INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

IFPRI

In partnership with

mastercard foundation

IFPRI Discussion Paper 02423

June 2026

Can Local Procurement for Food Aid Foster Market Development?

Evidence from Indirect Conditional Contracting in Uganda

Gashaw T. Abate

Serge Mugabo

Kalyani Raghunathan

Bjorn Van Campenhout

Markets, Trade, and Institutions Unit

Poverty, Gender, and Inclusion Unit

Development Strategies and Governance Unit

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

AUTHORS

Gashaw T. Abate (g.abate@cgiar.org) is a Senior Research Fellow in the Markets, Trade, and Institutions (MTI) Unit of the International Food Policy Research Institute (IFPRI), Washington, DC.

Serge Mugabo (S.Mugabo@cgiar.org) is a Senior Research Associate in IFPRI's Development Strategies and Governance (DSG) Unit, Kigali, Rwanda.

Kalyani Raghunathan (kalyani.raghunathan@gmail.com) was a Research Fellow in IFPRI's Poverty, Gender, and Inclusion (PGI) Unit at the time this work was conducted, New Delhi, India.

Bjorn Van Campenhout (B.VanCampenhout@cgiar.org) is a Senior Research Fellow in IFPRI's MTI Unit at IFPRI, Leuven, Belgium.

Abstract

Smallholder farmers in low-income countries often operate in fragmented markets characterized by volatile prices, weak bargaining power, and limited incentives to invest in productivity and quality. Large institutional buyers procuring locally can reshape these conditions by creating structured demand and embedding sourcing requirements in contracts with intermediaries, potentially transmitting incentives upstream to farmers. This study evaluates a maize procurement policy introduced in 2021 by a major institutional buyer in Uganda that required its large trader-aggregator suppliers to source at least 20 percent of deliveries directly from smallholder farmers through "indirect conditional contracting." Using survey data collected in 2024 from nearly 1,300 smallholder farmers and nearly 300 aggregators across six districts, we estimate effects on prices, technology adoption, quality upgrading, welfare, and resilience. Intent-to-treat (ITT) estimates show that residing in areas where the major buyer operates is associated with 5–6 percent higher farmgate prices on average, with instrumental variable (IV) estimates suggesting upper bound premiums of up to 45 percent. Farmers in the conditional contract group earn positive net returns and increase adoption of improved inputs and postharvest practices. Intermediary aggregators receive about 7 (ITT) to 30 (IV) percent lower selling prices but increase adoption of postharvest quality practices. Mediation analysis indicates that gains for farmers arise primarily through increased competition between intermediaries. However, downstream welfare outcomes remain inconclusive, with suggestive evidence that non-participating farmers in treatment areas may face lower prices due to market segmentation. Overall, our findings show that indirect conditional contracts can reshape value chain incentives by attracting intermediaries, increasing competition, and stimulating upstream investment, even as they generate uneven distributional effects.

Keywords: Local procurement, food aid, reliable markets, conditional contracts, smallholder farmers, maize value chain, Uganda.

Acknowledgments

This work was produced in the context of the Strengthening Food Systems to Promote Increased Value Chain Employment Opportunities for Youth (SFS4Youth) partnership with the Mastercard Foundation. It is a five-year initiative running between 2022 and 2027 to gain insight into the latest trends and challenges in agrifood systems and how addressing market inclusion and postharvest losses can enable dignified and fulfilling livelihoods for young women and men. The views expressed do not necessarily represent those of the Foundation, its staff, or its Board of Directors. We are grateful to Fantu Bachewe, Samuel Benin, Steven Were Omamo, Carla Degregorio, Phillip Hovmand, Violeta Palma-Perez, Ian Figgins, and Daniel Magada for their guidance and valuable inputs throughout the research process. We also thank Leocardia Nabwire, Richard Ariong, Charles Marc, and Wilberforce Walukano for their excellent research assistance. We further acknowledge John Ulimwengu for his thoughtful review of the initial draft, and Pamela Stedman-Edwards and colleagues in Communications and Public Affairs at the International Food Policy Research Institute for their valuable contributions to improving the clarity and presentation of the manuscript.

1. Introduction

Smallholder farmers in low-income countries operate in market environments characterized by high price volatility, thin trading networks, limited storage capacity, and weak enforcement of quality standards (Negede et al., 2024; Gilbert et al., 2017; Rapsomaniki, 2015; Barrett, 2008; Alene et al., 2008). These conditions reduce incentives to invest in productivity-enhancing technologies or postharvest quality management, as farmers face uncertainty not only about yields but also about whether output can be sold at remunerative prices. In staple crop markets in particular, fragmented supply chains and limited coordination between producers and downstream actors lead to underinvestment, limited quality differentiation, and persistent marketing risk. A growing body of work suggests that demand-side interventions—specifically, structured procurement by large institutional buyers—can reshape value chain incentives in ways that complement traditional supply-side approaches, such as input subsidies and extension services (Ashraf et al., 2009; Nehring et al., 2017; de Janvry and Sadoulet, 2020).

Several types of institutional buyers create structured demand in staple food markets: national grain reserve agencies purchasing for buffer stocks and price stabilization; governments procuring for social safety nets, including school feeding programs, and other public institutions; and international humanitarian agencies sourcing grain for emergency relief operations (e.g., Wright, 2012; Garg et al., 2013). Because these actors buy at scale and often impose quality and sourcing requirements, their procurement rules can influence price formation, competition among traders, and the incentives facing smallholder farmers. Yet, while a substantial literature has examined how direct contracting arrangements between buyers and producers affect smallholder outcomes (e.g., Meemken and Bellemare, 2020; Arouna et al., 2021), far less attention has been paid to how institutional buyers may reshape markets indirectly through conditions embedded in commercial supply relationships with intermediaries. This form of indirect conditional contracting, where requirements imposed by downstream buyers on midstream actors have up upstream effects on farmer-level outcomes, remains largely unstudied. Using primary survey data, this paper provides some of the first empirical evidence on the impacts of such an indirect conditional contracting arrangement imposed by a major institutional buyer, looking at the maize value chain in Uganda.

Uganda has experienced substantial local procurement activity from large institutional buyers, particularly in staple grain markets. Agencies such as the World Food Programme (WFP) have sourced significant quantities of maize, sorghum, and beans from Uganda to supply relief operations in neighboring countries, including Sudan, Somalia, and northern Kenya (WFP, 2019). Noteworthy initiatives include the WFP Purchase for Progress (P4P) pilot, in which Uganda was one of the pilot countries. P4P aimed to support smallholder farmers and foster equitable growth within local food markets. Evidence on its impact is mixed: some studies report improved market access, postharvest handling, and gender equity (e.g., Gelo et al., 2020; Davies and Menage, 2010; Upton and Hill, 2011; WFP, 2015), while others (e.g., Lentz and Upton, 2016), find no significant gains in farmer well-being despite increased commercialization.

We study a program in Uganda in which a major institutional buyer required its suppliers to demonstrate that at least 20 percent of the maize delivered was sourced directly from smallholder farmers, with a (nonbinding) preference for women and youth farmers. We exploit the buyer's geographic targeting to estimate the effects of this procurement modality by comparing areas where the buyer operates under indirect conditional contracting with areas where the buyer is absent. First, we ask, does indirect conditional contracting strengthen output market access and influence farmers' market participation, technology adoption, and investment in quality, and do these market-level effects translate into higher net returns? Second, how does the intervention redistribute rents between farmers and intermediary aggregators, and does it include or exclude marginalized groups—particularly women and youth—from its benefits? Third, does the buyer's presence in an area alter market outcomes for farmers who are not directly linked to the scheme, and if so, in what direction?

The procurement arrangement we study is "indirect" in that the major buyer contracts with wholesalers, who transmit the sourcing requirements to aggregators and, via them, ultimately to farmers. This structure implies that the effects of the intervention operate through intermediaries rather than through direct buyer–farmer contracts. We hypothesize that such indirect conditionality can influence upstream outcomes through several mechanisms. First, by creating credible and sustained demand for maize sourced from smallholders, the arrangement may reduce marketing risk and attract greater trader participation, thereby intensifying competition and raising farmgate prices. Second, by shifting sourcing incentives toward direct transactions with smallholders, it may expand farmers' market access and strengthen their bargaining power. Third, if aggregators respond by offering embedded services—such as input provision or quality management support—the conditionality may crowd in complementary investments that further enhance farmer productivity.

We test these mechanisms using data from farmers and traders across six districts, examining impacts on prices, market participation, technology adoption, quality upgrading practices, profits, and household welfare and resilience. In particular, we collect data along the maize value chain in four districts of Uganda targeted by the major buyer (Kasese, Kyegegwa, Kiryandongo, Masindi) and two comparable control districts where the major buyer was not active (Kabarole and Hoima). Our surveys include data from close to 1,300 smallholder maize farmers and 300 small traders and aggregators. We use descriptive analysis to identify patterns in the data and employ ordinary least squares (OLS) regressions as our primary intent-to-treat (ITT) estimator—capturing the average effect of residing in an area where the major buyer operates—augmented by instrumental variables (IV) analysis that bounds the private return to individual connection with the major buyer from above.

We find that the major buyer's procurement of maize under the indirect conditional contract arrangement benefited farmers, who receive higher prices for the maize they sell. Aggregators, on the other hand, report receiving lower prices for the maize they sell onward to wholesalers connected to the major buyer. The lower prices for aggregators appear to operate through increased competition, as the entry of a major buyer seems to attract more aggregators, which in turn reduces rent extraction and/or increases efficiency in this segment of the value chain. In addition to these large and significant price effects, we also find that the buyer's policy is associated with higher agricultural technology adoption among farmers, in part because aggregators provide access to these inputs. Both farmers and aggregators also invest more in postharvest quality-preserving and upgrading practices in areas where the major buyer is operating. Although these investments increase costs, the higher prices more than compensate for them, ultimately increasing farmers' profits.

These results suggest that indirect conditional contracts can reshape incentives along the value chain in ways that differ from more direct procurement approaches such as P4P. Rather than acting only through guaranteed purchase volumes, the arrangement leverages private sector intermediaries by embedding conditions that alter how traders compete for grain and how farmers access inputs and information. In effect, our results suggest that procurement rules imposed by a large institutional buyer can induce upstream adjustments in market structure, technology adoption, and quality upgrading, harnessing private actors' commercial incentives to deliver broader development benefits. Our findings thus speak to ongoing debates about how institutional buyer programs can be designed to strengthen local markets while minimizing the risk of distortion.

The remainder of the paper is organized as follows. Section 2 provides background on the maize value chain in Uganda and the indirect conditional contracting policy. Section 3 describes the data and methods used in the analysis, while Section 4 presents descriptive results. Section 5 reports the main findings on the effects of major buyers on prices, input adoption, quality upgrading, returns, and farmers' welfare and resilience. Section 6 discusses the results in relation to existing literature and highlights their policy implications. Finally, Section 7 concludes by summarizing the main findings.

2. Context

Maize is a priority crop in Uganda and is mainly produced in Buganda and Bunyoro. Across the country, over 65 percent of households grew maize on a land area of about 3.7 million acres and annual maize production, in 2021/22, was 2.2 million tons (Uganda Bureau of Statistics [UBOS], 2024). Maize serves both as a critical crop for food security and a vital source of income for farmers. Production is dominated by smallholder farmers, with average plot size of about 1.7 to 2 acres (UBOS, 2024). Despite government efforts to promote maize production and modern agricultural practices, many farmers continue to rely on traditional methods. Limited access to quality inputs and inefficient postharvest handling contribute to substantial losses and low productivity (Omotilewa et al., 2018; Bagamba et al., 2023). These constraints, combined with weak market access and limited processing capacity, reduce the competitiveness of Uganda's maize sector.

A typical maize value chain in Uganda involves a network of interconnected actors (Figure 1). Agro-input dealers, primarily located in towns and trading centers, supply improved seeds, fertilizers, pesticides, and farming tools to smallholder farmers. These farmers, in turn, cultivate maize by combining these inputs with knowledge, land, and labor. Once harvested, a marketable surplus is sold to aggregators (often at the farmgate or in local markets), who transport the grain using bicycles or motorcycles either directly to large processors or to wholesalers, who in turn supply processors or institutional buyers, including the major buyer examined in this study. Farmers may also take some of their maize to local mills for household consumption, while processors transform maize grain into flour that is distributed through retail markets.

Input use among farmers remains limited. While some farmers purchase improved seed varieties, many rely on seeds saved from previous harvests (UBOS, 2024; McGuire and Sperling, 2016). Programs promoting input adoption face persistent barriers related to affordability, access, and quality uncertainty. Farmers in rural areas often face high prices, long travel distances, and supply chain inefficiencies when purchasing inputs. Concerns about counterfeit or substandard products further discourage investment, as evidence shows that uncertainty about input quality significantly reduces adoption (Barriga and Fiala, 2020; Ashour et al., 2019; Bold et al., 2017; Miehe et al., 2023).

As a result of limited use of quality agricultural inputs and continued reliance on traditional farming practices, maize productivity remains low. Average annual yields are 730 kg/acre, at the lower bound of yields reported at research stations, which range from 730 to 1,820 kg/acre (Fermont and Benson, 2011; Gourlay, Kilic, and Lobell, 2019). Postharvest handling is another major challenge. Harvesting is largely manual, and maize is typically dried in the sun before shelling and storage (Omotilewa et al., 2018). Inadequate drying practices and poor storage infrastructure leads to substantial losses. Maize is commonly stored in traditional granaries or polypropylene bags, both of which are vulnerable to pests and moisture accumulation, resulting in quality deterioration, reduced market value, and increased vulnerability to seasonal price fluctuations.

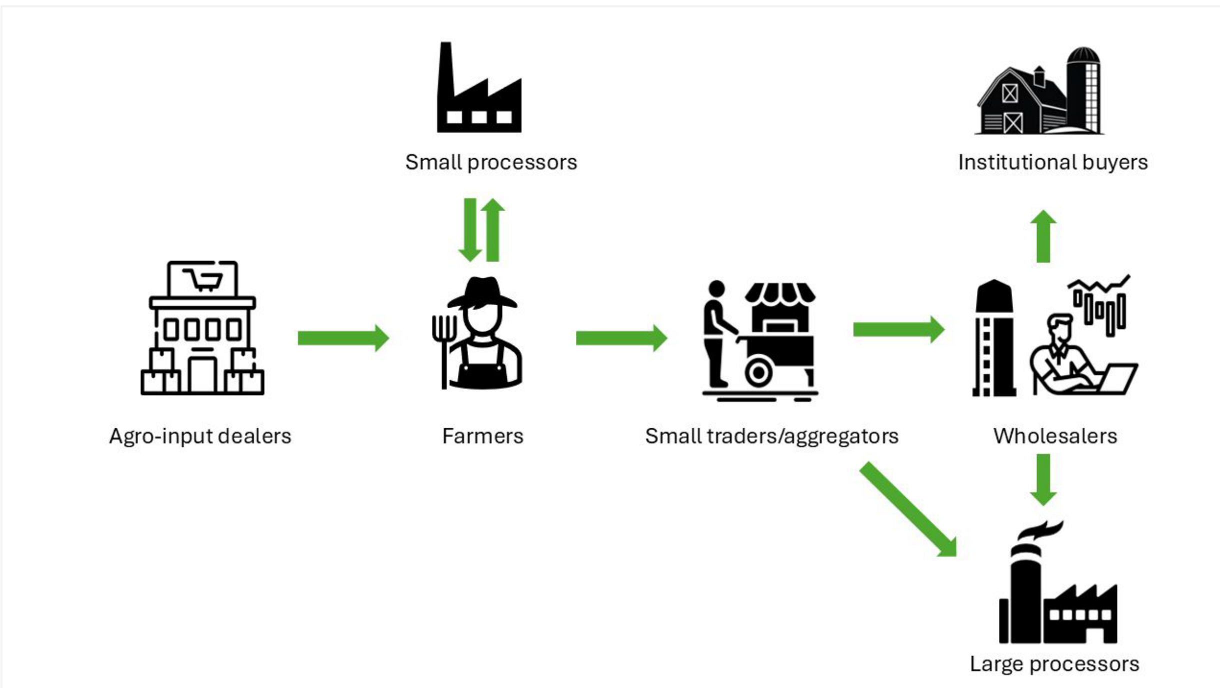
Smallholder farmers also face constraints in accessing markets. Many sell maize through informal channels, including farmgate sales to itinerant traders who aggregate grain in trading centers and small towns (Barrett, 2008). These traders—often operating bicycles or motorcycles (boda-boda)—play an important role in linking farmers to markets, but their operations are constrained by transportation limitations, storage capacity, credit constraints, and uncertain demand.[1] Processing is the next key stage of the value chain. Maize is primarily milled into flour used to prepare *posho*,

[1] The role of aggregators is often contested, and indeed many development interventions supported by NGOs try to "cut out the middlemen." This is because traders, both small and large, also engage to some extent in arbitrage to capitalize on price seasonality, buying up maize grain from farmers immediately postharvest when prices are low and selling during the lean season when maize is scarce and prices are high (Van Campenhout, Lecoutere, and D'Exelle, 2015; Burke, Bergquist, and Miguel, 2019). The story isn't so simple, however; research shows that traders enhance market participation, particularly for remote farmers who would otherwise struggle to sell their produce (Mather, Boughton, and Jayne, 2013; Sitko and Jayne, 2014).

a staple dish made by cooking maize flour with water. Processing enterprises range from small village mills powered by combustion engines (baga-baga) to large industrial processors producing fortified maize flour for commercial distribution and regional export markets.

The institutional buyer studied in this paper procures maize from wholesalers through public tenders that specify quantity and quality requirements. Only prequalified wholesalers are invited to bid, and selected suppliers deliver maize to the buyer. This buyer is typically one of several institutional clients served by wholesalers, alongside governments and institutions such as schools and prisons. Under the procurement arrangement examined here, wholesalers awarded contracts must document that at least 20 percent of the maize they deliver is sourced directly from smallholder farmers. When wholesalers procure through aggregators, these intermediaries must also document the origin of the maize to establish traceability.[2]

Figure 1. A canonical maize value chain



Source: Authors' illustration.

In the context of this study, smallholder farmers are defined as those cultivating less than 5 acres of land, consistent with the operational definition used by the buyer and the global definition of the Food and Agriculture Organization of the United Nations (Lowder et al., 2016). More than 90 percent of maize farmers in Uganda fall into this category (UBOS, 2022), and they account for most of the country's maize production. Roughly 60 percent of output is consumed on-farm, with the remainder entering marketed channels (UBOS, 2022).

[2] Qualitative evidence, however, suggests that this requirement was not always rigorously enforced.

Although the 20 percent direct-sourcing requirement may appear modest given the predominance of smallholders, the binding constraint was not the volume share but the requirement for documented traceability. Prior to the intervention, wholesalers sourced maize from traders, brokers, and farmers without systematically recording its origin. While much of the maize ultimately originated from smallholder farms, it typically passed through multiple intermediary layers without verifiable documentation. The procurement condition required wholesalers and their affiliated aggregators to record the farmers from whom maize was purchased, effectively creating more direct and traceable sourcing relationships from farmgate to delivery. The key change was therefore not in upstream suppliers—smallholders were already the primary source—but in the formalization of sourcing relationships through direct, documented linkages between aggregators and identified farmers. Failure to provide adequate documentation could lead to exclusion from future tenders, creating a credible enforcement mechanism.

Institutional arrangements may affect farmer behavior through several mechanisms. First, aggregators participating in the scheme typically purchased whatever quantities registered smallholders offered, without per farmer quotas, reducing rationing risk and providing farmers with a reliable outlet for their marketable surplus. Second, traceability requirements encouraged aggregators to establish direct and repeated relationships with specific farmers, potentially strengthening information flows, coordination, and access to embedded/complementary services. Third, by formalizing a segment of the value chain that is otherwise largely informal, the intervention may strengthen recordkeeping and quality management practices.

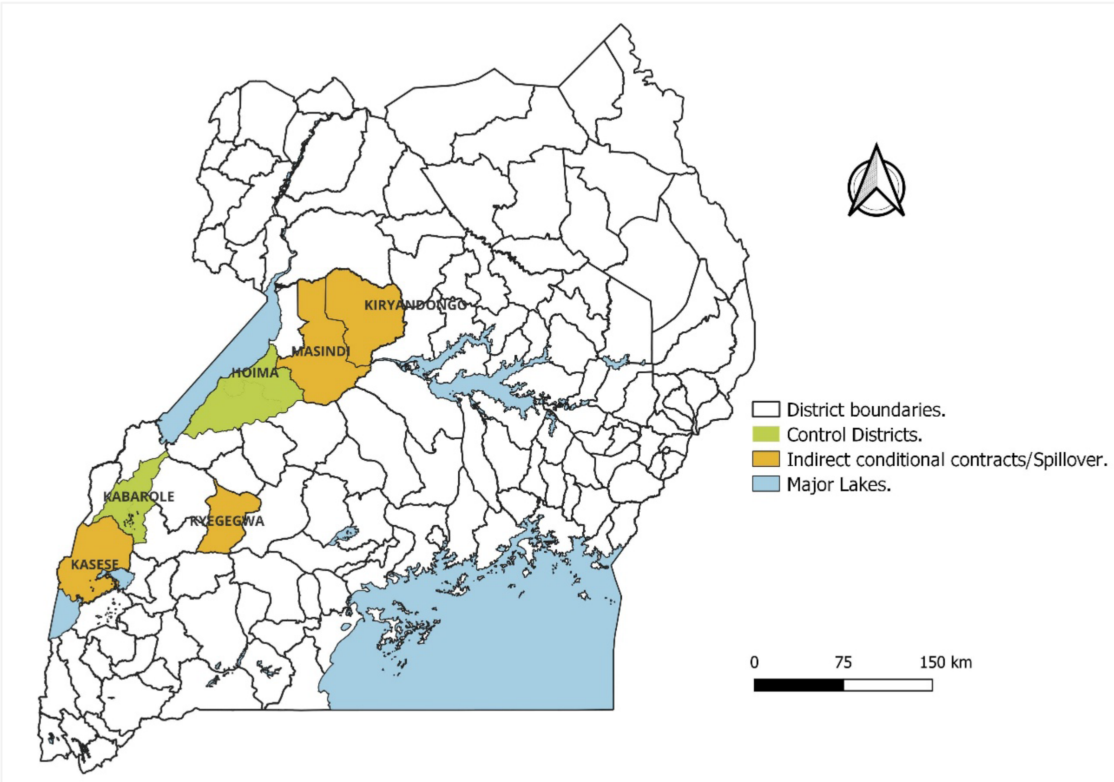
These mechanisms generate several testable predictions. Farmers connected to participating aggregators may experience improved market access and become more likely to sell maize through traceable channels. More reliable market access may increase production or marketed surplus. The intervention could also affect prices received if traceable maize commands a premium or if competition among aggregators intensifies as they compete for registered suppliers. Finally, stronger farmer–aggregator relationships may influence production and postharvest decisions through improved access to information, inputs, or other embedded services.

3. Data and methods

3.1 Data

This study uses primary data from the maize value chain in Uganda, collected in May–June 2024. We conducted our survey in Western and Central Uganda (Figure 2), where maize cultivation is a crucial part of the agricultural landscape. In these regions, maize is widely grown by smallholder farmers who rely on it for household consumption and income generation. Growing demand for maize from urban markets and agro-industrial processors (both for consumption in Uganda and for neighboring countries) has increased the crop's commercial value, in some instances encouraging investments in improved production practices and inputs, and in storage, handling, and aggregation midstream.

Figure 2. Study area, Western and Central Uganda



Source: Authors' illustration based on IFPRI's maize value chain survey conducted in May–June 2024.

Our survey gathered data from two distinct types of actors: smallholder farmers and small aggregators who act as intermediaries between these farmers and the wholesalers that provide maize to the major buyer. Farmers were selected at random after stratifying them into three groups:

Group 1: Farmers residing in two districts: Kabarole and Hoima, where the major buyer was not actively procuring maize. These districts were selected to have characteristics similar to the Group 2 districts (see below). Farmers in these two districts were selected in two stages: first, 50 villages were selected in each district from a list of all villages, with sampling probabilities proportional to the number of households living in the village. Second, 10 households were randomly selected in each village from lists obtained from the village headquarters. This group will be referred to as the "control" group.

Group 2: Farmers living in four districts: Kasese, Kyegegwa, Kiryandongo, and Masindi, where maize is procured from farmers under the indirect conditional contract modality. Kasese and Kyegegwa are located in the southwestern corner of the study area near Lake George and border Kabarole district. Kiryandongo and Masindi lie in the northern part of the study area, at the northeastern tip of Lake Albert, adjacent to Hoima district. In these districts, farmers were sampled from procurement lists spanning several previous years submitted to the major buyer by wholesalers as part of the traceability requirement of the conditional contract and shared with us by the major buyer. We refer to this group as the "conditional contract" or "treatment" group interchangeably.

Group 3: Farmers from the same four districts as Group 2, but who are not on the traceability lists of suppliers linked to the major buyer. Specifically, our interview protocol stipulated that the nearest neighbor of each Group 2 farmer would be interviewed as part of Group 3. This group will be referred to as the "spillover" group.

In all groups, efforts were made to interview an equal number of men and women smallholder farmers. Survey data were collected on general household characteristics of farmers, including welfare and food security indicators. The primary focus, however, was on marketing behavior. We gathered detailed information on farmers' maize sales following both the first and second agricultural seasons of 2023, and on maize cultivation during the first and second season of 2023 and the first season of 2024.[3] We also collected data on agricultural technology use and labor inputs. For more details on the survey, we refer the reader to Raghunathan et al. (2025).

Aggregators were identified through referral by farmers. We only have two groups of aggregators: those primarily sourcing from the districts where the major buyer is not active (group 1) and those operating in areas where the major buyer is active (group 2). By definition, the latter group could purchase from both conditional contract and spillover farmers. Aggregators were interviewed at the same time as the farmers, with a questionnaire that focused on both purchase and sales transactions for the first and second season of 2023. Additional data were gathered on aggregators' handling and storage practices, as well as their access to finance. Achieved sample sizes for farmers and aggregators are in Table **1**. Overall, we interviewed 1,284 farmers (Group 1: 503, Group 2: 392, Group 3: 389), of whom 624 were men and 660 women, and 297 traders (Group 1: 154. Group 2: 143), all but 11 of whom were men.

[3] The first season is the main maize-growing season and typically involves sowing in March–April and harvesting in June–July, while the second season involves sowing in September–October and harvesting in December–January.

Table 1. Achieved samples of maize farmers and aggregators by strata group

Category	Group 1: Control group	Group 2: Conditional contract	Group 3: Spillover	Total
Farmers				
Achieved sample	503	392	389	1,284
Men	270	176	178	624
Women	233	216	211	660
Aggregators				
Achieved sample	154	143		297
Men	147	139		286
Women	7	4		11

Note: Aggregators buy from multiple farmers in a given area, so it was not possible to separate aggregators who purchased maize from farmers linked to the major buyer via a conditional contract versus the spillover farmers in the same districts.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

3.2 Methods

Descriptive analysis

First, we use the survey data to provide a rich description of the maize value chain in the study areas across two agricultural seasons. We examine outcomes relating to market participation, input use, production, and seasonal price fluctuations; we study how the maize flows between the various actors in the value chain and how prices are transmitted; we investigate the inclusivity of the value chain and the extent to which it appears to be meeting the goals of the major buyer of greater involvement of women and youth maize farmers; and we investigate farmer profit and welfare outcomes, notably food security, dietary diversity, and the use of coping strategies in response to shocks. Descriptive comparisons are presented using summary tables and graphical analysis. We conduct mean and proportion tests to evaluate differences across three farmer groups and two trader groups.

Mediation analysis

To examine price transmission, we test whether competition among aggregators mediates the effects of the indirect conditional contract on the price received by farmers. To do this, we use mediation analysis, an application of structural equation modeling. Mediation analysis is a statistical method that helps explain how one variable influences another variable through a mediator variable, allowing us to parse the effects into direct and indirect (via the mediator) components. In our case, the independent variable is the presence of the major buyer; the dependent variable is the price received by the farmers, and the mediator variable is the level of competition among the aggregators, measured as the number of aggregators operating in each area.

Mediation analysis involves the joint estimation of two regression equations. First, the mediator is regressed on the independent variable:

$$M = \alpha_0 + \alpha_1 X + \alpha_2' W + \epsilon \tag{1}$$

where M is the mediator variable, here, the number of aggregators operating in an area; X is the independent variable, here, the presence of the major buyer; W is a vector of covariates; and ϵ is the error term. α_1 and the vector α_2 are to be estimated.

In a second regression, two explanatory variables are used, the mediator and the independent variable to explain the dependent variable:

$$Y = \beta_0 + \beta_1 X + \beta_2 M + \beta_3' W + \epsilon \tag{2}$$

Here, Y is the dependent variable, in our case, the price received by the farmers.

These two equations allow us to decompose the total effect of the major buyer's presence on farmgate prices into direct and indirect components. The **direct effect** is given by β_1, capturing the effect of the major buyer's presence holding aggregator entry constant. The **indirect effect** operates through the mediator and is given by the product $\alpha_1 \times \beta_2$, that is, the effect of the major buyer on aggregator entry multiplied by the effect of aggregator entry on prices.

For completeness, the **total effect** can be expressed as:

$$\text{Total effect} = \beta_1 + (\alpha_1 \times \beta_2)$$

We combine aggregator and farmer data to run the mediation analysis. To achieve this, we need to construct a farmer-level measure of competition, which we do by averaging aggregator level indicators of competition, weighted by the inverse distance between each farmer and the respective aggregators.

OLS regression analysis

We use regression analysis to test the effects of being linked to the major buyer either directly through the conditional contract or indirectly, on our outcomes of interest, controlling for individual-level covariates. Specifically, for a farmer i in season s and location g, we estimate:

$$Y_{isg} = \alpha + \beta BuyerDistrict_{ig} + \gamma' X_i + \delta_s + \epsilon_{igs} \tag{3}$$

where Y_{isg} is our outcome of interest: selling price in Ugandan shillings (UGX/kg) and indicators of farmer i's adoption of technologies, investment in quality upgrades, and profit/net return. $BuyerDistrict_{ig}$ is a variable indicating the "treatment", that is, whether the major buyer is active in the area where the farmer resides. X_i is a vector of individual- or household-level covariates. δ_s is a season fixed effect, and ϵ_{igs} is an individual-level error term.

Controlling for covariates in X_i serves several purposes. First, it helps improve the precision of the estimates by accounting for observable factors that influence the dependent variable. Second, including these controls helps mitigate concerns that the "treatment" may be correlated with other determinants of price beyond the trading relationship. For example, it is possible that the major buyer targets areas that differed systematically in infrastructure, market access, or farmer capacity.

We include seven control variables in X_i. First, farmer and household demographic variables, such as gender, age, and education level of the household head, because these variables may proxy for bargaining power, information access, or any other factor that affects the ability of the farmer to negotiate with buyers. For instance, more educated farmers can access more sources of information and may be better informed about prevailing market prices or may be more confident in bargaining. Similarly, male-headed households might be treated differently by traders than female-headed households due to prevailing gender norms (see for instance, Van Campenhout and Nabwire [2025] on buyer side discrimination in bargaining in Uganda), while the age of the household head could reflect experience and/or risk preferences (Schildberg-Hörisch, 2018).

We also include household size, as this may capture labor availability, which may positively affect production and marketing behavior. At the same time, due to subsistence needs, larger households may have less surplus to sell or be under more pressure to sell early in the season (Burke, Bergquist, and Miguel, 2019). We also control for the total amount of land owned, in acres, as a proxy for the scale of production and underlying wealth, both of which are likely to influence not only the volumes marketed but also the bargaining position of the farmer.

We control for farmer membership in a maize-focused co-operative because co-operatives may provide market access, storage facilities, collective bargaining opportunities, and access to information on inputs, production and productivity, and prices, all of which can impact transaction prices and investments in quality. Similarly, we control also for the quantity sold in each transaction, which helps address concerns that larger volumes may be associated with price discounts or premiums due to economies of scale or buyer preferences.

The identification strategy in Equation 3 relies on comparing average outcomes across the two farmer groups. We estimate the impact of the major buyer's procurement through the conditional contract modality by comparing farmers in Group 1 (those living in districts where the major buyer was not active) and Group 2 (those from whom the major buyer purchased maize in the recent past).

However, the groups we specify based on geography may yield biased estimates due to potential misclassifications of farmer exposure. For instance, some farmers in Group 1 may in fact be selling to aggregators or traders linked to the major buyer. Conversely, not all farmers in Group 2 need necessarily have sold to aggregators linked to the major buyer in the seasons under analysis, as inclusion in this group was based on having appeared on a procurement list in any season over the last few years.[4] This mismatch between the strata and actual trading relationships can lead to

[4] Indeed, in our data, approximately 23 percent of the farmers in Group 2 report selling directly to the major buyer or through a connected aggregator/trader. Among spillover farmers (Group 3), this figure is about 12 percent. However,

attenuation bias, underestimating the true impact of the intervention. Moreover, the geographic units used for treatment assignment are relatively coarse, and treatment and control households are often located far apart. As a result, differences in prices or market participation may be driven by unobserved spatial variation, such as differences in infrastructure, agroecological conditions, or market access, rather than the intervention itself. This geographic heterogeneity further complicates causal interpretation and underscores the need for more granular or behavior-based measures of exposure.

An alternative approach to measuring exposure would focus on actual trading relationships rather than geographic assignment. Our survey records whether farmers sold directly to aggregators linked to the major buyer, rather than through other channels such as non-linked aggregators or processors. Such measures arguably provide a more direct proxy for exposure than geographic assignment alone.

However, trading relationships are endogenous and likely reflect unobserved farmer and transaction characteristics. For instance, farmers with higher-quality maize, better market information, or stronger bargaining power may be more likely both to attract aggregators linked to the major buyer and to achieve better outcomes independently of the intervention. As a result, estimates based directly on observed trading relationships would be difficult to interpret causally and are therefore not presented as part of our main analysis.

Instead, we turn to an IV approach that uses geographic assignment to instrument exposure. However, as we show in the following section, the instrument primarily shifts market-level exposure rather than individual trading relationships per se, implying that the resulting estimates should not be interpreted as recovering a clean individual-level causal effect.

Instrumental variables approach

To complement the intent-to-treat analysis, we employ an IV approach. Specifically, we instrument whether a farmer trades with an aggregator linked to the major buyer using an indicator for whether the farmer resides in an area where the major buyer operates under indirect conditional contracting.

It is important, however, to be transparent about what this instrument identifies and what it does not. The instrument operates at the area level: it captures whether the major buyer is active in a given farmer's district, not whether the farmer is individually selected into a trading relationship. Entry of the major buyer alters local market structure by attracting aggregators, shifting competition, and changing the composition of buyers. These market-level changes affect outcomes even for farmers who never transact with connected aggregators, implying that geographic assignment affects outcomes through channels beyond individual connection.

---

none of the farmers in Group 1, the control group, reported any sales to aggregators/wholesalers connected to the major buyer.

This interpretation is supported by placebo tests presented with the price results below. Among farmers who did not transact with connected aggregators, those in treatment areas receive significantly lower prices than comparable non-connected farmers in control areas. This provides direct evidence that geographic assignment influences outcomes through market segmentation rather than exclusively through individual trading relationships.

Given these considerations, we interpret the specifications differently. The OLS specification using the treatment-area indicator (Columns 1–2 in each table) provides the ITT estimate: the average effect of living in an area where the buyer operates, capturing both gains to connected farmers and spillovers or displacement effects on non-participants. This is our primary estimand because it does not rely on the exclusion restriction. The IV (two-stage least squares, 2SLS) specification instead identifies the effect for compliers whose trading behavior responds to geographic assignment, but it should be interpreted as an upper bound on the private return to individual connection within a market already reshaped by buyer entry, rather than as a clean individual-level LATE.

The final limitation is that the major buyer operated exclusively through the conditional contracting modality during the study period and in the study areas. Consequently, we cannot disentangle the effects of conditionality itself from the broader effects of buyer presence, procurement scale, and stable market access. Our estimates therefore capture the intervention as implemented rather than the marginal contribution of conditionality alone. Disentangling these components remains an important avenue for future research.

4. Descriptive results

4.1 Reliable output markets

One of the main reasons why the major buyer initiated the indirect conditional contacts modality and one of the justifications for local and regional procurement modalities in general is the assumption that linking smallholder farmers to a large credible buyer creates a reliable and predictable market for them. Indeed, output market uncertainty has been found to be a key constraint to smallholder market participation, which in turn discourages investment in commercial agriculture and intensification (Barrett, 2008). Furthermore, the presence of a reliable market does not only affect producers. Van Campenhout, Minten, and Swinnen (2021) find that foreign direct investment in various large dairy processing plants in southwestern Uganda created a reliable market for raw milk that led to upgradies across the entire value chain.

In this section, we trace this impact pathway of reliable output markets for maize in Uganda. We do so by first testing if the presence of a large buyer using a conditional contract modality is correlated with market participation. We then look for associations between procurement by the major buyer and investment in technologies and practices. Finally, we assess production-related outcomes at the farmer level.

Market participation

Overall, 91 percent of farmers in our sample made at least one sales transaction in the first season of 2023, and 89 percent in the second season of 2023. While about 80–85 percent of the farmers in Group 1 report having sold maize in the two seasons of 2023 (Panel A of Table **2**) this number is considerably higher for farmers in Groups 2 and 3, with more than 90 percent of the farmers in these groups reporting having sold maize the previous year.

We also see significant differences in quantities sold (Panel B of Table **2**). Farmers in Group 2, the conditional contract group, sell a significantly larger volume of maize in the first season than farmers in Group 1, the control group (p-value 0.032), though farmers in Groups 1 and 3 are statistically indistinguishable. In fact, in the first season of 2023, quantities sold are lower among farmers in Group 3, the spillover group, than farmers in the control group, though the difference is not significant (p-value = 0.557). Finally, Panel C shows quantities sold as a share of quantities produced to arrive at a measure of marketable surplus. While the marketable surplus among farmers in Group 1 is not statistically different from farmers in Group 3 it is evident that farmers in Group 2 have a significantly larger marketable surplus than farmers in the other two groups. Taken together, these three sets of findings on market participation, quantities sold, and share of produce sold appear to indicate that the farmers in Group 2 who sell to the major buyer are able to participate more fully in market transactions.

Our survey also allows us to look at market participation patterns at the aggregator level. To examine trader entry into the market in areas where the conditional contract is operational, we collected information on the number of other maize aggregators or traders active in these locations. On average, 6.4 aggregators are operational in the control areas, compared to 9.2 in areas where the farmers are recorded as being linked to the major buyer. This difference is statistically significant (p-value = 0.002), suggesting that the implementation of the conditional contracting modality is positively related to the number of aggregators operating in the area. While this might seem suboptimal, the increase in the number of aggregators reflects intensified competition. Greater competition among aggregators can lead to higher prices offered to farmers and lower maize prices downstream, with potentially positive implications for the end consumers.

Table 2. Farmer market participation, by strata

	Group 1: Control	Group 2: Conditional contract	Group 3: Spillover	p-values		
				1 & 2	2 & 3	1 & 3
Panel A: Whether sold (yes/no, %)						
First season of 2023	85	96	94	0.000	0.244	0.000
Second season of 2023	81	94	92	0.000	0.810	0.000
Panel B: Quantity of maize sold (kg)						
First season of 2023	1,639	2,199	1,483	0.032	0.014	0.557
Second season of 2023	1,476	1,661	1,449	0.225	0.178	0.860
Panel C: Share of maize sold (%)						
First season of 2023	63	72	66	0.005	0.076	0.426
Second season of 2023	68	75	73	0.001	0.380	0.023
Obs.	503	392	389			

Note: The table reports market participation outcomes for the first and second agricultural seasons of 2023. "Whether sold" indicates whether the farmer made at least one maize sales transaction. Quantities sold are expressed in kilograms. The share sold is calculated as the proportion of total maize production sold in each season. Group 1 consists of farmers in districts where the major buyer was not active. Group 2 includes farmers who appeared on traceability lists of wholesalers supplying the major buyer under the indirect conditional contract modality. Group 3 includes the nearest neighbors of Group 2 farmers within the same districts but not on the traceability lists (spillover group). P-values correspond to pairwise tests of equality of means across groups.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Technology adoption

Next, we test if reliable market access crowds-in modern agricultural technologies such as the use of agrochemicals, improved crop varieties, and fertilizers (**Figure 3**). For the sake of space, we investigate this only for the first season of 2023.[5] We did not ask about input use and technology adoption on all maize plots but instead asked farmers to enumerate all plots and then randomly selected one plot on which detailed information about technology adoption was collected. This was done to keep the survey short and reduce respondent fatigue. As the plot was chosen randomly, plot-level outcomes provide an unbiased estimate for household-level averages. A limitation of this approach is that our adoption indicator captures the extensive margin—whether a farmer uses a given input on any plot—but may not fully reflect the intensive margin of adoption. Farmers may apply modern inputs selectively to some plots while relying on traditional practices on others. To the extent that such within-household variation exists, our single-plot measure provides an unbiased but potentially imprecise estimate, and the treatment effect on technology adoption may be understated.

The use of pesticides, herbicides, and fungicides is relatively high in Uganda. Many farmers use pesticides against fall armyworm (*Spodoptera frugiperda*) and maize stem borer (*Busseola fusca*),

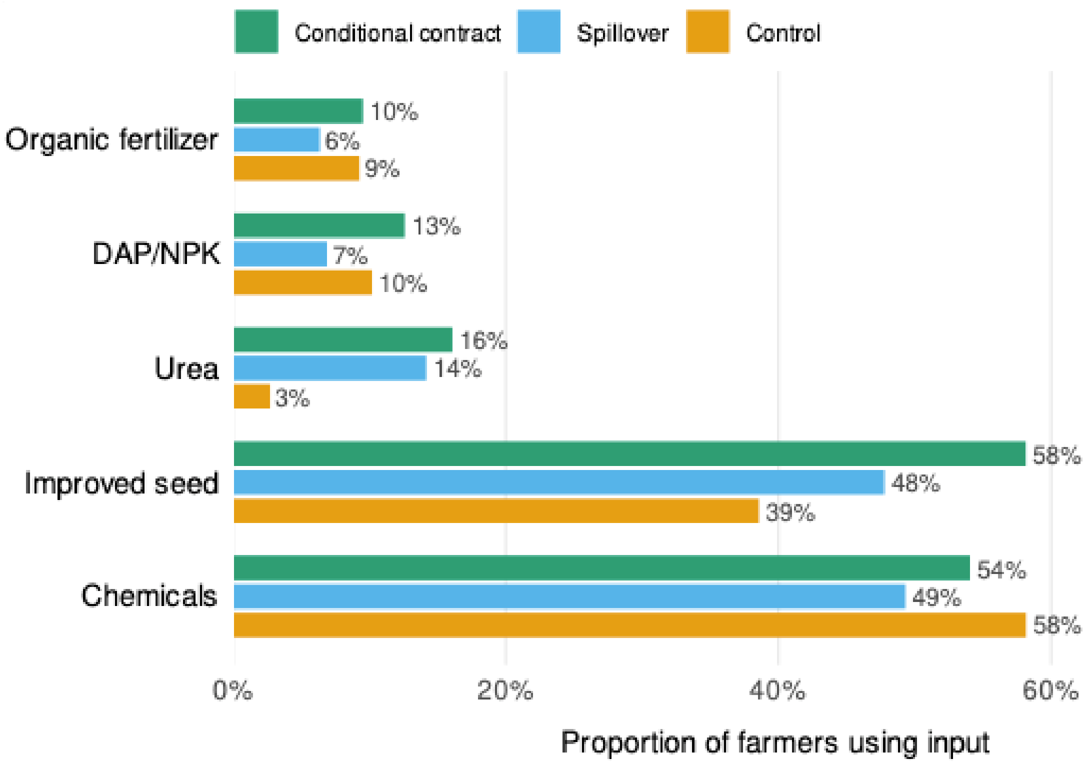
[5] The formal analysis in Section **Error! Reference source not found.** presents results for both seasons.

two common pests in the region. This is also reflected in our data. Just under 60 percent of the farmers in the control group report using some kind of chemical on a randomly selected maize plot, compared to less than 50 percent of farmers in the spillover group and around 55 percent of farmers in the conditional contract group. The lower use among Group 2 farmers may be due to stricter quality standards of the major buyer and linked aggregators that prevent farmers from using excessive amounts of chemicals. However, such differences may also be because of variation in the rate of infestations across treatment and control areas, or because of the seed varieties used.

Next, **Figure 3** depicts the use of improved maize seed varieties, such as hybrid seed or open pollinated varieties, obtained from a trusted source (as opposed to farmer-saved seed). Adoption of improved seed varieties is in line with expectations. About 39 percent of farmers in the control group indicate that they are using seed of an improved maize variety, compared to 48 percent among spillover farmers and 58 percent among farmers in the conditional contract group, suggesting that the conditional contract policy is positively associated with the adoption of improved crop varieties.

The picture for fertilizer use is mixed. As **Figure 3** illustrates, the share of farmers in Uganda using fertilizer is low. Only about 10 percent of farmers apply diammonium phosphate (DAP) and organic fertilizer, and this does not seem to be correlated to exposure to the indirect conditional contract policy. In the case of urea, we do see some evidence that adoption is positively correlated with residing in an area where the major buyer has procured maize through the conditional contract policy.

Figure 3. Adoption of agricultural inputs



Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Production and productivity

Next, we examine whether production-related outcomes differ across farmer groups. We begin by assessing whether farmers in areas where the conditional contract was implemented (Groups 2 and 3) are more likely to cultivate maize, and if so, whether they allocate a larger area to maize production. Panels A and B of Table 3 report the propensity to produce and the area under cultivation in three seasons for the three types of farmers in our sample. We see significant differences across farmers' groups (Table 3). For example, in the first season of 2023, approximately 93 percent of the farmers in the conditional contract group cultivated maize while only 87 percent of farmers in the control group did so (Panel A). The spillover farmers in Group 3 were as likely to produce maize as those in the conditional contract group. It is important to acknowledge that these figures may be somewhat inflated due to the inclusion criterion that required farmers to have cultivated maize in at least one season. Nonetheless, the key point is the observed distinction between the control group and those in the spillover and indirect contracting groups. Even though the proportion of farmers reporting that they were producing maize declines monotonically in each group from first season of 2023 to the first season of 2024, those farmers directly or indirectly affected by the policy remain considerably more likely to continue growing maize.

Panel B shows that area planted under maize is larger among farmers in the conditional contract group. In the first season of 2023, for instance, farmers in this group planted an average of 2.7 acres, compared to an average of 2.3 acres among farmers in the control group. The magnitude of the gap between farmers in Groups 1 and 2 declines across seasons, but farmers in Group 2 always cultivate at least as large an area as the farmers in Group 1 (the control areas). In contrast, the spillover farmers in Group 3 cultivate, on average, an area closer to or smaller than that of Group 1 farmers.

Panel C of Table **3** summarizes quantities produced. The first thing to note, suggested also by Panels A and B, is the sharp reduction in production in the first season of 2024. This was caused by erratic rainfall: it rained unseasonably early but then stopped, resulting in the planted seeds not germinating and farmers needing to replant. For the remainder of the season, there was inadequate rain until the critical stage of tasseling. Numbers for the first season of 2024 should, therefore, be treated as unusual. In the other two seasons, we see production numbers in line with our a priori expectations: in the first season of 2023, Group 1 farmers produced 1,872.1 kg, on average, as compared to 2,313.5 kg for farmers in Group 2, the conditional contract group, or 1,939.3 kg for farmers in Group 3, the spillover group. In the second season of 2023, average production is higher among Group 1 farmers and lower among Group 3, but in all three seasons, the largest quantities are produced by farmers in Group 2, the conditional contract group.

Average production volumes masks differences in areas cultivated, so Panel D of Table **3** summarizes the data on yields in kilograms per acre. Again, the first season of 2024 is an outlier, though overall yield reductions are mitigated somewhat by the reduction in plot size we saw in Panel B. Even after adjusting production for plot size, yields are highest among farmers in the conditional contract group, followed by spillover farmers, with farmers in the control group exhibiting the lowest yields in each of the three seasons we study.

Table 3. Production-related outcomes

	Group 1: Control	Group 2: Conditional contract	Group 3: Spillover	p-values		
				1 & 2	2 & 3	1 & 3
Panel A: Produce (yes/no, %)						
First season of 2023	87	93	92	0.001	0.525	0.007
Second season of 2023	78	88	87	0.000	0.814	0.000
First season of 2024	45	53	52	0.011	0.801	0.022
Panel B: Plot size (acres)						
First season of 2023	2.3	2.7	2.4	0.088	0.165	0.807
Second season of 2023	2.4	2.5	2.2	0.531	0.191	0.466
First season of 2024	2.2	2.2	1.9	0.947	0.091	0.109
Panel C: Production (kg)						
First season of 2023	1,872.1	2,313.5	1,939.3	0.052	0.117	0.769
Second season of 2023	2,021.1	2,351.7	1,897.5	0.154	0.058	0.595
First season of 2024	889.5	964.2	876.9	0.682	0.630	0.945
Panel D: Yield (kg/acre)						
First season of 2023	723.7	806	800.3	0.019	0.877	0.031
Second season of 2023	725.8	870.7	842.9	0.000	0.463	0.000
First season of 2024	362.5	440.6	444.1	0.042	0.928	0.036
Obs.	503	392	389			

Note: Group 1 consists of farmers in districts where the major buyer was not active. Group 2 includes farmers who appeared on traceability lists of wholesalers supplying the major buyer under the indirect conditional contract modality. Group 3 includes the nearest neighbors of Group 2 farmers within the same districts but not on the traceability lists (spillover group). "Produce" indicates whether the farmer cultivated maize in the given season. Plot size refers to the total area (acres) planted to maize. Production is total maize output (kg) reported for that season. Yield is calculated as production divided by plot size (kg/acre). p-values correspond to pairwise tests of equality of means between groups. The first season typically spans March–July; the second season spans September–January. Production in the first season of 2024 is unusually low due to erratic rainfall.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Seasonality

Most farmers typically sell the bulk of their harvest immediately after harvest. Over time, as stocks dwindle, less and less maize is brought to the market. During the lean season, and especially immediately before the harvest of the subsequent season, more maize is bought by farmers than sold. These demand and supply patterns result in seasonal/cyclical fluctuations in maize prices, which can be large; prices often more than double over the period from immediately postharvest to immediately preharvest of the next season. For resource-poor farmers with limited or no storage who do not have the capacity to engage in intertemporal arbitrage, this can lead to "sell-low, buy-high" patterns, as farmers sell maize at low prices right after the harvest, only to buy back similar amounts of maize later in the season for their own consumption, at significantly higher prices

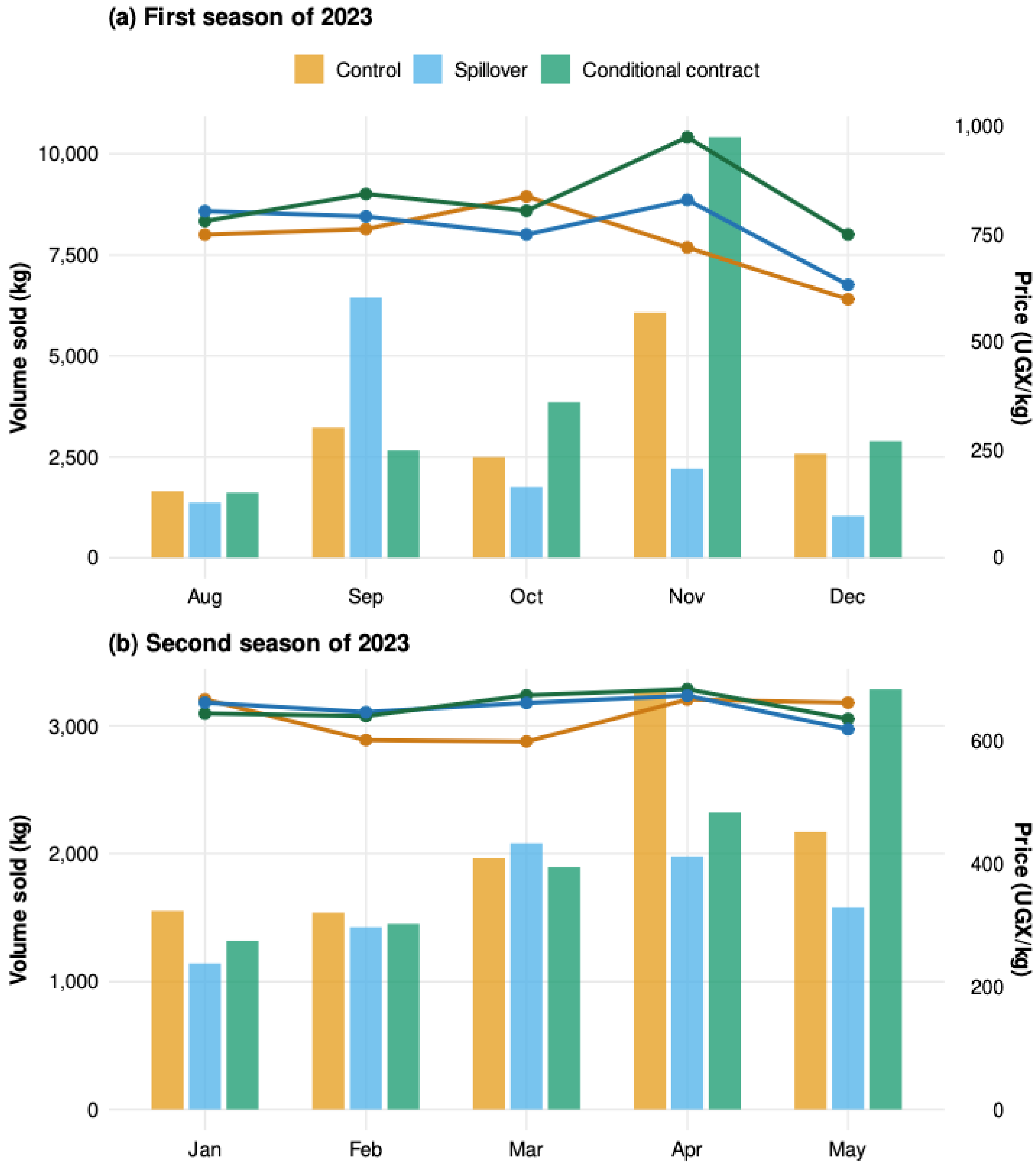
(Burke, Bergquist, and Miguel, 2019). Van Campenhout, Lecoutere, and D'Exelle (2015) argue that farmers face a double burden: not only do they bear the brunt of price volatility, but they are also likely to have transaction costs passed on to them by aggregators (Burke, Bergquist, and Miguel, 2019; Van Campenhout, Lecoutere, and D'Exelle, 2015b).

An important question to consider while discussing whether the presence of a major buyer who institutes a conditional contract resulting in reliable markets is, therefore, whether this presence increases or reduces seasonality in prices. If the major buyer purchases maize at low prices immediately postharvest (and potentially releases this maize during the lean season), its activities could have countercyclical price effects. However, if the major buyer delays procurement (for example, due to administrative reasons) or if aggregators speculate on the major buyer's purchase, price variation could increase.

Figure **4** uses farmer-level data to look at seasonality in maize volumes entering the market and in maize prices for the two seasons of 2023. Interestingly, we do not find that quantities sold are highest immediately after harvest. Especially in the second season, farmers seem to hold on to their maize until April or May. Comparing across farmer types, there is some suggestive evidence that farmers in the conditional contract group hold on to their maize longer. For instance, in the first season of 2023, the volumes of maize sold by farmers in the conditional contract group rose steadily to a peak in November, while in the second season, the peak in volume sold for these farmers is in May. Patterns are less clear for the other groups. In the first season, sales peak among spillover farmers early on, in September. In the second season, there is an unusual uptick in sales in April in the control group.

Prices seem to remain stable immediately after harvest. There is a notable increase in prices in the first season of 2023 in November, which is also the month when volumes sold peak in those areas where the major buyer is active. Interestingly, the increase in prices is highest in the group of farmers that are linked to the major buyer and lowest for those farmers in the control group. Overall, and in both seasons, prices reported by farmers in Groups 2 and 3 are generally higher, suggesting that purchases by the major buyer are associated with some degree of price inflation.

Figure 4. Seasonality in price and volumes



Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

4.2 Commodity flows

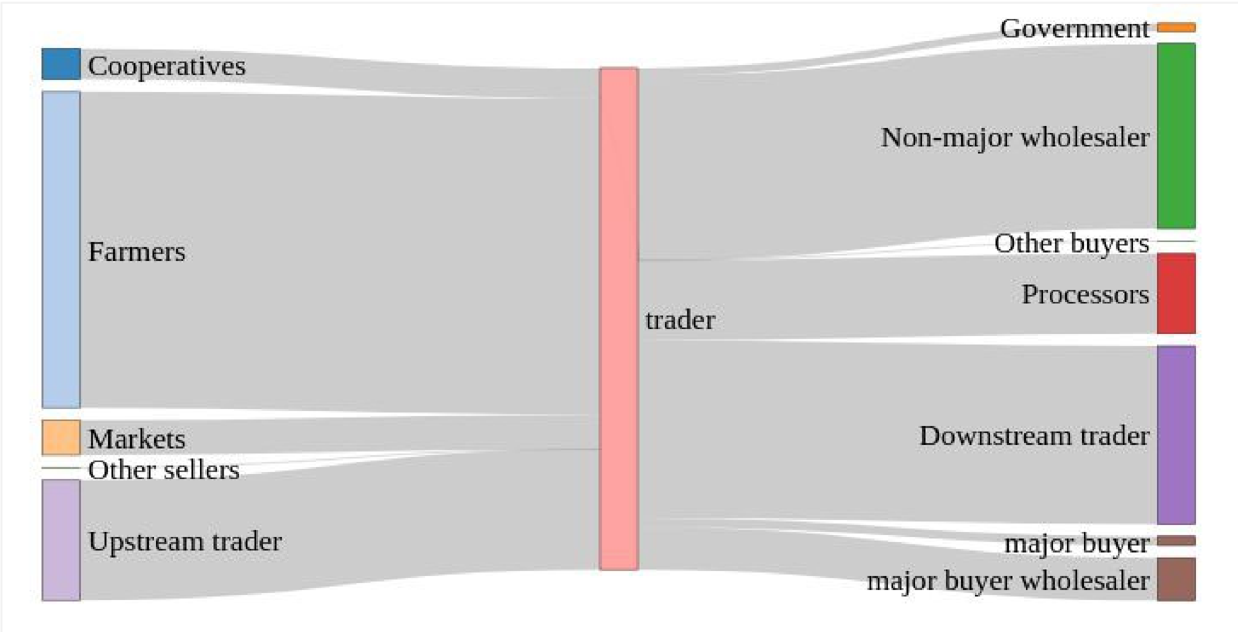
In this section, we take a closer look at commodity flows within the value chain. Specifically, we use aggregator level data to examine how the origin and destination of traded maize differ between farmer groups. We asked aggregators to report the origin of their purchases as a share of total volume, as well as to indicate the distribution of their sales across different buyer types, expressed as percentage shares.

Figure **5** depicts these flows. In both the areas served by the major buyer (Panel (a)) and the control areas (Panel (b)), approximately 65 percent of maize procured by aggregators comes directly from farmers. Fellow aggregators/upstream traders are also a significant source, constituting a slightly higher share in areas where the major buyer is active compared to the control group (24 versus 20 percent). Aggregators operating in areas where the major buyer is active source more maize from markets, and three times more from farmer co-operatives than their counterparts in the control areas. Qualitative insights suggest that this difference may stem from the conditional contract's requirement for farmer registration, a process that is often more straightforward when dealing with co-operatives that typically maintain farmer registries.

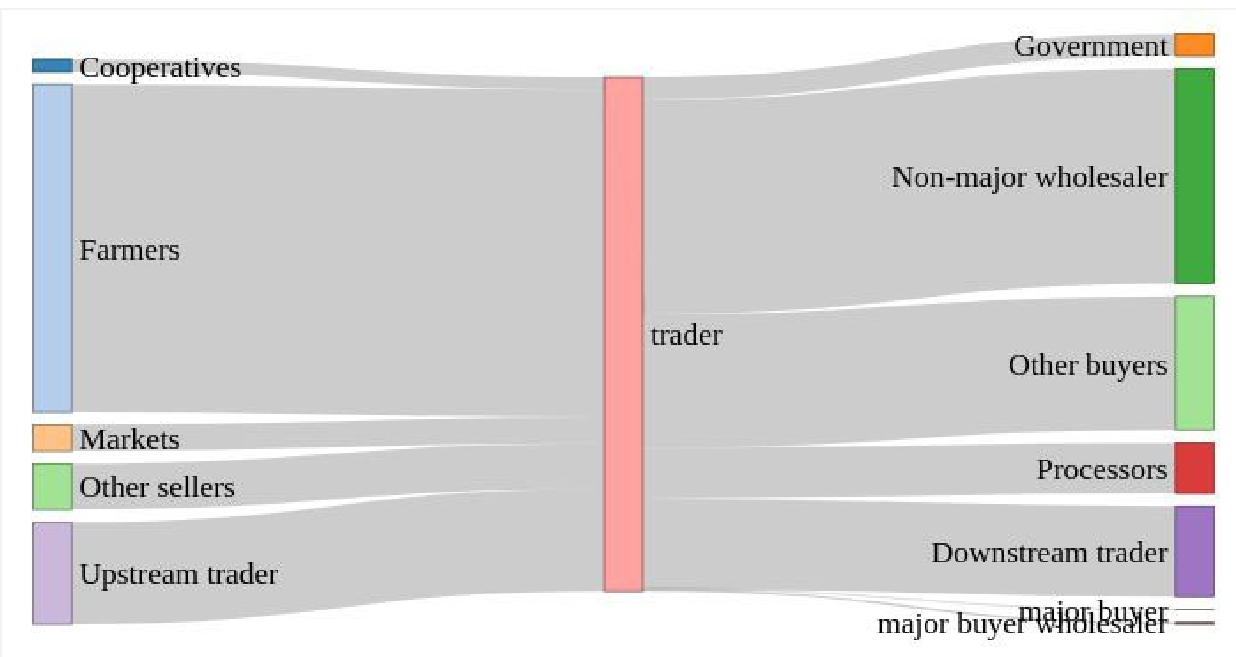
On the downstream side, most maize is sold to wholesalers not linked to the major buyer. In areas where the major buyer is active, a comparable share is also sold to other downstream traders (Panel (a)). This share is far smaller among aggregators operating in the control areas. Notably, in control areas, a large portion of sales is recorded under "other buyers," a residual category used when reported shares did not sum to 100 percent. As expected, aggregators in control areas rarely sell to the major buyer, either directly or through wholesalers affiliated with the major buyer; this contrasts to 10 percent of the maize that is supplied to the major buyer in areas where the major buyer is active.

Figure 5. Commodity flows

(a) Conditional contract and spillover areas



(b) Control areas



Source: Authors' calculation based on IFPRI's maize value chain survey conducted in May–June 2024.

4.3 Price, production costs, and net returns

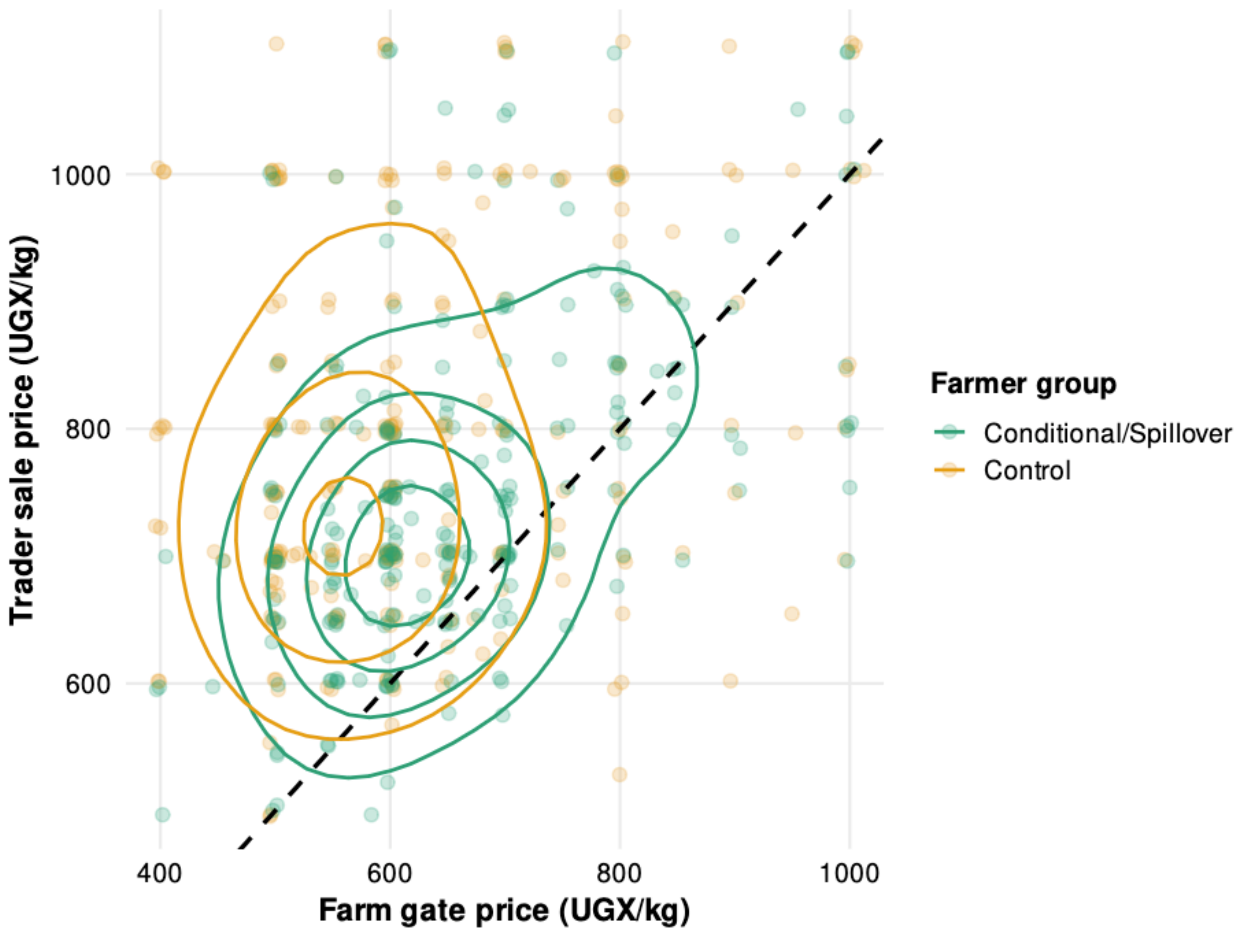
Price margins

The question of how rents are distributed across different value chain actors is central to value chain studies. A convenient way to illustrate this distribution is through price spread plots that depict prices received by the upstream actor (in our case, the farmer) against prices received by the downstream actor (in our case, the aggregators). Figure 6 plots observations for farmer–aggregator transactions, with control areas depicted in red and conditional contract and spillover areas in green. The 45-degree line represents the scenario where prices paid to upstream actors equal prices received from downstream actors. As such, points above the 45-degree line represent transactions where the downstream actor earns a positive margin, while points below the 45-degree line are instances where a loss is incurred as commodities are sold at lower prices than at which they were bought.

As can be seen, most points lie above the 45-degree line, though there also seem to be occasions where the price at which aggregators (reportedly) bought maize was higher than the price at which they sold. While some of these aggregators may indeed have incurred losses, this pattern may also reflect reporting error. In particular, aggregators were asked to report a single "average" buying price and a single "average" selling price for the entire season. If buying and selling occur at different moments in time, or at different volumes, then these reported averages may not correspond to the same set of transactions. As a result, the reported average selling price can appear lower than the reported average buying price even when the aggregator did not actually operate at a loss.

To deal with over-plotting, we added contour plots to the figure, with the same color coding as described above. For the control group, density is highest at points corresponding to a farmgate price of maize of about UGX 550/kg and a sales price of about UGX 725/kg, leading to an aggregator margin of about UGX 175/kg. In other words, in control areas, farmers receive about 75 percent of the price at which aggregators sell onward. For aggregators working in areas where the major buyer was purchasing under the conditional contract arrangement, the density is highest to the southeast of the control density plot. In particular, in these areas, aggregators pay about UGX 625/kg, while they sell onward at about UGX 700, leading to a margin of about UGX 125/kg, meaning that farmers receive about 90 percent of the price at which aggregators sell. Compared to the control areas, farmers in areas where the conditional contract policy was implemented get more at the farmgate, while those buying from aggregators pay less, suggesting that value chains are more efficient than in control areas.

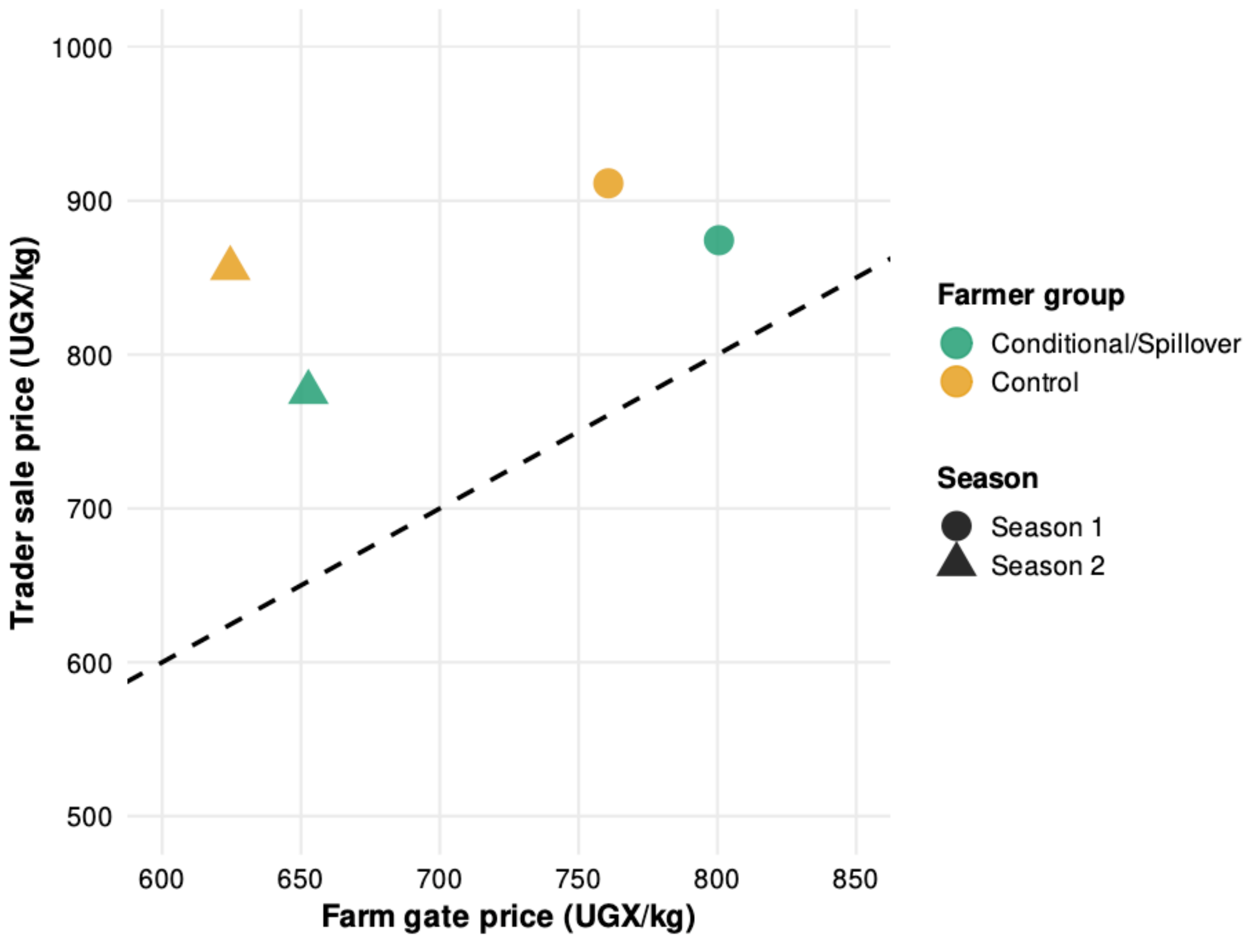
Figure 6. Price margin analysis using aggregator level data



Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

We also combine data at the farmer level with data at the aggregator level for each season to triangulate these important findings on price transmission. Figure 7 confirms that in areas where the major buyer was active, aggregators capture a smaller portion of the rents than in control areas, regardless of the season. For example, in the first season of 2023, farmers sold maize at about UGX 800/kg, while aggregators sold at about UGX 875/kg, implying a pass-through of about 90 percent. In the control areas, farmers sold at about 750 UGX/kg, while aggregators sold at 900 UGX/kg, implying that farmers only got about 83 percent of seller prices. We also see that the margin reduces with overall price levels. In the second season of 2023, farmers in treatment areas sold at around 650 UGX/kg, while aggregators sold at 775 UGX/kg, implying a pass-through of 83 percent; in control areas the pass-through reduces to 73 percent in this season.

Figure 7. Price margin analysis combining farmer and aggregator level data



Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

The higher farmgate prices we observe for farmers in areas where the major buyer is operating could reflect the direct effect of higher prices and volumes offered by the buyer. However, somewhat surprisingly, this is accompanied by a notable reduction in the prices at which aggregators sell maize onward. One possible explanation is that aggregators linked to the major buyer have limited ability to engage in intertemporal price arbitrage. Because they must meet the buyer's procurement timelines, they may be likely required to sell earlier in the season before prices peak. This constraint on timing could compress margins, particularly in years with strong seasonal price fluctuations, and may partly explain the lower resale prices observed among aggregators operating within the procurement framework of the major buyer.

Another explanation, which is consistent with the higher number of aggregators operating in areas where the major buyer is active (reported in Section 4), is that the entry of a large buyer leads to increased competition among aggregators, thereby squeezing margins in the midstream. We test this hypothesis formally using mediation analysis, as described in Section 3, with results presented in Table 4. To construct a farmer-level measure of competition, we compute for each farmer the inverse-distance-weighted average of the number of competing aggregators reported by traders in the area, using GPS coordinates to calculate Haversine distances between each farmer–trader pair. This continuous measure captures the intensity of aggregator competition faced by each farmer, giving greater weight to traders operating nearby.

Table 4 reports the path estimates from a structural equation model with bootstrapped standard errors (500 replications). The first-stage path (a) confirms that the presence of the major buyer is associated with significantly greater aggregator competition, equivalent to approximately two additional aggregators operating in the area ($p<0.001$). The second-stage path (b) indicates that each unit increase in the competition measure is associated with a farmgate price increase of UGX 13.72/kg ($p<0.001$). The direct effect of the major buyer on farmgate prices, controlling for competition, is UGX 26.69/kg but is not statistically significant ($p=0.233$). In contrast, the indirect effect operating through aggregator competition is UGX 27.89/kg, which is statistically significant ($p<0.001$), indicating that roughly half (51 percent) of the total price effect of UGX 54.58/kg is mediated by increased competition among aggregators. This is consistent with the finding above that farmer and aggregator prices move in opposite directions: the entry of a large buyer intensifies competition for farmer grain, compressing aggregator margins, and shifting rents toward producers.

Table 4. Mediation analysis: Aggregator competition as a channel for farmgate price effects

	Estimates	**SE**	**p-value**	**95% CI**
Path estimates				
Major buyer – Competition (number of aggregators) (a)	2.033***	0.175	<0.001	[1.666, 2.345]
Competition – Farmgate price (UGX/kg) (b)	13.720***	3.816	<0.001	[5.847, 21.321]
Major buyer – Farmgate price, direct (UGX/kg) (c’)	26.688	22.389	0.233	[-19.966, 67.099]
Effect decomposition				
Indirect effect (a x b)	27.887***	7.939	<0.001	[11.534, 42.810]
Direct effect (c’)	26.688	22.389	0.233	[-19.966, 67.099]
Total effect (c’ + a x b)	54.575	-	-	-
Share mediated (%)	51.1			

Note: Structural equation model estimated via R-package lavaan. Standard errors and confidence intervals obtained by percentile bootstrap (500 replications). The dependent variable is the average farmgate price in UGX/kg (first season of 2023). Competition is measured as the inverse-distance-weighted average number of aggregators operating in each farmer’s area, constructed using GPS-based Haversine distances. *** $p<0.01$.
Source: Authors’ calculations based on IFPRI’s maize value chain survey conducted in May–June 2024.

Production costs and net returns

A relevant question is whether the higher prices documented above compensate for any additional costs that farmers may incur to meet the quality and compliance requirements associated with the conditional contract. Table 5 disaggregates production costs and computes net returns for the three farmer groups across the two seasons of 2023.

Panel A of Table 5 reveals that conditional contract farmers incur systematically higher costs in several categories. Machine rental costs are approximately twice as high for conditional contract farmers compared to control farmers (201,440 vs. 90,780 UGX in the first season; $p=0.010$), consistent with the need to use mechanized shelling to maintain production quality. Postharvest handling costs are also substantially higher (103,012 vs. 57,053 UGX in the first season; $p=0.056$), reflecting investments in drying, cleaning, and moisture testing. Notably, family labor costs are significantly lower for conditional contract farmers (109,099 vs. 161,041 UGX in the first season; $p<0.001$), suggesting a substitution away from family labor toward mechanized and hired services.

Panel B shows that while total production costs are 29–39 percent higher for conditional contract farmers relative to control farmers, these differences are not statistically significant at conventional levels due to high within-group variance. Total revenue is higher for conditional contract farmers in the first season (2,339,131 vs. 1,833,335 UGX) but not in the second season.

The most informative comparison is presented in Panel C, which normalizes net returns by quantity sold. Control farmers exhibit negative net returns per kilogram in both seasons (−161 UGX/kg and −251 UGX/kg), indicating that on a per-unit basis, selling maize is a losing proposition for the average farmer in control areas. In contrast, conditional contract farmers earn positive net returns per kilogram (+117 UGX/kg and +104 UGX/kg). The difference is statistically significant ($p=0.001$ in the first season; $p<0.001$ in the second season), suggesting that the price premiums documented above more than compensate for the additional compliance costs. Spillover farmers also earn positive per unit net returns in the first season (+108 UGX/kg), but their performance weakens in the second season (−218 UGX/kg).

Table 5. Production costs, revenue, and net returns by farmer group

	Group 1: Control	Group 2: Conditional contract	Group 3: Spillover	p-values 1 & 2	p-values 2 & 3	p-values 1 & 3
Panel A: Production costs (UGX)						
Seed						
First season of 2023	85,514	95,430	105,724	0.695	0.845	0.683
Second season of 2023	68,452	81,113	86,894	0.627	0.913	0.707
Pesticides/herbicides						
First season of 2023	57,091	71,525	308,417	0.482	0.367	0.338
Second season of 2023	58,504	69,619	359,145	0.641	0.325	0.305
Hired labor						
First season of 2023	326,883	367,733	396,118	0.413	0.792	0.498
Second season of 2023	352,083	337,735	586,516	0.78	0.317	0.341
Family labor (imputed)						
First season of 2023	161,041	109,099	115,562	<0.001	0.626	<0.001
Second season of 2023	162,319	109,387	112,839	<0.001	0.793	<0.001
Machine rental						
First season of 2023	90,780	201,440	226,728	0.01	0.779	0.093
Second season of 2023	89,650	187,731	206,377	0.029	0.826	0.116
Postharvest handling						
First season of 2023	57,053	103,012	94,685	0.056	0.834	0.25
Second season of 2023	56,277	88,828	112,428	0.014	0.519	0.111
Panel B: Totals (UGX)						
Total cost						
First season of 2023	759,992	981,693	1,166,735	0.241	0.705	0.384
Second season of 2023	637,863	887,581	1,322,319	0.137	0.405	0.171
Total revenue						
First season of 2023	1,833,335	2,339,131	1,855,554	0.376	0.569	0.977
Second season of 2023	1,735,768	1,519,725	1,723,223	0.575	0.781	0.987
Net returns						
First season of 2023	867,981	1,295,149	592,840	0.322	0.069	0.437
Second season of 2023	818,373	671,311	195,839	0.644	0.285	0.196
Panel C: Net returns per unit						
Net returns per kg sold (UGX/kg)						
First season of 2023	−161	117	108	0.001	0.906	<0.001
Second season of 2023	−251	104	−218	<0.001	0.125	0.873
Net returns per acre (UGX/acre)						
First season of 2023	133,598	204,906	136,969	0.126	0.128	0.938
Second season of 2023	79,967	136,437	−159,541	0.238	0.242	0.339
Obs.	498	169	169			

Note: All monetary values in UGX. Family labor is imputed at 5,000 UGX per person-day. Total cost includes seed, fertilizer (DAP/NPK, urea), pesticides, hired labor, machine rental, family labor (imputed), and postharvest handling costs. Net returns = total revenue − total cost. p-values correspond to pairwise tests of equality of means across groups. The smaller sample for Groups 2 and 3 reflects that detailed cost data were collected only for a subsample of conditional contract and spillover farmers.

Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

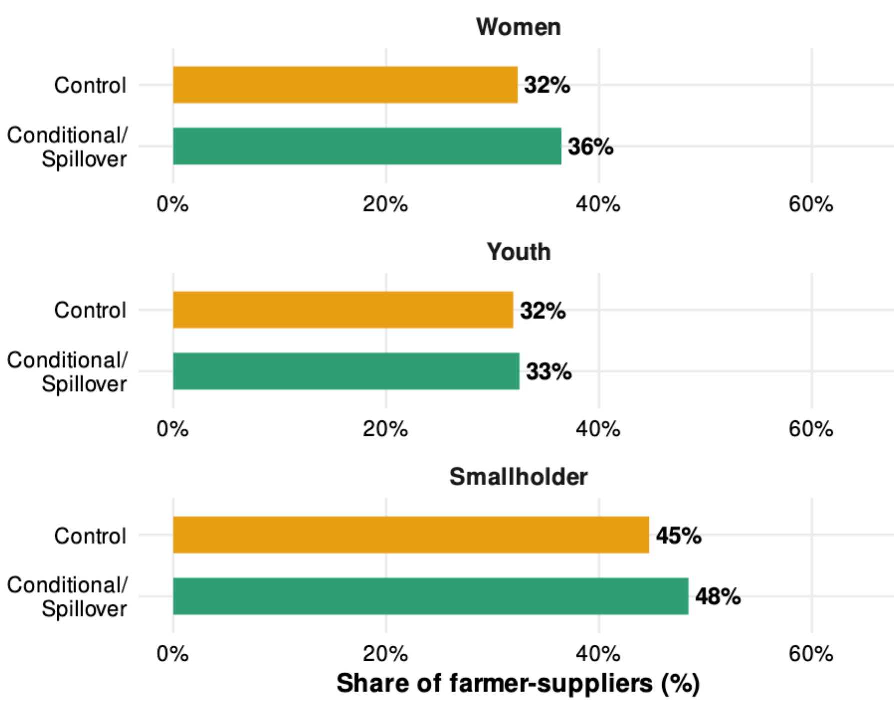
4.4 Inclusivity

Finally, we turn to inclusivity. An important objective of the major buyer's procurement policy is that the benefits arising from their procurement should reach vulnerable groups, especially women and youth. Additionally, one of the core objectives of the policy is to ensure that smallholder farmers are able to benefit the most from the major buyer's procurement activities. In this section, we examine whether the impact differs across groups, with a particular focus on farmgate prices as the key outcome variable.

To assess inclusivity, we asked aggregators to estimate the proportion of their farmer-suppliers who are women, youth, and smallholders. As shown in

Figure **8**, approximately 30 percent of sellers are women, with a slightly higher share observed in areas where the policy is implemented. Around 30 percent of the sellers are classified as youth, that is, age 35 or younger, with little variation between treated and comparison areas. Regarding smallholder farmers, defined as those operating less than 2 acres of land, we see a slightly higher percentage of smallholder farmers in the areas where the policy is active, suggesting that the intervention may be enhancing participation among this target group.

Figure 8. Characteristics of farmers selling to aggregators in the first season of 2023



Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Overall, therefore, while differences across groups in the proportion of farmers who are women, youth, or smallholders are small, the descriptive results do suggest that the implementation of the conditional contract policy does not exclude these marginalized groups from participating actively in the maize market.

5. Main Results

In this section, we revisit some of the most striking findings from the descriptive analysis of market participation, adoption of inputs, investments in quality, price margins, and net returns. In particular, we assess whether the observed descriptive patterns persist under more rigorous scrutiny using regression analysis based on OLS and IV estimation.

5.1 Effect on prices

To examine the association between exposure to conditional contracting and prices, we begin with the price margin analysis presented in Section 4, focusing first on farmgate prices. We use transaction-level data from the first two seasons of 2023. Following standard practice in price analysis, we use the natural logarithm of the farmgate price per kilogram as the dependent variable, which allows coefficients to be interpreted approximately as proportional effects and reduces the influence of outliers in the price distribution.

Column (1) of Table 6 reports our primary intent-to-treat (ITT) estimate: the average effect of residing in a treatment area without additional controls, but including season and month fixed effects. Farmers in treatment areas receive approximately 5 percent higher prices than farmers in control areas ($p=0.001$), consistent with the descriptive patterns in Figure 7. When controls are added in Column (2), the ITT estimate increases modestly to 6 percent ($p<0.001$). The ITT is our preferred estimand: it captures the total effect of the buyer's area-wide presence—combining direct gains for connected farmers and market-level effects on non-connected farmers—without requiring the exclusion restriction to hold.

Columns (3) and (4) present IV (2SLS) estimates that instrument individual major buyer connection with geographic assignment. As established in Section 3 and confirmed by the placebo results below, the instrument affects local market structure for all farmers in treatment areas, not only those who connect individually to major buyer-linked aggregators. The IV estimates should therefore be interpreted as an upper bound on the private return to individual connection, conditional on the buyer operating in the local market. Column (3) implies a price premium of approximately 40 percent for farmers who sold to aggregators linked to the major buyer ($p=0.002$); Column (4) with full controls yields approximately 45 percent ($p<0.001$).[6]

The IV-to-OLS ratio for farmgate prices is approximately 7.5, and we find ratios of similar magnitude for other farmer-level outcomes as well: about 7.5 times for the adoption index and 6.4 times for net returns per kilogram. Two mechanisms likely explain this divergence. First, OLS estimates based on location are likely attenuated by measurement error, since geographic

[6] In all IV regressions, the first stage is the virtually the same (apart from changes in the operational sample size). We report the F-statistic in the bottom panel of the table and report full first stage results in the Annex.

assignment imperfectly captures true program exposure. Second, the IV estimates identify a local average treatment effect (LATE) for compliers: farmers whose trading behavior is shifted by geographic assignment. Since only about 10 percent of observed transactions involve a connection to the major buyer, this complier group is small and may represent farmers whose marketing decisions are particularly responsive to the entry of connected aggregators, generating larger estimated effects than for the average farmer.

Table 6. Effect of major buyer connection on farmgate prices

	Dependent variable: log (farmers selling price UGX/kg)			
	OLS		**IV (2SLS)**	
	(1)	**(2)**	**(3)**	**(4)**
Connected	0.051***	0.059***	0.397***	0.442***
	(0.016)	(0.016)	(0.126)	(0.122)
Male, head		−0.000		0.005
		(0.016)		(0.018)
Age, head		-0.000		-0.000
		(0.001)		(0.001)
Head finished primary education		0.023		0.021
		(0.014)		(0.016)
Household size		−0.001		-0.002
		(0.002)		(0.003)
Land owned		0.002***		0.000
		(0.001)		(0.001)
Co-op member		−0.026		−0.046*
		(0.025)		(0.027)
Volume sold		0.000		0.000
		(0.000)		(0.000)
Constant	6.477***	6.477***	6.477***	6.519***
	(0.023)	(0.045)	(0.025)	(0.049)
Month FE	Yes	Yes	Yes	Yes
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			94.4	96.2
Obs.	2,210	2,099	2,210	2,099

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

The placebo results are instructive. Among farmers who transacted with aggregators linked to the major buyer, location does not significantly predict prices—conditional on connection, geographic assignment provides no additional explanatory power. But among farmers who did not transact with connected aggregators, those in treatment areas receive significantly lower prices than comparable non-connected farmers in control areas. This is not a residual nuisance: it is a market-segmentation effect operating through a channel distinct from individual connection with the major buyer. As additional aggregators enter treatment areas competing for major buyer-linked volumes, they concentrate purchasing effort on registered and quality-compliant suppliers. This reduces competition for maize outside the program, depressing prices for non-connected farmers (and may also partly explain lower market participation in this group that was documented in the descriptive analysis). Geographic assignment therefore affects prices through both the individual connection channel and this broader market-restructuring channel, confirming that the exclusion restriction does not hold in the narrow sense required for an individual-level IV. As noted in Section 3, we treat the ITT estimates as our primary estimand; the IV estimates bound the private return to connection from above.

The direction of this violation is informative. The negative price effect among non-connected farmers in treatment areas indicates that the IV estimates reflect a combination of a direct gain from trading through connected aggregators and an indirect loss borne by those who remain outside the scheme. The 2SLS estimates therefore overstate the net benefit of the major buyer's presence relative to a counterfactual in which the buyer did not operate in the area at all. They remain informative as an upper bound on the private return to becoming connected, conditional on the buyer's presence in the local market, which is the interpretation we carry forward throughout the results.

To gauge the economic significance of these price effects, we translate the per-kilogram estimates into seasonal income terms. The median farmer in our sample sells approximately 1,000 kg of maize per season. Applying the OLS point estimate of 6 percent to the control-group mean price of 701 UGX/kg implies a premium of roughly 42 UGX/kg, or a seasonal income gain of approximately 42,000 UGX (about US$12 at 2024 exchange rates). This is modest in absolute terms. For compliers identified by the IV, the implied gain is substantially larger: the estimated 44.2 percent premium translates to approximately 310 UGX/kg, so that a farmer selling 1,000 kg would earn an additional 310,000 UGX per season (approximately US$86).

To assess whether the price effects of the intervention differed across demographic groups, we explored heterogeneity in the intent-to-treat (ITT) estimates by interacting treatment assignment with indicators for female-headed households and youth-headed households (defined as household heads younger than 35 years). Overall, we find little evidence that the price effects differ systematically across these groups. None of the interaction terms reaches conventional levels of statistical significance, suggesting that the farmgate price gains associated with exposure to the major buyer's presence were broadly similar across gender and age categories.

Point estimates nevertheless suggest some suggestive patterns. Female-headed households appear to experience somewhat larger price gains relative to male-headed households, while youth-headed households show modestly larger price responses. These differences are imprecisely estimated and cannot be distinguished from zero. The main price effect remains stable across specifications, with estimated premiums remaining close to 5 percent.

We run a similar analysis at the aggregator level, focusing on the prices aggregators receive when selling maize onward (to the major buyer directly, to traders connected to the major buyer, or to other buyers). At the aggregator level, we lack detailed transaction-level data. However, for both the first and second seasons of 2023, we collected information on the outlets to which aggregators sold their maize and the shares in total sales going to each type of buyer. Aggregators were also asked to report on the prices they received from buyers connected to the major buyer and those not connected. We used this information to compute a weighted average price for each aggregator, using the reported shares sold to each buyer type as weights.

As with the farmer analysis, we use the log of selling prices as the dependent variable. Column (1) of Table 7 presents the regression counterpart of the y-axis in Figure 7, with season fixed effects. The results indicate that aggregators in treatment areas received approximately 7 percent lower prices than their counterparts in control areas (p=0.007). This aligns with the visual evidence from Figure 7, which shows that aggregators' margins are compressed in areas where the major buyer is active.

Similar to the farmer analysis above, relying solely on an aggregator's location to define exposure to the intervention can be misleading. Aggregators are inherently mobile and often operate across multiple areas, potentially sourcing from farmers in both treatment and control locations. Moreover, not all aggregators based in areas where the major buyer instituted the conditional contract are necessarily connected to the major buyer's supply chains. This geographic misclassification blurs the distinction between treatment and control groups, introducing attenuation bias. In addition, aggregators operating in different locations may not be directly comparable. Local market dynamics, transport infrastructure, and crop quality can vary substantially across areas, potentially confounding simple location-based comparisons.

As with the farmer analysis, this underscores the need for a more precise identification strategy based on actual trading relationships rather than geographic proxies. Using the location-based treatment indicator as an instrument, the 2SLS regression reported in Column (3) reveals a large and statistically significant reduction: aggregators who sell to the major buyer or to an affiliated wholesaler receive approximately 30 percent lower prices compared to those selling to other buyers (p=0.013). In Column (4), we extend the specification by adding aggregator-level and transaction-level controls. The estimated effect is similar at approximately 29 percent (p=0.014), reinforcing the robustness of the finding.

Table 7. Effect of major buyer connection on trader-level selling prices

	Dependent variable: log (traders selling price UGX/kg)			
	OLS		IV (2SLS)	
	(1)	(2)	(3)	(4)
Connected	-0.067***	-0.063***	-0.306**	-0.293**
	(0.025)	(0.024)	(0.123)	(0.119)
Male, head		-0.106		-0.175**
		(0.076)		(0.079)
Age, head		0.001		0.001
		(0.002)		(0.002)
Head finished primary education		0.045		0.048
		(0.029)		(0.029)
Household size		0.001		0.003
		(0.004)		(0.004)
Volume sold		0.000		0.000
		(0.000)		(0.000)
Constant	6.787***	6.804***	6.793***	6.871***
	(0.019)	(0.103)	(0.021)	(0.110)
Month FE	Yes	Yes	Yes	Yes
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			62.8	60.9
Obs.	543	541	543	541

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively. Clustered standard errors at the trader level. Columns 1–2: ITT; Columns 3–4: upper bound.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

In sum, the ITT analysis shows that residing in areas where the major buyer operates is associated with approximately 6 percent higher farmgate prices for farmers and approximately 6–7 percent lower selling prices for aggregators. These results are robust to the inclusion of controls and consistent across specifications. The IV estimates, approximately 40–45 percent for farmers and 29–31 percent for aggregators, should be interpreted as upper bounds on the private returns to individual connection, as discussed in Section 3. Taken together, the findings suggest that the intervention redistributed rents within the value chain: connected farmers captured price gains while aggregator margins compressed. Because the ITT estimates capture both direct effects and broader market-level adjustments, they provide the most policy-relevant measure of the intervention's area-wide impact.

The lower prices received by aggregators raise a natural question about the sustainability of participation incentives. Figure 7 suggests that the intervention redistributed rents within the value chain by increasing the share of downstream prices passed through to farmers. In the first season of 2023, farmers in treatment areas received roughly 90 percent of aggregator selling prices, compared to approximately 83 percent in control areas. Similar patterns persist in the second season, where pass-through reached approximately 83 percent in treatment areas compared to 73 percent in control areas. These patterns imply substantially narrower margins for aggregators operating in treatment areas.

While aggregators in treatment areas handled larger median volumes (approximately 20,000 kg versus 10,000 kg in control areas), the higher throughput may not fully offset narrower margins. Simple back-of-the-envelope calculations therefore suggest that gross seasonal profits could still be lower among treatment-area aggregators despite higher volumes.

Several factors may nevertheless sustain aggregator participation. First, relationships with the major buyer provide access to a reliable and recurring demand channel, reducing search costs and uncertainty relative to spot markets. Second, as documented in Section 4, connected aggregators are significantly more likely to provide inputs to farmers, potentially generating additional revenue streams through input resale margins. Third, expectations of continued or expanded procurement opportunities in future tender rounds may create incentives to maintain network positions even when short-run margins are compressed. Nevertheless, whether such margin compression remains sustainable over multiple seasons, particularly if additional entry further intensifies competition among aggregators, remains an open question and warrants monitoring in future rounds of the program.

5.2 Effects on adoption of inputs

Another key outcome we consider at the farmer level is adoption of agricultural inputs. The analysis in Section 4 suggested that for some inputs (urea and improved seed varieties), the policy seemed to have a positive effect, while use of pesticides seems to be reduced. Instead of running the regression analysis for each input separately, we combine them in an index following Anderson (2008). The Anderson index is an inverse-covariance weighted average of the standardized individual input indicators—use of improved seed, DAP/NPK fertilizer, urea, and pesticides—which accounts for the correlation structure among the component measures and gives more weight to inputs that provide independent information.

One complication in this analysis is that the measure of connections to the major buyer is recorded at the transaction level, while adoption is measured at the farmer level. To address this, we aggregate the transaction-level information by defining a farmer as connected to the major buyer if they engaged in at least one transaction with an aggregator linked to the major buyer during the season. If none of their transactions involved an aggregator linked to the major buyer, the farmer is considered not connected. This approach ensures that our farmer-level indicator of connection to the major buyer captures meaningful exposure to the intervention.

Table 8 presents the regression results and confirms the patterns observed in Figure 3. Adoption of improved agricultural technologies is significantly higher in areas where the policy is active (Column 1), with an ITT estimate of approximately 0.11 standard deviations on the Anderson index. As established in Section 3, the IV estimates in Columns (3) and (4) should be interpreted as upper bounds on the individual connection effect rather than as corrected causal estimates: they identify the return to connection for compliers in a market where the buyer's presence also affects non-connected farmers. Both ITT and IV regressions are robust to the inclusion of control variables.

Table 8. Effect of major buyer on adoption of inputs

	Dependent variable: Input adoption index			
	OLS		**IV(2SLS)**	
	(1)	**(2)**	**(3)**	**(4)**
Connected	0.108***	0.109***	0.845***	0.821***
	(0.027)	(0.027)	(0.222)	(0.218)
Male, head		0.033		0.043
		(0.031)		(0.034)
Age, head		−0.002**		−0.003***
		(0.001)		(0.001)
Head finished primary education		0.157***		0.146***
		(0.029)		(0.030)
Household size		0.016***		0.015***
		(0.005)		(0.005)
Land owned		0.009***		0.006***
		(0.002)		(0.002)
Co-op member		0.026		−0.003
		(0.048)		(0.049)
Constant	−0.019	−0.163**	−0.025	−0.101
	(0.021)	(0.082)	(0.023)	(0.083)
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			111.2	111.0
Obs.	2,226	2,129	2,226	2,129

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

We conducted a similar exercise for the adoption index to examine whether exposure to the intervention differentially affected technology uptake across demographic groups. As with prices, we find limited evidence of systematic heterogeneity. Interaction terms by gender and age are not statistically significant, suggesting that adoption responses were broadly similar across subgroups.

Point estimates indicate that female-headed households may have experienced somewhat smaller adoption gains than male-headed households, while differences between youth- and non-youth-headed households appear negligible. However, these estimates are imprecise and should be interpreted cautiously. Because the study was powered to detect average treatment effects rather than subgroup differences, these results should be viewed as exploratory. The estimated main effect on adoption remains stable across specifications, at approximately 0.12–0.14 standard deviations.

We also examine whether aggregators provide inputs such as seed, fertilizer, chemicals, or tarpaulins for drying, and test for differences between aggregators integrated in the major buyer's supply chains versus those that are not (Table 9). The ITT estimates show that major buyer-connected aggregators are significantly more likely to provide such inputs to farmers. The IV estimates in Column (3), which should be read as an upper bound on the individual connection effect, suggest near-complete input provision among connected aggregators, though this magnitude partly reflects the characteristics of the complier subpopulation.

Table 9. Effect of major buyer on traders providing inputs

	Dependent variable: Trader provides inputs (1=yes)			
	OLS		IV(2SLS)	
	(1)	(2)	(3)	(4)
Connected	0.280***	0.242***	1.131***	1.041***
	(0.056)	(0.060)	(0.270)	(0.291)
Male, head		0.179		0.406***
		(0.169)		(0.068)
Age, head		−0.007**		−0.006
		(0.003)		(0.004)
Head finished primary education		−0.041		−0.065
		(0.063)		(0.069)
Household size		0.018*		0.008
		(0.010)		(0.012)
Volume sold		−0.00001		−0.00002
		(0.000)		(0.000)
Constant	0.370***	0.433**	0.326***	0.202
	(0.039)	(0.207)	(0.050)	(0.193)
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			38.3	32.5
Obs.	297	281	297	281

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

In summary, the analysis shows that farmers' adoption of improved agricultural inputs is significantly higher among those connected to the major buyer. There is also a higher likelihood that aggregators that are linked with a major buyer provide inputs and related services. Taken together, these findings suggest that the policy not only enhances market access but also catalyzes the development of a complementary services sector through input provision and advisory support that facilitates productivity-enhancing investments.

5.3 Effects on investment in quality

In this section, we examine whether connection to the major buyer is associated with greater investment in quality by value chain actors. To capture whether farmers undertake basic postharvest practices when preparing maize for sale to aggregators connected to the major buyer, we constructed an index following the Anderson (2008) methodology using four survey items. These items record how the household shells maize (using a machine), how it dries grain prior to sale (on a tarpaulin), whether moisture content is checked, and whether it cleans grain before selling.

The results in Table **10** show a consistently positive association between exposure to the major buyer and household investment in postharvest quality practices, as captured by the composite quality index. In the OLS specifications (Columns 1 and 2), farmers connected to the major buyer score about 0.10 standard deviations higher on the index than those in control areas, a statistically significant difference. These estimates remain stable when household characteristics are included as controls.

Columns (3) and (4) present IV estimates, which as established in Section 3 should be interpreted as upper bounds on the individual connection effect. The IV estimates suggest that connection to the major buyer increases the quality index by approximately 0.58 to 0.62 standard deviations—five to six times larger than the ITT estimates. This amplification reflects the same two mechanisms discussed for prices: measurement error attenuating the ITT, and the IV identifying a LATE for a small subpopulation of compliers who may be systematically more responsive to quality standards. The direction and significance of the effect—that engagement with the major buyer is associated with substantially greater investment in postharvest handling—is robust across both estimators.

Table 10. Effect of a major buyer on farmer-level investment in quality

	Dependent variable: Investment in quality index			
	OLS		IV(2SLS)	
	(1)	**(2)**	**(3)**	**(4)**
Connected	0.102**	0.096**	0.620**	0.577**
	(0.041)	(0.039)	(0.251)	(0.237)
Male, head		−0.087**		−0.086**
		(0.042)		(0.043)
Age, head		−0.004***		−0.005***
		(0.002)		(0.002)
Head finished primary education		0.095**		0.092**
		(0.040)		(0.041)
Household size		0.013*		0.012*
		(0.007)		(0.007)
Land owned		0.005***		0.003
		(0.002)		(0.002)
Co-op member		0.116		0.101
		(0.110)		(0.109)
Constant	−0.066*	−0.051	−0.067*	−0.012
	(0.035)	(0.130)	(0.035)	(0.129)
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			65.2	64.6
Obs.	957	942	957	942

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

At the aggregator level, we assess investment in quality by constructing a binary indicator that captures consistent adherence to key postharvest practices. Specifically, an aggregator is coded as investing in quality if they always dry their maize, always measure moisture content, grade the maize, and clean it using either a screen/sieve or a mechanical cleaner. This composite measure captures a holistic approach to quality management, emphasizing both the physical condition of the maize and the consistency of practices across transactions. By requiring that all these conditions be met, the indicator reflects a sustained and deliberate investment in quality rather than occasional or partial compliance.

Table 11 presents the OLS and IV results. The ITT estimates in Columns (1) and (2) show a modest but significant positive association between location in treatment areas and trader quality investment. The IV estimate in Column (3), an upper bound on the individual connection effect, rises to 0.506 and remains robust in Column (4) with controls (0.590). The large IV-to-OLS ratio is consistent with the pattern observed for farmer-level outcomes and reflects the same combination of attenuation in the ITT and complier selection in the IV.

Table 11. Effect of a major buyer on trader-level quality investment

	Dependent variable: Invests in quality (1=yes)			
	OLS		IV(2SLS)	
	(1)	(2)	(3)	(4)
Connected	0.125***	0.137***	0.506***	0.590***
	(0.041)	(0.044)	(0.187)	(0.219)
Male, head		−0.026		0.102
		(0.152)		(0.212)
Age, head		0.001		0.001
		(0.002)		(0.003)
Head finished primary education		0.110**		0.096**
		(0.043)		(0.049)
Household size		0.018**		0.012
		(0.008)		(0.010)
Volume sold		−0.00001		−0.00001
		(0.00001)		(0.00002)
Constant	0.084***	−0.098	0.065**	−0.229
	(0.022)	(0.188)	(0.029)	(0.260)
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			38.3	32.5
Obs.	297	281	297	281

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

5.4 Effects on net returns

The descriptive evidence in Section 4 shows that conditional contract farmers earn higher net returns per kilogram sold despite facing higher production costs. Here, we test this relationship formally using the same OLS and IV framework employed in the preceding sections. The dependent variable is net returns per kilogram of maize sold, defined as (total revenue − total cost) /kilograms sold, where total cost includes purchased inputs (seed, fertilizer, pesticides), hired labor, machine rental, imputed family labor, and postharvest handling costs. We winsorize the outcome at the 1st and 99th percentiles to limit the influence of outliers.

Table 12 presents the results. In the OLS specification without controls (Column 1) farmers in the treatment areas earn approximately 234 UGX more per kilogram than control farmers ($p<0.001$). This estimate is stable after including household controls (Column 2: 239 UGX/kg, $p<0.001$). When we instrument actual connection to the major buyer with the location-based strata indicator (Columns 3 and 4), the estimated effect increases to approximately 1,535–1,545 UGX/kg ($p<0.001$).

Table 12. Effect of major buyer connection on net returns per kilogram sold (UGX/kg)

	Dependent variable: Net returns per kg sold (UGX/kg)			
	OLS		IV(2SLS)	
	(1)	(2)	(3)	(4)
Connected	233.900***	239.271***	1,535.713***	1,544.979***
	(52.885)	(53.545)	(402.045)	(399.045)
Male, head		−48.011		11.512
		(63.919)		(75.197)
Age, head		−5.834***		−5.568**
		(2.157)		(2.390)
Head finished primary education		−9.779		−22.850
		(60.138)		(66.664)
Household size		6.842		−4.934
		(8.910)		(10.552)
Land owned		9.092***		1.065
		(3.157)		(5.638)
Co-op member		−104.248		−173.900*
		(81.176)		(92.902)
Constant	−125.930***	204.516	−137.047***	308.824*
	(46.862)	(157.466)	(49.365)	(173.283)
Season FE	Yes	Yes	Yes	Yes
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			115.8	109.1
Obs.	1,294	1,220	1,294	1,220

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

For net returns specifically, the IV estimate of approximately 1,545 UGX/kg is large. Given mean farmgate prices of approximately 675 UGX/kg, this implies that connected compliers more than double their net returns per kilogram. As with the price and adoption estimates, this should be read as an upper bound on the private return to individual connection: it captures the return for a small subpopulation of marginal farmers who shift marketing channels in response to geographic assignment, and it does not account for the price depression experienced by non-connected farmers in the same areas. We place greater confidence in the direction of the effects—connection to the major buyer raises farmgate prices, increases input adoption, and improves net returns—than in the precise IV magnitudes.

5.5 Additional effects on farmer welfare and resilience

Beyond production and market-level outcomes such as adoption of input and prices, a central policy question is whether indirect conditional contracts affect household welfare. This section extends the regression framework used in the preceding sections to three welfare dimensions: food insecurity, dietary diversity, and livelihood coping strategies. We measure food insecurity using the Food Insecurity Experience Scale (FIES) index, an additive index (0–8) based on eight questions about the household's experience of food insecurity over the previous 12 months, following the FAO Voices of the Hungry methodology. Higher values indicate more severe food insecurity. Dietary diversity is measured using the Household Dietary Diversity Score (HDDS), which counts the number of distinct food groups consumed by the household in the 24 hours preceding the interview (0–8), with higher scores indicating better dietary quality. Finally, livelihood coping strategies are captured using the Livelihood Coping Strategies indicator (LCS-FS), which measures the number of stress, crisis, and emergency coping behaviors adopted by the household in response to food shortages over the 30 days prior to the survey, with higher values indicating greater reliance on coping mechanisms.

We estimate the effects on the welfare indicators separately for farmers and aggregators. As in the preceding sections, we estimate OLS (intent-to-treat) and 2SLS (upper bound on the private return to individual connection) specifications, with treatment assignment instrumenting actual connection to the suppliers of the major buyer.

Table A1 in the Annex reports the effect of connection with a major buyer on farmer food insecurity, dietary diversity, and livelihood coping strategy. The OLS intent-to-treat estimate in Panel A–Column (2) indicates that farmers in treatment areas have an FIES score 1.47 points higher than control farmers ($p < 0.01$), a substantial difference equivalent to roughly 82 percent of the control group mean. The 2SLS estimate in Panel A–Column (4), which instruments actual connection to the major buyer with treatment assignment, is considerably larger at 8.30 points ($p < 0.01$). The significant farmer results conflate the major buyer program targeting: local procurement operations may have been established in areas with higher food insecurity. Because our analysis is based on cross-sectional estimates, these results on food security are likely to reflect these pre-existing spatial differences rather than an adverse causal effect of the program.

Turning to dietary diversity, control-group farmers consume an average of 6.14 food groups, indicating relatively high dietary diversity. The ITT estimate in Panel B– Column (2) shows that farmers in treatment areas consume 0.43 fewer food groups than control farmers ($p < 0.01$), a modest but statistically significant difference of about 7 percent of the control mean. The 2SLS estimate in Column (4) indicates a reduction of 2.42 food groups for compliers ($p < 0.01$). The lower dietary diversity among treatment-area farmers mirrors the FIES results and reinforces the program-targeting interpretation. Areas selected for the major buyer's operations appear to have systematically lower dietary quality, a gap that the program's market-level benefits may be narrowing but have not yet closed.

For livelihood coping strategies, the control-group mean for farmers is 0.56, indicating that the average control household employs fewer than one coping strategy. The ITT estimate in Panel C–Column (2) is 1.31 ($p < 0.01$), more than doubling the control-group level. The 2SLS estimate of 7.38 additional strategies for compliers ($p < 0.01$) is again substantially amplified relative to the ITT. The greater reliance on coping strategies among treatment-area farmers is consistent with the

FIES and HDDS findings: households in areas targeted by the major buyer face more food stress and resort to coping mechanisms more frequently, reflecting pre-existing vulnerability in these locations.

Moving to traders, the mean FIES score is 1.13, consistent with their relatively better economic position in the value chain compared to farmers. Table A2 in the Annex shows that neither the ITT estimate (0.33, $p > 0.10$) nor the 2SLS estimate (1.36, $p > 0.10$) is statistically significant, indicating no detectable difference in food insecurity between treatment and control aggregators.

Dietary diversity among aggregators is also high, with a control-group mean of 6.52 food groups. As shown in Panel B of Table A2, treatment effects are negligible: the ITT estimate is 0.02 and the 2SLS estimate is 0.08, both far from conventional significance levels. Connection to the major buyer has no detectable effect on aggregator dietary diversity.

For livelihood coping strategies, the control-group mean for aggregators is 0.51, indicating limited reliance on coping behaviors. Panel C of Table A2 in the Annex reports positive but statistically insignificant estimates for both the ITT (0.24) and 2SLS (0.99) specifications, consistent with the null results for the other aggregator welfare outcomes.

Taken together, the welfare regressions reveal a consistent pattern: treatment-area farmers exhibit significantly worse outcomes across all three dimensions—higher food insecurity, lower dietary diversity, and greater reliance on coping strategies—while aggregator welfare is largely unaffected. The uniformity of the farmer results across indicators that capture distinct aspects of welfare (food access, diet quality, and behavioral responses to food shortages) points to a systematic spatial difference between treatment and control locations rather than heterogeneous causal effects of the program. This is consistent with the major buyer's operational practice of establishing local procurement in food-insecure areas. The positive market-level effects documented in the preceding sections—higher farmgate prices, greater adoption of improved inputs, and increased investment in quality—suggest that the program may be reducing pre-existing welfare gaps, even though treatment-area farmers have not yet reached parity with control-area farmers on welfare outcomes. Future work with baseline welfare data or a panel design would be needed to isolate the causal welfare effects of indirect conditional contracts from the confounding influence of program placement.

6. Discussion

This paper examines how conditional contracting by a major downstream buyer reshapes outcomes along an agricultural value chain. Using transaction-level data combined with maize farmer and aggregator surveys, we assess how a major buyer's sourcing requirements affect prices, technology adoption, quality investment, and net returns. Across outcomes, a consistent pattern emerges: farmers connected to aggregators supplying the major buyer receive higher farmgate prices, adopt more productivity-enhancing inputs, invest more in postharvest quality practices, and earn higher net returns. At the same time, margins among aggregators decline, suggesting a redistribution of value along the chain.

A striking result is the redistribution of value chain rents toward farmers participating in or exposed to the buyer-linked supply chain. Treatment-area farmers receive higher farmgate prices on average, while aggregators operating in areas where the major buyer is active receive lower selling prices than comparable traders outside these markets. Our ITT estimates indicate a farmgate price premium of 5–6 percent for treatment-area farmers on average, while IV estimates for compliers range from approximately 40–45 percent and should be interpreted as upper bounds on the private return to individual connection. These estimates can be situated within the broader contract farming literature: Ton et al. (2017) report price premiums ranging from 5 to 60 percent across 26 studies, while the WFP Purchase for Progress (P4P) pilot reported price increases of 5–19 percent across countries (Lentz and Upton 2016). Our ITT estimates lie toward the lower end of this range, consistent with the fact that only a fraction of treatment area farmers transact through buyer-linked channels. The larger IV estimates are more comparable to the upper end of the contract farming literature, where tightly linked arrangements often generate substantial premiums (Meemken and Bellemare 2020), though these estimates should be interpreted as upper bounds rather than population-average effects because of the exclusion restriction violations discussed in Section 3.

The mechanism underlying these price effects is illustrated by the mediation analysis, which suggests that increased aggregator competition is an important channel through which the major buyer's presence translates into higher farmgate prices. The buyer's procurement attracts approximately two additional aggregators per area, while each additional aggregator is associated with an increase in farmgate prices of roughly 14 UGX/kg. These findings provide direct empirical support for a mechanism hypothesized in earlier work on local and regional procurement. Upton and Hill (2011), surveying Ugandan maize traders, predicted that institutional procurement would induce trader entry and intensify competition for farmer grain, thereby increasing farmgate prices. Our findings are consistent with this prediction: indirect conditional contracts appear not only to alter sourcing requirements but also to reshape local market structure by increasing competition among intermediaries for quality-compliant supply. This intensified competition is also consistent with the descriptive evidence on narrower aggregator margins, which decline from approximately 150 to 75 UGX/kg in the first season as intermediaries compete more aggressively for farmer output.

Our findings also speak to a longstanding debate about the relative merits of direct versus indirect procurement channels for smallholder market development. The WFP's P4P pilot (2008–2014) worked primarily through direct contracts with farmer organizations (FOs), but its own retrospective assessment acknowledged that "indirect procurement through traders was often more efficient than direct procurement from FOs" (WFP 2015). P4P encountered persistent challenges with FO capacity, side-selling, and quality compliance—problems that arise in part because direct procurement attempts to bypass existing market intermediaries rather than work through them. The indirect conditional contract modality we study takes a fundamentally different approach: rather than contracting with farmers or their organizations, the major buyer contracts with wholesalers and embeds smallholder sourcing conditions in these commercial agreements, relying on aggregators' existing relationships with farmers to transmit quality requirements and price incentives downstream. Our results suggest this approach can effectively reach smallholders while preserving the efficiency advantages of working through established market channels. Ba et al. (2019), studying rice value chains in Viet Nam, found that intermediate forms of vertical coordination, which are looser than formal contracts but tighter than spot markets, achieved the best balance between inclusivity and efficiency. The indirect conditional contract fits precisely this description: a relational arrangement that leverages existing intermediary networks rather than replacing them.

These price results raise important distributional questions: who benefits from the conditional contracting arrangement and its embedded quality requirements, and who bears the costs? For farmers participating in the conditional contract arrangement, the evidence suggests that the price premium more than compensates for the additional costs associated with higher input use and compliance with quality requirements. Farmers in the conditional contract group spend more on improved seed, fertilizer, mechanization, and postharvest handling, indicating that participation entails real resource costs. Nevertheless, the net returns analysis suggests that these additional costs are offset by higher output prices: farmers in the conditional contract group earn positive net returns per kilogram sold (+117 UGX/kg in the first season), while farmers in control areas exhibit negative returns (−161 UGX/kg). These findings suggest that the price premium associated with participation can compensate for higher production and quality-related costs, though the magnitude of these gains should be interpreted cautiously given the descriptive nature of the comparison.

For farmers who remain outside the scheme, however, the evidence points in the opposite direction. Non-connected farmers in treatment areas receive lower prices than comparable farmers in control areas. This finding is notable because it provides some of the first empirical evidence of a negative spillover effect that has been theorized but rarely documented in the contract farming literature. Both Meemken and Bellemare (2020) and Ton et al. (2017) explicitly identified the absence of evidence on non-participant effects as a critical gap in the literature. Our results suggest that conditional contracting can create a segmented market: aggregators concentrate purchasing on registered and quality-compliant suppliers, reducing competition for maize sourced outside the program. The WFP's P4P reflections (WFP 2015) noted that quality requirements can create a "dual market" where farmers who meet standards access premium channels while those who do not are relegated to lower-price channels. Our evidence provides empirical support for this dual-market hypothesis. While our analysis identifies gains for participating farmers and losses for non-participants, it cannot recover the overall welfare effect at the market level because the counterfactual equilibrium without the major buyer is unobserved. Nonetheless, the distributional implications are important: if conditional procurement arrangements expand, attention should be paid not only to the benefits accruing to connected farmers but also to potential displacement effects for those who remain outside the scheme.

Beyond prices, the intervention is also associated with changes in production and marketing practices. Farmers connected to the major buyer's supply chain are significantly more likely to adopt improved seed varieties, fertilizers, and related inputs. At the same time, aggregators linked to the major buyer are substantially more likely to provide inputs and related services to farmers. These findings suggest that conditional contracting does more than alter price incentives; it also stimulates the development of complementary services within the value chain. Because compliance with the major buyer's standards requires reliable supply of higher-quality maize, aggregators have incentives to help farmers adopt productivity- and quality-enhancing technologies. In this sense, aggregators act not only as traders but also as intermediaries facilitating technology adoption. Ton et al. (2017) found that contracts bundling input provision and technical assistance generate the largest income effects, and our results are consistent with this pattern: the indirect conditional contract generates input provision not by mandating it from the top but by creating incentives for aggregators to voluntarily provide these services.

The results further show that both farmers and aggregators invest more in postharvest quality practices when connected to the major buyer's supply chain. Farmers are more likely to adopt practices such as drying maize on tarpaulins, cleaning grain before sale, using mechanical shelling, and monitoring moisture content. Aggregators likewise report more consistent adherence to quality management practices. These findings are consistent with a broad body of evidence that institutional buyers drive quality upgrading in agricultural value chains. Quality problems at the farmgate—high moisture, aflatoxin contamination, and foreign matter—are well-documented constraints in East African maize chains (Daly, Hamrick, and Gereffi, 2016), and conditional contracts appear to provide the incentive structure needed to address them.

On the other hand, the effects on downstream welfare outcomes, namely food security, dietary diversity, and coping strategies, are inconclusive. Control-group farmers report somewhat lower food insecurity than those in the conditional contract and spillover groups, though this likely reflects the major buyer's targeting of areas with initially worse-off farmers, in which case the intervention could be reducing rather than widening disparities. Our null welfare results are broadly consistent with the wider literature on contract farming and procurement programs. In a systematic review of 26 studies, Ton et al. (2017) found that food security impacts of contract farming were "mixed and generally insignificant." Similarly, Prifti and Daidone (2021), evaluating Zambia's home-grown school feeding program, found positive effects on agricultural production and sales but no significant effects on food insecurity or dietary diversity—a pattern closely mirroring our own results. Leao, Ferrera, and Zhao (2021), reviewing WFP's global procurement experience, concluded that procurement alone rarely achieves welfare outcomes without complementary programming such as nutrition education or direct livelihood support. These findings suggest that the market-level improvements we document—higher prices, better inputs, improved quality—may be necessary but not sufficient conditions for household-level welfare gains, and that complementary interventions may be needed to translate income improvements into measurable food security outcomes.

Our study has some important limitations and open questions. First, as established in Section 3, the IV estimates should be treated as upper bounds on the private return to individual connection rather than as unbiased causal effects. The exclusion restriction does not hold because geographic assignment alters local market structure for all farmers, not just compliers, and the IV identifies a LATE for a small subpopulation of particularly responsive compliers. We place greater confidence in the direction and statistical significance of the results, as well as the ITT estimates as the primary measure of the policy's area-wide effect, than in the precise IV magnitudes.

Second, the analysis captures relatively early stages of implementation. Longer-term dynamics, such as sustained technology adoption, changes in trader entry and exit, and responses by competing buyers, remain to be observed. Future research using longitudinal data could help assess whether the observed gains persist and how structured procurement systems reshape market structure and farmer participation over time. It would also be valuable to compare conditional and unconditional procurement arrangements to isolate the marginal contribution of the sourcing condition from the broader effect of a large institutional buyer's presence.

Third, the sustainability of the observed margin compression among aggregators remains uncertain. Aggregators connected to the major buyer earn substantially lower margins per kilogram than those outside the network, and higher trading volumes do not fully offset this reduction. Participation may nevertheless persist because supplying a large buyer offers a reliable demand channel that reduces search costs and market uncertainty, and connected aggregators are more likely to provide inputs to farmers, potentially generating additional revenue through input resale margins. Whether these incentives are sufficient to sustain participation in the longer run, particularly if additional aggregators enter the market, remains an open question for future research.

These limitations and open questions aside, the findings suggest that indirect conditional contracting can reshape agricultural markets by generating credible demand for quality-compliant supply, intensifying competition among intermediaries, and stimulating complementary service provision within the value chain. Our results provide the first rigorous evaluation of the indirect conditional contract modality—a procurement approach that several major buyers have adopted as an alternative to more direct arrangements. The evidence indicates that this modality can effectively transmit price incentives and quality requirements to smallholders through existing market channels, while generating important distributional effects that policymakers should monitor as these models expand.

7. Conclusions

This study examines the impact of an indirect conditional contracting arrangement introduced by a major institutional buyer in Uganda's maize value chain. Drawing on survey data from nearly

1,300 farmers and approximately 300 aggregators across six districts, we employ a combination of descriptive analysis, ordinary least squares (OLS), instrumental variables (IV), and mediation analysis. The analysis assesses how embedding smallholder sourcing conditions within commercial procurement contracts influences prices, market structure, technology adoption, and quality upgrading, as well as farmer profits and welfare.

The analysis shows that the policy reshaped maize market dynamics. Farmers in treatment areas are more likely to sell maize and allocate more land to maize cultivation, though effects on quantities sold vary by season. Intent-to-treat estimates show that treatment-area farmers receive 5–6 percent higher farmgate prices on average; IV estimates for compliers, which bound the private return to individual connection from above, range from approximately 40 to 45 percent. Aggregators receive lower selling prices, while descriptive evidence indicates substantially narrower margins in treatment areas, declining from roughly 150 to 75 UGX/kg in the first season.

Mediation results suggest that increased competition is a key mechanism underlying these price effects: the buyer's presence attracts approximately two additional aggregators per area, with each additional aggregator associated with an increase in farmgate prices of roughly 14 UGX/kg. Despite higher production and compliance-related costs, farmers in the conditional contract group earn positive net returns per kilogram sold (+117 UGX/kg in the first season), while farmers in control areas incur negative returns (−161 UGX/kg). The policy is also associated with greater technology adoption, increased input provision by aggregators, and stronger investment in postharvest quality.

These gains are not evenly distributed. Non-participating farmers in treatment areas receive lower prices than comparable farmers in control areas, confirming market segmentation as aggregators concentrate on compliant suppliers. IV estimates should therefore be interpreted as upper bounds on the private return to individual connection, not as area-wide welfare effects. We also cannot separate the effects of conditionality from those of the buyer's presence, as procurement operated exclusively through this model during our study period. On the aggregator side, margin compression raises sustainability concerns, though higher volumes and reliable demand may offset lower per-unit profits. Downstream welfare effects remain inconclusive: control farmers report lower food insecurity, possibly reflecting initial targeting of poorer areas by the buyer. In terms of inclusivity, participation among smallholders increased, while exploratory interaction tests find no statistically significant differential effects by gender or youth status, though the study was underpowered for subgroup heterogeneity.

For policy, the findings suggest that indirect conditional contracts can be an effective instrument for redistributing value chain rents toward producers and catalyzing upstream investments in technology and quality. The mechanism—leveraging private sector intermediaries through embedded sourcing conditions rather than contracting directly with farmers—offers a scalable alternative to more direct procurement approaches such as WFP's Purchase for Progress. However, policymakers considering scale-up should attend to three considerations: first, the distributional consequences for non-participating farmers who may face lower prices in segmented markets; second, the sustainability of aggregator margins under intensifying competition; and third, the need for complementary interventions if downstream welfare improvements are an explicit objective. Disentangling the marginal contribution of conditionality from buyer presence per se, for instance, by comparing conditional and unconditional procurement in otherwise similar settings, is an important direction for future research.

References

Alene, A.D., V.M. Manyong, G. Omanya, H.D. Mignouna, M. Bokanga, and G. Odhiambo. 2008. Smallholder market participation under transactions costs: Maize supply and fertilizer demand in Kenya. Food Policy 33 (4): 318–328.

Anderson, M.L. 2008. Multiple inference and gender differences in the effects of early inter vention: A reevaluation of the abecedarian, perry preschool, and early training projects. Journal of the American Statistical Association 103 (484): 1481–1495.

Arouna, A., J.D. Michler, and J.C. Lokossou. 2021. Contract farming and rural transformation: Evidence from a field experiment in Benin. Journal of Development Economics 151: 102626.

Ashour, M., D.O. Gilligan, J.B. Hoel, and N.I. Karachiwalla. 2019. Do beliefs about herbicide quality correspond with actual quality in local markets? Evidence from Uganda. Journal of Development Studies 55 (6): 1285–1306.

Ashraf, N., X. Giné, and D. Karlan. 2009. Finding missing markets (and a disturbing epilogue): Evidence from an export crop adoption and marketing intervention in Kenya. American Journal of Agricultural Economics, 91(4): 973–990.

Ba, H.A., Y. de Mey, S. Thoron, and M. Demont. 2019. Inclusiveness of contract farming along the vertical coordination continuum: Evidence from the Vietnamese rice sector. Land Use Policy 87: 104050.

Bagamba, F., P.R. Ntakyo, G. Otim, D.J. Spielman, and B. Van Campenhout. 2023. Policy and performance in Uganda's seed sector: Opportunities and challenges. Development Policy Review 41 (3): e12665.

Barrett, C.B. 2008. Smallholder market participation: Concepts and evidence from eastern and southern Africa. Food Policy 33 (4): 299–317.

Barriga, A., and N. Fiala. 2020. The supply chain for seed in Uganda: Where does it go wrong? World Development 130: 104928.

Bold, T., K.C. Kaizzi, J. Svensson, and D. Yanagizawa-Drott. 2017. Lemon technologies and adoption: Measurement, theory and evidence from agricultural markets in Uganda. The Quarterly Journal of Economics 132 (3): 1055–1100.

Burke, M., L.F. Bergquist, and E. Miguel. 2019. Sell low and buy high: Arbitrage and local price effects in Kenyan markets. The Quarterly Journal of Economics 134 (2): 785–842.

Daly, J., D. Hamrick, G. Gereffi, and A. Guinn. 2016. Maize value chains in East Africa. Center on Globalization, Governance & Competitiveness, Report F-38202-RWA-1, Duke University.

Davies, K., and N. Menage. 2010. Connecting farmers to markets: Insights from the Purchase for Progress Initiative. Revolution: From Food Aid to Food Assistance. Innovations in Overcoming Hunger. World Food Programme.

De Janvry, A., and E. Sadoulet. 2020. Using agriculture for development: Supply- and demand-side approaches. World Development 133: 105003.

Fermont, A., and T. Benson. 2011. Estimating yield of food crops grown by smallholder farmers: A review in the Uganda context. IFPRI Discussion Paper 1097. International Food Policy Research Institute.

Garg, T., C.B. Barrett, M.I. Gómez, E.C. Lentz, and W.J. Violette. 2013. Market prices and food aid local and regional procurement and distribution: A multi-country analysis. World Development 49: 19–29.

Gelo, D., E. Muchapondwa, A. Shimeles, and J. Dikgang. 2020. Aid, collective action and benefits to smallholders: Evaluating the World Food Program's purchase for progress pilot. Food Policy 97: 101911.

Gilbert, C.L., L. Christiaensen, and J. Kaminski. 2017. Food price seasonality in Africa: Measurement and extent. Food Policy 67: 119–132.

Gourlay, S., T. Kilic, and D.B. Lobell. 2019. A new spin on an old debate: Errors in farmer-reported production and their implications for inverse scale-productivity relationship in Uganda. Journal of Development Economics 141: 102376.

Leão, I., M. Ferrera, and Y. Zhao. 2021. Leveraging food procurement to achieve developmental goals: World Food Programme's practices and lessons learned. In Public Food Procurement for Sustainable Food Systems and Healthy Diets, eds. J. Swensson, D. Hunter, S. Schneider, and F. Tartanac. Food and Agriculture Organization of the United Nations.

Lentz, E., and J. Upton. 2016. Benefits to smallholders? Evaluating the World Food Programme's Purchase for Progress pilot. Global Food Security 11: 54–63.

Mather, D., D. Boughton, and T. Jayne. 2013. Explaining smallholder maize marketing in southern and eastern Africa: The roles of market access, technology and household resource endowments. Food Policy 43: 248–266.

McGuire, S., and L. Sperling. 2016. Seed systems smallholder farmers use. Food Security 8 (1): 179–195.

Meemken, E.M., and M.F. Bellemare. 2020. Smallholder farmers and contract farming in developing countries. Proceedings of the National Academy of Sciences 117 (1): 259–264.

Miehe, C., R. Sparrow, D. Spielman, and B. Van Campenhout. 2023. The (perceived) quality of agricultural technology and its adoption: Experimental evidence from Uganda. IFPRI Discussion Paper 2918. International Food Policy Research Institute.

Negede, B.M., H. De Groote, B. Minten, and M. Voors. 2024. Does access to improved grain storage technology increase farmers' welfare? Experimental evidence from maize farming in Ethiopia. Journal of Agricultural Economics 75 (1): 137–152.

Nehring, R., A. Miranda, and A. Howe. 2017. Making the case for institutional demand: Supporting smallholders through procurement and food assistance programmes. Global Food Security 12: 96–102.

Omotilewa, O.J., J. Ricker-Gilbert, J.H. Ainembabazi, and G.E. Shively. 2018. Does improved storage technology promote modern input use and food security? Evidence from a randomized trial in Uganda. Journal of Development Economics 135: 176–198.

Prifti, E., and S. Daidone. 2021. Evaluating the impact of home-grown school feeding programmes and complementary agricultural interventions: The case of Zambia. In Public Food Procurement for Sustainable Food Systems and Healthy Diets, eds. J. Swensson, D. Hunter, S. Schneider, and F. Tartanac. Food and Agriculture Organization of the United Nations.

Raghunathan, K., G.T. Abate, B. van Campenhout, L. Nabwire, E. Mukangabo, S. Mugabo, and S. Benin. 2025. Conditional contracts in indirect local procurement of maize from smallholder farmers in Uganda: A study design to assess impacts. SFS4Youth Project Note 2.

Rapsomanikis, G. 2015. The Economic Lives of Smallholder Farmers: An Analysis Based on Household Data from Nine Countries. Food and Agriculture Organization of the United Nations.

Schildberg-Hörisch, H. 2018. Are risk preferences stable? Journal of Economic Perspectives 32 (2): 135–154.

Sitko, N.J., and T. Jayne. 2014. Exploitative briefcase businessmen, parasites, and other myths and legends: Assembly traders and the performance of maize markets in eastern and southern Africa. World Development 54: 56–67.

Lowder, S.K., J. Skoet, J., and T. Raney. 2016. The number, size, and distribution of farms, smallholder farms, and family farms worldwide. World Development 87, 16–29.

Ton, G., S. Desiere, W. Vellema, S. Weituschat, and M. D'Haese. 2017. The effectiveness of contract farming in improving smallholder income and food security in low- and middle-income countries: A mixed-method systematic review. 3ie Systematic Review 38. International Initiative for Impact Evaluation (3ie).

UBOS (Uganda Bureau of Statistics). 2018. Uganda Annual Agricultural Survey 2018.

UBOS. 2022. Annual Agricultural Survey 2020.

UBOS. 2024. Annual Agricultural Survey 2021/22.

Upton, J., and E. Hill. 2011. Local and regional procurement of food aid in Uganda: The experience of maize traders. Tech. rep., Working Paper, March 2011.

Van Campenhout, B., and L. Nabwire. 2025. Buyer-side gender discrimination in bargaining: Evidence from seed sales in Uganda. Journal of Behavioral and Experimental Economics: 102404.

Van Campenhout, B., B. Minten, and J.F. Swinnen. 2021. Leading the way: Foreign direct investment and dairy value chain upgrading in Uganda. Agricultural Economics 52 (4): 607–631.

Van Campenhout, B., E. Lecoutere, and B. D'Exelle. 2015. Inter-temporal and spatial price dispersion patterns and the well-being of maize producers in southern Tanzania. Journal of African Economies 24 (2): 230–253.

Van Campenhout, B., L. Nabwire, B. Kramer, C. Trachtman, and G.T. Abate. 2025. Production and consumption traits and the adoption of improved maize varieties: Evidence from seed sample packs and cooking demonstrations. IFPRI Discussion Paper 2331. International Food Policy Research Institute. https://hdl.handle.net/10568/173943

WFP (World Food Programme). 2015. Purchase for Progress (P4P): Reflections on the Pilot.

WFP. 2019. WFP Uganda's Agricultural Market Support Programme - 2019.

Wright, B. D. 2012. International grain reserves and other instruments to address volatility in grain markets. The World Bank Research Observer 27(2): 222–260.

Annex: Supplementary tables

Table A1. Effect of major buyer connection on farmers' welfare (food insecurity, dietary diversity, and livelihood coping strategy)

	Panel A: Food Insecurity Experience Scale				Panel B: Dietary Diversity				Panel C: Livelihood Coping Strategy			
	OLS		**IV(2SLS)**		**OLS**		**IV(2SLS)**		**OLS**		**IV(2SLS)**	
	(1)	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**	**(1)**	**(2)**	**(3)**	**(4)**
Connected	1.508***	1.474***	8.896***	8.297***	−0.438***	−0.430***	−2.586***	−2.419***	1.284***	1.310***	7.575***	7.377***
	(0.186)	(0.196)	(1.508)	(1.453)	(0.100)	(0.104)	(0.667)	(0.647)	(0.137)	(0.151)	(1.193)	(1.182)
Male head		−0.206		−0.080		−0.043		−0.080		0.030		0.142
		(0.209)		(0.264)		(0.118)		(0.125)		(0.136)		(0.202)
Age head		0.007		0.008		0.00003		−0.0002		0.010**		0.011*
		(0.007)		(0.008)		(0.004)		(0.004)		(0.005)		(0.007)
Head completed primary education		0.057		−0.074		0.114		0.152		0.176		0.060
		(0.192)		(0.230)		(0.105)		(0.112)		(0.131)		(0.177)
Household size		−0.009		−0.063		0.023		0.039*		0.005		−0.043
		(0.032)		(0.046)		(0.017)		(0.020)		(0.022)		(0.036)
Land owned		0.007		−0.038		0.005		0.018		−0.006		−0.046**
		(0.016)		(0.026)		(0.010)		(0.015)		(0.009)		(0.023)
Co-op member		0.216		−0.121		0.104		0.202		0.283		−0.017
		(0.292)		(0.321)		(0.168)		(0.185)		(0.204)		(0.268)
Constant	1.785***	1.414***	1.714***	2.091***	6.137***	5.820***	6.157***	5.623***	0.562***	−0.330	0.501***	0.272
	(0.104)	(0.527)	(0.115)	(0.627)	(0.059)	(0.302)	(0.063)	(0.332)	(0.060)	(0.360)	(0.071)	(0.517)
Strata2 used as instrument	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
First-stage F-Statistic			90.5	89.2			90.5	89.2			90.5	89.2
Obs.	836	786	836	786	836	786	836	786	836	786	836	786
R2	0.078	0.077	−0.547	−0.469	0.024	0.028	−0.176	−0.137	0.112	0.116	−0.785	−0.719

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively. The analysis excludes spillover farmers (Group 3) to obtain a clean intent-to-treat comparison between conditional contract and control farmers.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A2. Effect of major buyer connection on traders' welfare (food insecurity, dietary diversity, and livelihood coping strategy)

	Panel A: Food Insecurity Experience Scale				Panel B: Dietary Diversity				Panel C: Livelihood Coping Strategy			
	OLS		IV(2SLS)		OLS		IV(2SLS)		OLS		IV(2SLS)	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Connected	0.290	0.325	1.169	1.361	0.026	0.020	0.105	0.084	0.235	0.235	0.948	0.985
	(0.244)	(0.245)	(1.013)	(1.001)	(0.131)	(0.134)	(0.527)	(0.555)	(0.185)	(0.182)	(0.775)	(0.785)
Male head		0.959***		1.198***		0.020		0.038		0.612***		0.823***
		(0.332)		(0.460)		(0.619)		(0.614)		(0.115)		(0.279)
Age head		0.003		0.003		0.002		0.002		−0.008		−0.007
		(0.012)		(0.012)		(0.007)		(0.007)		(0.009)		(0.009)
Head completed primary education		−0.092		−0.115		0.099		0.097		0.060		0.043
		(0.282)		(0.295)		(0.151)		(0.149)		(0.240)		(0.251)
Household size		0.053		0.045		0.001		0.001		−0.011		−0.016
		(0.043)		(0.046)		(0.022)		(0.021)		(0.020)		(0.022)
Volume sold		−0.0001***		−0.0001***		0.00002***		0.00002**		−0.00003***		−0.00004**
		(0.00001)		(0.00002)		(0.00001)		(0.00001)		(0.00001)		(0.00002)
Constant	1.130***	−0.170	1.084***	−0.413	6.519***	6.324***	6.515***	6.305***	0.506***	0.261	0.470***	0.032
	(0.162)	(0.662)	(0.189)	(0.780)	(0.087)	(0.691)	(0.101)	(0.704)	(0.103)	(0.501)	(0.120)	(0.565)
Strata2 used as instrument	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
First-stage F-Statistic			38.3	33.8			38.3	33.8			38.3	33.8
Obs.	297	294	297	294	297	294	297	294	297	294	297	294
R2	0.005	0.016	−0.050	−0.035	0.0001	0.008	0.001	0.008	0.006	0.016	−0.069	−0.057

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively. The analysis excludes spillover farmers (Group 3) to obtain a clean intent-to-treat comparison between conditional contract and control farmers.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A3. Production costs, revenue, and net returns by farmer group

	Group 1: Control	Group 2: Conditional contract	Group 3: Spillover	p-values 1 & 2	2 & 3	1 & 3
Panel A: Production costs (UGX)						
Seed						
First season of 2023	85,514	95,430	105,724	0.695	0.845	0.683
Second season of 2023	68,452	81,113	86,894	0.627	0.913	0.707
Pesticides/herbicides						
First season of 2023	57,091	71,525	308,417	0.482	0.367	0.338
Second season of 2023	58,504	69,619	359,145	0.641	0.325	0.305
Hired labor						
First season of 2023	326,883	367,733	396,118	0.413	0.792	0.498
Second season of 2023	352,083	337,735	586,516	0.78	0.317	0.341
Family labor (imputed)						
First season of 2023	161,041	109,099	115,562	<0.001	0.626	<0.001
Second season of 2023	162,319	109,387	112,839	<0.001	0.793	<0.001
Machine rental						
First season of 2023	90,780	201,440	226,728	0.01	0.779	0.093
Second season of 2023	89,650	187,731	206,377	0.029	0.826	0.116
Postharvest handling						
First season of 2023	57,053	103,012	94,685	0.056	0.834	0.25
Second season of 2023	56,277	88,828	112,428	0.014	0.519	0.111
Panel B: Totals (UGX)						
Total cost						
First season of 2023	759,992	981,693	1,166,735	0.241	0.705	0.384
Second season of 2023	637,863	887,581	1,322,319	0.137	0.405	0.171
Total revenue						
First season of 2023	1,833,335	2,339,131	1,855,554	0.376	0.569	0.977
Second season of 2023	1,735,768	1,519,725	1,723,223	0.575	0.781	0.987
Net returns						
First season of 2023	867,981	1,295,149	592,840	0.322	0.069	0.437
Second season of 2023	818,373	671,311	195,839	0.644	0.285	0.196
Panel C: Net returns per unit						
Net returns per kg sold (UGX/kg)						
First season of 2023	-161	117	108	0.001	0.906	<0.001
Second season of 2023	-251	104	-218	<0.001	0.125	0.873
Net returns per acre (UGX/acre)						
First season of 2023	133,598	204,906	136,969	0.126	0.128	0.938
Second season of 2023	79,967	136,437	−159,541	0.238	0.242	0.339
Obs.	498	169	169			

Note: All monetary values in UGX. Family labor is imputed at 5,000 UGX per person-day.
Total cost includes seed, fertilizer (DAP/NPK, urea), pesticides, hired labor, machine rental, family labor (imputed), and postharvest handling costs. Net returns = total revenue − total cost. p-values correspond to pairwise tests of equality of means across groups.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A4. Effect of major buyer connection on technology adoption

	Dependent variable: Technology adoption index			
	OLS		IV (2SLS)	
	(1)	(2)	(3)	(4)
Connected	0.108***	0.109***	0.845***	0.821***
	(0.027)	(0.027)	(0.222)	(0.218)
Male head		0.033		0.043
		(0.031)		(0.034)
Age head		−0.002**		−0.003***
		(0.001)		(0.001)
Primary head		0.157***		0.146***
		(0.029)		(0.030)
HH size		0.016***		0.015***
		(0.005)		(0.005)
Land owned		0.009***		0.006***
		(0.002)		(0.002)
Co-op member		0.026		−0.003
		(0.048)		(0.049)
Constant	−0.019	−0.163**	−0.025	−0.101
	(0.021)	(0.082)	(0.023)	(0.083)
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			111.2	111
Observations	2,226	2,129	2,226	2,129

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively.

Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A5. First stage: Strata assignment predicting connection to major buyer (technology adoption/quality sample)

	Dependent variable: Connected to major buyer (0/1)	
	(1)	(2)
Treatment area	0.192***	0.206***
	(0.015)	(0.016)
Male head		−0.043*
		(0.022)
Age head		−0.0002
		(0.001)
Head finished primary education		0.058***
		(0.019)
HH size		0.004
		(0.004)
Land owned		0.004***
		(0.001)
Co-op member		−0.039
		(0.039)
Constant	0.014***	0.017
	(0.005)	(0.061)
Weak instrument F-statistic	107.6	116.4
Observations	1,284	1,224
R^2	0.077	0.103
Adjusted R^2	0.077	0.098

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively. This first stage applies to both adoption and farmer quality IV specifications.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A6. First stage: Strata assignment predicting connection to major buyer (farmer price sample)

	Dependent variable: Connected to major buyer (0/1)	
	(1)	(2)
Treatment area	0.127***	0.134***
	(0.013)	(0.014)
Male head		−0.013
		(0.022)
Age head		0.001
		(0.001)
Head finished primary education		0.006
		(0.019)
HH size		0.002
		(0.003)
Land owned		0.004***
		(0.001)
Co-op member		0.044*
		(0.024)
Volume sold		0.00000
		0.00000
Constant	0.001	−0.104*
	(0.027)	(0.061)
Month FE	Yes	Yes
Weak instrument F-statistic	94.4	96.2
Observations	2,210	2,099
R^2	0.057	0.077
Adjusted R^2	0.050	0.067

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A7. First stage: Strata assignment predicting connection to major buyer (net returns sample)

	Dependent variable: Connected to major buyer (0/1)	
	(1)	(2)
Treatment area	0.192***	0.206***
	(0.015)	(0.016)
Male head		−0.043*
		(0.022)
Age head		−0.0002
		(0.001)
Head finished primary education		0.058***
		(0.019)
HH size		0.004
		(0.003)
Land owned		0.004***
		(0.001)
Co-op member		−0.039
		(0.039)
Constant	0.014***	0.017
	(0.005)	(0.061)
Season FE	Yes	Yes
Weak instrument F-statistic	115.8	109.1
Observations	2,568	2,448
R^2	0.077	0.103
Adjusted R^2	0.077	0.100

Note: Estimates with ***, ** and * are significant at 1%, 5%, and 10%, respectively.

Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A8. First stage: Strata assignment predicting connection to major buyer (trader price sample)

	Dependent variable: Connected to major buyer (0/1)	
	(1)	(2)
Treatment area	0.210***	0.211***
	(0.035)	(0.035)
Male head		−0.236
		(0.162)
Age head		−0.001
		(0.002)
Head finished primary education		0.002
		(0.040)
HH size		0.009
		(0.007)
Constant	0.007	0.220
	(0.011)	(0.181)
Season FE	Yes	Yes
Weak instrument F-statistic	62.8	62.6
Observations	569	569
R^2	0.102	0.120
Adjusted R^2	0.099	0.110

Note: Estimates with ***, ** and * are significant at 1%, 5%, and 10%, respectively.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A9. First stage: Strata assignment predicting connection to major buyer (trader quality/input sample)

	Dependent variable: Connected to major buyer (0/1)	
	(1)	(2)
Treatment area	0.235***	0.238***
	(0.041)	(0.040)
Male head		−0.213
		(0.157)
Age head		−0.0003
		(0.002)
Head finished primary education		0.015
		(0.045)
HH size		0.009
		(0.007)
Constant	0.039**	0.196
	(0.016)	(0.184)
Weak instrument F-statistic	34.8	34.5
Observations	294	294
R^2	0.107	0.119
Adjusted R^2	0.103	0.104

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively.
This first stage applies to both trader quality and trader inputs IV specifications
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A10. Effect of major buyer connection on farmer net returns (UGX)

	Dependent variable: Net returns (UGX)			
	OLS		IV (2SLS)	
	(1)	(2)	(3)	(4)
Connected	12,696.850	95,582.520	83,363.410	617,178.700
	(150,559.100)	(154,051.200)	(987,846.800)	(997,826.400)
Male head		108,827.300		132,605.200
		(141,576.300)		(155,271.000)
Age head		−15,752.580***		−15,646.320***
		(5,342.252)		(5,303.141)
Head finished primary education		9,540.211		4,318.444
		(171,018.800)		(170,259.800)
HH size		−8,261.608		−12,965.730
		(30,319.130)		(32,528.940)
Land owned		35,058.980*		31,852.070*
		(20,152.360)		(17,834.320)
Co-op member		−286,974.900		−314,799.300
		(291,189.100)		(289,043.900)
Constant	728,206.200***	1,542,567.000***	727,602.700***	1,584,235.000***
	(103,569.200)	(428,860.100)	(107,983.500)	(428,188.300)
Season FE	Yes	Yes	Yes	Yes
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			115.8	109.1
Observations	1,294	1,220	1,294	1,220

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively. Net returns = total revenue − total cost (inputs + family labor + post-harvest). Winsorized at 1st and 99th percentiles. Clustered standard errors at farmer level.

Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A11. Effect of major buyer connection on net returns per kg sold (UGX/kg)

	Dependent variable: Net returns per kg sold (UGX/kg)			
	OLS		IV (2SLS)	
	(1)	(2)	(3)	(4)
Connected	233.900***	239.271***	1,535.713***	1,544.979***
	(52.885)	(53.545)	(402.045)	(399.045)
Male head		−48.011		11.512
		(63.919)		(75.197)
Age head		−5.834***		−5.568**
		(2.157)		(2.390)
Head finished primary education		−9.779		−22.850
		(60.138)		(66.664)
HH size		6.842		−4.934
		(8.910)		(10.552)
Land owned		9.092***		1.065
		(3.157)		(5.638)
Co-op member		−104.248		−173.900*
		(81.176)		(92.902)
Constant	−125.930***	204.516	−137.047***	308.824*
	(46.862)	(157.466)	(49.365)	(173.283)
Season FE	Yes	Yes	Yes	Yes
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			115.8	109.1
Observations	1,294	1,220	1,294	1,220

Note: Estimates with ***, ** and * are significant at 1%, 5%, and 10%, respectively.

Net returns per kg = (total revenue - total cost)/kg sold. Winsorized at 1st and 99th percentiles. Clustered standard errors at farmer level.

Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A12. Effect of major buyer connection on trader providing inputs

	Dependent variable: Trader provides inputs (1=yes)			
	OLS		IV (2SLS)	
	(1)	(2)	(3)	(4)
Connected	0.280***	0.242***	1.131***	1.041***
	(0.056)	(0.060)	(0.270)	(0.291)
Male head		0.179		0.406***
		(0.169)		(0.068)
Age head		−0.007**		−0.006
		(0.003)		(0.004)
Prim head		−0.041		−0.065
		(0.063)		(0.069)
HH size		0.018*		0.008
		(0.010)		(0.012)
Volume sold		−0.00001		−0.00002
		(0.00002)		(0.00001)
Constant	0.370***	0.433**	0.326***	0.202
	(0.039)	(0.207)	(0.050)	(0.193)
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			38.3	32.5
Observations	297	281	297	281

Note: Estimates with ***, **, and * are significant at 1%, 5%, and 10%, respectively.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A13. Effect of major buyer connection on farmgate prices

	Dependent variable: Price			
	OLS		IV (2SLS)	
	(1)	(2)	(3)	(4)
Connected	23.050*	30.605***	180.850*	228.190***
	(11.781)	(11.615)	−93.096	−88.557
Male head		−4.195		−1.337
		(12.306)		(12.971)
Age head		0.130		−0.033
		(0.396)		(0.421)
Head finished primary ed.		17.039		15.715
		(10.573)		(10.961)
HH size		−1.147		−1.685
		(1.723)		(1.799)
Land owned		1.322***		0.396
		(0.510)		(0.667)
Co-op member		−20.668		−30.696
		(18.426)		(19.571)
Volume sold		0.003		0.002
		(0.002)		(0.002)
Constant	675.921***	670.681***	675.805***	694.346***
	(17.885)	(34.555)	(18.298)	(35.543)
Month FE	Yes	Yes	Yes	Yes
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			94.4	96.2
Observations	2,210	2,099	2,210	2,099

Note: Estimates with ***, ** and * are significant at 1%, 5%, and 10%, respectively.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A14. Effect of major buyer connection on trader-level selling prices

	Dependent variable: Selling Price (UGX/kg) Price			
	OLS		IV (2SLS)	
	(1)	(2)	(3)	(4)
Connected	−61.514***	−57.041**	0.005	0.007
	(23.355)	(22.164)	(0.013)	(0.018)
Male head		−83.963		−148.436**
		(71.106)		(71.429)
Age head		1.269		0.964
		(1.917)		(1.984)
Head finished primary education		46.550*		46.648
		(27.530)		(28.558)
HH size		1.605		4.030
		(4.206)		(4.424)
Volume sold			−292.875**	−272.461**
			(120.243)	(112.597)
Constant	923.344***	910.076***	925.452***	972.217***
	(20.289)	(104.373)	(21.152)	(108.861)
Season FE	Yes	Yes	Yes	Yes
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			62.8	60.9
Observations	569	565	569	565

Note: Estimates with ***, ** and * are significant at 1%, 5%, and 10%, respectively.
Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

Table A15. Effect of major buyer connection on trader-level quality investment

	Dependent variable: Invests in quality (1=yes)			
	OLS		IV (2SLS)	
	(1)	(2)	(3)	(4)
Connected	0.125***	0.137***	0.506***	0.590***
	(0.041)	(0.044)	(0.187)	(0.219)
Male head		−0.026		0.102
		(0.152)		(0.212)
Age head		0.001		0.001
		(0.002)		(0.003)
Prim head		0.110**		0.096**
		(0.043)		(0.049)
HH size		0.018**		0.012
		(0.008)		(0.010)
Volume sold		−0.00001		−0.00001
		(0.00001)		(0.00002)
Constant	0.084***	−0.098	0.065**	−0.229
	(0.022)	(0.188)	(0.029)	(0.260)
Buyer district used as instrument	No	No	Yes	Yes
First-stage F-statistic			38.3	32.5
Observations	297	281	297	281

Note: Estimates with ***, ** and * are significant at 1%, 5%, and 10%, respectively.

Source: Authors' calculations based on IFPRI's maize value chain survey conducted in May–June 2024.

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