SOCIAL LEARNING AND PEER INFLUENCE IN SMALLHOLDER COMMERCIALIZATION

Working Paper
Nº 305
January - 2026

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RIMISP
Centro Latinoamericano
para el Desarrollo Rural

Citation

Dzanku, F., Liverpool-Tasie, S., Reardon, T. (2026). Social Learning and Peer Influence in Smallholder Commercialization (Working Paper Series No. 305). INCATA: Linked Farms and Enterprises for Inclusive Agricultural Transformation in Africa and Asia, Rimisp.

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This document is the result of the INCATA proyect: Linked Farms and Enterprises for Inclusive Agricultural Transformation in Africa and Asia, coordinated by Rimisp – Latin American Center for Rural Development, and made possible through funding from the Gates Foundation. We also extend our gratitude to our local partners — Tegemeo Institute in Kenya, the International Food Policy Research Institute (IFPRI) in Odisha, India, and Michigan State University (MSU) — for their collaboration in the work carried out within the framework of this project.

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ABSTRACT

This paper examines how peer behavior influences small-scale producers' (SSPs) decisions to purchase inputs and sell outputs in six sub-Saharan African countries. Using comparable nationally representative panel data and a correlated random effects framework, we assess the extent and shape of social interactions driving input and output market participation. We find strong and positive peer effects for seed, fertilizer, and pesticide adoption in Ghana, Nigeria, and Ethiopia, but weaker or negative effects in Tanzania, Uganda, and Malawi. For output markets, peer commercialization strongly predicts individual commercialization intensity in Ghana, Ethiopia, and Malawi. Nonlinear analyses reveal inverted-U or U-shaped relationships, indicating that peer effects strengthen at early diffusion stages but diminish or reverse beyond saturation thresholds. These findings highlight that commercialization is socially embedded and that leveraging peer dynamics can enhance agricultural market participation.

Key words: Small-scale producers, Social learning, Peer effects, Agricultural commercialization, Input adoption, Output market participation, Sub- Saharan Africa, Panel data.

RESUMEN EJECUTIVO

Este artículo examina cómo el comportamiento de los pares influye en las decisiones de los pequeños productores (SSP, por sus siglas en inglés) de adquirir insumos y vender productos en seis países del África subsahariana. Utilizando datos de panel comparables y representativos a nivel nacional, junto con un marco de efectos aleatorios correlacionados, evaluamos la magnitud y la forma de las interacciones sociales que impulsan la participación en los mercados de insumos y de productos. Encontramos efectos de pares fuertes y positivos en la adopción de semillas, fertilizantes y pesticidas en Ghana, Nigeria y Etiopía, pero efectos más débiles o negativos en Tanzania, Uganda y Malawi. En los mercados de productos, la comercialización de los pares predice fuertemente la intensidad de la comercialización individual en Ghana, Etiopía y Malawi. Los análisis no lineales revelan relaciones en forma de U invertida o en forma de U, lo que indica que los efectos de pares se fortalecen en las primeras etapas de difusión, pero se debilitan o incluso se revierten una vez superados ciertos umbrales de saturación. Estos hallazgos destacan que la comercialización está socialmente integrada y que aprovechar las dinámicas entre pares puede mejorar la participación en los mercados agrícolas.

Palabras clave: pequeños productores, aprendizaje social, efectos de pares, comercialización agrícola, adopción de insumos, participación en mercados de productos, África subsahariana, datos de panel.

1. INTRODUCTION

Linking small-scale producers (SSPs) to input and output markets is important for promoting and accelerating inclusive agricultural transformation (Hazell et al., 2017; Mellor & Malik, 2017; Timmer, 1988), particularly in sub-Saharan Africa (SSA). The literature on commercialization and economic transformation in developing countries often focuses on structural constraints, and much less on how smallholder commercialization is shaped by social and behavioral factors. Farmers learn from peers, imitate successful behaviors, and coordinate marketing activities. Yet cross-country evidence on peer effects in commercialization—beyond technology adoption—is scarce. This paper addresses an important gap in the literature by examining how peer behavior within a community influence individual SSP decisions to participate in input and output markets. Thus, beyond structural constraints, this paper deals with the social embeddedness of economic behavior in rural agrarian settings and implications for commercialization and inclusive transformation across six African countries.

Our analysis of the role of peer influence in SSP commercialization is grounded in theories of social learning and embedded economics. We posit that peer influence operates through information diffusion, imitation, and collective risk mitigation. Smallholders often operate under conditions of limited information, liquidity constraints, and high uncer- tainty, making them responsive to what peers do. Adoption of improved inputs and engagement in markets may be influenced by learning effects, imitation, and social norms. A rich literature has demonstrated how social networks influence technology adoption (Bandiera & Rasul, 2006; Beaman et al., 2021; Conley & Udry, 2010) and how economic actions are embedded in social structures (Granovetter, 1985; Polanyi, 2002). In contexts where trust and reputation shape marketing relationships (Dzanku et al., 2024; Fafchamps, 2004), peer behavior may serve as an informal signal for market participation. Understanding peer dynamics can inform the design of scalable interventions—for example, through the strategic targeting of lead farmers or influential adopters (Banerjee et al., 2019).

In combining insights from institutional economics, spatial equilibrium theory, and social network analysis, this study contributes to a deeper understanding of how agricultural markets form, evolve, and deepen in smallholder settings. We also contribute to the thin debate in the literature about nonlinearities in peer effects, that is, peer influence rising initially with exposure but plateauing or reversing when saturation leads to competition or crowding. Peer influence may follow an inverted-U pattern, with moderate peer adoption encouraging own participation through social learning, and high peer commercialization creating crowding or competition effects (Bandiera & Rasul, 2006). To test these hypotheses, we incorporate quadratic terms for key covariates and provide graphical evidence of the shape and turning points of these relationships. This allows for a richer and more policy-relevant understanding of how commercialization unfolds across the distribution of market exposure and social embeddedness.

By using nationally representative panel data spanning more than a decade across six sub-Saharan African countries, this study also contributes to the literature by expanding the scope and depth of existing work on peer effects in agricultural production and marketing. Existing work tends to be geographically limited, often focusing on single countries or small samples in specific geographic zones of a country.

We contribute to the literature on peer effects and social learning by examining how smallholder commercialization decisions are influenced by the behavior of other producers in the same community. While prior studies—such as Bandiera and Rasul (2006), Conley and Udry (2010), and Beaman and Dillon (2018)—focus on technology adoption and rely on social networks defined by friends or kin, we assess community-level peer effects on a range of commercialization outcomes: adoption of seeds, fertilizer, and pesticides, as well as output market participation and sales intensity. Our approach captures broader social dynamics that shape input and output behavior and offers a scalable proxy for peer influence relevant for policy targeting.

2. DATA AND METHODS

2.1 Description of data

The study uses survey data for six countries in SSA (Ghana, Nigeria, Tanzania, Uganda, Ethiopia and Malawi). Except, for Ghana, the data comes from the Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS- ISA). These are nationally representative panel surveys with an extended focus on agriculture households. The Ghana data comes from the Ghana Living Standards Survey (GLSS), which is a nationally representative repeated cross- sectional household survey with comparable samples. The sample designs and questionnaires are comparable. The survey period spans the period 2006-2020, albeit the majority of the sample covers a 10-year period (2010-2020). All surveys followed the so called complex survey sampling design, mostly a two-stage design whereby enumeration areas or clusters were drawn at the first stage from each defined stratum. A random sample of households is then drawn from each cluster using a sample frame with probability proportional to size. The samples are thus mostly not self-weighting; therefore, appropriate sampling weights are applied whenever necessary. All key variables are constructed from identical questions across the countries.

Table 1. Sample used for the regressions.

	First set of regressions	Second set of regressions
Ghana	2006, 2013, 2017	2017
Nigeria	2011, 2013, 2016	2019
Tanzania	2015, 2020	2009, 2011, 2013
Uganda	2016, 2020	2010, 2012, 2014
Ethiopia	2012, 2014, 2016	2019
Malawi	2011, 2013, 2016, 2019	2016, 2019

Most of the panel surveys collected three waves of data and thereafter only a small subsample of the original panel was maintained during subsequent surveys. Therefore, in constructing the panel datasets for the econometric analyses, we try to balance panel length and sample size to achieve reasonable statistical power. For this reason, some of the analyses are based on more than one set of panel data per country. For some countries, we also utilize the most recent cross-sectional data available. Table 1 shows details of the sample for each country.

2.2 Description of main variables

The key variables used in the analyses are described here.

- Small-scale producer (SSP). We define a crop producing household as SSP in a given survey round if its total cultivated land in that round is less than or equal to the 90th percentile of cultivated area computed from the baseline sample. Baseline means the earliest sample survey. Whereas the threshold is fixed over time, household classification as SSP may vary from round to round. Let A_{it} be cultivated area for household i at time t, and $Q_{90}(A_0)$ be the 90th percentile of baseline cultivated area across the baseline full sample. SSP_{it}, which is the indicator of whether household i is a small-scale producer at time t is:

$$SSP_{it} = \begin{cases} 1 & \text{if } A_{it} \leq Q_{90}(A_0) \\ 0 & \text{otherwise} \end{cases}$$

- Commercialization. We define commercialization to include input and output market engagement by *SSPs*. On the input side, our analysis focuses on binary indicators of whether *SSP* household I purchased a given input j (seeds, chemical fertilizer, or pesticides) in period t, denoted as.

$$I_{j,it} = \begin{cases} 1 & \text{if input } j \text{ was purchased in year } t \\ 0 & \text{otherwise} \end{cases}$$

On the output side, we use three complementary measures:

- Extensive margin – an indicator of whether *SSP* household i sold any harvested crop at time t:

$$O_{it} = \begin{cases} 1 & \text{if any crop was sold in year } t \\ 0 & \text{otherwise} \end{cases}$$

- Intensive margin – the total constant value of crops sold by SSP-household i in period t, denoted V_{it}.

- Degree of commercialization – the proportion of output harvested (in value terms) that was sold:

$$S_{it} = \frac{V_{it}}{H_{it}},$$

where H_{it} is the total value of crops harvested by *SSP* household i in period t.

Peer influence: we define peer (herd) behavior indicator on both the input and output sides of the market.

- On the input side, the peer effect for input k (improved seeds, fertilizer, pesticides) is defined as the weighted share of neighboring SSPs in the same community who purchased the input, excluding *SSP* i. Let $I_k = 1$ if *SSP* j purchased input k (seeds, fertilizer, pesticides) at time t, and zero otherwise, $N—i$ = other SSPs in the same community, c, at time t, excluding *SSP* i. Then the input market participation peer indicator is given by: $P\ w_{jct} \cdot I_k$

$$PeerInput_{ict}^{k} = \frac{\sum_{j \in N_{ct}^{-i}} w_{jct} \cdot I_{jct}^{k}}{\sum_{j \in N_{ct}^{-i}} w_{jct}}$$

- On the output side, the commercialization peer effect indicator is defined as the weighted average share of output sold by other SSPs in the same community, excluding individual SSP i. This serves as a proxy for social learning or behavioral influence. Let S_{jct}= the share of output sold by *SSP* j at time t, w_{jct}= sampling weight, $i \in N—i$ = other *SSPs* in cluster c at time t, excluding *SSP* i. Then the output commercialization peer effect indicator is given by:

$$PeerShare_{ict} = \frac{\sum_{j \in N_{ct}^{-i}} w_{jct} \cdot S_{jct}}{\sum_{j \in N_{ct}^{-i}} w_{jct}}$$

2.3 Regression models and estimation approach

With panel data and limited dependent variables, most of our regressions are based on the correlated random effects (CRE) approach, commonly referred to as the Mundlak-Chamberlin device (Chamberlain, 1982; Mundlak, 1978; Wooldridge, 2010; Wooldridge, 2019). Essentially, the approach allows correlation between unobserved heterogeneity and observed covariates by including time-averaged values of time-varying regressors as additional explanatory vari- ables. We could also use the standard fixed effects (FE) estimator but in that case one cannot identify time-invariant covariates that are important to our analysis. Given the several limited dependent variable outcomes used in this study the Mundlak-Chamberlin formulation provides a computationally and statistically tractable solution by allowing us to model heterogeneity without estimating a large number of unit-specific fixed effects.

We address the primary research question of this paper—the extent to which peer behavior influences individual SSP decisions to purchase inputs or sell outputs—by estimating the following equation:

$$Com_{ict} = \alpha + \delta_1 PE_{ict} + \delta_2 \overline{PE_i} + X'_{ict}\beta + \overline{X'_i}\varphi + X'_{ct}\pi + \overline{X'_c}\theta + u_c + \tau_t + \varepsilon_{ict},$$

where

- Com_{ict}: market engagement indicator for household i in community c in time t either on the output or input side,
- $\mathrm{PE}_{\mathrm{ict}}$: peer influence indicator where $\mathrm{PE}_{\mathrm{ict}} \in \left[\mathrm{PeerShare}_{\mathrm{ict}}, \mathrm{PeerInput}^{\mathrm{k}}_{\mathrm{ict}}\right]$
- $\overline{PE_i}$: time-average of peer influence
- $\boldsymbol{X_{ict}}$: household-level time-varying controls
- $\overline{\boldsymbol{X_i}}$: time-averages of household-level controls
- $\boldsymbol{X_{ct}}$: community-level time-varying controls
- $\overline{\boldsymbol{X_c}}$: time-averages of community-level controls
- $\boldsymbol{L_i}$: time-invariant controls such as agro-ecology
- u_c: cluster-level fixed effects
- τ_t: time fixed effects
- ε_{ict}: random error term.

We also explore nonlinear relationships between key covariates and all outcomes by including quadratic terms of these covariates in all our models to explicitly test the presence of threshold effects. We also test possible nonlinear effects of infrastructure variables (road density and distance to markets) in all the regressions.

Binary outcomes are estimated using the Correlated Random Effects (CRE) probit estimator. For fractional dependent variables such is the share of output sold, the CRE fractional probit estimator is employed. As often is the case with agricultural household data in developing countries, many producers do not sell any of their harvest. Therefore, output sales present a corner solution outcomes which we empirically model using Cragg's Hurdle model (Cragg, 1971; Wooldridge, 2010). An advantage of the hurdle approach is that it allows us to model extensive and intensive margins separately. By extensive margin, we mean the market participation decision, and intensive margin is the amount sold conditional on participation.

The double-hurdle model framework that we use recognizes that peer effects may operate differently across these margins—through information diffusion and social learning in the participation decision, and through behavioral emulation or coordination in the sales intensity stage. By estimating these processes separately rather than jointly, the approach provides a clearer empirical test of whether peer behavior primarily facilitates market entry or deepens engagement among existing participants, offering a more nuanced understanding of commercialization dynamics, which is a nontrivial contribution of this paper.

An important caveat in interpreting the estimated peer effects from Equation (1) is that they may not satisfy strict causal interpretation due to potential endogeneity concerns. Apparent peer influences could partly reflect correlated exposure to unobserved factors—such as common market signals, local price movements, weather shocks, or infrastructure improvements—that simultaneously shape individual and peer behavior. While our empirical strategy incorporates an extensive set of controls, including household, community, and time-specific fixed effects, and applies population weights to enhance representativeness, these adjustments may not fully purge the estimates of endogeneity bias. Consequently, the estimated peer-effect coefficients should be interpreted as conditional associations rather than definitive causal effects.

3. RESULTS AND DISCUSSION

3.1 Descriptive summary statistics

Table A1 summarizes the mean values of key variables across the first and last rounds of the multi-country surveys. Substantial cross-country heterogeneity in smallholder commercialization is evident. At baseline, about three-quarters of households in Ghana sold some output, compared with roughly half in Malawi. By the most recent round, participation remained broadly stable, with modest declines in Ghana and marginal gains in Nigeria and Tanzania. The intensity of sales—the share of total harvest marketed—was consistently highest in Ghana and lowest in Malawi, confirming persistent differences in market orientation across settings.

Patterns of peer behavior broadly mirror individual commercialization. The share of peers who sold output was highest in Ghana at the outset but declined slightly by endline, while peer commercialization rose in Nigeria, Tanzania, Ethiopia, and Malawi. Uganda experienced a small contraction. On the input side, peer adoption of improved seed and fertilizer was more modest, suggesting thinner networks for information and demonstration effects in input markets than in output transactions. Notably, fertilizer use expanded in several countries—especially Ghana, Tanzania, and Malawi—while pesticide use increased sharply in Ghana and Nigeria, pointing to some diffusion of input market participation within peer groups.

Household endowments also vary markedly across countries. Cultivated land is largest in Ghana and smallest in Malawi, with most countries averaging around 1-1.5 hectares. Non-land assets increase across the board, albeit from a low base, indicating gradual capital accumulation. Livestock ownership is highest in Ethiopia and Nigeria and lowest in Malawi and Uganda, reflecting differences in agro-ecological potential and production systems. Road density improved in nearly all countries over the study period, but distance-to-market patterns remain uneven: Malawi and Nigeria show improved proximity, whereas Ghana, Tanzania, Uganda, and Ethiopia record greater average distances, underscoring persistent spatial disparities.

Overall, the descriptive patterns reveal a stable yet heterogeneous landscape of smallholder commercialization. While levels of market participation and peer exposure remain modest, changes over time differ sharply across contexts, suggesting localized drivers of diffusion and adoption. The coexistence of stagnant commercialization in some settings and gradual expansion in others highlights the potential importance of social learning and peer effects—issues explored more rigorously in the econometric analysis that follows.

3.2 Effect of peer influence on individual SSP commercialization decisions

This section presents and discusses the results from estimating equation (2). We begin by examining whether peers influence input market participation, and then explore whether SSPs engage in output markets through social learning, based on the premise that economic behavior is socially embedded.

Peer influence effects on input market participation

To what extent does peer influence affect agro-input purchase decisions? Figures 1-3 and Tables A2-A4 (Appendix) show the regression results. Across both sets of estimates (Panels A & B), we find strong and consistent evidence of positive peer effects on input market participation in Ghana, Nigeria, and Ethiopia, particularly for seeds, fertilizer, and pesticides. In these countries, a higher share of peers purchasing inputs significantly increases a household's likelihood of participating in input markets, consistent with the broader literature on social learning and technology diffusion (Beaman & Dillon, 2018; Conley & Udry, 2010). The magnitudes are substantial, suggesting that peer-driven information flows and demonstration effects are critical to adoption decisions in these settings. In contrast, results for Tanzania, Uganda, and Malawi are more mixed: peer effects are generally weaker, sometimes statistically insignificant, and even negative in a few cases, particularly for seed and pesticide adoption. This heterogeneity aligns with more recent extensions of the social learning literature, which emphasize that the strength and direction of peer effects depend on the structure of networks, observability of outcomes, and the risks associated with input adoption (Maertens, 2017).

Notably, the comparison between panel and cross-sectional results shows a broadly consistent pattern in terms of which countries exhibit strong peer effects, but with some variations in magnitude and significance, especially in the supplementary data. For instance, the positive peer effects observed in Ghana, Nigeria, and Ethiopia are somewhat smaller but remain statistically significant in the cross-sectional estimates, while countries with weaker peer effects in the panel (e.g., Malawi) also show weaker or inconsistent effects in the cross-sections. These results suggest that while social learning is robust over time in some contexts, peer influence can attenuate or fluctuate depending on cohort dynamics, market changes, or evolving network structures.

Delving deeper, we identify that, as Bandiera and Rasul (2006) found in the localized context of northern Mozambique, peer effect on input adoption is nonlinear in Ghana, Tanzania, Uganda and Ethiopia (Figures 4, 5 and A1-A3, Appendix).

Figure 1. CRE probit regression results of the effect of peer influence on seeds market participation.

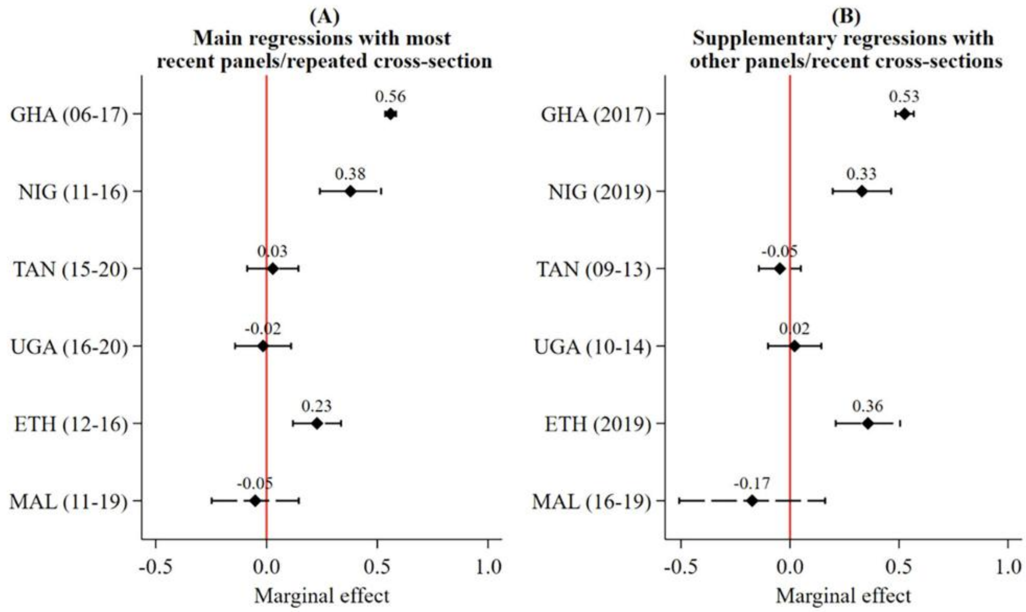


Figure 2. CRE probit regression results of the effect of peer influence on fertilizer market participation.

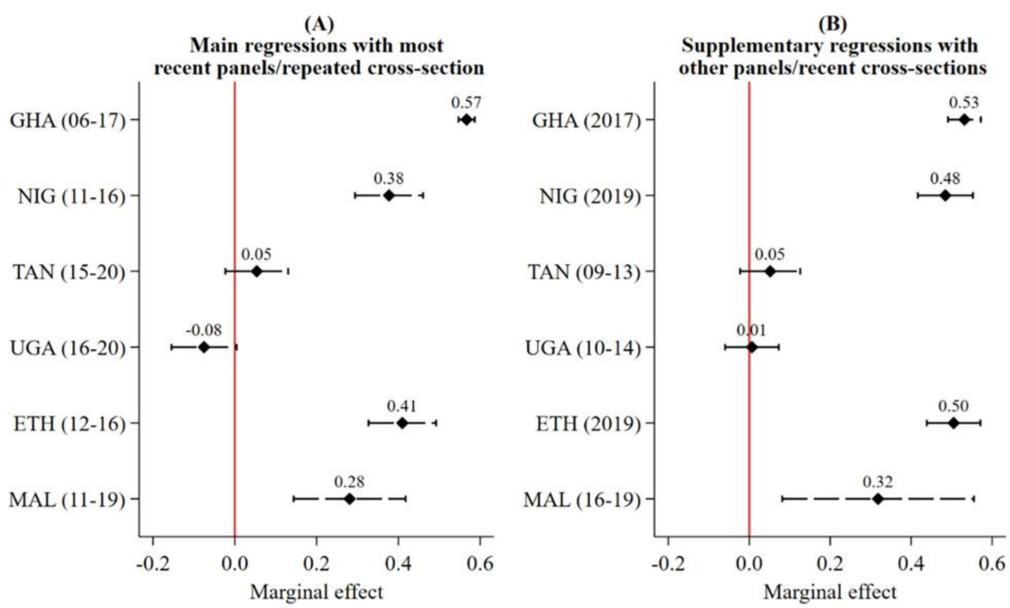
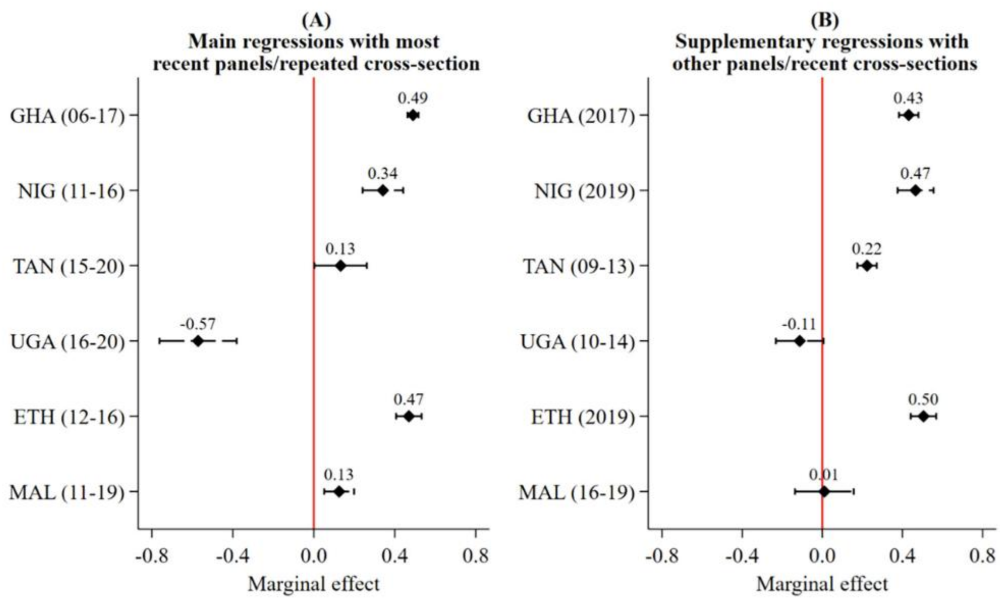
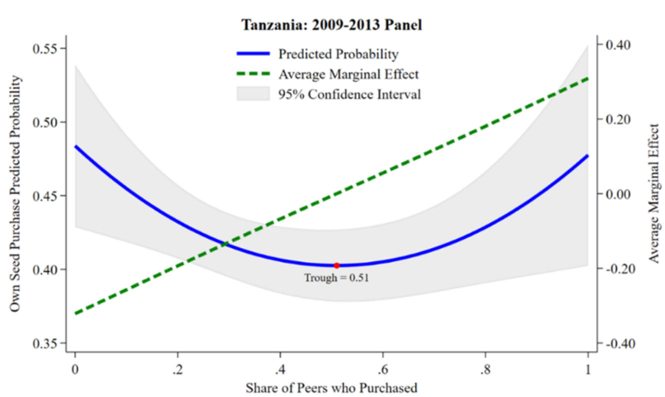


Figure 3. CRE probit regression results of the effect of peer influence on pesticides market participation.



The analysis reveals that peer effects on smallholder input adoption are nonlinear, threshold-dependent, and highly heterogeneous, both across countries and within countries by input type. In most settings, participation initially rises with peers but peaks at intermediate levels of community participation before declining—forming an inverted U-shape. However, the exact turning point and shape of this relationship vary widely. For example, in Tanzania (Figure 4), peer effects on seed adoption follow a U-shape, while fertilizer and pesticide adoption show clear inverted U-patterns (Figure 5) with different peak points across periods. Similarly, in Uganda, peer influence on seed purchases peaks around 51% peer participation, whereas for pesticides the peak occurs much earlier, at just 19%. These patterns suggest that even within the same country, different inputs generate distinct social dynamics, possibly reflecting variation in observability, risk, learning costs, or complementarities.

Figure 4. Nonlinear peer influence on improved seed market participation in Tanzania.



Cross-country comparisons further underscore the diversity of peer learning environments. In Ethiopia, adoption probabilities for fertilizers and pesticides increase almost monotonically, yet the marginal effect of peer adoption declines beyond relatively low thresholds, indicating early saturation. In contrast, Ghana and Nigeria show strong initial peer effects that taper off more sharply. These findings are consistent with social learning models that predict diminishing returns to peer influence but add nuance by showing that these dynamics are not uniform across technologies or locations. Overall, the results highlight the need for input-specific, context-sensitive strategies when designing interventions to leverage peer networks, with particular attention to saturation points and the social diffusion characteristics of each input.

Overall, the findings reinforce that peer effects are an important but context-dependent driver of smallholder market behavior, supporting the idea that policies aimed at accelerating input adoption should be tailored to local social environments and leverage credible peer networks where they exist.

Peer influence effects on output commercialization

While localized studies have explored peer influence on input adoption, evidence on herd effects in output commer- cialization remains scarce. This subsection examines the extent to which peer dynamics shape smallholder decisions to engage in output markets. The results are presented in Tables A5-A7 as well as Figures 6-8. We find positive and significant peer effects in Ghana, Ethiopia, and Malawi across all commercialization indicators. For instance, in Ethiopia, a 10 percentage point increase in the proportion of peers who sell their output is associated with an increase of approximately $87 in the value of sales and approximately 6 percentage points rise in the share of output sold. Ghana and Malawi show similarly strong patterns. These results suggest that social interactions shape not only input uptake but also downstream market engagement, possibly by reducing uncertainty about marketing channels, improving bargaining confidence, or enabling bulk sales through informal coordination.

The effects, however, are highly heterogeneous across space and time. In Tanzania, Uganda, and Nigeria, peer effects on commercialization are weaker, insignificant, or even negative in some years and outcomes. For example, the Nigerian 2019 cross-section reveals a negative relationship between peer sales and own market participation, contrasting with earlier panel evidence. These mixed results suggest that the influence of peers on commercialization could be contingent on market structure and temporal shifts in institutional conditions. The divergence across countries and periods highlights that peer effects are not automatic but may be dependent on complementary factors such as aggregation services, trader presence, or cooperative activity. Together, these findings underscore the importance of context-sensitive peer-based interventions that extend beyond input diffusion and consider the full agricultural value chain, particularly in settings where social spillovers may enable or constrain commercialization. Notably, peer influence is generally stronger on the intensive margin, indicating that social dynamics are particularly important for determining how much farmers commercialize, not just whether they participate.

Figure 5. Nonlinear peer influence on improved fertilizer and pesticide market participation in Tanzania, using two sets of panels.

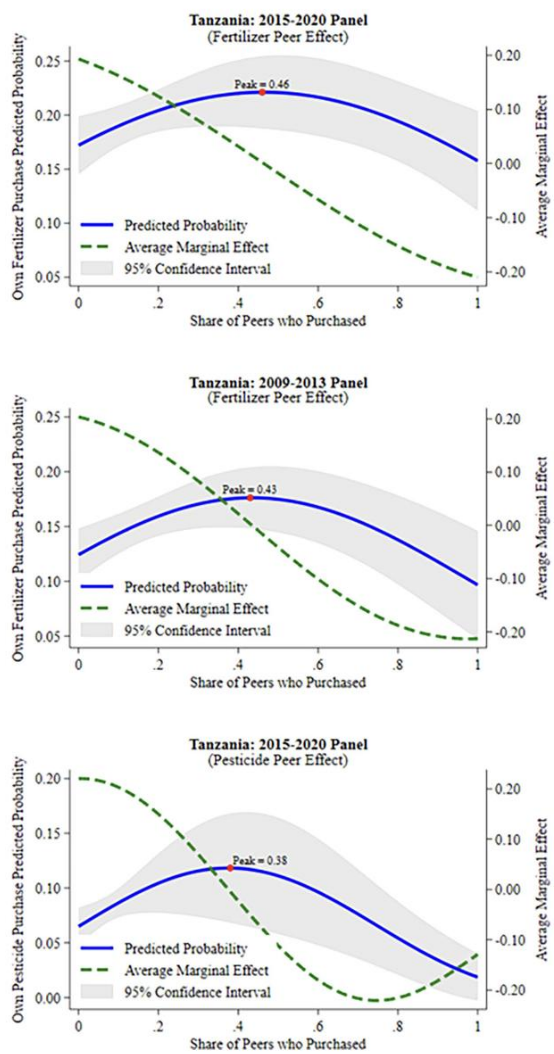


Figure 9 and Figures A2-A6 (Appendix) reveal nonlinear relationships between peer commercialization and individual commercialization outcomes. Across the six Sub-Saharan African countries, we find robust evidence that peer effects on smallholder commercialization are nonlinear, temporally dynamic, and highly context-specific. In Ghana, Ethiopia, Malawi, and Nigeria (2011–2016), peer influence follows a clear inverted U-shape: own market participation, sales value, or share of output sold increases sharply as peers begin to commercialize, but marginal peer effects peak at relatively low thresholds (between 20% and 35%) and decline thereafter—often turning negative. This suggests that peer learning and coordination benefits are strongest at early diffusion stages, but saturation, competition, or trader constraints quickly limit further gains as peer commercialization intensifies. In contrast, Nigeria (2019), Tanzania, and Uganda exhibit U-shaped relationships, where moderate peer commercialization is associated with lower own commercialization, but strong peer engagement (>50%) ultimately increases individual participation. This may reflect a shift in the underlying social dynamics: from crowding or uncertainty at intermediate levels to critical-mass-driven coordination as more peers engage. The contrast between Nigeria's earlier inverted U-shape and later U-shape underscores that peer effects evolve over time, depending on the maturity of market linkages, availability of buyers, and aggregation infrastructure. These findings extend the social diffusion literature beyond input adoption, showing that commercialization behavior is also socially mediated—but in complex, nonlinear ways. They highlight the importance of designing threshold-sensitive interventions: peer-based promotion strategies may be highly effective during early diffusion but require complementary market coordination once saturation approaches. Timing, targeting, and the nature of peer spillovers thus matter greatly for sustaining commercialization gains at scale.

Figure 6. Regression results of the effect of peer influence on output market participation.

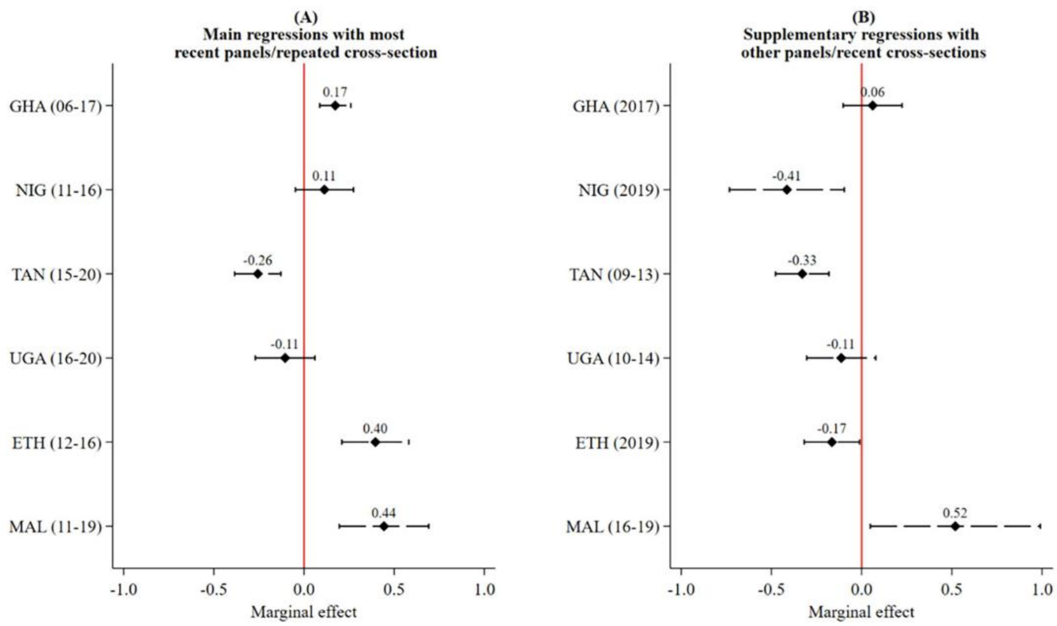
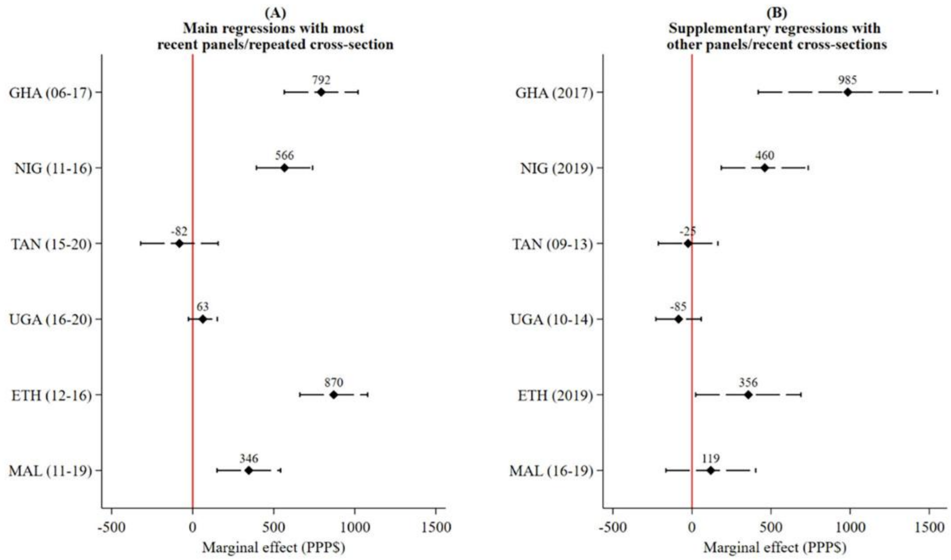


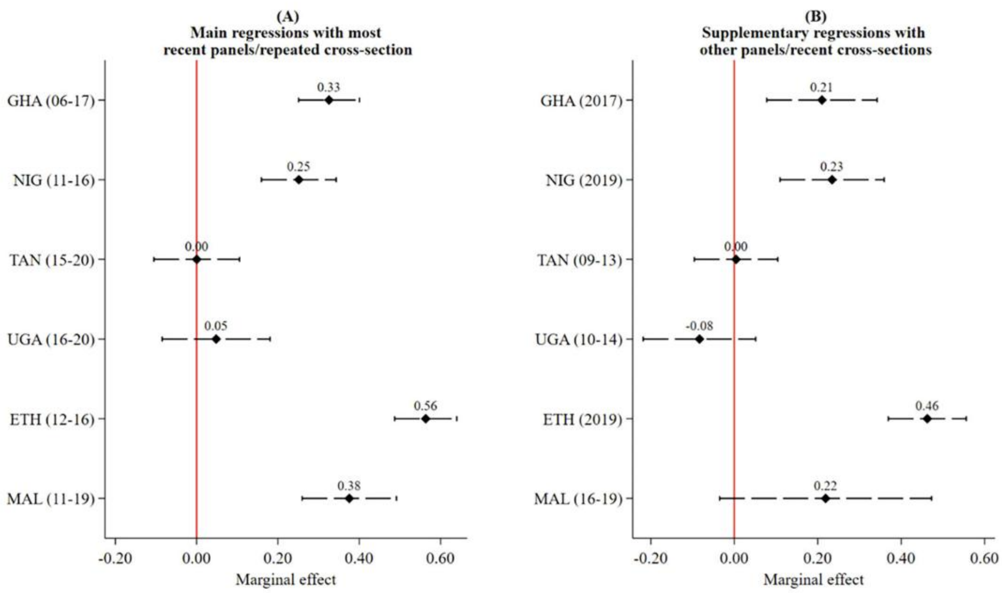
Figure 7. Regression results of the effect of peer influence on value of harvest sold.



3.3 Heterogeneity analysis

To deepen our understanding of how social learning operates in smallholder commercialization, we examine whether peer effects are moderated by key household and community characteristics. Specifically, we assess whether the strength or direction of peer influence varies systematically across observable dimensions that shape farmers' access to information, resources, and markets. Our working hypothesis is that peer effects are not uniform but contingent on the context in which farmers make production and marketing decisions. We expect stronger peer influence among farmers cultivating similar crop types, operating smaller farms where learning externalities are more salient, or residing in communities with better infrastructure that facilitates information exchange and market access. Likewise, the presence of state-led input supply or output procurement programs may amplify or dampen peer effects depending on how such interventions interact with private networks. Socio-demographic factors such as the gender and education of the household head, the size and composition of peer groups, agroecological zone, and survey period may also condition behavioral responses to peer behavior. Results from these heterogeneity analyses are presented graphically in the appendix (Figures A7–A43).

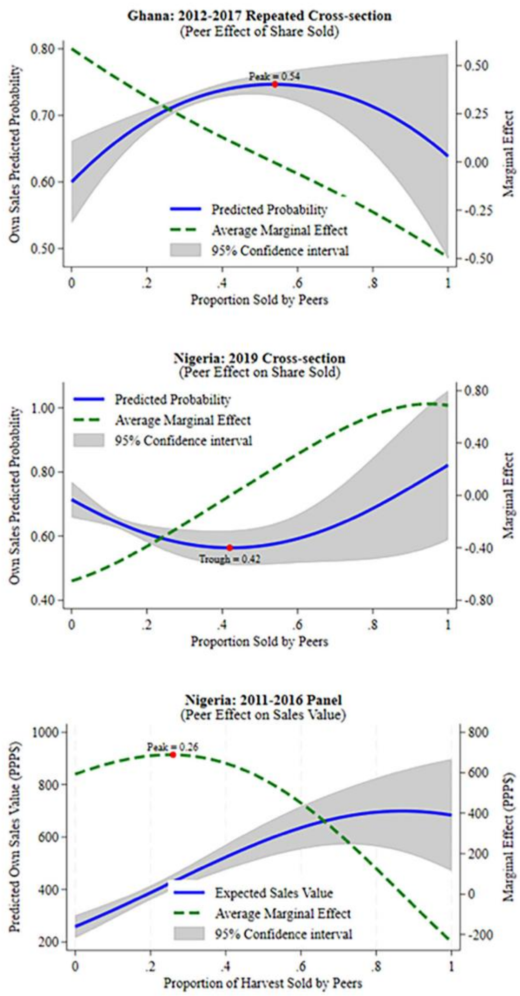
Figure 8. Regression results of the effect of peer influence on share of harvest sold.



First Peer effects on market participation exhibit strong heterogeneity by literacy status (Figs. A7–A8). In Uganda (Fig. A7 Panels A & B), illiterate farmers consistently display higher fertilizer market participation than literates, with the gap widening as peer participation rises, indicating stronger social learning among the less educated. In Ghana (Fig. A7 Panels C & D), literates have an initial advantage in pesticide participation at low peer engagement, but this narrows and reverses as peer effects intensify, suggesting that peer networks can offset literacy-related information gaps. Ethiopia (Fig. A7 Panels E & F) shows a non-linear pattern, with literates leading at intermediate peer levels but with weaker differences at low and high engagement. For output markets, Ethiopia alone shows literacy heterogeneity: during 2012– 2016 (Fig. A8), literates sold more crops and a larger share of harvest, but by 2019, illiterates surpassed them at higher peer levels. This reversal implies that strong peer networks can compensate for literacy disadvantages, facilitating knowledge diffusion and collective market access among less-educated farmers.

Second, we analyzed peer effects by gender and found several cases of heterogeneity. For input commercialization, peer effects on fertilizer market participation exhibit notable gender heterogeneity across countries (Figs. A9 & A10). In Ghana, peer participation raises fertilizer market participation for both male- and female-headed households, but the marginal effects reveal that the gap widens in favor of males—albeit at a decelerating rate—as peer engagement intensifies (Fig. A9, Panels A & B). By contrast, in Uganda, female participation declines as peer participation increases, while male participation rises, leading to widening gender disparities that peer networks appear to exacerbate rather than bridge (Fig. A9, Panels C & D). In Ethiopia (Fig. A10, Panels A & B), female-headed households have an initial participation advantage in seed markets at low peer participation levels, but this advantage diminishes and eventually reverses in favor of male-headed households as peer participation grows, although this reversal is not statistically significant. Conversely, in Nigeria (Panels C & D), female-headed households begin with lower pesticide participation rates at low peer levels but experience relatively larger gains as peer participation rises, with marginal effects turning positive for females at higher peer participation levels, again insignificantly. Overall, these patterns suggest that peer networks can either narrow or widen gender gaps depending on country, structural and cultural contexts. In some settings, persistent structural barriers may limit women's ability to respond to peer-driven adoption signals, while entrenched social norms that centralize decision-making in men's hands may prevent women from fully benefiting from peer influence, especially where input acquisition involves substantial financial commitments or formal transactions.

Figure 9. Nonlinear effect of peers output market participation intensity on own intensity in Ethiopia.



Output commercialization exhibits notable gender heterogeneities across countries. In Ghana, female-headed households follow an inverted U-shape with peer commercialization—initially lagging behind males, gaining a significant advantage at mid-levels, but being overtaken again at higher levels (Fig. A11). In Tanzania, males quickly surpass females as peer commercialization rises, with the gap widening and becoming significant, while in Nigeria, male-headed households consistently achieve higher crop sales, and the gap widens sharply with stronger peer effects as female sales remain largely unresponsive (Fig. A12). In Ethiopia, female sales increase steadily with peer commercialization while male sales peak and then decline, but wide confidence intervals imply no significant female advantage, and females are significantly behind at moderate peer levels (Fig. A12). These patterns suggest that peer networks amplify male advantages in Nigeria but help narrow gender gaps in Ethiopia, albeit without conclusive female dominance. In Tanzania, gender disparities in the share of output sold widened during 2009–2013 but have since disappeared, indicating a more uniform peer influence over time (Fig. A13).

The strength and nature of peer effects can depend on the scale of the peer network. For instance, larger peer groups may amplify social learning, information sharing, and normative pressures, leading to stronger behavioral changes. Therefore, we next examine effect heterogeneity by peer group size. For input market participation, we find evidence of some heterogeneity by group size in Ghana and Nigeria (Fig. A14), but not the other countries. Fig. A14 shows that peer effects on input market participation generally strengthen with larger peer group sizes. In Ghana, this trend is clear across seeds, fertilizer, and pesticides, while in Nigeria, the effect is weaker and less pronounced. Similarly, Fig. A15 shows that in Nigeria and Ethiopia (Panels A & B), peer effects on the value of sales transition from being statistically insignificant at smaller group sizes to significantly positive as peer groups expand, highlighting stronger commercialization gains in larger networks. In Malawi (Panel D), the effect on the proportion sold is initially insignificant but becomes positive and significant with larger peer groups. Conversely, in Uganda (Panel C), peer effects on the proportion sold are significantly positive at smaller group sizes but fade and turn insignificant as peer groups grow, indicating diminishing influence in larger peer networks.

We examine how peer effects vary by crop specialization first for input market participation and second for output commercialization. Fig. A16 shows that in Ghana's seed markets, non-producers (NP) consistently have higher participation rates than tree crop producers (P), with the gap widening as peer participation rises. Producers exhibit an inverted U-shaped response, peaking at mid-levels before declining. In Malawi, producer participation declines with peer engagement, while non-producers remain steady, creating a widening, significant gap in favor of non-producers. Fig. A17 shows a similar pattern for fertilizer in Ghana, where non-producers outperform producers, particularly at high peer levels. In Ethiopia, non-producers dominate at low peer participation, but producers benefit more as peer effects strengthen, narrowing the gap, although this advantage is not statistically significant. Fig. A18 indicates that non- producers of oilseeds in Ghana have higher participation at low peer levels, but producers catch up and surpass them as peer engagement grows—significantly so for pesticides but not fertilizer. Fig. A19 highlights that fruit and vegetable producers in Ghana outperform non-producers, with the gap widening and becoming significant at higher peer levels, while in Malawi, peer effects diverge: non-producer participation rises, whereas producer participation falls. Finally, Fig. A20 shows that industrial crop producers benefit more from peer effects, especially in Tanzania and Malawi's fertilizer markets where their participation rises monotonically, unlike non-producers who exhibit an inverted U-shaped response.

In Ghana, Nigeria, and Ethiopia (Fig. A21), tree crop producers consistently achieve higher commercialization intensity than non-producers, with the gap widening as peer commercialization rises. A similar pattern holds for output market participation in Ghana (Fig. A22, Panels A & B), while in Ethiopia (Fig. A22, Panels C & D), producer sales follow an inverted U-shape, peaking at moderate peer levels before declining; the marginal effects indicate a significant producer advantage at mid-range peer levels. In Malawi, peer effects amplify commercialization for industrial crop producers (Fig. A23, Panels A & B), oilseed producers (Figs. A24 & A25, Panels C & D), and fruit and vegetable producers (Fig. A27, Panels C & D), whereas in Ethiopia's latest cross-section (Fig. A23, Panels C & D), producer advantages disappear as peer commercialization strengthens. For fruits and vegetables, Ghana and Uganda show relative disadvan- tages for producers in commercialization intensity and market participation, respectively (Fig. A26). These findings suggest that peer effects can amplify existing commercialization advantages for certain crop producers (e.g., industrial crops and oilseeds), but may not benefit all groups equally. Peer-based interventions may thus require crop-specific tailoring, especially to support lagging groups such as fruit and vegetable producers, and to maximize the positive spillovers of peer networks.

Finally, we examine heterogeneous peer effects on input market participation and output commercialization measures across survey years (Figs. A28–A43). The results tell the following overall story. Peer effects on both input market participation and output commercialization exhibit notable variation across survey years, reflecting shifts in market dynamics and policy environments. In some countries (e.g., Uganda and Nigeria), peer influence on input adoption (such as seeds or fertilizer) has strengthened over time, indicating that social learning and network effects have become more pronounced as markets mature. Conversely, in countries like Ethiopia and Malawi, peer effects on input use have either weakened or shifted, suggesting that formal market mechanisms and institutional interventions may have reduced reliance on peer-driven adoption.

For output commercialization, temporal patterns show that in Ghana and Nigeria, peer effects on both participation and sales were stronger in earlier survey years but have attenuated in later years, possibly due to expanded trader networks and improved infrastructure that reduce dependence on peer influence. In contrast, Ethiopia and Malawi display mixed temporal dynamics: in some cases, peer effects on commercialization have intensified (e.g., value of sales in certain years), while in others, the impact has plateaued, indicating a potential saturation of peer-driven spillovers. Overall, these findings suggest that peer effects are not static; they evolve with market development, infrastructure improvements, and policy interventions. This highlights the importance of considering time-varying peer dynamics when designing interventions that leverage social networks for input adoption and commercialization.

CONCLUSION AND IMPLICATIONS

This paper uses multi-country nationally representative panel data to provide new evidence on the roles of peer influence in driving smallholder commercialization. The paper specifically examines if, how and in which contexts peer behaviors shapes smallholder decisions to adopt inputs and commercialize outputs? The use of a harmonized set of indicators across multiple countries in sub-Saharan Africa allows us to offer broader insights into the generalizability of social learning mechanisms and their heterogeneous effects on commercialization both on the input and output sides of the market. By distinguishing between the extensive and intensive margins of market participation, the paper breaks grounds and provides insights into whether peer behavior primarily facilitates the diffusion of commercialization decisions or also deepens the degree of engagement among participating farmers.

We find strong evidence of peer influence in shaping input adoption. In countries such as Ghana, Nigeria, and Ethiopia, higher rates of peer input use significantly raise individual adoption probabilities, underscoring the importance of social learning and information diffusion in technology uptake. However, the absence or reversal of peer effects in countries like Tanzania, Malawi, and Uganda illustrates that these dynamics are context-specific and can be influenced by trust, information asymmetries, or risk perceptions. We extend the analysis to examine peer influence on output commercialization and find that peer effects are particularly pronounced for commercialization intensity. Yet this relationship is nonlinear: peer influence tends to diminish or even reverse at higher levels of local commercialization, likely due to market congestion, increased competition for buyers, or price suppression.

These findings carry important policy implications. Peer influence offers a valuable, scalable mechanism for encouraging market participation. Extension strategies that work through lead farmers, group-based learning models, or community-based demonstrations can leverage social spillovers to stimulate adoption. However, the heterogeneity and nonlinearity of peer effects highlight the importance of tailoring these interventions to local conditions. In areas with low commercialization, peer effects can be catalytic. In more saturated markets, however, rising peer engagement may lead to crowding-out effects or price competition. In such settings, it becomes critical to complement social learning interventions with investments that expand market access, attract new buyers, and improve aggregation, transport, and storage infrastructure.

The subgroup analyses show that peer influence on smallholder input and output commercialization are highly context- specific and shaped by structural, institutional, and household-level factors. In particular, peer effects exhibit complexity, with heterogeneity by literacy, gender, crop specialization, and peer group size. Peer networks enhance market participation and commercialization by facilitating information diffusion, social learning, and collective behavior. However, these effects are not uniform: literacy-based gaps may narrow or reverse depending on peer engagement, and gender disparities are often exacerbated by cultural norms that limit women's ability to capitalize on peer signals, especially in input markets. Peer effects also amplify existing commercialization advantages for certain crops (e.g., industrial crops and oilseeds) while leaving others (e.g., fruit and vegetable producers) at a relative disadvantage. Moreover, peer effects strengthen with larger group sizes in some contexts but weaken in others, reflecting the balance between social learning and free-riding within networks.

In conclusion, peer effects emerge as a powerful yet context-dependent channel for accelerating smallholder commercialization. Social learning can amplify the diffusion of market participation, but its potency varies with structural and institutional conditions. The heterogeneity analyses highlight that peer influence is not self-propelling: it interacts with constraints such as gender gaps, literacy, infrastructure, and program design. Harnessing this mechanism therefore requires interventions that are targeted and locally adaptive—leveraging trusted networks, farmer associations, and inclusive communication platforms to reach marginalized groups. As agricultural systems evolve, dynamic and time- sensitive strategies become critical, since the marginal returns to peer influence may attenuate once commercialization norms take hold.

Software/code

Fuica Barrios, A. A. (2025). Replication Data for INCATA Working Document: Social Learning and Peer Influence in Smallholder Commercialization (Version V1) [Data set]. Harvard Dataverse. https://doi.org/10.7910/DVN/SSIKK0

This project contains the following replication code:

- **Question2.do:** Stata script to construct variables, estimate all econometric models, and reproduce the main tables and figures.

Ethical approval

This study does not involve human participants. All analyses are based solely on secondary, de-identified data obtained from the World Bank (LSMS-ISA initiative) and Ghana's Living Standards Survey. As no primary data was collected and no individual participants were contacted or identifiable, formal ethical approval and informed consent were not required.

Data and software availability

Underlying data
Repository: "Replication Data for INCATA Working Document: Social Learning and Peer Influence in Smallholder Commercialization". Harvard Dataverse. https://doi.org/10.7910/DVN/SSIKK0

This project contains the following underlying data:

- **EthPanel.dta:** Country-level panel data for Ethiopia used in all econometric analyses.
- **MalPanel.dta:** Country-level panel data for Malawi used in all econometric analyses.
- **TanPanel.dta:** Country-level panel data for Tanzania used in all econometric analyses.
- **UgaPanel.dta:** Country-level panel data for Uganda used in all econometric analyses.
- **NigPanel.dta:** Country-level panel data for Nigeria used in all econometric analyses.
- **GhaData.dta:** Country-level cross-section data for Ghana used in all econometric analyses.

Data are available under the terms of the Creative Commons Zero "No rights reserved" data waiver (CC0 1.0 Public Domain Dedication).

Extended data

Fuica Barrios, A. A. (2025). Replication Data for INCATA Working Document: Social Learning and Peer Influence in Smallholder Commercialization (Version V1) [Data set]. Harvard Dataverse. https://doi.org/10.7910/DVN/SSIKK0

File name: Annex_Tables_EXTDATA_PeerInfluence.docx. DOI: https://doi.org/10.7910/DVN/SSIKK0 License: CC0 1.0.

Extended data include:

- **Table A1.** Descriptive summary statistics for first and last rounds of data collection for Ghana, Nigeria, Tanzania, Uganda, Ethiopia and Malawi (household commercialization, peer behavior, input use, assets, income sources and local market access).
- **Table A2.** Peer effect on own seed market participation (Correlated Random Effects regressions by country and period).
- **Table A3.** Peer effect on own fertilizer market participation (Correlated Random Effects regressions by country and period).
- **Table A4.** Peer effect on own pesticides market participation (Correlated Random Effects regressions by country and period).
- **Table A5.** Peer effect on own market participation (first hurdle of Cragg hurdle model for binary participation, by country and period).
- **Table A6.** Peer effect on own value of sales in constant 2021 PPP dollars (second hurdle of Cragg hurdle model, by country and period).
- **Table A7.** Peer effect on own share of output sold (Correlated Random Effects Fractions Probit regressions, by country and period).
- **Figures A1–A6.** Nonlinear peer influence on improved seed, fertilizer and pesticide use and on output market participation and commercialization outcomes in selected countries (Ghana, Uganda, Ethiopia, Tanzania and Malawi).
- **Figures A7–A27.** Heterogeneous peer effects on input market participation and output commercialization by household literacy status, sex of farm household head and crop specialization (tree crops, oilseeds, fruits and vegetables, industrial crops) across countries.

- **Figures A28–A43.** Heterogeneous peer effects on input and output market outcomes across survey years (panel decompositions of predicted probabilities, value of sales and share of output sold; and marginal effects of later survey waves relative to baseline years) for Ghana, Nigeria, Tanzania, Uganda, Ethiopia and Malawi.

Acknowledgments

This document is part of the INCATA: Linked Farms and Enterprises for Inclusive Agricultural Transformation in Africa and Asia project. Special thanks are extended to colleagues from the INCATA partner institutions, including Benjamin Belton and Sudha Narayanan (IFPRI South Asia), Lilian Kirimi (Tegemeo Institute at Egerton University), Carolina Trivelli, Andrés Fuica and Mauricio Espinoza (RIMISP – Latin American Center for Rural Development), and MingDa Li, and Aditi Gautam (Michigan State University) for their generous collaboration on the methodology and review of this work.

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