IFPRI Discussion Paper 02435

August 2026

Market Intelligence, Entrepreneurial Behavior, and Profitability in Agriculture

Evidence from a Randomized Controlled Trial in Northern Uganda

Hiroyuki Takeshima

Eduardo Maruyama

Futoshi Yamauchi

Agrifood Innovation and Resilience Unit

Markets, Trade, and Institutions Unit

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

AUTHORS

Hiroyuki Takeshima (H.Takeshima@cgiar.org) is a Senior Research Fellow in the Agrifood Innovation and Resilience (AIR) Unit of the International Food Policy Research Institute (IFPRI), Washington, DC.

Eduardo Maruyama (E.Maruyama@cgiar.org) is a Research Coordinator in IFPRI's Markets, Trade, and Institutions (MTI) Unit, Lima, Peru.

Futoshi Yamauchi (F.Yamauchi@cgiar.org) is a Senior Research Fellow in IFPRI's MTI Unit, Washington, DC.

Notices

Abstract

Smallholder farmers often make production decisions with limited information about market conditions, leading to suboptimal farm profits. This challenge is particularly important in the production of fruits and vegetables, which are often rich in micronutrients and can serve as high-value cash crops but are also highly perishable. We evaluate a bundled, market-oriented horticulture intervention in northern Uganda designed to shift farmers' mindset from "grow and sell" to "grow to sell", by promoting their engagement in active market intelligence activities, in addition to support for production. Using a cluster-randomized design combined with panel data methods, we find that treated farmers increased production revenues by 20–25%, profit margins by about 11 percentage points, and prices received by roughly 20%, without increasing family labor use. These gains are accompanied by noticeable behavioral changes, including more frequent and more diverse collection of price information and expanded buyer networks. Mediation analysis indicates that improvements in market intelligence explain a meaningful share of these effects. The results suggest that interventions that strengthen farmers' ability to align production decisions with market demand can generate substantial income gains. These findings highlight the importance of integrating market intelligence into agricultural extension systems.

Keywords: Market-oriented extension; market intelligence; difference-in-differences; inverse probability weighting; causal mediation; spillovers.

Acknowledgments

This work was funded by the Government of Japan and conducted as part of the CGIAR Rethinking Food Markets Initiative and the CGIAR Science Program on Better Diets and Nutrition (BDN), both led by the International Food Policy Research Institute (IFPRI). The authors thank the farmers who participated in the study, as well as the field teams and partner organizations whose contributions made this research possible, particularly the Sasakawa Africa Association for its support in implementing the intervention.

1 Introduction

Smallholder farmers in developing countries often make production decisions with limited information about market conditions. This disconnect between production and markets can lead to inefficiencies, including producing crops that are poorly aligned with demand, selling in suboptimal markets, or mistiming sales (Fafchamps & Hill, 2005; Stephens & Barrett, 2011). These challenges are particularly pronounced for perishable, high-value crops such as horticultural products, where prices vary substantially across locations and over time (Aung & Chang, 2014; Li et al., 2019). In such contexts, access to timely and relevant market information can play a critical role in improving farm profitability, particularly as agricultural development increasingly depends on stronger market integration and commercialization (World Bank, 2008).

Despite this, agricultural extension systems have traditionally focused on improving on-farm production practices—such as input use, crop management, and yields—while placing less emphasis on helping farmers understand and respond to market dynamics (Benin et al., 2011; Davis et al., 2020). As smallholders become increasingly integrated into local and regional value chains (Carletto et al., 2017; Christiaensen, 2017), the ability to make informed marketing decisions—what to produce, when to sell, and where to sell—becomes an essential component of agricultural productivity and income generation. A growing body of evidence suggests that reducing information asymmetries between farmers and traders can improve market outcomes, including prices received and market participation (Goyal, 2010; Mitra et al., 2018).

This paper evaluates a bundled, market-oriented horticulture intervention in northern Uganda designed to address this gap. In addition to general components that support production increase, the intervention aimed to shift farmers' behavior from "grow and sell" to "grow to sell" by encouraging active market intelligence—specifically, the systematic collection and use of information on prices, demand, and market conditions to inform production decisions. Unlike many information interventions that primarily improve marketing outcomes ex post (Goyal, 2010; Mitra et al., 2018), this approach targets decisions made ex ante, including crop choice, production timing, and market selection. The intervention was implemented through a cluster-randomized design at the farmer-group level in Adjumani district, a refugee-hosting region characterized by high poverty and rapidly evolving local markets (AGRA, 2020).

We find that the intervention led to substantial improvements in economic outcomes. Treated farmers increased production revenues by approximately 20–25%, profit margins by about 10 percentage points, and prices received by around 20%. Importantly, these gains were achieved without significant increases in family labor use, suggesting improvements in allocative efficiency rather than input intensification. Consistent with this interpretation, treated farmers were more likely to shift into vegetable production and to adjust their marketing strategies, indicating that improved market intelligence affected production decisions as well as sales outcomes. These findings are in line with evidence that reducing information frictions can improve market performance (Goyal, 2010; Mitra et al., 2018), while extending this literature by showing effects on production choices.

To better understand the specific roles of market intelligence component in generating these overall effects, we conduct causal mediation analysis following Imai et al. (2010, 2011). The results indicate that market intelligence activities—capturing the collection of price information from multiple sources, commodities, and markets—explain a meaningful share of the observed improvements in production and profitability outcomes. This finding highlights the importance of behavioral change as a key pathway through which the intervention operates, consistent with broader evidence on the role of information and learning in agricultural decision-making (Davis et al., 2020).

This study contributes to the literature in three main ways. First, it provides experimental evidence that improving access to and use of market information can influence production decisions—not only marketing behavior—thereby affecting both productivity and profitability. While previous studies have shown that reducing information asymmetries can improve prices received and market participation (Goyal, 2010; Mitra et al., 2018), we show that market intelligence can also reshape production choices. Second, the paper identifies market intelligence as a key mechanism linking behavioral change to economic outcomes, contributing to the literature on information frictions in agricultural markets (Fafchamps & Hill, 2005; Stephens & Barrett, 2011). Third, it shows that relatively low-cost, behaviorally oriented interventions can generate large income gains without requiring substantial increases in inputs, complementing existing evidence on agricultural extension systems (Benin et al., 2011; Davis et al., 2020).

The remainder of the paper is structured as follows. Section 2 describes the intervention and study context. Section 3 outlines the empirical strategy. Section 4 presents the data and descriptive statistics. Section 5 discusses the main results, including mediation and spillover analyses. Section 6 concludes with policy implications.

2 Intervention and study context

2.1 Study context

The study was conducted in Adjumani district in northern Uganda, a region characterized by high levels of poverty and a large population of refugees, primarily from South Sudan and the Democratic Republic of Congo. The location of the study area is shown in Figure 1, while the spatial distribution of treatment and control farmer groups is presented in Figure 2.[1] Agriculture is the main livelihood activity for both host communities and refugees, with smallholder farmers producing a mix of staple and horticultural crops.

In recent years, increasing market integration and the growth of local trading centers have created new opportunities for commercialization, particularly for high-value and perishable products such as vegetables (AGRA, 2020). At the same time, farmers in the region face substantial constraints in accessing reliable market information. Prices for horticultural products vary considerably across markets and seasons (Table 1), reflecting both perishability and limited market integration (Aung & Chang, 2014; Li et al., 2019). Traders and intermediaries often possess better information than producers, contributing to persistent information asymmetries in agricultural markets (Fafchamps & Hill, 2005).

Baseline data further highlight the economic context in which farmers operate. Households are typically smallholders with relatively low levels of income and asset ownership (Table 2 and Table ***3***), generating modest agricultural revenues (Table 4). Behavioral indicators also suggest limited engagement with market information prior to the intervention, with only a fraction of farmers collecting price information from multiple sources or markets (Table 5). These features make the region a relevant setting to evaluate interventions aimed at improving farmers' ability to engage with markets.

2.2 Intervention design

The intervention was designed to promote a shift in farmers' behavior from "grow and sell" to "grow to sell" by strengthening their capacity to collect and use market information. Implemented by the Sasakawa Africa Association, the program builds on principles similar to

[1]These *farmer groups* are standard organizations in Uganda, that had already existed in each village prior to the intervention.

those of the Smallholder Horticulture Empowerment and Promotion (SHEP) approach developed by the Japan International Cooperation Agency, which emphasizes linking production decisions to market demand (Sayanagi & Aikawa, 2016).

A central component of the intervention was participatory market engagement. Farmer group representatives were supported to visit local markets, interact directly with traders and wholesalers, and gather information on prices, demand patterns, quality requirements, and seasonal variations for key horticultural products. These activities aimed to reduce information asymmetries between farmers and market actors and to encourage farmers to incorporate market signals into their production decisions. Based on these market surveys, farmer groups were guided in selecting crops with stronger demand and commercial potential.

The intervention also included complementary agronomic training to support the production of selected crops. Through farmer learning platforms, participants received training on improved practices such as land preparation, input use, seedling management, and post-harvest handling. These activities were intended to ensure that farmers could respond effectively to market opportunities identified through the market engagement component, consistent with evidence that combining knowledge and market access can enhance agricultural outcomes (Davis et al., 2020).

Finally, the program provided limited supporting technologies and equipment, including access to small-scale irrigation systems and tools for storage and transportation. While these inputs facilitated production and marketing, they were not the primary focus of the intervention. Instead, the core objective was to change how farmers make decisions by integrating market intelligence into their production strategies.

2.3 Targeting and implementation

The intervention was implemented at the farmer-group level using a cluster-randomized design. In Adjumani district, 80 farmer groups with at least 25 members were identified as active groups. Among these, 60 groups were randomly selected to receive the intervention, while 20 groups were assigned to the control group for evaluation purposes. The geographic distribution of these groups is illustrated in Figure 2.

Primary data for the evaluation were collected through baseline and endline surveys of 20 farmers per group, in 20 treatment groups selected from the 60 treatment groups and the entire sample of 20 control groups. The final sample consists of 800 farmers observed in both periods, with detailed information on production, sales, and market behavior collected at both the household and plot levels (Table 4). The data also include a range of household and plot characteristics used in the empirical analysis (Table 2 and Table ***3***).

Intervention activities took place between August 2021 and July 2022, covering both dry and wet agricultural seasons. This timing allowed farmers to apply newly acquired market and production knowledge across different seasonal conditions, which is particularly relevant given observed variation in rainfall between pre- and post-intervention periods (Table 6). Within each selected group, all members were eligible to participate in training and related activities.

3 Empirical strategy

3.1 Identification approach

To estimate the impact of the intervention, we exploit the cluster-randomized design combined with panel data collected before and after implementation. Treatment was assigned at the farmer-group level, while outcomes are observed at both the household and plot levels (Table

4). This setting allows us to estimate treatment effects using a difference-in-differences (DID) framework, comparing changes in outcomes over time between treated and control farmers.

We estimate the average treatment effect on the treated (ATT) using the following specification:

$$Y_{igt} = \alpha + \beta(T_g \times Post_t) + \gamma T_g + \delta Post_t + X'_{ig0}\theta + \varepsilon_{igt}$$

where Y_{igt} denotes the outcome of interest for farmer i in group g at time t, T_g is an indicator for whether group g was assigned to the intervention, and $Post_t$ is an indicator for the post-intervention period. The coefficient β captures the ATT.

Although treatment was randomly assigned, the relatively small number of clusters (40 farmer groups) raises the possibility of residual imbalance in finite samples. To improve estimation precision and account for potential differences in baseline characteristics, we combine DID with inverse probability weighting (IPW), following the class of DID propensity score estimators developed in the literature (Heckman et al., 1997, 1998; Smith & Todd, 2005; Takeshima et al., 2023).[2]

Specifically, each observation is weighted by the inverse of the estimated propensity score, defined as the probability of belonging to a treated farmer group conditional on baseline characteristics. These characteristics include household demographics, wealth indicators, farm characteristics, social networks, prior exposure to extension services, and agroclimatic conditions (Table 2 and Table ***3***). Weighting helps ensure comparability between treated and control groups and reduces bias arising from residual imbalance.

---

[2] The small number of clusters in our sample also complicates the application of other potential specifications, including the estimation of Intention-to-Treat (ITT) effect through the ANCOVA (Analysis of Covariance) specification, because the cluster-RCT with a small number of clusters can lead to finite-level violations of randomness (e.g., Hayes & Moulton 2009). Using cluster-RCT is still useful, because it facilitates the construction of comparable samples through IPW, which is more difficult even with IPW if treatment and control groups have very different characteristics.

Compared to matching estimators, the IPW approach is particularly suitable in this setting because it allows for straightforward estimation of standard errors that account for clustering at the farmer-group level (Moulton, 1990; Wooldridge, 2002). Given the relatively small number of clusters, adjusting standard errors for cluster-level correlation is essential for valid inference (Wooldridge, 2003). All standard errors reported in the paper are therefore clustered at the farmer-group level.

A more detailed description of the weighting procedure and estimation is provided in Appendix A.

3.2 Outcome variables

We focus on two broad categories of outcomes: (i) production and profitability, and (ii) behavioral indicators related to market intelligence.

Production outcomes include total production revenues and profit margins, measured at both the household and plot levels (Table 4). We also examine whether farmers engage in vegetable production, which serves as a proxy for a shift toward higher-value crops. In addition, we analyze sales prices received for major commodities among farmers observed in both periods (Table 1).

Behavioral outcomes capture farmers' engagement with market information and market actors. These include whether farmers collect price information from multiple sources, gather information on different commodities, and obtain price information from more than one market (Table 5). We also consider indicators of market engagement, such as visits to input suppliers and processors, the number of buyers known personally, and the number of markets in which farmers sell their products. Together, these variables capture the extent to which farmers adopt the market-oriented practices promoted by the intervention.

3.3 Causal mediation analysis

To examine the mechanisms underlying the observed treatment effects, we conduct causal mediation analysis following Imai et al. (2010, 2011). The objective is to assess the extent to which changes in market intelligence behavior mediate the impact of the intervention on production and profitability outcomes.

Let M_{igt} denote the mediator capturing market intelligence behavior. The mediation analysis is based on the following system of equations:

$$M_{igt} = \alpha_m + \beta_m(T_g \times Post_t) + \gamma_m T_g + \delta_m Post_t + X'_{ig0}\theta_m + u_{igt}$$

$$Y_{igt} = \alpha_y + \beta_y(T_g \times Post_t) + \phi M_{igt} + \gamma_y T_g + \delta_y Post_t + X'_{ig0}\theta_y + v_{igt}$$

where Y_{igt} is the outcome of interest and M_{igt} captures the mediator. The parameter ϕ reflects the relationship between market intelligence behavior and outcomes, conditional on treatment and other covariates.

By combining these equations, we decompose the total treatment effect into:

- a direct effect of the intervention, and
- an indirect effect operating through changes in market intelligence behavior.

The mediation analysis is implemented within a DID framework, which helps mitigate concerns about unobserved time-invariant confounders. Results are reported along with sensitivity analyses assessing the robustness of the mediation effects to potential violations of identification assumptions.

3.4 Spillover and local market effects

Finally, we examine whether the estimated treatment effects may be influenced by spillover effects on control farmers. In particular, the intervention could affect local input or output markets in ways that indirectly influence control groups—for example, through increased demand for inputs or changes in local prices.

To assess this possibility, we extend the DID-IPW framework by incorporating a measure of exposure to treatment based on geographic proximity, using a generalized propensity score (GPS) approach (Imbens, 2000; Cattaneo, 2010; Flores & Mitnik, 2013). Specifically, we estimate:

$$\Delta Y_{ig} = f\left(Distance_{ig}\right) + X'_{ig0}\theta + \varepsilon_{ig}$$

where ΔY_{ig} represents the change in outcomes for farmer i in group g, and $Distance_{ig}$ measures the distance to the nearest treated farmer group. The function $f(\cdot)$ is modeled flexibly using polynomial terms, allowing for non-linear relationships between proximity and outcomes.

Distances are calculated using geographic coordinates of farmer groups, as illustrated in Figure 2. The GPS approach adjusts for observable characteristics while estimating the relationship between proximity and outcomes. If negative spillovers were present, we would expect outcomes among control farmers to worsen as proximity to treated groups increases.

As discussed below, we find no evidence of negative spillover effects, supporting the interpretation that the estimated treatment effects reflect improvements among treated farmers rather than declines among control groups.

4 Data and descriptive statistics

4.1 Data and sample

The analysis is based on primary survey data collected from farmers in treatment and control groups before and after the intervention. The evaluation sample consists of 800 farmers—400 in treatment groups and 400 in control groups—randomly selected from farmer groups included in the study. Each farmer was surveyed in both the pre- and post-intervention periods, generating a balanced panel.

The data include detailed information on agricultural production, input use, sales, and prices, collected at both the household and plot levels. In total, information is available for 1,128 plots cultivated by sample farmers across the two survey rounds. These data are complemented by spatial agroclimatic variables, including rainfall, elevation, and soil characteristics.

4.2 Baseline characteristics and balance

Table 2 and Table ***3*** present summary statistics of key household- and plot-level characteristics at baseline. Overall, the sample consists of smallholder farmers with relatively limited asset holdings and modest access to financial services. Households typically cultivate multiple plots, with average farm sizes of around 4 hectares and plots located at some distance from the homestead.

Baseline differences between treatment and control groups are generally small, particularly after applying inverse probability weighting. The weighted statistics reported in Table 2 and Table ***3*** show that most observable characteristics are well balanced across groups, supporting the validity of the empirical strategy. These results are consistent with the balancing properties of the propensity score weighting approach discussed in Section 3.

4.3 Production and income patterns

Table 4 summarizes key production outcomes at both the household and plot levels. At baseline, farmers generate relatively low levels of agricultural income, with average annual production revenues ranging from approximately 1 to 2 million UGX at the household level. Profit margins are moderate, with a substantial share of revenues absorbed by production costs.

A notable feature of the data is the variation in outcomes over time. In particular, production revenues among control farmers decline in the post-intervention period, which coincides with lower rainfall levels relative to the baseline period (Table 6). This pattern highlights the importance of controlling for time effects when estimating treatment impacts and provides useful context for interpreting the difference-in-differences estimates.

4.4 Market behavior and price variation

Table 5 presents descriptive statistics on farmers' market-related behaviors. At baseline, a substantial share of farmers report collecting some price information, but relatively few engage in more advanced forms of market intelligence, such as gathering information from multiple sources or markets. Farmers typically interact with a limited number of buyers and sell their products in a small number of markets. These patterns are consistent with the presence of information frictions and limited market engagement.

Table 1 shows the distribution of sales prices for major commodities among farmers observed in both survey rounds. Prices exhibit considerable variation across crops and over time, particularly for horticultural products. This variation reflects both seasonality and spatial differences in market conditions and underscores the potential value of improved market intelligence for farmers' decision-making.

4.5 Summary

Taken together, the descriptive statistics highlight three key features of the study context. First, farmers operate in a low-income environment with limited assets and exposure to markets. Second, there is meaningful variation in production outcomes over time, partly driven by external factors such as rainfall. Third, baseline levels of market intelligence and engagement are relatively low, suggesting scope for interventions that improve access to and use of market information.

5 Results

5.1 Effects on production and profitability

Table 7 presents the estimated effects of the intervention on key production outcomes. The results indicate that the intervention led to substantial improvements in both revenues and profitability. The magnitude of these effects is large relative to many agricultural interventions, particularly given that the program did not rely on substantial transfers of inputs or capital.

At the plot level, treated farmers increased revenues by approximately 25%, while profit margins rose by about 16 percentage points. At the household level, total production revenues increased by around 20%, and profit margins increased by roughly 11 percentage points. These effects are economically meaningful relative to baseline income levels (Table 4), suggesting that the intervention generated sizable gains for participating farmers.

Importantly, these improvements are not driven by increased labor use. As shown in Table 7, there is no statistically significant effect on family labor input, indicating that the observed gains reflect higher productivity rather than input intensification. This finding is consistent with the interpretation that improved decision-making—rather than increased effort—underlies the observed changes in outcomes.

The intervention also led to a significant increase in the likelihood of vegetable production, with treated farmers being approximately 10–15 percentage points more likely to grow vegetables relative to the control group (Table 7). Given that vegetables are higher-value but more market-dependent crops, this shift is consistent with the objective of encouraging farmers to align production decisions with market opportunities and with evidence that diversification into horticulture can increase farm incomes (Weinberger & Lumpkin, 2007).

5.2 *Effects on market behavior*

Table 8 shows that the intervention led to significant changes in farmers' market-related behaviors. Treated farmers were more likely to collect price information from multiple sources and markets and to gather information on a broader set of commodities. These changes suggest that the intervention successfully increased farmers' engagement with market information.

The intervention also strengthened farmers' connections with market actors. Treated farmers reported interacting with a larger number of buyers and selling in more markets (Table 8), indicating expanded market participation. In addition, farmers were more likely to visit input suppliers and processors, suggesting broader engagement with the value chain.

These behavioral changes are large in magnitude. For example, the probability of collecting price information from multiple sources increases by over 15 percentage points, while the number of buyers known personally increases by approximately 0.26, or about 9% relative to the treatment-group baseline. Together, these results provide strong evidence that the intervention altered how farmers gather and use market information.

5.3 *Effects on sales prices*

Table 9 reports the effects of the intervention on prices received by farmers. The results indicate that treated farmers obtained higher prices for their products, with an overall increase of approximately 20% across crops. For vegetables and legumes, the increase is even larger, at around 30%.

Although the sample for this analysis is smaller—since it includes only farmers selling the same crops in both periods—the results are consistent with the broader pattern of improved market outcomes. Higher prices are likely driven by better market selection, improved timing of sales, and stronger bargaining positions resulting from enhanced market information.

5.4 Spillover and local market effects

Finally, Table 10 and Figure 3 examine whether the estimated treatment effects may be influenced by spillover effects on control farmers. In particular, we assess whether proximity to treated farmer groups is associated with changes in outcomes among control farmers.

The results show no evidence of negative spillover effects. Outcomes among control farmers do not systematically decline as proximity to treated groups increases. Instead, the relationship between distance and outcomes is weak and non-monotonic, as illustrated in Figure 3.

These findings suggest that the estimated treatment effects reflect genuine improvements among treated farmers rather than declines among control groups. The absence of heterogeneous price effects by distance suggests that spatial differences in market conditions within the study area did not substantially moderate the intervention's impact. This does not necessarily imply that farmers were well integrated into markets: as discussed earlier, many farmers initially had limited access to price information and buyer networks.

5.5 Mechanisms: the role of market intelligence

To assess the extent to which changes in market intelligence behavior explain these results, Table 11 presents the findings from the causal mediation analysis. The results indicate that a meaningful share of the intervention's impact on production and profitability operates through improvements in market intelligence.

Specifically, the mediator—capturing the collection of price information from multiple sources and markets—accounts for a non-trivial portion of the total treatment effect on both revenues and profit margins. At the household level, mediation effects explain approximately 15–20% of the total impact on key outcomes. These findings suggest that improved access to and use of market information is an important mechanism through which the intervention affects economic outcomes.

Sensitivity analyses reported in Table 11 indicate that these mediation effects are reasonably robust to potential violations of identification assumptions. Overall, the results provide evidence that behavioral changes in market engagement play a central role in driving the observed improvements in productivity and profitability.

6 Discussion

6.1 Why does market intelligence matter?

The results suggest that improving farmers' access to and use of market information can generate substantial gains in agricultural productivity and profitability. A key mechanism is the reduction of information asymmetries between farmers and market actors (Fafchamps & Hill, 2005). In the absence of reliable market information, farmers may produce crops that are poorly aligned with demand, sell in less favorable markets, or lack bargaining power when negotiating prices (Stephens & Barrett, 2011). By encouraging farmers to actively collect and use information on prices, demand, and market conditions, the intervention enables more informed decision-making across both production and marketing stages.

Importantly, the findings indicate that market intelligence affects decisions made ex ante, not only outcomes realized ex post. Rather than simply improving where or when farmers sell, the intervention leads farmers to adjust what they produce and how they engage with markets. The observed increase in vegetable production and higher prices received are consistent with farmers responding to more accurate and timely market signals, in line with evidence that reducing information frictions can improve market performance (Goyal, 2010; Mitra et al., 2018), while extending this literature to production decisions.

The results also highlight the importance of integrating production and marketing decisions. Rather than treating these as separate activities, the intervention promotes a more entrepreneurial approach in which farmers select crops, timing, and market outlets based on expected returns. This is particularly relevant in contexts characterized by spatial and temporal price variation, such as horticultural markets (Aung & Chang, 2014; Li et al., 2019).

6.2 Why are the effects large?

Taken together, the magnitude of the estimated impacts and the mediation results suggest that limited market intelligence is an important constraint on farmers' commercialization and profitability. However, the findings also indicate that other production and market constraints may remain important.

Two features of the context likely contribute to these large impacts. First, horticultural markets exhibit considerable price variation across space and time due to perishability and limited storage, creating significant returns to improved market information (Aung & Chang, 2014; Li et al., 2019). Second, baseline levels of market engagement and information use are relatively low (Table 5), implying substantial scope for behavioral change.

In such environments, even relatively simple interventions that facilitate access to and use of market information can generate large gains. Notably, these improvements occur without significant increases in family labor use, indicating that the intervention enhances allocative efficiency rather than input intensity. This distinction is important, as it suggests that income gains can be achieved without requiring additional resource constraints to be relaxed.

The magnitude of the effects is also notable relative to many agricultural interventions that rely on input provision or capital investments (Benin et al., 2011; Davis et al., 2020). By contrast, the intervention studied here primarily targets behavior and decision-making, highlighting the potential of low-cost, information-based approaches to improve agricultural outcomes.

6.3 Implications for agricultural extension systems

The results have important implications for the design of agricultural extension systems. Traditional extension approaches have largely focused on improving production practices, with less emphasis on helping farmers understand and respond to market conditions (Benin et al., 2011; Davis et al., 2020). The findings from this study suggest that incorporating market intelligence into extension services can substantially enhance their effectiveness, particularly in contexts where market access and price variability play a central role in determining farm incomes (World Bank, 2008).

A key feature of the intervention is its emphasis on experiential learning and direct engagement with market actors. Rather than passively receiving information, farmers actively interact with traders and markets, which may improve both the relevance of the information and their ability to interpret and apply it. This aligns with broader evidence that learning-by-doing and participatory approaches can strengthen the effectiveness of extension services (Davis et al., 2020).

Moreover, the intervention appears to be relatively low-cost and scalable, as it relies primarily on training and facilitation rather than large transfers of inputs or infrastructure. This suggests that similar approaches could be integrated into existing extension systems in other settings, particularly where markets are evolving rapidly and information constraints remain significant.

6.4 External validity and limitations

The external validity of these findings is likely to depend on key features of the context, particularly the degree of price dispersion and the baseline level of farmers' engagement with market information. Impacts are likely to be larger in settings where prices vary substantially across locations and over time, and where farmers have limited access to reliable market information. In more integrated markets, or where farmers are already well-informed, the marginal returns to additional market intelligence may be smaller.

The analysis focuses on short- to medium-term impacts, and longer-term effects may depend on the persistence of behavioral changes and the evolution of market conditions. For example, increased production of certain crops could eventually affect local prices if supply expands substantially, although we find no evidence of negative spillovers in the short run (Table 10 and Figure 3).

Finally, while the mediation analysis provides useful evidence on mechanisms, it relies on identifying assumptions that cannot be fully tested (Imai et al., 2010, 2011). Although sensitivity analyses suggest that the results are reasonably robust, these findings should be interpreted with appropriate caution.

6.5 Summary

Overall, the results indicate that improving farmers' ability to access and use market information can be a powerful lever for increasing agricultural incomes. By addressing information constraints and promoting more market-oriented decision-making, interventions of this type can complement traditional production-focused approaches and contribute to more efficient and profitable farming systems. These findings underscore the importance of integrating market intelligence into agricultural development strategies, particularly in settings characterized by high price variability and limited information flows.

7 Conclusion

This paper evaluates the impact of a bundled horticulture intervention which included a component that promotes the use of market intelligence to transform farmers' mindset from "grow and sell" to "grow to sell".[3] Using a cluster-randomized design combined with panel data methods, we find that the intervention led to substantial improvements in agricultural outcomes. Treated farmers increased production revenues by 20–25%, profit margins by approximately 10 percentage points, and the prices they received by around 20%.

These gains are accompanied by significant changes in behavior. Farmers exposed to the intervention were more likely to collect price information from multiple sources and markets, engage with a broader set of buyers, and participate more actively in output markets. Mediation analysis indicates that these changes in market intelligence account for a meaningful share of the observed impacts and can significantly complement the intervention components that focus on production increase, highlighting the importance of behavioral responses as a mechanism linking the intervention to improved outcomes.

The findings suggest that improving farmers' ability to analyze market information and develop entrepreneurial skills can be a powerful innovation in traditional production-focused agriculture. In settings characterized by high price variability and limited information flows, relatively low-cost interventions that promote market engagement can generate substantial income gains. By enabling farmers to better align production decisions with market demand, such

[3] In this specific context, the paper tests the relevance of Schultz's (1964) concept of the ability to deal with disequilibria.

approaches can enhance both productivity and profitability without requiring large increases in inputs.

From a policy perspective, the results highlight the value of integrating market intelligence into agricultural extension systems. Interventions that help farmers actively collect and analyze market information—through direct engagement with market actors—can complement traditional production-focused approaches and generate substantial income gains at relatively low cost. As agricultural development increasingly depends on market integration and commercialization, strengthening farmers' capacity to align production decisions with market demand may be a particularly effective and scalable strategy.

References

AGRA. 2020. *Africa Agriculture Status Report. Feeding Africa's Cities: Opportunities, Challenges, and Policies for Linking African Farmers with Growing Urban Food Markets* (Issue 8). Nairobi, Kenya: AGRA.

Aung MM & YS Chang. 2014. Temperature management for the quality assurance of a perishable food supply chain. *Food Control 40*:198-207.

Benin S, E Nkonya, G Okecho, J Randriamamonjy, E Kato, G Lubade & M Kyotalimye. 2011. Returns to spending on agricultural extension: the case of the National Agricultural Advisory Services (NAADS) program of Uganda. *Agricultural Economics 42*(2):249-267.

Carletto C, P Corral & A Guelfi. 2017. Agricultural commercialization and nutrition revisited: Empirical evidence from three African countries. *Food Policy 67*:106-118.

Cattaneo MD. 2010. Efficient semiparametric estimation of multi-valued treatment effects under ignorability. *Journal of Econometrics 155*:138-154.

Christiaensen L. 2017. Agriculture in Africa–Telling myths from facts: A synthesis. *Food Policy 67*:1-11.

Davis K, SC Babu & C Ragasa. 2020. *Agricultural Extension: Global Status and Performance in Selected Countries*. Washington, DC: IFPRI.

Fafchamps M & RV Hill. 2005. Selling at the farmgate or travelling to market. *American Journal of Agricultural Economics 87*(3):717-734.

Flores CA & OA Mitnik. 2013. Comparing treatments across labor markets: an assessment of nonexperimental multiple-treatment strategies. *Rev. Econ. Stat. 95*(5):1691-1707.

Goyal A. 2010. Information, direct access to farmers, and rural market performance in central India. *American Economic Journal: Applied Economics 2*(3):22-45.

Hayes R & L Moulton. 2009. *Cluster randomised trials.* Chapman and Hall/CRC Press, Boca Raton, FL.

Heckman J, H Ichimura & P Todd. 1997. Matching as an econometric evaluation estimator: evidence from evaluating a job training programme. *Rev. Econ. Stud. 64*(4):605-654.

Heckman J, H Ichimura, J Smith & P Todd. 1998. Characterizing selection bias using experimental data. *Econometrica*, 66(5):1017-1098.

Imai K, L Keele & T Yamamoto. 2010. Identification, inference, and sensitivity analysis for causal mediation effects. *Statistical Science 25*(1):51-71.

Imai K, L Keele, D Tingley & T Yamamoto. 2011. Unpacking the black box of causality: Learning about causal mechanisms from experimental and observational Studies. *American Political Science Review 105*(04):765-789.

Imbens GW. 2000. The role of the propensity score in estimating dose-response functions. *Biometrika 87*(3):706-710.

Li Y, MA Palma, CR Hall, H Khachatryan & O Capps Jr. 2019. Measuring the effects of advertising on green industry sales: A generalized propensity score approach. *Applied Economics 51*(12):1303-1318.

Mitra S, D Mookherjee, M Torero & S Visaria. 2018. Asymmetric information and middleman margins: An experiment with Indian potato farmers. *Review of Economics and Statistics 100*(1):1-13.

Moulton BR. 1990. An illustration of a pitfall in estimating the effects of aggregate variables on micro units. *Review of Economics and Statistics* 72(2):334-338.

Sayanagi NR & J Aikawa. 2016. *The motivation of participants in successful development aid projects: A self-determination theory analysis of reasons for participating*. JICA-RI Working Paper.

Schultz, T. W. (1964). Transforming Traditional Agriculture. New Haven, CT: Yale University Press.

Smith J & P Todd. 2005. Does matching overcome LaLonde's critique of nonexperimental estimators? *J. Econometrics 125*(1-2):303-353.

Stephens EC & CB Barrett. 2011. Incomplete credit markets and commodity marketing behaviour. *Journal of Agricultural Economics 62*:1-24.

Takeshima H, F Yamauchi, HO Edeh & M Hernandez. 2023. Solar-Powered Cold-Storage and Agrifood Market Modernization in Nigeria. *Agricultural Economics 54*(2):234-255.

Weinberger K & TA Lumpkin. 2007. Diversification into Horticulture and Poverty Reduction: A Research Agenda. *World Development 35*(8):1464-1480.

Wooldridge J. 2002. *Econometric Analysis of Cross Section and Panel Data*. Cambridge, MA: MIT Press.

Wooldridge J. 2003. Cluster-sample methods in applied econometrics. *Amer. Econ. Rev. 93*(2):133-138.

World Bank. 2008. *World Development Report 2008: Agriculture for Development*. Washington, DC: World Bank.

Table 1. Sales prices (UGX/kg) for major commodities (medians, panel sample)

Commodity	Treated			Control		
	N	Pre	Post	N	Pre	Post
Maize	44	931	1,500	56	983	1,038
Legumes	30	2,086	2,000	39	2,000	2,000
Vegetables	40	1,250	1,533	52	1,452	1,583

Notes: Medians reported. Sample includes farmers observed in both periods.

Table 2. Baseline plot-level characteristics (raw and IPW-weighted)

Variable	Raw			IPW		
	Treated	Control	Diff	Treated	Control	Diff
Panel A: Plot characteristics and land use						
Plot size (hectares)	1.400	1.399		1.297	1.202	
Years cultivated	13.717	14.594		14.119	14.161	
Plot left fallow in previous first season (1 = yes)	0.200	0.331	***	0.246	0.254	
Plot left fallow in previous second season (1 = yes)	0.218	0.351	***	0.271	0.274	
Panel B: Soil and environmental conditions						
Soil erosion in previous year (1 = yes)	0.248	0.272		0.214	0.210	
Panel C: Land tenure and property rights						
Male member holds plot certificate (1 = yes)	0.067	0.076		0.072	0.070	
Female member holds plot certificate (1 = yes)	0.048	0.059		0.049	0.050	
Male member has plot use rights (1 = yes)	0.513	0.568		0.539	0.545	
Female member has plot use rights (1 = yes)	0.319	0.300		0.306	0.304	
Male member has plot sale rights (1 = yes)	0.469	0.521		0.496	0.498	
Female member has plot sale rights (1 = yes)	0.166	0.175		0.168	0.169	
Threats to ownership or use rights (1 = yes)	0.089	0.078		0.082	0.079	
Land dispute in previous 12 months (1 = yes)	0.061	0.059		0.062	0.059	

Notes: ***1% **5% *10%. Values are sample means. Statistical significance is based on standard deviations adjusted for FG-cluster effects. IPW = inverse probability weighting.

Table 3. Baseline household, farm, and environmental characteristics (raw and IPW-weighted)

Variable	Raw			IPW		
	Treated	Control	Diff	Treated	Control	Diff
Panel A: Household demographics						
Age of household head (years)	43.268	42.195		42.642	42.900	
Female household head (1 = yes)	0.244	0.216		0.227	0.231	
Years of education (working-age members)	6.245	6.167		6.266	6.271	
Male household members aged 0–14 (number)	1.598	1.661		1.611	1.613	
Female household members aged 0–14 (number)	1.795	1.615	*	1.668	1.633	
Male household members aged 15–60 (number)	1.821	1.744		1.751	1.762	
Female household members aged 15–60 (number)	1.833	1.878		1.848	1.846	
Male household members aged over 60 (number)	0.084	0.050		0.063	0.060	
Female household members aged over 60 (number)	0.084	0.081		0.082	0.085	
Panel B: Economic characteristics and assets						
Value of farming assets (million UGX)	0.303	0.317		0.317	0.299	
Value of non-farm assets (million UGX)	7.528	7.412		7.598	7.642	
Livestock value (million UGX)	3.314	3.118		3.355	3.043	
Has non-farm wage income (1 = yes)	0.553	0.475	**	0.519	0.515	
Has government employment (1 = yes)	0.136	0.126		0.133	0.130	
Number of income sources	0.576	0.659		0.617	0.612	
Panel C: Financial access and credit						
Has bank account (1 = yes)	0.600	0.599		0.595	0.587	
Can obtain loan from banks (1 = yes)	0.411	0.347		0.375	0.370	
Can obtain loan from microfinance institutions (1 = yes)	0.355	0.391		0.363	0.362	
Number of buyers providing credit (count)	0.106	0.029	**	0.069	0.056	
Panel D: Farm structure and land access						
Farm size owned (hectares)	3.380	3.246		3.343	2.788	
Number of plots owned	2.432	2.369		2.377	2.378	
Number of plots cultivated	3.152	2.933		3.026	2.998	
Average distance to plots (minutes)	27.538	27.261		27.383	27.643	
Panel E: Social networks and market exposure						
Relative of key farmer group representative (1 = yes)	0.688	0.622		0.666	0.657	
Friend of key farmer group representative (1 = yes)	0.688	0.725		0.707	0.706	
Visited markets (non-selling purposes) in past 12 months (1 = yes)	0.878	0.854		0.867	0.863	
Distance to nearest town (20,000 population, hours)	1.832	2.553	*	2.042	2.221	
Exposure to crop demonstrations (index)	1.170	1.289		1.172	1.302	
Panel F: Soil and agroclimatic characteristics						
Soil sand content (%)	41.260	41.753		41.519	41.535	
Soil organic carbon (g/kg)	18.833	18.967		18.608	18.632	
Cation exchange capacity (meq/100g)	17.209	16.379		16.524	16.510	
Bulk density (tons/m³)	1.350	1.345		1.350	1.349	
Elevation (1,000 meters)	0.746	0.765		0.756	0.757	
Historical rainfall, first season (1,000 mm)	0.858	0.879		0.865	0.866	
Historical rainfall, second season (1,000 mm)	1.154	1.175		1.162	1.161	

Notes: ***1% **5% *10%. Values are sample means. Statistical significance is based on standard deviations adjusted for FG-cluster effects. Exchange rate: USD1 = approximately 3,600 UGX. IPW = inverse probability weighting.

Table 4. Summary statistics for production outcomes (household and plot levels)

Outcome	Treated		Control	
	Pre	Post	Pre	Post
Panel A: Household-level outcomes				
Revenue (million UGX, all crops)	1.873	1.889	1.836	1.554
Grows vegetables (1 = yes)	0.388	0.503	0.390	0.408
Panel B: Plot-level outcomes				
Revenue (million UGX, all crops)	0.696	0.702	0.717	0.607
Profit margin (all crops)	0.376	0.472	0.360	0.385
Grows vegetables (1 = yes)	0.224	0.289	0.237	0.265

Notes: Values are sample means.

Table 5. Market behavior and information use, pre- and post-intervention

Outcome	Treated		Control	
	Pre	Post	Pre	Post
Panel A: Information collection				
Collects price information (multiple sources) (1 = yes)	0.573	0.667	0.603	0.640
Collects price information on multiple commodities (1 = yes)	0.355	0.555	0.465	0.535
Collects price information from multiple markets (1 = yes)	0.328	0.495	0.412	0.475
Believes frequent price information collection is important (1 = yes)	0.915	0.877	0.935	0.860
Panel B: Market engagement				
Visits agrochemical suppliers (1 = yes)	0.035	0.025	0.060	0.013
Visits processors (1 = yes)	0.013	0.025	0.003	0.000
Number of buyers known personally	3.002	2.871	3.125	2.699
Number of output markets sold in	1.555	1.761	1.718	1.776

Notes: Values are sample means.

Table 6. Average rainfall in pre- and post-intervention periods

Period	Treatment	Control
Pre-intervention period (12 months)	1,256.6	1,296.8
Post-intervention period (12 months)	964.7	986.1

Notes: Rainfall measured in millimeters.

Table 7. Impact of the intervention on production outcomes (IPW-DID estimates)

Outcome	Estimate	Std. Error	N
Panel A: Plot-level outcomes			
Plot cultivated (1 = yes)	0.037	(0.041)	2,289
Log of revenue (all crops)	0.252**	(0.119)	1,128
Profit margin (all crops)	0.159**	(0.065)	1,128
Log of family labor use	0.035	(0.101)	1,128
Panel B: Household-level outcomes			
Log of revenue (all crops)	0.209**	(0.082)	800
Profit margin (all crops)	0.114**	(0.056)	800
Log of family labor use	0.079	(0.133)	800
Grows vegetables (1 = yes)	0.146**	(0.073)	800

Notes: Estimates correspond to average treatment effects on the treated (ATT) from IPW-DID regressions. Standard errors in parentheses are clustered at the farmer-group level. All regressions include baseline covariates. *** p<0.01, ** p<0.05, * p<0.10.

Table 8. Impact of the intervention on market intelligence and behavior

Outcome	Estimate	Std. Error	N
Panel A: Information collection			
Collects price information (multiple sources) (1 = yes)	0.151***	(0.052)	800
Collects price information on multiple commodities (1 = yes)	0.127***	(0.049)	800
Collects price information from multiple markets (1 = yes)	0.112**	(0.036)	800
Believes frequent price information collection is important (1 = yes)	0.079**	(0.040)	800
Panel B: Market engagement			
Visits agrochemical suppliers (1 = yes)	0.070*	(0.042)	800
Visits machinery suppliers (1 = yes)	0.025*	(0.014)	800
Visits processors (1 = yes)	0.016*	(0.009)	800
Number of buyers known personally	0.256*	(0.142)	800
Number of output markets sold in	0.116**	(0.055)	800

Notes: Estimates correspond to average treatment effects on the treated (ATT) from IPW-DID regressions. Standard errors in parentheses are clustered at the farmer-group level. All regressions include baseline covariates. *** p<0.01, ** p<0.05, * p<0.10.

Table 9. Impact of the intervention on prices received (IPW-DID estimates)

Outcome	Estimate	Std. Error	N
Log price (all crops)	0.192**	(0.088)	254
Log price (vegetables and legumes)	0.318*	(0.197)	161

Notes: Estimates correspond to average treatment effects on the treated (ATT) from IPW-DID regressions. Sample restricted to farmers observed in both periods selling the same crop. Standard errors in parentheses are clustered at the farmer-group level. *** p<0.01, ** p<0.05, * p<0.10.

Table 10. Spillover effects: proximity to treated groups and outcomes among controls

Variable	Log of revenue	Profit margin
Distance to nearest treated group	-4.790***	-2.615*
	(1.398)	(1.366)
Distance squared	2.187**	1.226
	(0.776)	(0.733)
Distance cubed	-0.305**	-0.172
	(0.125)	(0.115)
Observations	400	400

Notes: Standard errors in parentheses are clustered at the farmer-group level. All regressions include baseline covariates. Distance is measured to the nearest treated farmer group. *** p<0.01, ** p<0.05, * p<0.10.

Table 11. Mediation effects of market intelligence on production outcomes

Effect	Revenue	Profit margin
Panel A: Plot-level outcomes		
All crops		
Indirect effect (ACME)	0.030**	0.011**
	[0.012, 0.049]	[0.002, 0.021]
Direct effect	0.176**	0.137***
	[0.044, 0.317]	[0.060, 0.221]
Total effect (ATE)	0.205**	0.148***
	[0.069, 0.331]	[0.061, 0.230]
Share mediated	0.146***	0.076**
	[0.088, 0.432]	[0.049, 0.166]
ρ at which ACME = 0	0.15	0.15
Vegetables and legumes		
Indirect effect (ACME)	0.182*	0.038*
	[0.014, 0.397]	[0.003, 0.084]
Direct effect	0.048	-0.034
	[-0.360, 0.483]	[-0.146, 0.086]
Total effect (ATE)	0.230	0.004
	[-0.413, 0.641]	[-0.115, 0.123]
Share mediated	0.493	0.174
	[-2.357, 4.286]	
ρ at which ACME = 0	0.31	0.25
Sample size: 1,128 (all crops), 285 (vegetables and legumes)		
Panel B: Household-level outcomes		
All crops		
Indirect effect (ACME)	0.040**	0.016**
	[0.012, 0.068]	[0.005, 0.029]
Direct effect	0.171***	0.080**
	[0.051, 0.299]	[0.018, 0.146]
Total effect (ATE)	0.211***	0.096***
	[0.088, 0.337]	[0.035, 0.161]
Share mediated	0.190***	0.171**
	[0.118, 0.452]	[0.101, 0.463]
ρ at which ACME = 0	0.17	0.15
Sample size: 800		

Notes: ACME = average causal mediation effect. ATE = average treatment effect. Estimates obtained using Stata commands medeff and medsens (Imai et al., 2010, 2011). Values in brackets are 95% confidence intervals. *** p<0.01, ** p<0.05, * p<0.10.

Figure 1. Study area: Adjumani district, Uganda
Source: Authors' modification based on Google Earth.

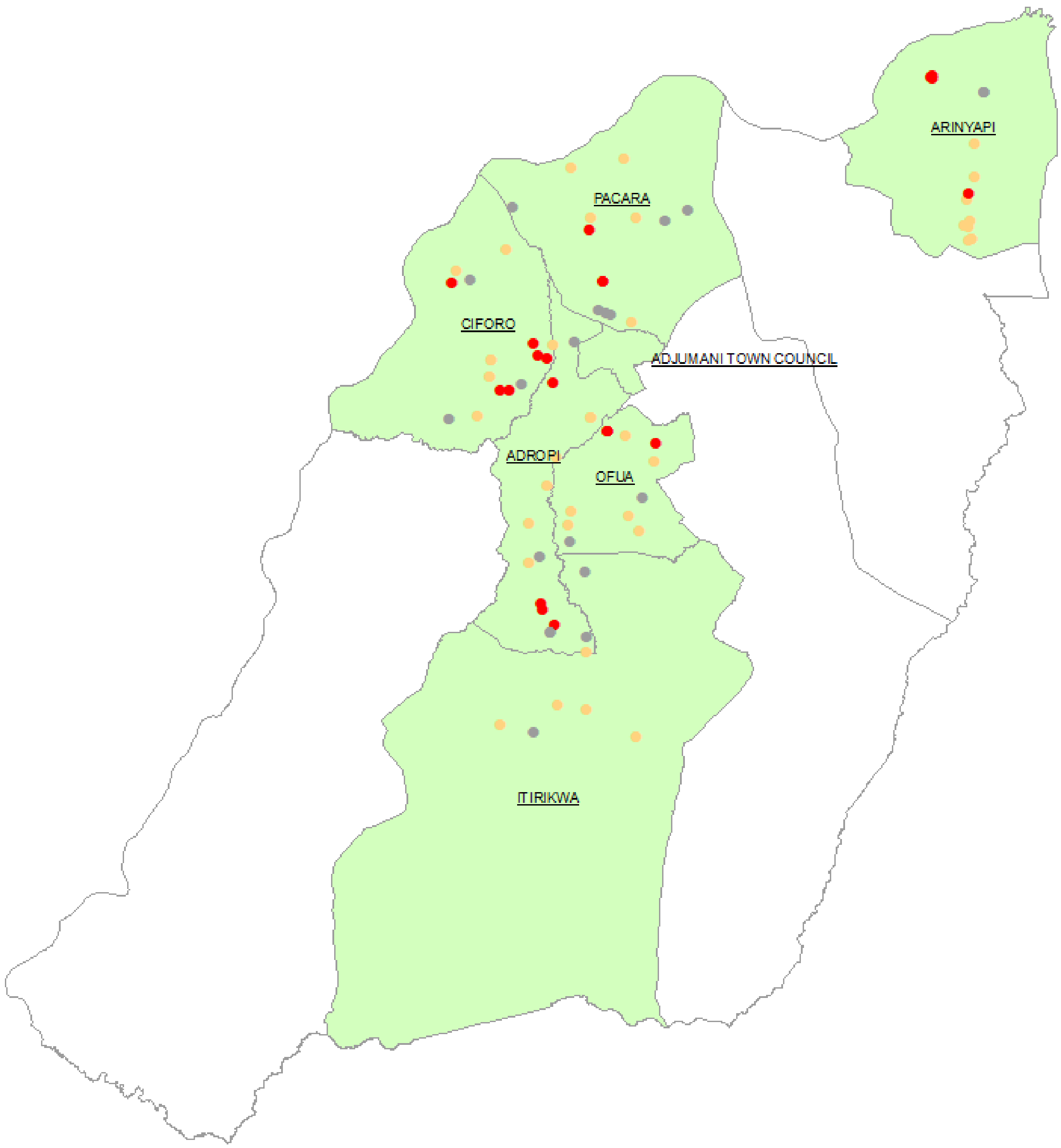

Figure 2. Spatial distribution of treatment and control farmer groups
● = treatment group (surveyed); ● = treatment group (non-surveyed); ● = control group (surveyed)
Source: Authors.

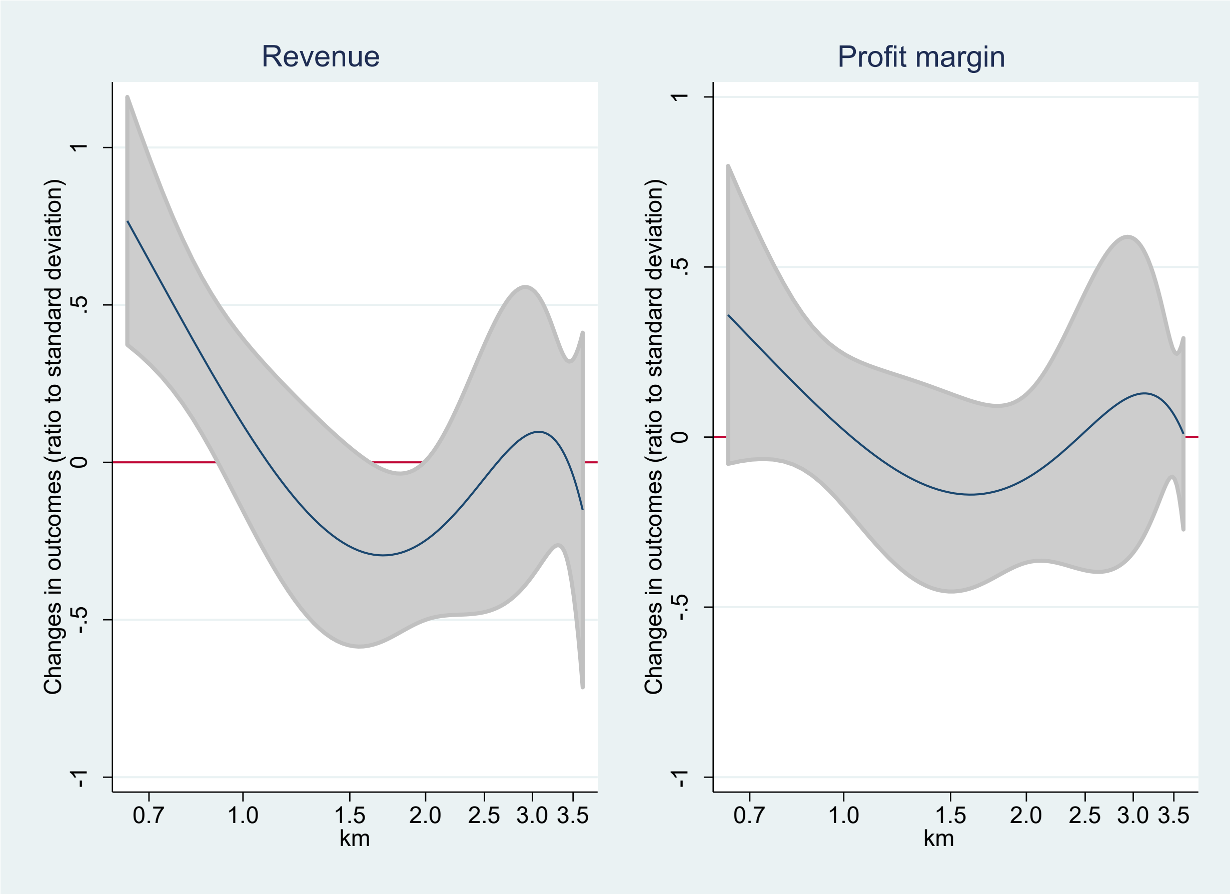

Figure 3. Spillover analysis: outcomes by distance to treated groups

Source: Authors' estimations.

Note: Horizontal axis measures the straight-line distance to the nearest treated farmer group. Shaded areas indicate 95% confidence intervals.

Appendix A: Estimation details for IPW and generalized propensity score approaches

This appendix provides additional details on the estimation procedures used in the main analysis, including the construction of inverse probability weights (IPW) and the generalized propensity score (GPS) approach used to assess potential spillover effects.

A.1 Inverse probability weighting

To improve comparability between treated and control groups, we implement inverse probability weighting based on the estimated propensity score. The propensity score is defined as the probability of belonging to a treated farmer group conditional on baseline characteristics.

Specifically, we estimate the propensity score using a logit model of treatment assignment as a function of pre-intervention covariates, including household demographics, wealth indicators, farm characteristics, social networks, prior exposure to extension services, and agroclimatic variables (Table 2 and Table ***3***). The resulting propensity scores are then used to construct weights that re-balance the sample, ensuring that treated and control groups are comparable in terms of observable characteristics.

As discussed in Section 3, combining IPW with the difference-in-differences framework helps reduce bias arising from residual imbalance in finite samples while preserving the advantages of the randomized design (Heckman et al., 1997, 1998; Smith & Todd, 2005).

A.2 Generalized propensity score and spillover analysis

To examine potential spillover effects, we extend the IPW framework using a generalized propensity score (GPS) approach that accounts for variation in exposure to treatment across control farmers.

Following Imbens (2000) and subsequent applications (e.g., Cattaneo, 2010; Flores & Mitnik, 2013), we treat the distance from each control farmer to the nearest treated farmer group as a continuous measure of treatment exposure. Let D_i denote this distance and X_i the vector of baseline covariates. The GPS is defined as the conditional density of D_i given X_i, denoted by:

$$r(D_i, X_i) = f_{D|X}(D_i|X_i)$$

In the first stage, we estimate the conditional distribution of distance as a function of covariates using a parametric specification. In the second stage, we estimate the relationship between changes in outcomes and treatment exposure, adjusting for the GPS to ensure comparability across observations with different levels of exposure.

The dose–response function is obtained by evaluating predicted outcomes at different values of distance, holding the GPS constant. This approach allows us to assess whether proximity to treated groups is associated with changes in outcomes among control farmers, after controlling for observable characteristics.

As described in Section 3 and shown in Table 10 and Figure 3, the results provide no evidence of negative spillover effects.

A.3 Balancing properties

To assess the validity of the weighting procedures, we examine the balancing properties of the estimated propensity scores. Following standard practice, we compare covariate distributions between treated and control groups after weighting, as well as across subsamples defined by levels of treatment exposure in the GPS framework.

The results indicate that the weighting procedures substantially improve balance across observable characteristics, supporting the validity of the empirical approach. Detailed balance statistics are available from the authors upon request.

ALL IFPRI DISCUSSION PAPERS

All discussion papers are available **here**

They can be downloaded free of charge

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
www.ifpri.org

IFPRI HEADQUARTERS
1201 Eye Street, NW
Washington, DC 20005 USA
Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org