{ict}, and let X_{ict} be a vector of production inputs. The stochastic frontier model is specified as:

$$\ln Y_{ict} = f(X_{ict}; \beta) + v_{ict} - u_{ict} \quad (1)$$

where $f(\cdot)$ represents the deterministic production frontier, $v_{ict} \sim N(0, \sigma_v^2)$ is a symmetric random error term capturing statistical noise, and $u_{ict} \geq 0$ represents technical inefficiency. The inefficiency term is assumed to follow a one-sided distribution, typically half-normal or truncated-normal.

Within this framework, technical efficiency is defined as:

$$TE_{ict} = \exp(-u_{ict}) \in (0,1] \quad (2)$$

with conditional inefficiency estimates obtained following Jondrow et al. (1982).

To examine the determinants of inefficiency, we adopt the inefficiency effects specification proposed by Battese and Coelli (1995), modeling inefficiency as a function of observable characteristics:

$$u_{ict} = Z_{ict}\delta + w_{ict} \quad (3)$$

where Z_{ict} includes farm-level and local contextual characteristics, and $w_{ict} \sim N^+(0, \sigma_u^2)$. This one-step maximum likelihood approach allows the production frontier and inefficiency determinants to be estimated simultaneously.

Over the past two decades, substantial methodological progress has been made in extending the cross-sectional stochastic frontier framework to panel data. In two influential contributions, Greene (2005a, 2005b) emphasized the importance of disentangling unobserved, time-invariant heterogeneity from time-varying technical inefficiency. This distinction is crucial because persistent differences across production units—such as soil quality, managerial ability, or long-term infrastructure access—may affect the production technology itself and should not be conflated with inefficiency. Failure to separate these components risks attributing structural heterogeneity to inefficiency, leading to biased or misleading estimates. Subsequent refinements have further clarified the conceptual distinction between time-invariant heterogeneity and time-invariant inefficiency and proposed flexible modeling strategies to accommodate both (Filippini & Greene, 2016; Tsionas & Kumbhakar, 2014).

In panel settings, the stochastic frontier model becomes:

$$\ln Y_{ict} = f(X_{ict}; \beta) + \mu_i + v_{ict} - u_{ict} \quad (4)$$

where μ_i captures unobserved, time-invariant farm-specific heterogeneity.

Greene (2005a, 2005b) proposes two alternative approaches for handling this component: the True Fixed Effects (TFE) model and the True Random Effects (TRE) model. In the TFE specification, farm-specific intercepts are estimated via unit-specific dummy variables, allowing arbitrary correlation between the individual effects and the regressors. While flexible, this approach does not permit the estimation of time-invariant regressors and may become computationally demanding in panels with large numbers of units or limited time dimensions.

The TRE specification instead treats μ_i as a random variable, $\mu_i \sim N(0, \sigma_\mu^2)$, thereby separating persistent heterogeneity from time-varying inefficiency while retaining the ability to estimate contextual determinants of inefficiency. In agricultural applications, where unobserved differences in land quality, infrastructure, or long-term production conditions are likely to be important, explicitly accounting for time-invariant heterogeneity is essential. At the same time, modeling inefficiency as time-varying is crucial for identifying how changes in market participation and local market conditions relate to performance.

Given these considerations, the empirical analysis employs the True Random Effects framework. This approach provides a tractable and flexible structure for distinguishing structural heterogeneity from inefficiency while preserving the ability to model inefficiency as a function of market participation and local economic variables. In settings where panel data are unavailable, the model reduces to a pooled stochastic frontier specification with time indicators, maintaining consistency in the production technology.

4.3 Analytical Framework

This subsection operationalizes the stochastic frontier framework described above by specifying the production technology and the empirical structure used in the estimations. The production frontier is specified using a Translog functional form (Christensen, Jorgenson, & Lau, 1973), which provides a flexible second-order approximation to an arbitrary production technology. Unlike the Cobb–Douglas specification commonly employed in applied agricultural frontier studies (e.g., Bravo-Ureta et al., 2007; Ogundari, 2014), the Translog allows output elasticities and returns to scale to vary with input levels and permits interaction effects between inputs. This flexibility is particularly important in a multi-country setting characterized by substantial heterogeneity in farm size, input intensity, and production conditions.

The baseline production frontier is given by:

$$ln\, Y_{ict} = \mu_i + \sum_{t=1}^{T} \gamma_t + \beta_1\, ln\, L_{ict} + \beta_2\, ln\, A_{ict} + \frac{1}{2}\, \beta_{11}\, (ln\, L_{ict})^2 + \frac{1}{2}\, \beta_{22}\, (ln\, A_{ict})^2$$
$$+ \beta_{12}\, (ln\, L_{ict} \times ln\, A_{ict}) + \textstyle\sum_{s=1}^{S} \theta_s G_{sict} + v_{ict} - u_{ict} \qquad (5)$$

where Y_{ict} denotes the value of crop production for farm i in country c and year t, and L_{ict} and A_{ict} represent labor and land inputs, respectively. The term μ_i captures time-invariant farm-specific heterogeneity under the True Random Effects specification, while γ_t are time indicators that account for common technological change and macroeconomic shocks. The variables G_{sict} denote indicators for modern input use—such as fertilizer, pesticides, improved seeds, and irrigation—which enter as Hicks-neutral shifters of the production frontier. In this specification, these inputs shift the level of the frontier without altering substitution patterns among primary inputs (Battese & Coelli, 1995).

The stochastic frontier model is estimated separately for each country. This strategy allows the underlying production technology to differ across institutional, agroecological, and structural environments, rather than imposing a common frontier across heterogeneous settings. Given substantial cross-country variation in input intensity, land distribution, climatic conditions, and market structures, pooling countries under a single technological frontier would risk conflating technological differences with inefficiency. Estimating country-specific frontiers ensures that technical efficiency is measured relative to the relevant local production possibility set, consistent with the conceptual distinction between technology and efficiency.

As part of supplementary analysis, the model is extended to include agroecological controls such as average temperature and precipitation, climate anomalies, and soil quality indicators. These extensions are motivated by the growing empirical literature linking climatic variability and soil constraints to agricultural productivity (Dell et al., 2014; Lachaud et al., 2017, 2022). The inclusion of these controls does not materially alter the estimated relationships between market integration and technical inefficiency.

All stochastic frontier models are estimated by simulated maximum likelihood (Greene, 2008), ensuring consistent estimation of both the production parameters and the inefficiency effects within a unified framework.

5. DATA SOURCES AND SUMMARY STATISTICS

This section describes the data sources and key variables used in the empirical analysis. We combine nationally representative farm household surveys from six Sub-Saharan African countries with spatial measures of local market conditions and food system structure. For Ethiopia, Malawi, Uganda, Tanzania, and Nigeria, we rely on panel survey data that follow farm households over multiple waves; for Ghana, we use repeated cross-sections. Across settings, the household surveys provide detailed information on agricultural production, input use, commercialization, and household characteristics, while the spatial data capture features of the local market environment—including trader density, infrastructure, and proxies for local economic activity. Together, these data allow us to link farm production decisions to market integration and local economic context, and to document substantial heterogeneity in productivity and market engagement across countries and households.

5.1 Data Sources and Sample Structure

The empirical analysis draws on harmonized household- and farm-level data obtained primarily from the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA), supplemented by nationally representative household surveys with comparable designs where LSMS-ISA data are not available. These surveys provide consistent measures of crop production, land and labor inputs, input use, and a range of household characteristics, alongside community-level information on local conditions. The multi-country structure of the dataset supports a consistent analysis of smallholder production behavior across diverse agroecological and institutional environments.

The sample includes farming households observed between 2006 and 2020 across Ethiopia, Malawi, Nigeria, Tanzania, and Uganda, combined with repeated cross-sectional survey rounds for Ghana. For Ethiopia, Malawi, Nigeria, Tanzania, and Uganda, households are observed over multiple waves, yielding unbalanced panels. In contrast, the Ghana data consist of repeated cross-sections and do not track the same households over time. Table 3 summarizes the survey instruments, waves, and data structure used in the analysis.

Table 3. Survey Sources, Waves, and Data Structure by Country

Country	Survey Names	Waves	Panel Data
Ethiopia	Ethiopia Socioeconomic Survey (ERSS)	2011, 2013, 2015	Yes
Malawi	Integrated Household Panel Survey (IHPS)	2010, 2013, 2016, 2019	Yes
Uganda	Uganda National Panel Survey (UNPS)	2014, 2016, 2020	Yes
Tanzania	Tanzania National Panel Survey (TZNPS)	2014, 2020	Yes
Nigeria	General Household Survey (GHS)	2010, 2012, 2015, 2018	Yes
Ghana	Ghana Living Standards Survey (GLSS)	2006, 2013, 2017	No

5.2 Variables

Production Function Variables

Agricultural output is measured as the total value of crop production at the household level and expressed in logarithmic form. Output values are constructed using self-reported quantities harvested and corresponding farm-gate prices. These values are harmonized across survey waves and countries to ensure comparability in measurement and aggregation.

The production technology is specified using two primary inputs: land and labor. Land input is measured as the total cultivated area during the agricultural season, while labor input captures total labor use in crop production—including both family and hired labor—expressed in adult-equivalent days. Both inputs enter the production function in logarithmic form.

To allow for flexible substitution patterns and non-constant returns to scale, we adopt a Translog production function (Christensen, Jorgenson, and Lau, 1973). The specification includes squared terms and interaction effects between land and labor, thereby relaxing the restrictive assumptions of constant elasticities and unitary substitution inherent in the Cobb–Douglas form. This flexibility is particularly important in multi-country settings where production technologies and factor intensities may differ substantially.

In addition to primary inputs, we include binary indicators for the use of key modern inputs—chemical fertilizers, pesticides, improved seeds, and irrigation. These variables enter the frontier as Hicks-neutral shifters, allowing them to shift the level of the production frontier without altering input elasticities. Modeling technological factors as neutral shifts is standard in stochastic frontier applications (see Battese and Coelli, 1995; Kumbhakar and Lovell, 2000), and reflects the idea that modern inputs enhance productivity while preserving the underlying substitution structure between land and labor. Finally, time dummies are included to capture common technological change, policy shifts, and macroeconomic shocks across survey waves.

Determinants of Technical Inefficiency

Technical inefficiency is modeled as a function of market participation, local market structure, farm organization, and household characteristics that may influence farmers' ability to combine inputs effectively. In line with the central objective of the paper, particular emphasis is placed on variables capturing both farm-level commercialization and the surrounding market environment.

The first set of variables relates to market participation and local market structure. At the farm level, commercialization is measured through a dummy indicating whether the household sells part of its crop production. This variable captures direct engagement with output markets and exposure to price signals, buyer requirements, and marketing opportunities. Complementing this measure, trader density captures the thickness of local output markets. It is defined as the ratio of producers in the locality who report selling production to traders relative to the total number of producers. This measure reflects the intensity of trader intermediation in the local economy and serves as a proxy for market thickness, competition among buyers, and the potential availability of marketing outlets. Together, commercialization and trader density capture two distinct but related dimensions of market integration: the household's own participation in output markets and the broader structure of the local trading environment.

A second group of variables captures additional farm-level linkages to markets and institutions. Participation in micro, small, and medium-sized enterprises (MSMEs) proxies broader entrepreneurial engagement beyond farming. Access to hired labor reflects integration into local labor markets and the ability to relax family labor constraints. Access to credit captures liquidity conditions that may facilitate input purchases and risk management. Membership in cooperatives and participation in agricultural training programs proxy exposure to collective action, extension services, and knowledge diffusion.

A third set of variables captures farm structure and income diversification. The number of parcels owned reflects potential fragmentation and coordination costs, while the crop diversification index measures the extent to which production is spread across multiple crops, potentially increasing managerial complexity. The share of non-farm income in total household income captures diversification strategies that may either relax liquidity constraints or divert managerial attention away from agriculture.

Finally, we include contextual and demographic characteristics. At the local level, the share of fertilizer users and the share of households engaged in off-farm activities capture input adoption externalities and local economic clustering effects. Average nighttime lights serve as a spatial proxy for local economic activity and infrastructure development. Household characteristics—including age, gender, and years of education of the household head—capture experience, human capital, and potential gender-specific constraints, while household size proxies family labor availability within the production unit.

5.3 Descriptive Statistics

Table 4 reports country-level mean values for the main variables included in the production function and inefficiency equations. The descriptive statistics reveal substantial heterogeneity across countries in output levels, input use, commercialization patterns, and local market structure. This variation underscores the diversity of smallholder farming systems across Sub-Saharan Africa and motivates an empirical strategy that distinguishes differences in production technology from differences in technical efficiency.

Average agricultural output varies markedly across settings. Uganda and Ghana display the highest mean values of crop output, followed closely by Nigeria, while Ethiopia, Malawi, and Tanzania exhibit lower average output levels. This ranking broadly mirrors the cross-country patterns in land and labor productivity documented in Section 2 using aggregate USDA data, where Ghana and Uganda appear among the highest-productivity settings and Tanzania, Malawi, and Ethiopia among the lower-performing ones. The consistency between macro-level and farm-level evidence suggests that these productivity differences are structural rather than purely compositional.

Factor use patterns also differ substantially. Farm size ranges from less than one hectare on average in Malawi (0.78 ha) to over three hectares in Ghana (3.13 ha). Labor use broadly reflects these differences: Nigeria and Uganda exhibit relatively high labor input per farm, whereas Malawi reports lower average labor intensity. Adoption of modern inputs is uneven across countries. Fertilizer use is widespread in Ethiopia and Nigeria but considerably lower in Tanzania and Uganda. Pesticide use is nearly universal in Uganda and Malawi but limited in Tanzania, and irrigation remains rare in most contexts. Together, these differences point to substantial cross-country variation in production environments, input intensity, and the technological conditions under which farms operate.

Turning to the key variables of interest—market participation and local market structure—the data reveal equally pronounced contrasts. The share of farms engaged in commercial agriculture ranges from 35 percent in Malawi to 66 percent in Ghana, indicating wide variation in direct integration into output markets. Trader density also varies considerably, with relatively higher values in Nigeria and Tanzania and lower values in Malawi. This variation suggests meaningful differences in local market thickness and intermediary presence across countries. Participation in MSMEs is particularly high in Nigeria and Uganda, indicating stronger linkages between farm and non-farm entrepreneurship in these settings.

Additional variables highlight differences in farm organization and diversification strategies. The average number of parcels owned ranges from 1.37 in Tanzania to 3.47 in Ethiopia, reflecting differing degrees of land fragmentation. Crop diversification indices are broadly similar across countries, though slightly higher in Ethiopia and Uganda. Non-farm income shares are especially high in Malawi and Uganda, suggesting stronger reliance on off-farm activities in those contexts. Local contextual indicators further illustrate variation in economic environments: for example, the share of households engaged in off-farm work is particularly high in Uganda and Ghana, while nighttime light intensity—a proxy for local economic activity—is highest in Malawi and Ghana.

Table 4: Summary Statistics by Country (Means)

Variable	Ethiopia	Malawi	Nigeria	Tanzania	Uganda	Ghana
Agricultural output and production input factors (Production Function)						
Value of ag. output	1,239	805	1,549	777	1,638	1,446
Log output	6.23	5.94	6.68	5.89	6.59	6.57
Farm size (ha)	1.67	0.78	1.41	2.59	1.69	3.13
Log farm size	-0.03	-0.55	-0.38	0.33	0.00	0.65
Labor (adult-equivalent days)	205.4	77.9	340.3	144.7	254.7	11.1
Log labor	4.89	3.97	5.05	4.55	5.28	1.93
Pesticides (share)	0.31	0.90	0.44	0.07	0.99	0.61
Fertilizer (share)	0.56	0.40	0.44	0.15	0.06	0.36
Purchased seeds (share)	0.55	0.56	0.32	0.65	0.66	0.22
Irrigation (share)	0.13	0.02	0.03	0.02	0.04	0.00
Drivers of technical inefficiency (efficiency equation)						
Commercial agriculture (share)	0.42	0.35	0.50	0.58	0.61	0.66

Trader density	0.25	0.12	0.31	0.29	0.25	0.24
Has MSME (share)	0.24	0.22	0.59	0.36	0.45	0.37
Hired labor (share)	0.92	0.26	0.65	0.43	0.41	0.55
Access to credit (share)	0.29	0.22	0.43	0.08	0.13	0.16
Village has agri. cooperative (share)	0.16	0.38	0.34	0.35	0.02	0.27
Agricultural training (share)	0.28	0.62	0.11	0.11	0.20	.
Local density of fertilizers	0.56	0.41	0.44	0.15	0.06	0.38
Local density of off-farm work	0.49	0.86	0.73	0.77	0.89	0.87
Log average Nighttime Lights	2.02	2.10	1.90	1.94	1.88	2.14
Number of parcels owned	3.47	1.72	1.81	1.37	1.77	1.46
Crop diversification index	0.48	0.37	0.43	0.43	0.44	0.43
Non-farm income share	0.17	0.77	0.52	0.55	0.76	0.45
Head's age	46.83	44.63	52.04	47.59	49.50	48.43
Female head (share)	0.19	0.27	0.12	0.26	0.31	0.21
Years of education	1.57	5.07	3.79	4.43	5.65	4.38
Household size	5.36	5.05	6.41	5.59	6.49	5.18

Notes: Table reports country-level means. Output is measured as the total value of crop production. Land is measured as cultivated area (hectares) and labor as total labor input in crop production. For Ghana, labor input is measured in adult-equivalent units due to data availability.

Household characteristics also differ across settings. Educational attainment of the household head ranges from 1.6 years in Ethiopia to over 5.6 years in Uganda, and the share of female-headed households varies from 12 percent in Nigeria to 31 percent in Uganda. Such differences in human capital, gender composition, and demographic structure may shape farmers' ability to respond to market incentives and manage production efficiently.

Taken together, these descriptive patterns reveal substantial heterogeneity in both production conditions and market environments across countries. They suggest that productivity differences may arise not only from variation in land and labor endowments or input use, but also from differences in commercialization intensity, intermediary presence, and local economic structure. These stylized facts provide a strong rationale for employing a stochastic frontier framework that separates technology from inefficiency and allows the determinants of technical efficiency—including market integration variables—to be examined explicitly. The following section uses these data to estimate stochastic production frontiers and to analyze differences in technical efficiency across households.

6. RESULTS

This section presents the empirical results from the stochastic frontier analysis. We begin by discussing the estimated production technology, focusing on output elasticities and scale properties across countries. We then turn to the determinants and distribution of technical efficiency, with particular emphasis on commercialization and local market structure.

6.1 Production Function Estimates

The production function estimates summarize the relationship between output, land, and labor across countries and provide evidence on scale properties in smallholder agriculture. The estimated output elasticities and implied returns to scale from the country-specific TRE-SPF models are reported in Table 5. Across all settings, both land and labor elasticities are positive and statistically significant, confirming that variation in cultivated area and labor input explains a substantial share of output differences among smallholder farms. At the same time, the magnitude of these elasticities differs markedly across countries, highlighting heterogeneity in production technologies and factor intensities.

Table 5: TRE-SPF results, Production Factor Estimates by Country

	(1)	(2)	(3)	(4)	(5)	(6)
	Ethiopia	**Malawi**	**Nigeria**	**Tanzania**	**Uganda**	**Ghana**
Land Elasticity	0.469***	0.671***	0.428***	0.501***	0.270***	0.572***
	(0.017)	(0.022)	(0.011)	(0.023)	(0.020)	(0.011)
Labor Elasticity	0.223***	0.178***	0.114***	0.303***	0.397***	0.296***
	(0.016)	(0.018)	(0.009)	(0.023)	(0.027)	(0.012)
Returns to Scale	0.692***	0.849***	0.542***	0.804***	0.667***	0.868***
	(0.018)	(0.020)	(0.014)	(0.022)	(0.029)	(0.013)
Constant returns to scale test						
Chi2(1)	285	55	1,066	76	135	105
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000
Log simulated likelihood	-8,627	-5,218	-8,288	-2,598	-5,570	-12,788
Akaike's information criterion	17,318	10,501	16,641	5,255	11,204	25,637
Observations	6,123	4,107	6,660	2,066	3,998	10,426
Number of farms	2,285	1,577	2,431	1,033	1,642	

Note: Production function full results are presented in Table A1 in the Appendix

In Ethiopia, Malawi, Nigeria, Tanzania, and Ghana, land elasticities exceed labor elasticities, suggesting that land remains a relatively binding factor in these systems. This pattern is consistent with land scarcity and limited scope for area expansion in many smallholder contexts. Uganda stands out as the only case where labor elasticity is comparatively larger, indicating a more labor-intensive production structure. These cross-country differences align with variation in farm size, cropping patterns, and labor allocation documented in the descriptive statistics, and justify the estimation of country-specific frontiers rather than imposing a common technology.

The implied returns to scale are below unity in all countries, ranging from 0.54 in Nigeria to 0.87 in Ghana. Formal tests reject constant returns to scale in every case. These results indicate decreasing returns to proportional expansions in land and labor among smallholders. Such scale properties may reflect structural constraints, coordination frictions, or missing complementary inputs—such as capital, mechanization, or irrigation—that are not fully captured in the parsimonious production specification. In other words, expanding land and labor alone appears insufficient to generate proportional output gains.

Taken together, these estimates suggest that productivity differences across farms cannot be attributed solely to scale expansion. The presence of decreasing returns reinforces the relevance of technical efficiency as a key margin of adjustment: improvements in output are likely to arise not only from increasing factor use, but also from better coordination and management of existing inputs. This provides the foundation for the subsequent analysis of inefficiency determinants and the role of market integration.

6.2 Determinants of technical (in)efficiency

This subsection examines how farm-level characteristics, market participation, and local economic environments are associated with variation in technical efficiency. Table 6 reports the estimates from the inefficiency equation of the stochastic frontier model. Because inefficiency enters the model multiplicatively, negative coefficients indicate factors associated with lower inefficiency (higher technical efficiency), while positive coefficients correspond to greater inefficiency.

Market participation and local market structure

The most consistent and economically meaningful patterns relate to market integration. Across all six countries, participation in commercial agriculture is strongly associated with lower inefficiency. The magnitude of this relationship is substantial in Ethiopia, Malawi, Nigeria, Tanzania, Uganda, and Ghana, suggesting that farms engaged in output markets operate closer to the production frontier than subsistence-oriented farms. This result is consistent with mechanisms through which commercialization enhances managerial discipline, improves access to information and input suppliers, strengthens price incentives, and facilitates learning through repeated interaction with buyers and intermediaries.

Local trader density also exhibits important associations with efficiency, although the pattern is more heterogeneous across countries. In Ethiopia, Malawi, and Nigeria, higher trader density is associated with significantly lower inefficiency, pointing to the role of thicker local markets in improving farmers' performance. A denser network of intermediaries may reduce transaction costs, increase competition among buyers, enhance information flows, and provide more reliable marketing outlets. In Tanzania and Uganda, by contrast, the association is weaker or statistically insignificant, suggesting that the benefits of market thickness may depend on the broader institutional or infrastructural environment. Interestingly, in Ghana the coefficient is positive, indicating higher inefficiency in areas with greater trader density. This may reflect reverse causality—traders locating in areas with structurally weaker production systems—or local market segmentation where intermediary presence does not necessarily translate into improved input allocation or managerial performance. Overall, while the direction and magnitude vary across settings, the results underscore that local output market structure is closely related to technical efficiency.

Complementary indicators of market engagement reinforce this interpretation. Participation in micro, small, and medium-sized enterprises (MSMEs) is associated with lower inefficiency in several countries, particularly Ethiopia, Malawi, and Ghana, suggesting that off-farm entrepreneurial activity may enhance managerial skills or relax liquidity constraints. The use of hired labor is likewise linked to lower inefficiency in most settings, consistent with labor market access facilitating better input allocation and reducing production bottlenecks. Together, these findings support the view that integration into broader market networks—whether through output markets, labor markets, or entrepreneurial activity—plays a central role in shaping farm-level performance.

Table 6: TRE-SPF results, Inefficiency Coefficients

	(1)	(2)	(3)	(4)	(5)	(6)
	ETH	MLW	NGR	TZN	UGD	GHN
Commercial agriculture (dummy)	-0.731***	-0.800***	-0.536***	-1.272***	-1.629***	-2.056***
	(0.084)	(0.113)	(0.076)	(0.140)	(0.225)	(0.145)
Density of Traders in the area	-1.640***	-0.727*	-0.767***	0.061	0.100	0.455***
	(0.191)	-0.396	(0.164)	(0.211)	(0.304)	(0.155)
Has a MSMS (dummy)	-0.187*	-0.263**	0.147	-0.116	0.160	-0.172**
	(0.102)	(0.110)	(0.092)	(0.135)	(0.130)	(0.077)
Hired labor (dummy)	-0.237**	-0.220**	-0.260***	-0.655***	-0.427***	-0.030
	(0.117)	(0.112)	(0.069)	(0.134)	(0.143)	(0.078)
Access to credit (dummy)	-0.043	-0.210**	0.152**	-0.175	0.412**	0.422***
	(0.072)	(0.100)	(0.072)	(0.196)	(0.172)	(0.098)
Agricultural. Cooperative (dummy)	-0.350***	-0.138	-0.041	-	-	0.254***
	(0.088)	(0.085)	(0.073)	-	-	(0.078)
Agricultural training (dummy)	0.005	0.164*	-0.302***	-0.500***	-0.378*	-
	(0.079)	(0.089)	(0.111)	(0.186)	(0.201)	-
Local share using fertilizers	-0.046	-1.377***	-0.873***	-1.139***	0.133	-0.960***
	(0.131)	(0.261)	(0.125)	(0.296)	(0.697)	(0.256)
Local share with off-farm income	1.060***	-0.052	-0.170	0.102	0.022	-1.395***
	(0.229)	(0.324)	(0.148)	(0.363)	(0.431)	(0.265)
Average Nighttime Lights	-0.347***	-0.279***	0.105	0.173	-0.328	-0.048
	(0.118)	(0.103)	(0.105)	(0.436)	(0.293)	(0.052)
Number of parcel owned	-0.042***	-0.059	-0.051*	0.105**	0.064	0.078***
	(0.014)	(0.050)	(0.027)	(0.047)	(0.062)	(0.026)
Crop diversification index	-2.607***	-0.588***	-1.770***	-0.484**	-2.745***	-1.561***
	(0.143)	(0.178)	(0.144)	(0.222)	(0.333)	(0.190)
Non-farm income share	0.636***	0.828***	0.339***	0.276	0.030**	0.794***
	(0.139)	(0.203)	(0.126)	(0.181)	(0.013)	(0.118)

Farmer's age	-0.007***	-0.004	0.009***	0.006*	-0.002	0.007***
	(0.002)	(0.003)	(0.002)	(0.004)	(0.005)	(0.002)
Female (dummy)	0.013	0.135	0.801***	0.041	0.460***	0.629***
	(0.089)	(0.092)	(0.113)	(0.138)	(0.142)	(0.083)
Farmer's years of education	-0.064***	-0.039***	0.023***	-0.019	-0.016	-0.017**
	(0.014)	(0.013)	(0.007)	(0.017)	(0.016)	(0.008)
Household size	-0.006	0.020	-0.075***	-0.069***	-0.064***	-0.053***
	(0.017)	(0.020)	(0.015)	(0.022)	(0.023)	(0.014)
Model parameters						
σ_v	2.283***	0.685	0.301	0.033	1.247*	-0.685***
	(0.296)	(0.450)	(0.249)	(0.858)	(0.673)	(0.031)
σ_u	-1.125***	-1.362***	-1.337***	-1.629***	-0.811***	0.903***
	(0.055)	(0.080)	(0.059)	(0.156)	(0.070)	(0.320)
θ	0.408***	0.328***	0.362***	0.413***	0.657***	NA
	(0.018)	(0.022)	(0.015)	(0.028)	(0.021)	NA
Log simulated likelihood	-8,627	-5,218	-8,288	-2,598	-5,570	-12,788
Observations	6,123	4,107	6,660	2,066	3,998	10,426
Number of farms	2,285	1,577	2,431	1,033	1,642	10,426

Human capital and demographic characteristics

Farmer characteristics also matter, though their effects are less uniform across settings. Years of education are negatively associated with inefficiency in Ethiopia, Malawi, and Ghana, indicating that human capital enhances farmers' ability to combine inputs effectively and adopt improved practices. In Nigeria, however, the coefficient on education is positive, suggesting higher inefficiency among more educated farmers. This pattern may reflect selection into non-farm opportunities, whereby more educated individuals allocate less effort to farming or diversify toward other activities, potentially reducing managerial focus on agricultural production. Age exhibits mixed effects: in some contexts older farmers appear more efficient, possibly reflecting accumulated experience, while in others the relationship is weaker or statistically insignificant. Gender differences are notable in several countries, with female-managed farms in Nigeria, Uganda, and Ghana exhibiting significantly lower inefficiency, though these patterns likely reflect broader structural and selection effects rather than purely managerial differences. Household size is generally associated with lower inefficiency, suggesting that family labor availability can mitigate seasonal labor constraints in smallholder systems.

Land structure and production organization

Landholding structure shows heterogeneous associations across countries. A higher number of parcels is associated with greater inefficiency in Tanzania and Ghana, consistent with land fragmentation increasing coordination costs and managerial complexity. In contrast, in Ethiopia and Nigeria, parcel multiplicity is linked to lower inefficiency, possibly reflecting risk diversification across heterogeneous agroecological conditions rather than fragmentation per se. Crop diversification is negatively associated with inefficiency across all countries, indicating that more diversified production is correlated with higher technical efficiency. One interpretation is that diversification may reduce exposure to crop-specific shocks and improve overall input allocation across plots and seasons, or it may proxy for stronger managerial capacity among farms able to coordinate multiple crops effectively.

Financial access, training, and local externalities

Access to credit displays heterogeneous relationships with inefficiency across countries. In Ethiopia, Malawi, and Tanzania, credit access is associated with lower inefficiency, although the effect is statistically significant only in Malawi. This suggests that, in some contexts, financial access may facilitate the acquisition of productivity-enhancing inputs or relax liquidity constraints that limit optimal input use. By contrast, in Nigeria, Uganda, and Ghana, credit access is associated with higher inefficiency. This pattern may reflect selection effects—less efficient or more liquidity-constrained farms may be more likely to seek credit—or the possibility that credit is not consistently allocated to productive investments. It may also capture differences in credit conditions, repayment structures, or complementary services across countries.

Agricultural training programs likewise exhibit heterogeneous effects. Training participation is associated with lower inefficiency in Nigeria, Tanzania, and Uganda, consistent with the role of knowledge transfer in improving managerial practices and input allocation. However, in Malawi, training is positively associated with inefficiency. This counterintuitive pattern may reflect targeting toward struggling farms, differences in program quality, or time lags between training participation and observable efficiency gains. Taken together, these results underscore the importance of institutional context in shaping how financial and extension services translate into productive performance.

Importantly, local production environments also shape efficiency outcomes. A higher local share of producers using fertilizers is strongly associated with lower inefficiency in most countries, pointing to input adoption externalities and peer learning effects. Exposure to input-using neighbors may facilitate knowledge diffusion, reduce uncertainty, and improve farmers' ability to apply technologies effectively. By contrast, a higher local share of producers engaged in off-farm income activities is generally associated with higher inefficiency, suggesting that communities with greater non-agricultural orientation may allocate less attention or resources to farm management.

Finally, nighttime lights—used as a proxy for local economic activity and market development—exhibit heterogeneous effects across countries. In Ethiopia and Malawi, higher nighttime light intensity is associated with lower inefficiency, consistent with better infrastructure and market connectivity. In other contexts, however, the relationship is weaker, suggesting that local economic dynamism does not automatically translate into farm-level performance gains without complementary institutional mechanisms.

Summary

Taken together, the results indicate that technical efficiency is shaped not only by factor endowments and household characteristics, but critically by market participation and local market structure. Commercialization and trader density consistently emerge as central correlates of efficiency, supporting the hypothesis that integration into output and input markets enhances farmers' ability to operate closer to the production frontier. The heterogeneity observed across countries further underscores the importance of contextual factors in mediating these relationships.

6.3 Technical efficiency distribution and heterogeneity

We now examine the distribution of technical efficiency (TE) scores across countries and crops in order to characterize the extent of within- and between-country heterogeneity. Efficiency scores are derived from the stochastic frontier estimates discussed above and measure the ratio of observed output to potential output, conditional on the estimated production technology. Table 7 reports summary statistics by country, while Figures 4 and 5 display the full distributions by country and by main crop, respectively.

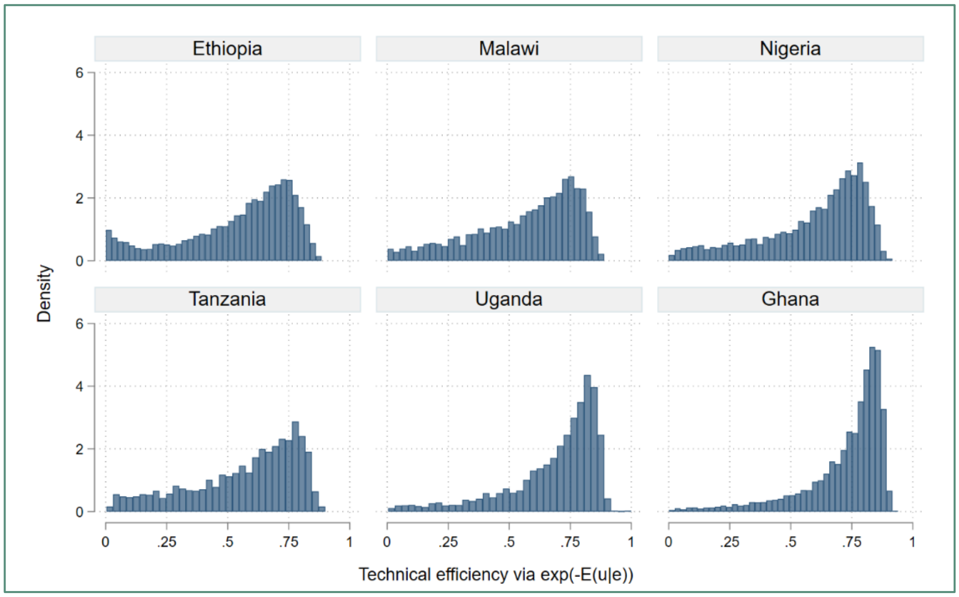
Substantial cross-country differences emerge. Mean efficiency ranges from 0.55 in Ethiopia to 0.72 in Ghana, with Malawi, Nigeria, and Tanzania occupying intermediate positions and Uganda closer to the upper end of the distribution. Median values closely mirror this ranking, indicating that differences are not driven solely by outliers but reflect systematic shifts in the central tendency of the distributions. Dispersion also varies across settings. Uganda and Ghana exhibit relatively lower standard deviations but markedly stronger negative skewness and high kurtosis, indicating a concentration of farms operating near the frontier alongside a thinner but persistent lower tail of less efficient producers. By contrast, Ethiopia and Tanzania display broader dispersion and less pronounced skewness, suggesting more evenly distributed performance gaps across farms.

Table 7: Technical efficiency descriptive statistics, by country

Country	Mean	p50	SD	Min	Max	Skewness	Kurtosis
Ethiopia	0.55	0.61	0.22	0.00	0.88	-0.87	2.79
Malawi	0.57	0.62	0.21	0.00	0.89	-0.77	2.67
Nigeria	0.59	0.66	0.21	0.00	0.92	-0.97	3.01
Tanzania	0.57	0.63	0.22	0.00	0.90	-0.79	2.61
Uganda	0.68	0.75	0.19	0.00	1.00	-1.45	4.70
Ghana	0.72	0.78	0.17	0.00	0.94	-1.75	5.96

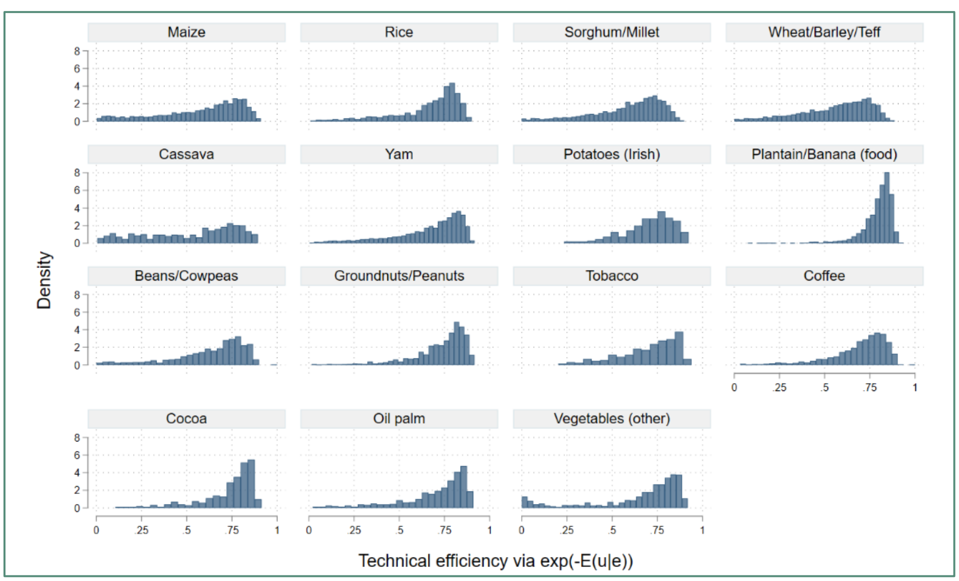
Figure 4 further illustrates the magnitude of within-country heterogeneity. In every country, efficiency scores span a wide interval—from farms operating close to the frontier to others performing substantially below potential. Even in Ghana, where average efficiency is highest, the lower tail remains sizable. This coexistence of high- and low-performing farms within the same technological and agroecological context suggests that differences in managerial practices, input allocation, access to markets, and institutional engagement are likely to play an important role in shaping productivity outcomes. In other words, technology alone cannot account for the observed dispersion.

Figure 4: Distribution of Technical Efficiency, by country



Heterogeneity is also evident across crop types. As shown in Figure 5, crops such as rice, coffee, vegetables, cocoa, and oil palm exhibit distributions concentrated at relatively higher efficiency levels, whereas maize, cassava, and sorghum display broader dispersion and lower central tendency. These patterns are consistent with differences in commercialization intensity, input use, and exposure to organized value chains. Export-oriented or higher-value crops often involve closer interaction with traders, cooperatives, or processing firms, potentially facilitating access to information and inputs that improve production performance. In contrast, staple crops that are more subsistence-oriented tend to exhibit wider variation and lower average efficiency.

Figure 5: Distribution of Technical Efficiency, by crop



Overall, the distributional evidence highlights two central features of the data. First, technical efficiency differs markedly across countries, reflecting structural and institutional variation in agricultural systems. Second, and perhaps more importantly, there is substantial heterogeneity within countries and across crops, indicating significant unrealized productivity potential even under existing technologies. These patterns motivate the subsequent analysis of how market participation and local market structure are associated with efficiency along the distribution, rather than merely at the mean.

6.4 Distributional Effects of Commercialization and Market Structure

While previous sections focused on mean effects and parametric determinants of technical efficiency, average relationships may conceal substantial heterogeneity across the efficiency distribution. In particular, commercialization and local market structure may affect low-efficiency and high-efficiency farms differently. To explore these distributional patterns more formally, we estimate quantile regressions of technical efficiency.

Specifically, for each quantile $\tau \in (0.1, 0.25, 0.5, 0.75, 0.9)$, we estimate:

$$Q_\tau(\ln(TE_{ict}) \mid X_{ict}) = \alpha_\tau + \beta_{1\tau}^c \, Commercialization_{ict} + \beta_{2\tau}^c \, TraderDensity_{ict} + \gamma_\tau' Z_{ict} + \mu_c + \lambda_t$$

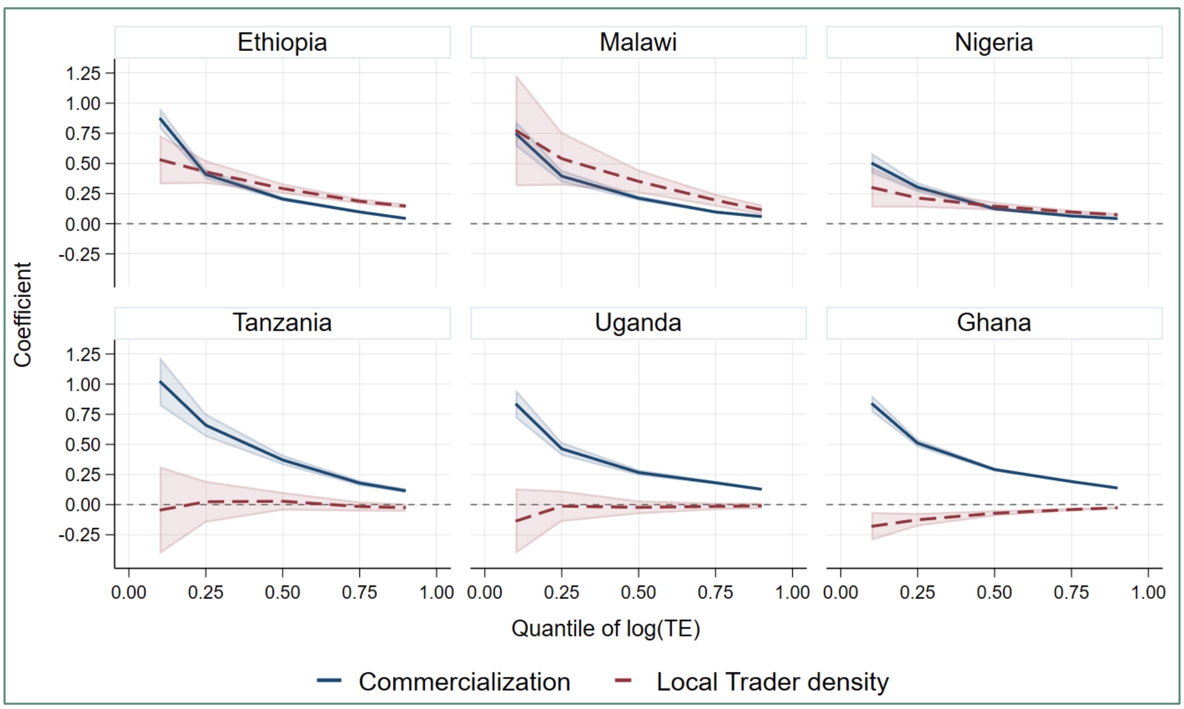
where $Q_\tau(\cdot)$ denotes the conditional τ-th quantile, TE_{ict} is technical efficiency for farm i in country c and year t, Z_{ict} includes farm-level controls (land, labor, input use, and demographics). Country (μ_c) and year (λ_t) fixed effects absorb time-invariant country characteristics and common macroeconomic shocks. To allow for heterogeneous slopes across countries —consistent with the country-specific frontier framework adopted in the stochastic frontier estimation— commercialization and trader density are interacted with country indicators, yielding country-specific quantile effects $\beta_{1\tau}^c$and $\beta_{2\tau}^c$. Estimating separate regressions by country yields virtually identical results, confirming that the patterns are not driven by pooling assumptions.

Figure 6 presents the estimated quantile effects for each country. Two robust patterns emerge. First, the association between commercialization and technical efficiency is strongly decreasing across quantiles in all settings. The estimated coefficients are largest at the lower tail of the efficiency distribution and decline monotonically toward the upper tail. This gradient is particularly pronounced in Tanzania and Ethiopia, where commercialization exhibits very large effects at the 10th and 25th percentiles that shrink substantially by the 75th and 90th percentiles. Malawi and Uganda display a similar downward pattern at somewhat lower magnitudes. Even in Nigeria and Ghana—where overall efficiency levels differ—the same declining profile is evident. These results indicate that commercialization is most strongly associated with efficiency improvements among farms operating far from the frontier, whereas among farms already close to best practice, the marginal association is considerably smaller.

Second, the effects of trader density are more moderate and more heterogeneous across contexts. In Ethiopia and Malawi, trader density is positively associated with efficiency at lower and intermediate quantiles, with effects flattening toward the top of the distribution. In Tanzania and Uganda, the association is concentrated at the bottom tail and becomes statistically weak or indistinguishable from zero at higher quantiles. In Nigeria and Ghana, the estimated effects are small throughout the distribution. Taken together, these findings suggest diminishing marginal efficiency gains from additional local intermediaries once a certain degree of market thickness has been reached.

Although magnitudes vary across countries—consistent with differences in production technologies, institutional settings, and value chain organization—the qualitative distributional pattern is remarkably consistent. Market integration appears most strongly associated with improvements among relatively inefficient farms. In other words, commercialization and local trader presence are linked more to "catch-up" dynamics than to uniform upward shifts of the entire efficiency distribution.

Figure 6: Quantile Effects of Commercialization and Trader Density on Technical Efficiency, by Country



One plausible mechanism underlying this pattern relates to information, incentives, and input access associated with market integration. Engagement in output markets may expose farmers to price signals, quality standards, and buyer requirements that encourage more disciplined input allocation and production practices. Interaction with traders and intermediaries can facilitate information diffusion regarding improved seeds, fertilizer use, and crop management techniques, while also reducing uncertainty about output marketing. These channels are likely to generate larger marginal gains among farms that initially operate far from the frontier, where managerial constraints, information gaps, or coordination failures are more binding. By contrast, farms already close to best practice may have limited scope for additional efficiency improvements from further market exposure, leading to the declining gradient observed across quantiles.

This interpretation aligns with the descriptive evidence presented in Appendix Figure A1, which shows locally weighted smoothing plots of technical efficiency against trader density. The lowess curves reveal a nonlinear but generally positive association at low and intermediate levels of market density that flattens at higher densities. The quantile regression results extend this descriptive evidence by formally demonstrating that the strength of the association varies systematically along the efficiency distribution and is concentrated at the lower tail.

Taken together, these findings suggest that commercialization and local market access operate primarily by reducing inefficiency dispersion rather than by uniformly shifting the production frontier. Market engagement appears to help farms that are initially further from the frontier "catch up," while already efficient farms exhibit more limited marginal gains.

7. DISCUSSION AND CONCLUSION

This paper examines the relationship between market integration and farm productivity in smallholder agriculture, with a particular emphasis on technical efficiency as a central component of performance. Using harmonized farm household data from six Sub-Saharan African countries and a stochastic frontier True Random-Effects model, we document substantial heterogeneity in efficiency both across and within countries. While differences in production technologies and factor intensities matter, a significant share of productivity gaps reflects variation in how effectively farmers combine available inputs. The wide dispersion of technical efficiency scores indicates considerable scope for productivity gains through improved managerial performance and resource allocation, even in the absence of frontier-shifting technological change.

A central finding of the analysis is that commercialization is systematically associated with lower inefficiency, but the strength of this association varies along the efficiency distribution. Quantile regressions reveal that market participation is most strongly linked to improvements among farms operating at the lower tail of the efficiency distribution, with progressively smaller associations among farms closer to the frontier. This pattern suggests that commercialization operates primarily through "catch-up" dynamics rather than uniform upward shifts in productivity. In contexts characterized by decreasing returns to scale, expansion alone does not guarantee higher output; instead, the capacity to use inputs effectively becomes critical. Market engagement appears to relax informational, coordination, and incentive constraints that disproportionately affect less efficient farms.

The structure of local markets further conditions these relationships. Denser networks of intermediaries—the so-called hidden middle—are associated with lower inefficiency in several countries, particularly at lower efficiency quantiles. These patterns are consistent with mechanisms through which intermediaries reduce transaction costs, facilitate information diffusion, stabilize marketing channels, and improve access to inputs. At the same time, the effects are heterogeneous across settings, reflecting differences in institutional environments, infrastructure, and crop composition. Complementary household characteristics—including education, gender, and access to training—also shape efficiency outcomes, reinforcing the idea that market integration interacts with human capital and local economic environments rather than operating in isolation.

Taken together, the results contribute to the literature in two ways. First, they distinguish clearly between technological differences and efficiency-related sources of productivity variation in smallholder agriculture. Second, they demonstrate that market integration influences not only average productivity levels but also the dispersion of efficiency outcomes. Importantly, improving productivity does not necessarily require immediate shifts in the production frontier—while technological innovation remains essential in the long run, it is often costly, slow to diffuse, and unevenly adopted. An alternative and complementary pathway lies in enabling producers to move closer to the existing frontier. The evidence presented here suggests that commercialization and local market development can contribute to such catch-up dynamics by reducing technical inefficiency through improved information flows, learning and peer effects, enhanced input access and quality upgrading, and lower transaction costs. From a policy perspective, this implies that investments aimed at strengthening rural markets, deepening intermediary networks, and facilitating farmers' integration into output markets may generate substantial productivity gains by improving the use of existing technologies—particularly among farms operating furthest from the frontier.

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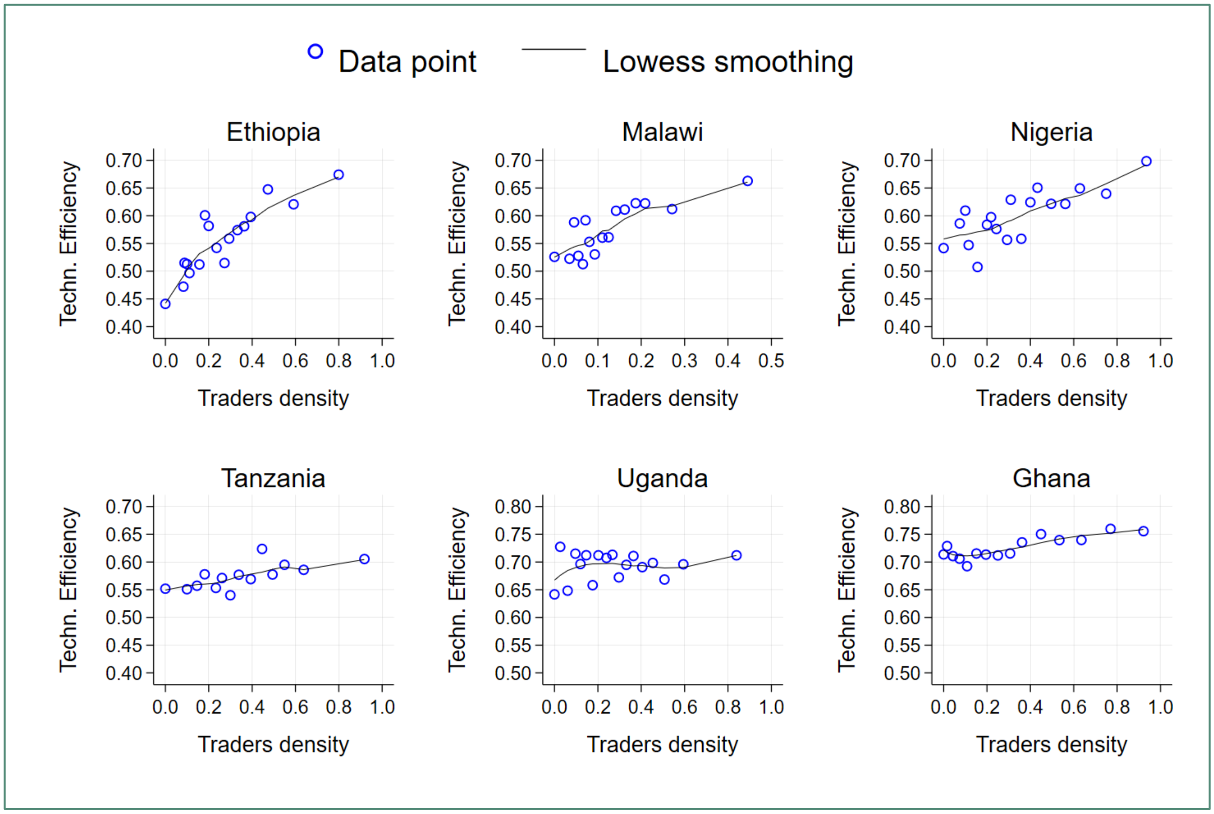
APPENDIX

Table A1: TRE-SPF results, Production Function Full Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	ETH	**MLW**	**NGR**	**TZN**	**UGD**	**GHN**
ln(A)	0.110	0.226**	0.125***	-0.215*	-0.424***	0.467***
	(0.081)	(0.111)	(0.032)	(0.112)	(0.140)	(0.021)
ln(L)	0.854***	0.566***	0.462***	0.659***	0.816***	0.513***
	(0.117)	(0.092)	(0.047)	(0.143)	(0.247)	(0.038)
$ln(A)^2$	-0.047***	-0.020	-0.057***	-0.077***	-0.050***	-0.005
	(0.009)	(0.018)	(0.006)	(0.016)	(0.012)	(0.007)
$ln(L)^2$	-0.064***	-0.041***	-0.033***	-0.045***	-0.040*	-0.066***
	(0.012)	(0.011)	(0.005)	(0.016)	(0.023)	(0.009)
ln(A) x ln(L)	0.073***	0.106***	0.051***	0.168***	0.131***	0.058***
	(0.016)	(0.024)	(0.006)	(0.025)	(0.027)	(0.012)
Pesticide (dummy)	0.125***	-0.121***	0.186***	0.150**	0.067	0.207***
	(0.027)	(0.041)	(0.022)	(0.070)	(0.154)	(0.019)
Fertilizer (dummy)	0.133***	0.254***	0.055**	-0.007	0.130**	0.122***
	(0.028)	(0.027)	(0.022)	(0.055)	(0.059)	(0.018)
Purchased Seeds (dummy)	-0.033	-0.063**	-0.030	0.054	-0.104***	-0.064***
	(0.025)	(0.026)	(0.022)	(0.038)	(0.032)	(0.020)
Irrigation (dummy)	0.074**	-0.223**	0.037	0.255**	-0.184***	
	(0.034)	(0.088)	(0.050)	(0.108)	(0.068)	
Constant	3.839***	5.690***	6.076***	4.293***	4.014***	5.252***
	(0.297)	(0.211)	(0.119)	(0.315)	(0.695)	(0.060)
Log simulated likelihood	-8,627	-5,218	-8,288	-2,598	-5,570	-12,788
Observations	6,123	4,107	6,660	2,066	3,998	10,426
Number of idd	2,285	1,577	2,431	1,033	1,642	NA

Figure A1: The Nonlinear Relationship between Technical Efficiency and Trader Density



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