Conditional Contracts in Indirect Local Procurement

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Abstract

Since 2004, the World Food Programme (WFP) has increasingly recognized its potential to support local market development by improving small-scale traders' and farmer organizations' access to stable and profitable markets. In 2019, WFP introduced the Local and Regional Food Procurement Policy (LRFP), a strategic initiative designed to enhance procurement efficiency through greater engagement with private sector actors, while also promoting broader development objectives such as improved nutrition, resilience, smallholder incomes, livelihoods, and gender equality. A key feature of the LRFP is the use of indirect conditional contracts, which require that large traders, acting as intermediaries in WFP's supply chain, procure a specified share of their contracted volume directly from smallholder farmers. This report draws on systematically collected survey data from farmers and traders in western Uganda to evaluate the extent to which the LRFP policy has contributed to these objectives and helped drive transformation in local agricultural value chains.

1 Introduction

In crisis situations such as armed conflicts or natural disasters, timely food aid plays a critical role. It not only prevents famine and acute malnutrition in the short term, but also protects households from depleting their assets, thereby reducing long-term hardship (Dercon, 2002). The United Nations World Food Programme (WFP) is at the forefront of these efforts, leveraging a vast

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logistics network of up to 5,000 trucks, 80 aircraft and 20 ships in motion daily to deliver food assistance on an immense scale, reaching 152 million people in 2023 alone (WFP, 2023). In war-torn nations like Syria and Yemen (with conflicts beginning in 2011 and 2015, respectively), WFP has sustained millions of people with staple foods month after month, peaking at about 5.6 million recipients per month in Syria and 13 million in Yemen during the worst periods of conflict. The impact of such timely assistance is evident: a famine that emerged in South Sudan in early 2017 was ended within four months due to a concerted large-scale humanitarian response. WFP has also been crucial in sudden natural disasters – for instance, after the February 2023 earthquake in Syria and Turkey, it rapidly provided hot meals and ready-to-eat rations to survivors cut off by the destruction.

Traditionally, WFP obtained the food it distributed directly from donor countries. Tied aid such as this has faced increasing criticism since the late 20th century for its economic inefficiency and negative impacts on recipient countries. The shift towards untied aid gained momentum with international agreements like the 2005 Paris Declaration on Aid Effectiveness, advocating for aid that aligns more closely with the development priorities of recipient countries. WFP followed this trend and started relying more and more on Local purchases (that is, in the affected country) or regional purchases (that is, in a neighboring country or a third country in the region) of the food it needs for its food aid operations.

Uganda, a stable country in a conflict-prone region, has become a crucial player in WFP's efforts to combat food insecurity. As the largest buyer of food commodities in low- and middle-income countries, WFP injected $50 million into Uganda's economy in 2018, purchasing significant quantities of maize, sorghum, and beans. Various WFP initiatives, such as the Purchase for Progress (P4P) pilot, aim to enhance market access for smallholder farmers, improve agricultural outcomes, and foster equitable growth within local food markets. Despite the positive impacts, challenges persist, such as for instance higher costs, market fragmentation and high quality requirements, which compromises the benefits to smallholder farmers. Recent policy shifts towards indirect conditional contracts, which are agreements between WFP and wholesale maize traders requiring that a portion of procurement be sourced directly from smallholder farmers, aim to better integrate these farmers into the supply chain and ensure they benefit more from WFP's stable demand.

Maize, one of the most extensively cultivated staple crop in Uganda, occupies about 30% of the country's cropped land, serving as both a critical food security crop and a vital source of income for farmers. The government has prioritized maize production in its agricultural strategy to enhance national food security and support household livelihoods. The maize value chain in Uganda involves numerous interconnected actors, from agro-input dealers who supply essential inputs like seeds and fertilizers to smallholder farmers, to traders and processors who turn the harvested maize into products like flour for consumer purchase.

Despite government efforts to promote modern agricultural practices, many farmers continue to rely on traditional methods and face challenges such as access to quality inputs, low productivity, and inefficient post-harvest handling that leads to significant losses. These issues, coupled with inefficient market access and processing capabilities, stifle the overall competitiveness of Uganda's maize sector. Traders and small-scale processors play a crucial role in linking farmers to markets and enhancing market participation, even as the sector grapples with challenges in storage, transportation, and price fluctuations influenced by seasonal and regional dynamics.

This report utilizes observational data that was collected through careful stratification from about 300 trader and 1300 farmers. We also collected qualitative data from wholesalers. Extensive exploratory and descriptive analysis will identify patterns in the data, while econometric techniques like fixed effects models and matching methods will be applied to rigorously attribute causality and separate the effect of indirect conditional contracts from external influences, thereby enhancing the reliability and depth of the findings.

There have been surprisingly few studies on local and regional procurement and virtually none on LRP through the indirect conditional contract modality. Note that while emergency aid corresponds to a supply shock for the recipient country, the country where the food is procured incurs a demand shock, generally due to a single buyer that enters the market with known contracting mechanisms and quality standards. The study that is probably closest to ours is (Upton and Hill, 2011) who examined the effects of local and regional procurement (LRP) of food aid in Uganda through a survey of 120 maize traders, highlighting the complex impacts on local markets. Their study revealed that while LRP can potentially stimulate local economies, it also raises consumer prices and market volatility, complicating the benefits for poor consumers and small-scale farmers.

The remainder of this report is structured as follows. We begin with an explanation of the new procurement modality, focusing on indirect conditional contracting. Next, we provide an overview of Uganda's maize sub-sector, highlighting the roles of farmers, traders, and wholesalers within the value chain. The methods section then outlines the research questions and describes how these are addressed using stack survey data. This is followed by the results, starting with a descriptive analysis and then moving to a more analytical section that explores potential causal relationships. The report concludes with a summary of key findings and policy recommendations based on the evidence.

2 WFP Conditional Contracting

Uganda is a relatively stable country in a region affected by conflict and food insecurity (Upton and Hill, 2011). As a result, it is a key contributor to the World Food Programme (WFP), the world's largest humanitarian organization, which buys more food commodities for its food assistance programs from Uganda than from any other low- and middle-income country. In 2018, WFP invested 50 million USD in the Ugandan economy and purchased over 188,000 metric tons of local food commodities—mainly maize, sorghum and beans—

through open tendering from large traders (World Food Programme, 2019). WFP's food assistance programs support disadvantaged populations, including food-insecure households, young children and refugees and internally displaced persons. In Uganda, these programs help address food insecurity and malnutrition and support the growing refugee population while bolstering the country's national social protection system. This is important given that Uganda is currently Africa's largest refugee hosting country (Global Compact on Refugees, 2018).

Smallholder farmers have been a core focus of WFP's procurement policies for at least two decades. In 2004, the "Food Procurement in Developing Countries" policy was initiated, recognizing the role WFP had to play in developing markets, supporting small traders and farmers' groups and using procurement to encourage smallholder farmers and farmer groups to enter reliable and lucrative markets (World Food Programme, 2006). In 2007, WFP's Home-Grown School Feeding (HGSF) program was launched with the support of the Bill and Melinda Gates Foundation, once again emphasizing the need for local procurement from small producers. Building on the HGSF but greatly expanding its scope and ambition, WFP then launched a 20-country pilot of its Purchase for Progress (P4P) initiative in the wake of the 2007-08 food price crisis. P4P explored procurement modalities with the potential to improve agricultural outcomes and develop country-level food markets in a way that would benefit smallholder farmers (World Food Programme, 2015). In addition to its focus on high quality locally sourced food commodities, the P4P pilot initiative also aimed to strengthen the capacity of smallholder farmers and farmer organizations, and to build linkages to input and service providers and processors (World Food Programme, 2015).

Uganda was one of the pilot countries for the P4P initiative, along with Ethiopia, Kenya, Rwanda, South Sudan and Tanzania in east Africa, and other countries in central, southern and western Africa, Asia and Latin America. Evidence of the impacts of the P4P initiative is mixed: early studies indicate that it improved farmers' access to markets and post-harvest handling (Davies and Menage, 2010 as cited in Upton and Hill, 2011) and improved gender equity (World Food Programme, 2015), though Lentz and Upton (2016) do not find evidence of improved farmer wellbeing in the context of Tanzania despite greater commercialization. In Uganda specifically, large-scale local procurement by WFP appears to have accentuated price speculation among traders and resulted in an equilibrium where two types of maize quality exist: high quality, sold to WFP, and low quality, directed towards the local market (Upton and Hill, 2011).

Despite the fact that 80-90% of food procured was produced by smallholder farmers, WFP procures only a small fraction directly from smallholder farmers via farmer organizations (Leao et al., 2021). An analysis of Uganda's maize value chain revealed fragmentation, lack of integration among players and lack of credit and access to transport for farmers (World Food Programme, 2019). Using regular contracts and open tendering with large traders resulted in about 50% of the cash (market value) reaching smallholder farmers, suggesting that employing both indirect and direct pro-smallholder contract modalities could address imbalances in the maize value chain, potentially increasing benefits for smallholder farmers (Leao et al., 2021). To tackle this, WFP shifted to various contract modalities including both direct and indirect conditional contracts to ensure that smallholder farmers benefit from WFP's stable demand (World Food Programme, 2019).

WFP's current Local and Regional Food Procurement Policy (LRFPP) policy was approved in 2019 and began being implemented in 2020 (World Food Programme (WFP), 2024). Uganda was one of the first countries to implement the indirect conditional contracts to procure maize, instituted in 2021. Conditional indirect contracting generally follow the same principles as traditional contracting, where purchases are announced in the form of national tenders that specify quantity and quality. However, under this type of contract, the condition is added that 20% of the total volume of maize provided by traders must be sourced directly from smallholder farmers, with evidence of purchase (traceability evidence). This conditional contract is the focus of this study.

3 Context and description of maize value chains in Uganda

Maize is one of the most widely cultivated staple crops in Uganda, serving both as a vital food security crop and a key source of income for farmers. Recognizing its importance, the government has prioritized maize production as part of its agricultural strategy to support household livelihoods and strengthen national food security. Maize accounts for approximately 30% of the total cropped land in Uganda, making it the most extensively grown crop, followed by beans at 15% (Uganda Annual Agricultural Survey, 2018).

A typical maize value chain in Uganda involves a network of interconnected actors. At the upstream level, agro-input dealers supply essential inputs such as improved seeds and fertilizers to smallholder farmers. These farmers, in turn, cultivate maize by combining these inputs with land and labor. Once harvested, a marketable surplus is sold to traders, who transport the grain to wholesalers or directly to large processors. Wholesalers generally sell to large processors. Farmers may also take part of the maize they consume themselves to small processors. Processors then transform the raw maize into final products, such as maize flour, which is distributed to retailers and ultimately purchased by consumers. Figure 1 provides an illustration of a stylized maize value chain in Uganda.

Most farmers in Uganda continue to rely on traditional farming methods with limited use of modern agricultural inputs. While some purchase improved seed varieties, such as hybrids or open-pollinated varieties (OPVs), many still depend on saved seeds from previous harvests, constraining potential yield improvements (McGuire and Sperling, 2016). Despite government efforts to promote input use, challenges related to affordability and accessibility persist. Agro-

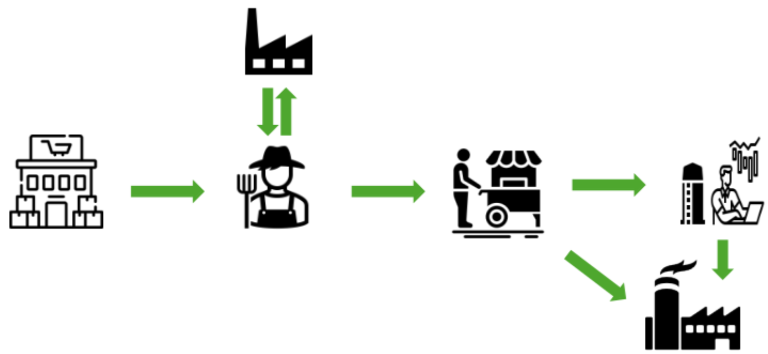

Figure 1: A canonical maize value chain

input dealers, primarily based in towns and trading centers, supply essential inputs such as improved seeds, fertilizers, pesticides, and farming tools. However, rural farmers often struggle to access high-quality inputs due to distance, cost barriers, and supply chain inefficiencies. Additionally, concerns over counterfeit or substandard products further discourage investment in improved technologies, as studies have shown that input quality issues are a significant deterrent for farmers (Barriga and Fiala, 2020; Ashour et al., 2019; Bold et al., 2017; Miehe et al., 2023).

As a result of traditional farming methods, maize productivity remains low, with average farm yields of about 600 kg per acre, considerably lower than the potential yields reported by research stations, which range from 730 kg to 1,820 kg per acre (Fermont and Benson, 2011; Gourlay, Kilic, and Lobell, 2019). Furthermore, harvesting in Uganda is largely manual, and post-harvest handling remains a significant challenge. Farmers typically dry maize under the sun before shelling and storing it, but inadequate drying techniques and poor storage facilities lead to high post-harvest losses. Common storage methods include traditional granaries and polypropylene bags, though both are vulnerable to pest infestations and moisture buildup, further deteriorating grain quality. These post-harvest inefficiencies contribute to reduced market value and increased vulnerability to seasonal price fluctuations.

Market access is another key challenge for maize farmers. Many smallholder farmers sell maize through informal channels, including farmgate sales to itinerant traders who aggregate maize in trading centers and small towns. Small traders, often using bicycles or motorbikes (boda-bodas), play a crucial role in linking farmers to markets, yet their capacity is constrained by transportation limitations, storage capacity challenges, credit constraints and unpredictable demand.

The role of traders 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 post harvest when prices are low and selling during the lean season when maize is scarce and prices are high (Van Campenhout, Lecoutere, and D'Exelle, 2015a; Burke, Bergquist, and Miguel, 2019). At the same time, research also shows that traders enhance market participation, particularly for remote farmers who would otherwise struggle to sell their produce (Barrett, 2008a; Mather, Boughton, and Jayne, 2013; Sitko and Jayne, 2014).

Processing is another critical node in the value chain, where maize is transformed into flour, primarily consumed as *posho*—a staple dish made by cooking maize flour with water into a porridge or dough-like consistency. Processing businesses vary widely, from small-scale mills powered by combustion engines (*baga-baga*) that provide milling services for local farmers to large-scale industrial processors that produce fortified maize flour for commercial distribution. High-quality maize flour production requires multiple milling passes and advanced machinery, with some mills equipped for packaging and export.

4 Methods

4.1 Research questions

The primary goal of the study is to assess the overall impact of WFP entering the market and implementing the indirect conditional contracting modality. We will thus look at the impact of the policy on maize value chain transformation or upgrading. Within this broader goal, our study poses the following research questions:

- Does WFP's indirect conditional tendering approach lead to reliable output markets and how does this affect market participation, technology adoption, production and welfare outcomes for actors involved in the value chains?

- Does the presence of WFP with its condition affect value chain inclusivity and equity? That is, are there changes in which actors participate in the value chains and which actors extract most of the rents when WFP enters the market with conditionality? Do marginalized populations get excluded when WFP starts procuring large quantities of maize? Does it affect seasonality?

In addition to looking at the impact of the policy, we will also investigate potential general equilibrium or spillover effects of the policy. In particular, the indirect conditional contracting may drive up prices in the area, such that farmers that are not linked to WFP through a trader are also affected. Analysis of spillover effects may also be informative to answer the following question:

- Does the indirect conditional contracting modality have additional effects over and above the effect of a significant buyer entering the market (without conditionality).

4.2 Data and identification

The study took place in Western and Central Uganda (see Figure 2). Maize cultivation plays a vital role in the agricultural landscape of Western and Central Uganda. In these regions, maize is widely grown by smallholder farmers who rely on it for household consumption, income generation, and food security. Additionally, the growing demand for maize from urban markets and agro-industrial processors (both for consumption in Uganda or neighboring countries) has increased its commercial value, encouraging investments in improved production practices and inputs and in storage, handling and aggregation midstream.

The survey for the study of conditional contracts aimed to gather data from three distinct types of actors: smallholder farmers, small traders who act as intermediaries between these farmers and large suppliers, and the large suppliers that are supplying WFP. In a first step, farmers were selected randomly after stratifying them into three groups:

- Group 1: Farmers residing in two districts (Kabarole and Hoima) where the WFP was not actively procuring maize through large buyers. Farmers in these two districts were randomly selected in two stages: first villages 50 villages were selected from a list of all villages, with sampling probabilities proportional to the number of households living in the village. Next, in each village 10 households were randomly selected from the list obtained from the village headquarters. This group will also be referred to as the control group.

- Group 2: Farmers who live in districts with characteristics similar to those in Group 1, but where maize is procured from farmers under the indirect conditional contract modality. Specifically, we sample from four districts: Kasese, Kyegegwa, Kiryandongo, and Masindi. 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 are sampled from lists submitted to WFP by wholesalers, as part of the contractual requirement to document purchases directly from farmers. This group will also be referred to as the indirect contracts or treatment group.

- Group 3: Farmers from the same four districts as group 2, but who are not on the traceability list of WFP linked suppliers. In particular, the interview protocol stipulated that nearest neighbor of each Group 2 farmer also needed to be interviewed. This group will also be referred to as the spillover group.

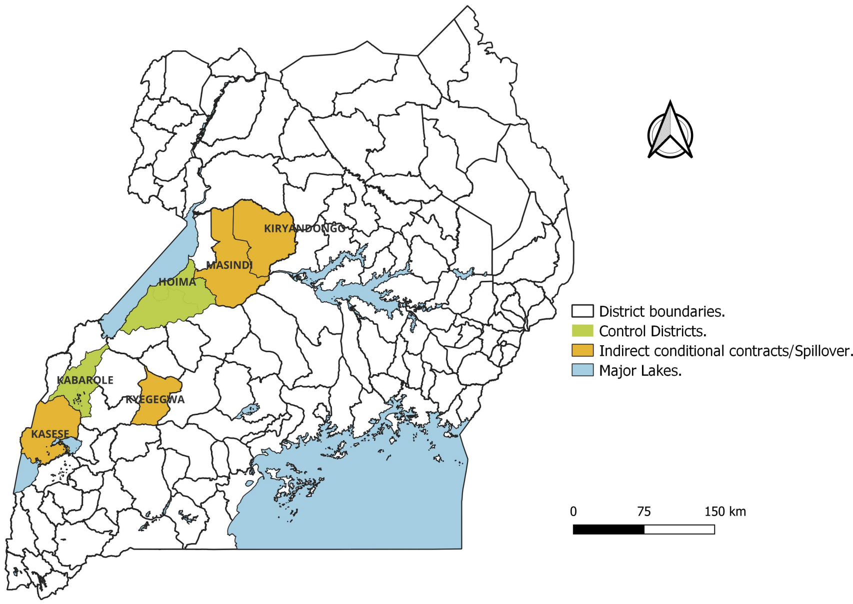

Figure 2: Study area

Traders were identified through referral by farmers. For traders, we only have two groups: those that are operating in areas where WFP was active and those that are operating in areas where WFP is not active. Sample sizes are in Table 1.

The primary identification strategy relies on comparing average outcomes across the three farmer groups for farmer-level indicators, and across two trader groups for trader-level outcomes. At the farmer level, we estimate the impact of WFP's procurement through the indirect conditional contract modality by comparing farmers in treatment areas (Group 2) to those in control areas (Group 1). To explore potential spillover effects, we compare outcomes between farmers in Group 2 to those in the same area but not directly liked to WFP linked traders (Group 3).

It is important to note that the groups we specify are likely to be only proxies to the latent variables we would need to answer the research questions in Section 4.1. For instance, some farmers in Group 1 may in fact be selling to traders linked to WFP through the indirect conditional contracting modality. Conversely, not all farmers in Group 2 necessarily sold to WFP-linked buyers in the season under analysis, as inclusion in this group was based on having appeared on a procurement list in any season. Similarly, farmers in Group 3 may have indirect exposure to WFP, since sellers were only required to register 20 percent of their suppliers to comply with the contract's conditionality.[1]

[1]From group 2, approximately 23% reported selling directly to WFP or through a connected

Table 1: Achieved samples of maize farmers and traders by stratification group

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

Furthermore, because WFP operated exclusively through the conditional contracting modality, it is not possible to isolate the effect of conditionality from the broader impact of engagement with a large, stable buyer—an important and policy-relevant distinction. Some of these limitations will be further addressed in a separate section by complementing the group-based comparisons with data on farmers' and traders' actual transactions with WFP-linked buyers (Section 6).

Survey data were collected on general household characteristics of farmers and traders, 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. For traders, data was collected on both purchase and sales transactions for the first and second season of 2023. Additional data was gathered on actors' core business activities: for farmers, this included agricultural technology use and labor inputs; for traders, this encompassed handling and storage practices, as well as access to finance.

5 Descriptive Analysis

5.1 The impact of reliable output markets

One of the main reasons why WFP initiated the indirect conditional contacts modality (and local and regional procurement modalities more 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, 2008b). 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 southwester Uganda created a reliable market for raw milk that led to upgrading across the entire value chain. In this section, we trace this impact pathway by first testing if indirect conditional contracts are correlated to market participation. We the look for associations between indirect contracting and investment in technologies and practices. Finally, we look at some production related outcomes.

5.1.1 Market participation

We find that 91 percent of farmers make at least one sales transaction in the first season of 2023, while this figure is 89 in the second season of 2023. The top panel of Table 2 shows how this differs between the three groups of farmers in our sample. In both seasons, while about 85 percent of farmers sell to the market

trader. Among spillover farmers (group 3), this figure is about 12%. In contrast, no farmers in control areas reported any sales to WFP.

Table 2: market participation

	Control	Spillover	Indirect
	sold (yes/no) (%)		
Season 23A	85	94	96
Season 23B	81	92	94
	quantity sold (kg)		
Season 23A	1639	1483	2199
Season 23B	1476	1449	1661
	share sold (%)		
Season 23A	63	66	72
Season 23B	68	73	75

in the control areas, this is closer to 95 percent in the indirect contract group. This suggests that the policy is correlated with increased market participation.

We also find significant differences in quantities sold. For instance, we find that quantity sold is higher in the indirect contract group than in the control group, significantly so in the first season (p-value = 0.067). However, quantities sold are similar in control and spillover groups. In fact, in the first season of 2023, quantities sold are actually lower in the spillover group than in the control group, but the difference is not significant (p-value = 0.458).

Finally, the table also shows quantities sold as a share of quantities produced to arrive a measure for marketable surplus. While it is not clear that the marketable surplus is higher in the spillover group than in the control group, the surplus clearly dominates in the indirect conditional contract group.

Our stack survey allows us to also look at market participation patterns at the trader level. To check if the intervention led to traders entering the market, we asked how many other maize buyer/traders operate in the areas where the trader usually buys maize. We find that on average, there are about 6.41 other traders working in the control area. This is 9.23 in areas where the policy is implemented, and the difference is significant (p-value = 0.002). This seems to suggest that the policy is positively related to competition among aggregators.

5.1.2 Adoption of technologies

We next test if reliable market access crowds in modern agricultural technologies such as improved seed varieties and fertilizer. For the sake of space, we investigate this only for the first season of 2023. Results of adoption by different groups are summarized in Table 3.

A first outcome we look at is the use of chemicals. Use of pesticides, herbicides and fungicides is surprisingly high in Uganda. Most farmers use pesticides against fall armyworm and maize stem borers. We see that in the control group,

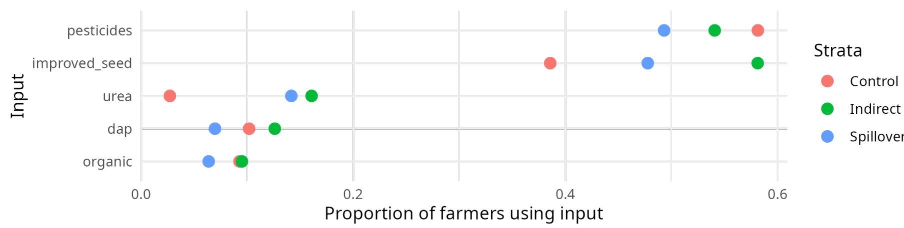

Figure 3: Adoption of agricultural inputs

just under 60 percent of farmers are using some kind of chemical on a randomly selected maize plot.[2] This is slightly lower in the indirect and spillover groups. It may be that stricter quality standards refrain farmers from using excessive amounts of chemicals.

Next, we look at use of improved maize seed varieties obtained from a trusted source (as opposed to farmer saved seed). Adoption of improved seed varieties is in line with expectations. In the control group, 39 percent of farmers indicate that they are using improved seed varieties on the randomly selected plot. This increases to 48 percent for spillover farmers and 58 percent for farmers for the indirect contract group. This suggests that WFP's procurement policy is positively associates with the adoption of improved seed varieties.

The picture for fertilizer use is mixed. First of all, Figure 3 illustrates that farmers in Uganda are not in a habit of using fertilizer. Only about 10 percent of farmers apply DAP and organic fertilizer, and this does not seem to be correlated to exposure to the policy, either directly or indirectly. For Urea, we do see that for farmers that live in areas affected by the policy, adoption improves substantially.

5.1.3 Production

Finally we test if the policy also leads to changes in terms of production. We start by testing if farmers that are likely to be affected by the policy, either directly or indirectly, are more likely to cultivate maize, and if so, if they allocate a larger area to maize production. Table 3 illustrates both the propensity to produce and the area under cultivation in three seasons. For example, in the first season of 2023, approximately 94 % of the farmers who were directly exposed to the policy cultivated maize. In comparison, only 88 % of farmers in the control group did so.

It is important to acknowledge that these figures may be somewhat inflated due to the inclusion criterion that required farmers to have cultivated maize

[2]We did not ask about adoption on all maize plots, but instead asked farmers to enumerate all plots and then randomly selected one plot on which detailed questions on technology adoption were asked. This is done to save costs, as we expect that inputs and practices used on plots are highly correlated within households, so surveying more plots does not yield a lot of new information. As the plot was chosen randomly, plot level outcomes provide an unbiased estimate for household level outcomes.

Table 3: Production related outcomes

	Control	Spillover	Indirect
	produce (yes/no) (%)		
Season 23A	88	93	94
Season 23B	81	90	89
Season 24A	62	83	84
	plot size (acres)		
Season 23A	2.3	2.4	2.7
Season 23B	2.4	2.2	2.5
Season 24A	2.2	1.9	2.2
	production (kg)		
Season 23A	1872.1	1939.3	2313.5
Season 23B	2021.1	1897.5	2351.7
Season 24A	889.5	876.9	964.2
	yield (kg/acre)		
Season 23A	723.7	800.3	806
Season 23B	725.8	842.9	870.7
Season 24A	362.5	444.1	440.6

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. Over time, even as the overall proportion declines, the data increasingly indicate that farmers influenced by the policy are more likely to continue growing maize.

The table also shows that area planted seems to be larger in locations that are exposed to indirect conditional contracting. For instance, while the average area planted with maize is about 2.7 acres in the first season of 2023 for treatment and spillover farmers, this is only 2.3 acres for control farmers.

Next, the table turns to production. We see a sharp reduction in production in the first season of 1014. This was caused by erratic rainfall, where it rained early but stooped, causing seeds to not germinate and farmers needed to replant. For the remainder of the season, there was inadequate rain until the critical stage of tasseling. In the first season of 2023, we get the expected pattern where lowest average production is found in the control areas and highest production in the indirect conditional contract subgroup. In the second season of 2023 average production in the control area is slightly higher. However, in all seasons, largest quantities are produced in the indirect conditional contract group.

Combining plot size and production to obtain yields, we find that overall yield reductions in the first season of 2024 are substantial, but mitigated somewhat by the reduction in plot size. We now also find that average productivity in the control group in is lowest in across seasons. Yields in the spillover and indirect conditional contract groups also seem similar.

Figure 4 brings a slightly different perspective on maize productivity by examining how it evolves over time across the different groups. In the figure, the vertical axis displays changes in production between consecutive seasons. With data spanning three seasons, the figure thus captures two changes: the change from the first to the second season of 2023 (indicated by circles) and from the second season of 2023 to the first season of 2024 (indicated by triangles).

Between the first and second seasons of 2023 (23A–23B) there is no change in average quantity of maize produced in the control group. Similarly, for this group, the average area from which this quantity was obtained remained the same, leading us to conclude that productivity was stable in this group. For the indirect conditional contracting group as well as the spillover farmers, production also remained the same on average. However, for these groups, the area on which maize was grown declined, leading us to conclude that productivity increased between the first and second season.

Between the second season of 2023 and the first season of 2024 (23B-24A), all groups experience significant declines in both production and area used for maize. However, at least for the spillover group, the reduction in production is smaller than the reduction for the control, while the reduction in plot size is larger than for the control. As such, while productivity reduced for both groups, reduction in productivity is largest in the control group.

The trader level equivalent of production would be volumes of maize moved through trader networks. We find that in the first season of 2023, the average trader in the control group traded about 73.04 metric tons of maize. In the

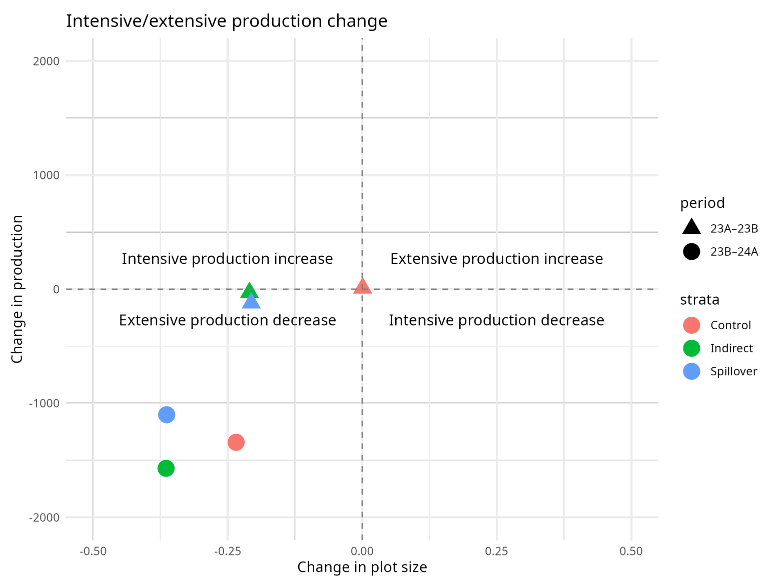

Figure 4: Production and plot size change over time

indirect/spillover group, traders handle about 79.45 metric tons of maize. In the second season of 2023, the figures are 74.78 metric tons and 98.64 metric tons respectively. This suggests that the policy does not only draw traders into the market (see Section 5.1.1), it may also incentivize greater investment in aggregation, processing, or transport capacity, thereby amplifying market throughput. The growing divergence in trade volumes across seasons reinforces the idea that WFP's procurement modality can stimulate scaling behaviors among intermediaries, potentially improving efficiency in the maize value chain.

5.2 Commodity flows

The previous section showed that the policy was associated with increased production and higher volumes handled. In this section, we take a closer look at commodity flows within the value chain. Specifically, using trader level data, we examine how the origin and destination of traded maize differs between groups.

In addition to collecting information on the quantities of maize procured (see Section 5.1.3, we asked traders to report the origin of their purchases as a share of total volume. Similarly, traders were also asked to indicate the distribution of their sales across different buyer types, expressed as percentage shares. This information is summarized in Figure 5.

The figure illustrates that the majority of maize procured by traders—approximately 65 percent—comes directly from farmers, with this share being consistent across both groups. Fellow traders also represent a significant source, with a slightly higher share observed in policy-exposed areas compared to the control group (24 percent versus 20 percent). In addition, traders operating in areas where the policy was implemented source more maize from markets than their counterparts in control areas, while the volume procured from cooperatives is three times higher in policy exposed areas than in control areas. Qualitative insights suggest that this difference may stem from the policy's requirement for farmer registration, a process that is often more straightforward when dealing with cooperatives, which typically maintain farmer registries.

At the downstream side, most maize is sold to wholesalers not linked to WFP. In areas affected by the policy, a similar share is also sold to other downstream traders. 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, traders in control areas rarely sell to WFP, either directly or through WFP-affiliated wholesalers. In contrast, approximately 10 percent of maize traded in the treatment areas is supplied to WFP.

5.3 Price margin analysis

Central to many value chain studies is the question of how rents are distributed over different value chain actors. A convenient way to illustrate this is by price spread plots, that plot prices received by the actor upstream (eg the farmer) against prices received by the actor downstream (eg the trader). One can then plot a 45 degree line, were prices paid to upstream actors are equal to prices received from downstream actors. As such, points above the 45 degree line represent transactions were 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.

Figure 6 plots observations for farmer-trader transactions in control areas in red, and observations for farmer-trader transactions in areas exposed to the policy in green. As can be seen, most points are above the 45 degree line, though there also seem to be occasions where the price at which traders (reportedly) bought maize was higher than the price at which they sold. While some of these traders may have made a loss, some if it will also be measurement error since it may be hard for traders to name a single average price over an entire season.

To deal with over-plotting, we added contour plots with the same color coding to the figure. For the control group, density is highest at points corresponding to a farm gate price of about UGX550 per kilogram of maize and a sales price of about UGX725 per kilogram, leading to a trader margin of about UGX175 per kilogram of maize. In other words, in control areas, farmers receive about 75 percent of the price at which traders sell. For traders working in areas where the policy was implemented, density is highest to the southeast of the control density plot. In particular, in these areas traders pay about UGX625 per kilogram, while traders sell onward for about UGX700, leading to a trader margin of about UGX125 per kilogram. In these areas, farmers receive about 90 percent of the price at which traders sell. Note that compared to the control areas, farmers get more at the farm-gate, while consumers are likely to pay less. This seems to suggest that value chains are more efficient in areas where WFP

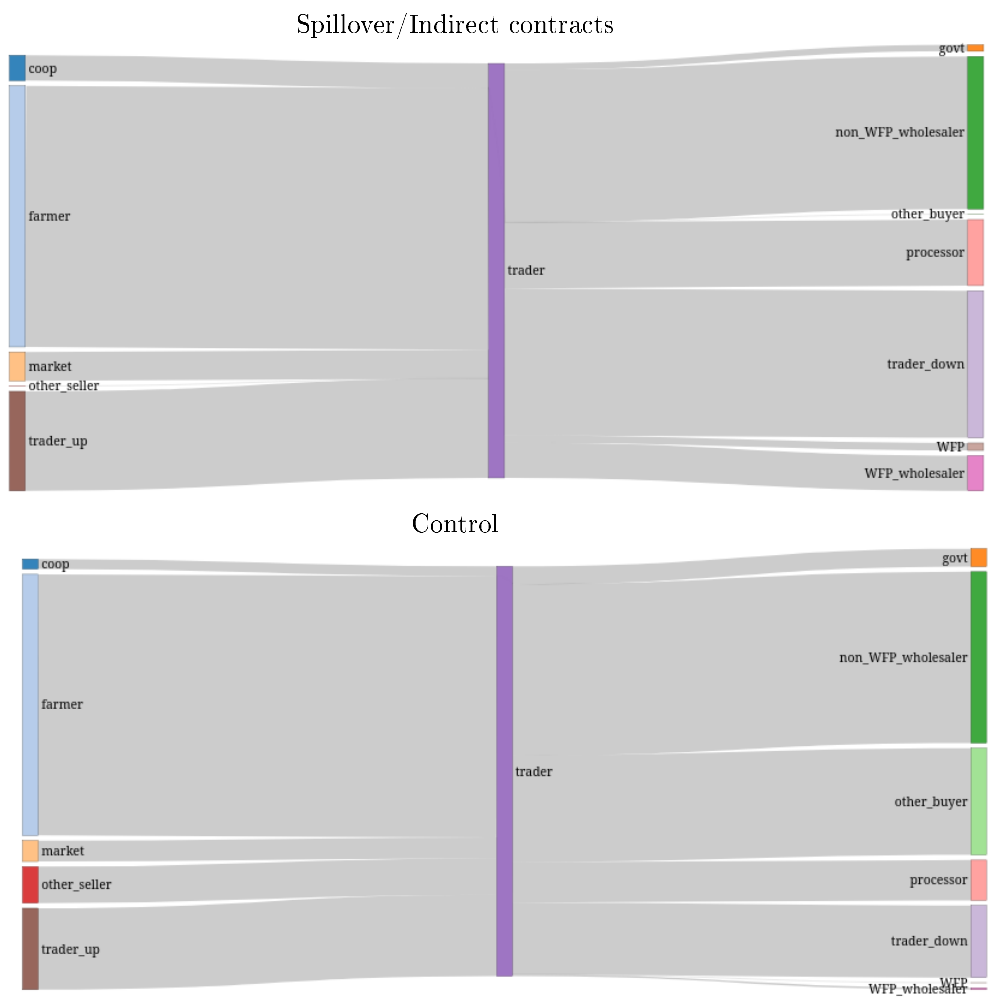

Figure 5: Commodity flows

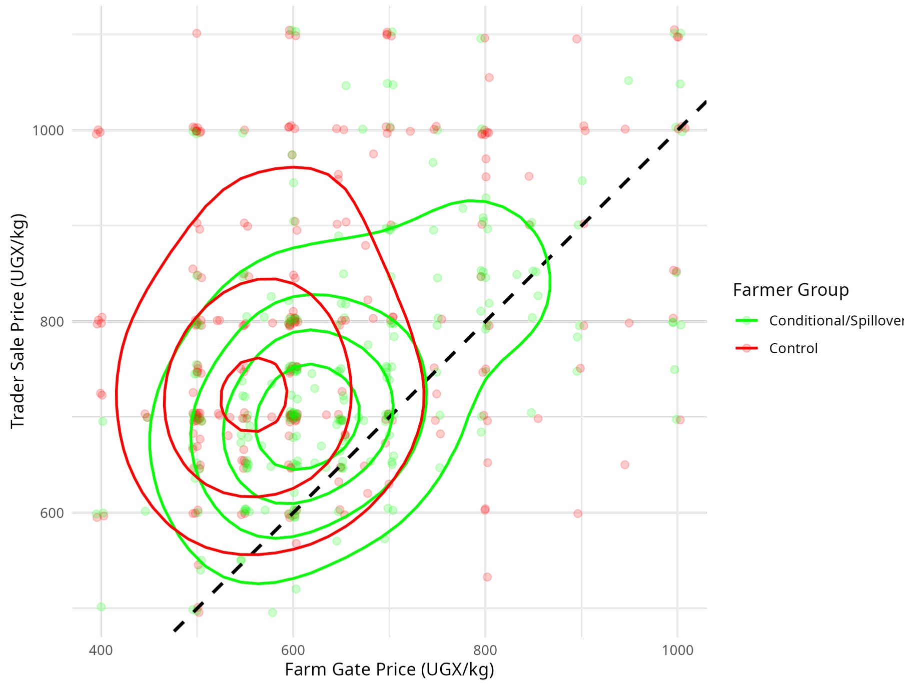

Figure 6: Price margin analysis using trader level data

is procuring.

We can also combine data at the farmer level with data at the trader level to triangulate these important findings. We also split that data by season. Figure 7 confirms that in areas where WFP was active with Indirect conditional contracting, traders capture less of the rents than in control ares, and this is the case in both seasons. For example, in the first season of 2023, farmers sold maize at about UGX800 per kg, while traders sold at about 875, implying a pass through of about 90 percent. In the control areas, farmer sell at about 750, while traders sell at 900, implying farmers get only 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 the treatment areas sold at 650, while traders sold at 775, implying a pass through of 83 percent; in control areas pass through reduces to 73 percent.

The increase in price may be a direct effect of increased prices and quantities demanded by a significant and credible buyer. However, there are many be other indirect pathways through which the policy may increase prices. One such indirect pathway would be that the entry of a large buyer leads to market entry by traders (Upton and Hill, 2011). We already established in section 5.1.1 that the policy is positively related to competition between traders. The increased competition among traders could then be responsible for (part of the)

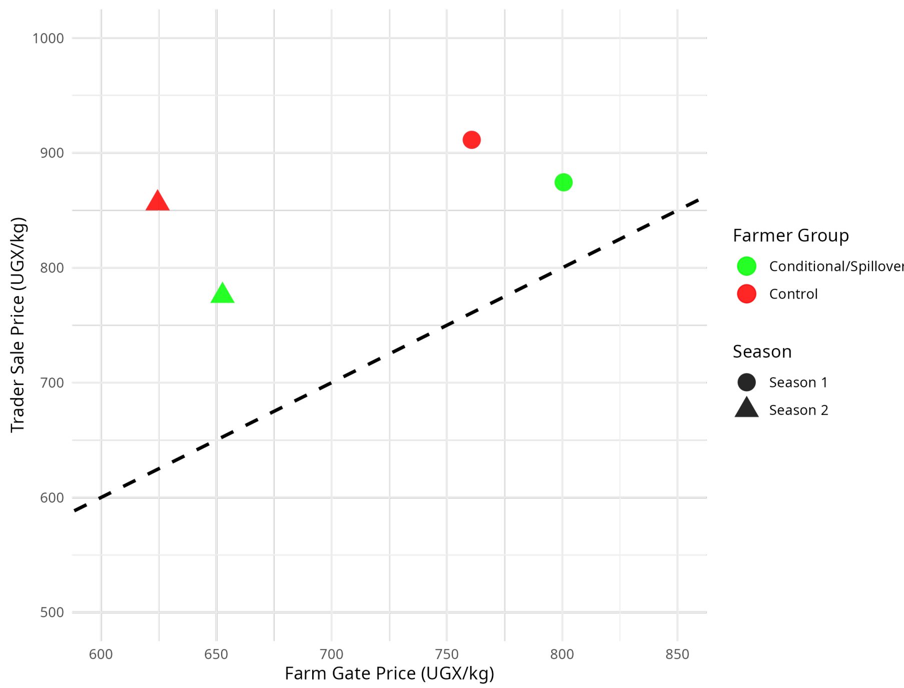

Figure 7: Price margin analysis combining farmer and trader level data

price increase at the farmer level.

To test if competition among traders mediates the impact of an intervention on the price received by farmers, we use structural equation modeling, which includes techniques like path analysis and mediation analysis. Mediation analysis helps in understanding how an independent variable (in this case, indirect conditional contracting) influences a dependent variable (price received by farmers) through a mediator variable (the level of competition proxied by the number of traders in the area).

Mediation analysis involves the joint estimation of two regression equations. First, the intervention is regressed on the mediator variable. In a second regression, two explanatory variables are used (the mediator and the intervention indicator) to explain the outcome (in our case the price farmers receive). This allows one to separate the total effect of the intervention into a direct effect (which is the effect of indirect conditional contacting on the farmgate price while controlling for trader entry) and an indirect effect (which is the effect of indirect contracting on trader entry multiplied by the effect of trader entry on farmgate prices while controlling for the indirect contracting).

We combine trader level and farmer level data to run the mediation analysis. To achieve this, we construct a farmer-level measure of competition. This is done by averaging trader level indicators of competition, weighted by the inverse distance between each farmer and the respective traders.

Running the analysis then at the farmer level gives us a total effect of UGX 54.58 that can be decomposed into a direct effect of UGX 26.69 and a mediated effect of UGX 27.89. For the mediated effect, in the treatment area, there are on average 2 additional traders active, and each additional trader is correlated with a price increase of UGX 13.72. Importantly, only the indirect effect is statistically significant, suggesting that the price gains observed by farmers are driven by heightened competition among traders. This aligns with our earlier finding that farmer and trader prices move in opposite directions, implying that competitive pressure is compressing trader margins.

5.4 Seasonality

Most farmers typically sell most of their harvest immediately after harvesting. Over time, as stocks dwindle, less maize is brought to the market. During the leans season and especially immediately before the harvest of the subsequent season, more maize is bought than sold. These demand and supply patterns result in seasonal price movements in maize prices.

These cyclical price movements can be large, with prices often more than doubling over time. For poor farmers that do not have the capacity to engage in inter-temporal arbitrage, this can lead to so called sell-low buy high patterns, where farmers sell maize at low prices only to buy back similar amounts of maize later in the season at significantly high prices (Burke, Bergquist, and Miguel, 2019). Van Campenhout, Lecoutere, and D'Exelle (2015b) argue that farmers face a double whammy as in addition to the loss incurred by price swings, traders are also likely to pass transaction costs to the farmers.

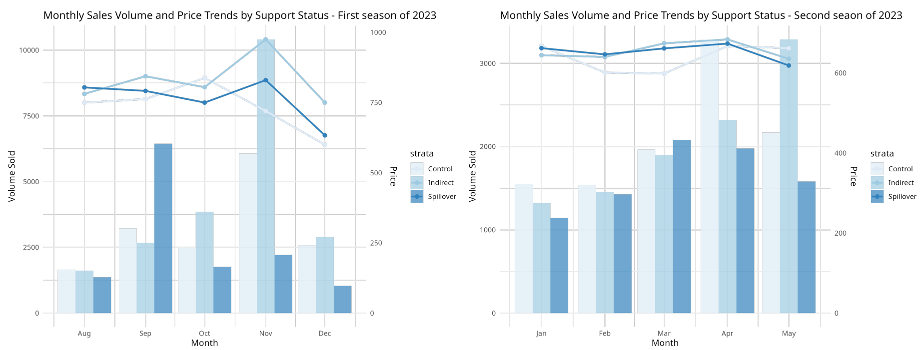

Figure 8: Seasonality in price and volumes

An important question therefore is whether the indirect conditional contracting modality increases or reduces seasonality in prices. If WFP purchases target low prices and writes out tenders immediately post harvest (and potentially distributes food aid during the lean season), its activities could have counter cyclical effects. However, if WFP faces delays in procurement due to administrative reasons, or if traders speculate on WFPs purchase, price variation could increase.

Figure 8 uses farmer level data to look at seasonality in volumes entering the market and prices. 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. There is some suggestive evidence supporting the hypothesis that farmers in the indirect conditional contacting group hold on longer to their maize. For instance, in the first season of 2023, volumes marketed in this group rose steadily to a peak in November. in the second season, the peak is May. Patterns are less clear for the other groups. In the fist season, there is 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 fairly 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 sales peak in the Indirect conditional contract group. Interestingly, the increase in prices is highest in the group of farmers that are linked to WFP buyers, and lowest in the control group. Overall, and in both seasons, prices reported by farmers that are directly linked to WFP generally report higher prices. This seems to suggest that WFP purchases indeed led to some degree of price inflation.

5.5 Inclusivity

An important concern raised by WFP is whether the benefits arising from indirect conditional contracts reach vulnerable groups, such as women and youth.

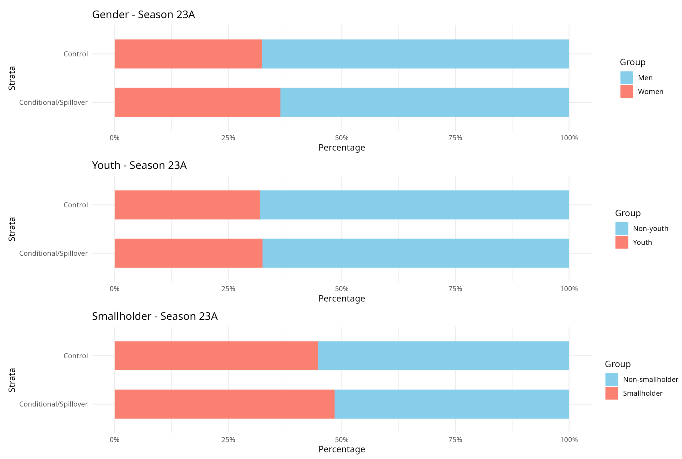

Figure 9: Gender, age and scale of farmer bought from

Additionally, one of the core objectives of the project is to ensure that smallholder farmers are able to benefit from WFP's procurement activities. In this section, we examine whether the impact of these contracts differs across groups, with a particular focus on farm-gate prices as the key outcome variable.

To assess inclusivity, we asked traders to estimate the proportion of their farmer-suppliers who are women, youth, and smallholders. As shown in Figure 9, approximately 30 percent of sellers are women, with a slightly higher share observed in areas where the policy is implemented. A similar share of sellers—around 30 percent—are classified as youth, with little variation between treated and comparison areas. Regarding smallholder farmers, traders report a notable difference: in areas where the policy is in place, nearly half of the sellers are smallholders, suggesting that the intervention may be enhancing participation among this target group.

5.6 Food and nutrition insecurity, coping

To look at food security, we use the **Food Insecurity Experience scale (FIES)** questions refer to the experiences of the individual respondent or of the respondent's household as a whole. The questions focus on self-reported food-related behaviors and experiences associated with increasing difficulties in accessing food due to resource constraints.

Figure 10 compares food insecurity status across treatment groups for two populations—farmers (left panel) and traders (right panel). Among farmers, food insecurity is notably higher in the Indirect and Spillover groups compared to the Control group. While a majority of farmers across all groups are food secure, the proportion is highest in the Control group, and declines in both Indirect and Spillover groups. These two treatment groups also exhibit slightly higher proportions of moderate and severe food insecurity.

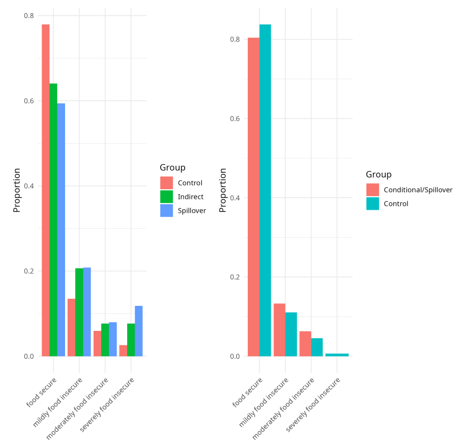

Figure 10: Food insecurity for farmers and traders

In contrast, traders display significantly higher overall food security, with over 80% classified as food secure across both the Control and Conditional/Spillover groups. Mild and moderate food insecurity are present but relatively limited, and severe food insecurity is rare. Interestingly, the Conditional/Spillover group shows marginally higher food insecurity than the Control group, though the differences are small. These patterns imply that traders, likely benefiting from more stable incomes and market access, are less vulnerable to food insecurity, and the interventions did not produce substantial differences in outcomes for this group.

The **Household Dietary Diversity Score (HDDS)** was released in 2006 as part of the FANTA II Project as a population-level indicator of household food access. Household dietary diversity can be described as the number of food groups consumed by a household over a given reference period, and is an important indicator of food security for many reasons. A more diversified household diet is correlated with caloric and protein adequacy, percentage of protein from animal sources, and household income (Swindale & Bilinsky, 2006). The HDDS indicator provides a glimpse of a household's ability to access food as well as its socioeconomic status based on the previous 24 hours (Kennedy et al., 2011). Typically, 0–3 means low dietary diversity very limited access to diverse foods; possible food insecurity. 4–5 Medium dietary diversity Somewhat better access, but still at risk nutritionally. 6–12 High dietary diversity Good access to a variety of foods; better food security.

The left panel of Figure 11 illustrates the distribution of dietary diversity (measured by the number of food groups consumed) among farmers, disaggregated by Control, Indirect, and Spillover groups. The distribution peaks around 6 to 7 food groups for all groups, but the Spillover group shows a higher proportion of individuals achieving 7 or more food groups, suggesting a positive

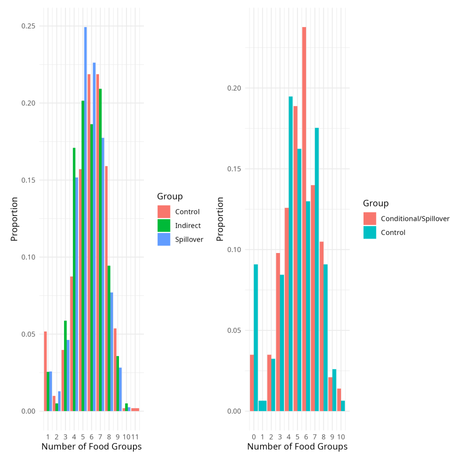

Figure 11: Diet diversity score

diffusion effect of the intervention on non-directly treated farmers. The Indirect group also shows a slight shift toward higher dietary diversity compared to the Control, indicating that even partial exposure or association with the intervention may have improved nutrition outcomes for farmers.

The right panel focuses on traders, comparing those in the Conditional/Spillover group with those in the Control group. The Conditional/Spillover group displays a notable shift toward higher dietary diversity, with the highest proportion of traders consuming around 6 food groups, and a visibly lower proportion consuming fewer than 4 food groups compared to the Control group. This suggests that the intervention had a broader reach, not only affecting participating farmers but also influencing the dietary behavior of traders—possibly through increased incomes, improved food availability, or learning effects. Overall, the figure highlights meaningful improvements in dietary diversity among both farmers and traders exposed directly or indirectly to the intervention.

The **Livelihood Coping Strategies – Food Security (LCS-FS)** is an indicator used to understand households' medium and longer-term coping capacity in response to lack of food or money to buy food and their ability to overcome challenges in the future. The indicator is derived from a series of questions regarding the households' experiences with livelihood stress and asset depletion to cope with food shortages.

Figures 12 illustrates the severity of livelihood coping strategies among farmers (left panel) and traders (right panel), segmented by treatment groups. Among farmers, a lower proportion of households in the Indirect and Spillover groups report using no coping strategies compared to the Control group, indicating higher stress. These groups also show a higher incidence of stress, crisis, and emergency-level coping strategies. Notably, the Indirect group reports the highest share of crisis strategies, while Spillover households show slightly elevated

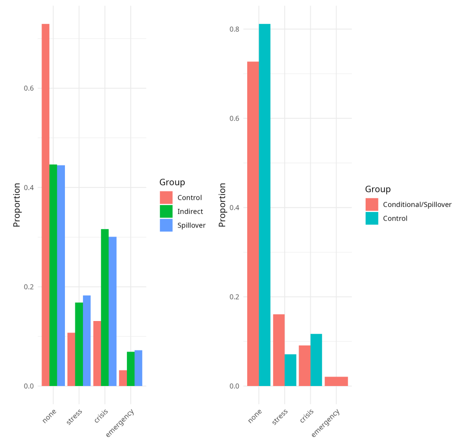

Figure 12: Livelihood coping strategies

use of emergency strategies. This pattern suggests that food or economic shocks may have pushed these households to adopt more severe strategies, potentially due to limited direct benefits from the intervention or unmet expectations.

Traders, shown in the right panel, exhibit a more favorable coping profile, with over 80% of households in the Control group and over 70% in the Conditional/Spillover group reporting no use of coping strategies. However, traders in the Conditional/Spillover group demonstrate somewhat greater reliance on stress and crisis strategies compared to the Control group, though emergency strategies remain very low in both. This indicates that while most traders are not resorting to harmful coping behaviors, those in the treatment group may still be experiencing marginally more pressure than their Control counterparts—perhaps due to market disruptions or unmet expectations associated with the intervention.

6 Regression Analysis

In this section, we take a closer look at some of the most striking findings from the descriptive analysis. In particular, we assess whether the observed patterns hold up under more rigorous scrutiny using regression analysis and instrumental variables as an identification methods.

We start with the price margin analysis presented in Section 5.3, first looking at the prices received by farmers. Data is at the transaction level and we pool data from 2023A and 2023B. As in Section 5.3, we compare average farm-gate prices between farmers located in areas where WFP implemented indirect conditional contracts (combining both spillover and indirect contract groups) and those in areas where WFP was not active (control areas).

In the first column of Table 4, we show results for a regression equivalent of what is on the x-axis of Figure 7 (but with added controls for the month when transaction took place). It shows that farmers that live in areas where the policy is implemented received about UGX 23 per kg more for the maize they sold than farmers that live in control areas. This is only slightly lower than what we found in Figure 7 where price differences were about 35 UGX in season 1 and 25 UGX in season 2.

While this comparison is informative, it may yield biased estimates due to potential misclassification of farmer exposure. Specifically, some farmers in control areas may in fact supply WFP-connected traders, while some farmers in WFP-implementation areas may transact with traders who are not linked to WFP. This mismatch between geographic assignment and actual trading relationships can lead to 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 that address these concerns focuses on actual trading relationships rather than geographic assignment. For each transaction, the survey recorded whether the farmer sold directly to WFP or through a WFP-linked trader, as opposed to other channels such as non-linked traders or processors. Column (2) of Table 4 presents results from a regression comparing prices received by farmers with such links to those without. The estimated price difference is notably larger (approximately 54 UGX per kg), suggesting that self-reported trading relationships may provide a more accurate measure of policy exposure than location-based assignment alone.

While this alternative approach provides a more direct measure of farmer exposure to the intervention, it is not without limitations. Most notably, the decision to sell to WFP or through a WFP-linked trader is endogenous and may reflect unobserved characteristics of the farmer or the transaction. For instance, farmers with higher-quality maize, better market information, or stronger bargaining power may be more likely to attract WFP-linked traders and command higher prices, regardless of the intervention. As a result, the observed price premium could partly reflect selection effects rather than a causal impact of trading with WFP-linked buyers. Without addressing this endogeneity, the estimated price difference may overstate the true effect of the intervention.

This is why we turn to an instrumental variables approach in Column (3) of Table 4. We use whether the farmer resides in an area where WFP implemented indirect conditional contracts as an instrument for trading with a WFP-linked buyer. This location-based instrument is relevant, as the intervention was explicitly designed to increase such trading relationships in targeted areas. Relevance is also demonstrated by a strong first stage with an F-statistic of 94.38. Under the assumption that geographic implementation affects farmgate prices only through its impact on trader linkages—and not through other local price determinants—the IV approach isolates the causal effect of selling to a WFP-linked trader.[3] The two-stage least squares estimate suggests that farmers connected to WFP-linked traders received approximately 180 UGX more per kg than those who were not. This estimate exceeds the non-instrumented difference, indicating that attenuation bias from exposure misclassification likely outweighs any positive selection bias.

In column (4), we add additional controls to the 2SLS of column (3). Controlling for additional variables serves several purposes. First, it helps improve the precision of the estimates by accounting for observable factors that influence farm-gate prices, such as quantity sold and farmer characteristics like education or farm size. Second, including these controls helps mitigate concerns that the instrument (location) may be correlated with other determinants of price beyond the trading relationship. For example, if WFP targeted areas that differ systematically in infrastructure, market access, or farmer capacity, this violates the exclusion restriction. By conditioning on these covariates, we reduce the risk that omitted variable bias distorts our IV estimates and strengthen the credibility of the exclusion restriction. Essentially, the goal is to ensure that the identifying variation in trader linkage is as exogenous as possible, conditional on observed characteristics.

We include eight control variables. First, we control for the gender, age, and education level of the household head because these variables may proxy for bargaining power, information access, or ability to negotiate with buyers. For instance, more educated farmers 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 head could reflect experience or risk preferences (Schildberg-Hörisch, 2018).

Household size is included as it may capture labor availability and subsistence needs, both of which can affect production choices and marketing behavior. Larger households may have more surplus to sell or be under more pressure to sell early in the season (Burke, Bergquist, and Miguel, 2019). Likewise, the total acreage of land owned serves as a proxy for the scale of production and underlying wealth, which are likely to influence not only the volumes marketed but also the bargaining position of the farmer.

Membership in a maize-focused cooperative is included because cooperatives may provide market access, storage facilities, and collective bargaining opportunities, all of which can impact transaction prices. Similarly, controlling for

[3]This assumption may appear to run counter to our earlier analysis, which left open the possibility of spillover effects. To assess this, we conducted a placebo test, examining whether residing in a WFP-implementation area affects the price received by farmers who did not sell to WFP-linked traders. The results indicate that it does not. We also tested whether location has predictive power within the subset of farmers who did trade with WFP-linked traders, and again found no significant effect. Taken together, these findings provide supportive evidence for the validity of the exclusion restriction: the instrument appears to affect prices only through its influence on trading relationships, rather than through alternative pathways.

the quantity sold in the transaction helps address concerns that larger volumes may be associated with price discounts or premiums due to economies of scale or buyer preferences.

Finally, the number of traders a household reports knowing provides a proxy for local market structure and the farmer's market access. Farmers who know more traders may face more competition among buyers, which can improve their bargaining position and lead to better prices. Including this variable helps mitigate omitted variable bias stemming from unobserved variation in market competitiveness. Adding controls further increases the estimate of the impact of policy on the prices farmers receive. Farmers that are connected to WFP linked traders get about 260 UGX more than farmers that are not linked to WFP.

Table 4: Effect of WFP connection on farm-gate prices

	Dependent variable: Price			
	Price			
	OLS		*instrumental variable*	
	OLS Exogenous	OLS Endogenous	IV	IV + Controls
	(1)	(2)	(3)	(4)
Strata (instrument)	23.050*			
	(11.781)			
WFP connected (endogenous)		54.195***	180.850*	257.127***
		(15.974)	(93.096)	(97.322)
Male head				3.080
				(13.231)
Age head				−0.053
				(0.428)
Primary head				19.908*
				(11.437)
HH size				−1.540
				(1.852)
Land owned				0.281
				(0.679)
Coop member				−26.738
				(19.795)
Volume sold				0.002
				(0.002)
Num traders				−17.990**
				(8.207)
Month FE	Yes	Yes	Yes	Yes
Strata2 used as instrument	No	No	Yes	Yes
Estimation	OLS	OLS	2SLS	2SLS
Observations	2,210	2,210	2,210	2,099
R^2	0.083	0.086	0.055	0.026
Note:				*p<0.1; **p<0.05; ***p<0.01

We run a similar analysis at the trader level, focusing on the prices traders received when selling maize onward (to WFP directly, to WFP-connected traders, or to other buyers). At this 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 traders sold their maize and the share of total sales going to each type of buyer. Traders were also asked to report the prices they received from WFP and non-WFP-connected buyers. We used this information to compute a weighted average price for each trader, using the reported shares sold to each buyer type as weights.

In Section 5.3, we also compare prices between traders located in areas where WFP implemented indirect conditional contracts and those in control areas where WFP was not active. Column (1) of Table 5 presents the regression counterpart of the y-axis in Figure 7, but now with the addition of season fixed effects. The results indicate that traders in treatment areas received, on average, approximately UGX 60 less per kilogram than their counterparts in control areas. This aligns with the visual evidence from Figure 7, which shows that in season A, traders in treatment areas received about UGX 35 less than in control areas, with the gap widening to around UGX 75 per kilogram in season B.

Similar to the farmer analysis above, relying solely on a trader's location to define exposure to the intervention can be misleading. Traders are inherently mobile and often operate across multiple areas, potentially sourcing from farmers in both treatment and control locations. Moreover, not all traders based in WFP implementation areas are necessarily connected to WFP-related supply chains. This geographic misclassification blurs the distinction between treatment and control groups, introducing attenuation bias and leading to an underestimation of the true effect of the intervention on trader-level prices. In addition, traders 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. This further underscores the need for a more precise identification strategy based on actual trading relationships rather than geographic proxies.

To more directly estimate the effect of WFP connections on the prices received by traders, we re-run the analysis using a binary indicator as the independent variable. This indicator equals one if the trader sold maize either directly to WFP or to a wholesaler affiliated with WFP, and zero if the trader sold to any other type of buyer. The results, presented in column (2) of Table 5, reveal no statistically significant difference in the prices received by traders with a direct WFP connection. However, this measure of connectivity is likely to be affected by selection bias. Traders linked to WFP may differ systematically from others—potentially operating in surplus-producing areas, being more professionalized, or located closer to procurement hubs. If such characteristics are also associated with lower prevailing prices, the estimated effect of WFP connectivity may be biased downward. At the same time, confounding factors could mask the true effect: traders who sell to WFP may also possess traits that help them secure higher prices from other buyers—such as better capital, stronger logistics, or more consistent quality. These traits could partially offset the negative price effect of selling to WFP, making the OLS estimate appear close to zero even if a true effect exists. To address this, we instrument WFP connectivity using geographic strata defined during the sampling design. These strata reflect variation in the likelihood that a trader is connected to WFP, based on where traders were sampled, and provide a source of plausibly exogenous variation for identification. Using this approach, we find that the effect becomes significantly negative, suggesting that once selection is accounted for, traders connected to WFP receive lower prices. This may reflect WFP's market power, standardized pricing, or quality-related deductions, and highlights the importance of correcting for selection bias when evaluating the impact of institutional procurement on market outcomes.[4]

The parsimonious 2SLS regression reported in column (3) reveals a large and statistically significant reduction in the prices received by traders who sell to WFP or to a WFP-connected wholesaler. On average, these traders receive nearly 300 UGX less per kilogram of maize compared to those selling to other buyers. In column (4), we extend the specification by adding trader-level and transaction-level controls—mirroring the approach used in the farmer-level regressions presented in Table 5. Including these covariates slightly reduces the magnitude of the estimated effect, but the negative and significant relationship between WFP connectivity and trader prices persists, reinforcing the robustness of the finding.

[4]Similar to the regression at the farmer level, we find a first stage F-statistic that is substantial, suggesting that the instrument is relevant. We also ran both placebo tests and find that among farmers who did not trade with WFP-linked traders, those residing in WFP implementation areas actually received significantly lower prices. Among farmers who did trade with WFP-linked traders, location does not significantly predict prices.

Table 5: Effect of WFP Connection on Trader-Level Selling Prices

	Dependent variable: Selling Price (UGX/kg)			
	Price			
	OLS		*instrumental variable*	
	OLS Exogenous	OLS Endogenous	IV	IV + Controls
	(1)	(2)	(3)	(4)
Strata (instrument)	−61.514***			
	(23.355)			
WFP connected (endogenous)		−32.291	−292.875**	−272.461**
		(30.684)	(120.243)	(112.597)
Male head				−148.436**
				(71.429)
Age head				0.964
				(1.984)
Prim head				46.648
				(28.558)
HH size				4.030
				(4.424)
VolumeSold				0.007
				(0.018)
Season FE	Yes	Yes	Yes	Yes
Strata used as instrument	No	No	Yes	Yes
Estimation	OLS	OLS	2SLS	2SLS
Observations	569	569	569	565
R^2	0.043	0.028	−0.101	−0.060

Note: *p<0.1; **p<0.05; ***p<0.01

Another key outcome we consider at the farmer level is adoption of agricultural inputs. The analysis in Section 5.1.2 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 analysis for each input separately, we combine them in an index following Anderson (2008).

One complication in this analysis is that the measure of WFP connectivity 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 WFP if they engaged in at least one transaction with a WFP-linked trader during the season. If none of their transactions involved a WFP-linked trader, the farmer is considered not connected. This approach ensures that our farmer-level connectivity variable captures meaningful exposure to the intervention.

Table 6: Effect of WFP connection on adoption

	Dependent variable: Price			
	adoption_index			
	OLS		*instrumental variable*	
	OLS Exogenous	OLS Endogenous	IV	IV + Controls
	(1)	(2)	(3)	(4)
Strata (instrument)	0.108***			
	(0.027)			
WFP connected (endogenous)		0.175***	0.845***	0.709***
		(0.054)	(0.222)	(0.240)
Male head				0.028
				(0.034)
Age head				−0.003***
				(0.001)
Primary head				0.136***
				(0.030)
HH size				0.014***
				(0.005)
Land owned				0.006***
				(0.002)
Coop member				−0.012
				(0.048)
Num traders				0.052**
				(0.021)
Month FE	Yes	Yes	Yes	Yes
Strata2 used as instrument	No	No	Yes	Yes
Estimation	OLS	OLS	2SLS	2SLS
Observations	2,226	2,226	2,226	2,129
R^2	0.020	0.019	−0.114	−0.007
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6 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. The estimated effect increases when using the endogenous measure of connectivity as the explanatory variable. Instrumental variable regressions further support a positive and statistically significant impact of the policy on adoption outcomes, reinforcing the interpretation that the observed differences are not solely driven by selection or confounding factors.

At the trader level, we assess investment in quality by constructing a binary indicator that captures consistent adherence to key post-harvest practices. Specifically, a trader 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 7 shows the by now familiar table with OLS and 2SLS results. The OLS regression in column (2) finds no significant relationship between WFP connectivity and quality investment (coefficient = 0.030), suggesting that simple correlations may underestimate the true effect. However, once endogeneity is addressed using strata as an instrument in a 2SLS framework (column 3), the estimated effect increases substantially to 0.506 and becomes statistically significant at the 1% level. This effect remains robust and slightly increases (to 0.590) after including controls for trader demographics and transaction volume in column (4), with significance maintained at the 5% level.

Notably, none of the control variables are statistically significant, though signs are as expected: older traders and those with more household members appear slightly less likely to invest in quality, while male traders and those with more education are more likely, albeit not significantly so. The jump from the insignificant OLS to a strong IV estimate again suggests that traders who connect with WFP may be systematically different from others in unobserved ways—perhaps more professional or better networked—and that failing to account for this masks the true causal effect. The consistently positive and significant IV estimates across specifications indicate that WFP's indirect conditional contracting model successfully incentivizes higher standards in post-harvest handling among participating traders.

Table 7: Effect of WFP Connection on Trader-Level Quality Investment

	Dependent variable: Invests in quality (1=yes)			
	qual			
	OLS		*instrumental variable*	
	OLS Exogenous	OLS Endogenous	IV	IV + Controls
	(1)	(2)	(3)	(4)
Strata (instrument)	0.125^{***}			
	(0.041)			
WFP connected (endogenous)		0.030	0.506^{***}	0.590^{***}
		(0.059)	(0.187)	(0.219)
Male head				0.102
				(0.212)
Age head				0.001
				(0.003)
Prim head				0.096^{**}
				(0.049)
HH size				0.012
				(0.010)
VolumeSold				−0.00001
				(0.00002)
Strata used as instrument	No	No	Yes	Yes
Estimation	OLS	OLS	2SLS	2SLS
Observations	297	297	297	281
R^2	0.032	0.001	−0.243	−0.254
Note:				*p<0.1; **p<0.05; ***p<0.01

Another outcome we look at is provision of inputs like seed, fertilizer and chemicals and/or a tarpaulin that can be used for drying of maize grains. Results are in Table 8. OLS estimates in column (2) show that WFP-connected traders are significantly more likely to invest in inputs (coefficient = 0.310, $p<0.01$), but this relationship may be endogenous. Instrumental variable (IV) estimates in column (3), using geographic strata as an instrument, yield a much larger coefficient (1.131), suggesting that selection bias may downwardly bias OLS estimates. While the IV estimate is only marginally significant due to a larger standard error, the effect remains large and statistically significant at the 5% level in column (4), which includes trader-level controls such as gender, age, education, household size, and transaction volume. None of the controls are strongly predictive, though older traders are slightly less likely to invest. These findings suggest that WFP's procurement model leads to meaningful changes in trader behavior, encouraging investment in input provision and improving quality along the supply chain.

Table 8: Effect of WFP Connection on Trader providing inputs

	Dependent variable: Invests in quality (1=yes)			
	inputs			
	OLS		*instrumental variable*	
	OLS Exogenous	OLS Endogenous	IV	IV + Controls
	(1)	(2)	(3)	(4)
Strata (instrument)	0.280***			
	(0.041)			
WFP connected (endogenous)		0.310***	1.131***	1.041***
		(0.059)	(0.187)	(0.219)
Male head				0.406*
				(0.212)
Age head				−0.006**
				(0.003)
Prim head				−0.065
				(0.049)
HH size				0.008
				(0.010)
VolumeSold				−0.00002
				(0.00002)
Strata used as instrument	No	No	Yes	Yes
Estimation	OLS	OLS	2SLS	2SLS
Observations	297	297	297	281

Note: *p<0.1; **p<0.05; ***p<0.01

7 Conclusion and Policy recommendations

This study set out to assess the impact of indirect conditional contracts implemented by the World Food Programme (WFP) in Uganda, with a specific focus on their role in transforming the maize value chain. Our analysis was guided by four core research questions: (1) What is the impact of the conditional contract on key outcomes—price realization, amount sold, household income and other welfare indicators—of actors along the value chain, especially for smallholder farmers and small maize traders? (2) Do conditional contracts create access to reliable markets and result in value chain transformation or upgrading? (3) Does the presence of a formal/institutional buyer in an area (e.g. a WFP-affiliated trader or contract scheme) indirectly improve outcomes for nearby smallholders and traders who are not directly contracted? (4) What are the challenges or barriers faced with respect to conditional contracts?

To answer these questions, we collected rich, stratified data from over 1,300 farmers and nearly 300 traders from six districts in Western and Central Uganda. Stratification was done conditional on how farmers and traders were likely to be exposed to the indirect conditional contract programme. In a first group, farmers that were connected to a WFP buyer are included. In a second group, we interviewed their neighbors. A third group was in a district where WFP was not active. For traders, we only differentiated between traders working in areas where WFP is active versus districts where they are not. We then attempt to learn about the impact by comparing the groups. We applied both descriptive and econometric techniques—mediation analysis and instrumental variables regression—to disentangle the effects of the procurement policy from other factors.

We find that farmers in areas exposed to the policy were significantly more likely to participate in markets and to sell larger quantities of maize. They also cultivated larger areas of maize and adopted improved seed varieties and, to a lesser extent, fertilizer. The policy also led to higher prices for farmers and lower margins for traders, suggesting a more efficient value chain. Mediation analysis revealed that part of the price increase was directly due to the policy, while part was mediated through enhanced competition among traders.

Traders in policy-affected areas handled significantly more maize, indicating improved aggregation and possibly greater investments in storage and transport infrastructure. They also sourced more from cooperatives and engaged more frequently with WFP, signaling that the policy may be reinforcing more formal and traceable sourcing arrangements.

The policy may also influence price seasonality, with some evidence that farmers in treated areas delay sales to benefit from higher prices later in the season. This has implications for both farmer incomes and consumer access. Despite WFP's commitment to inclusivity, the policy did not result in significantly different price effects across gender or age groups. There was also no different impact on small farmers.

We find suggestive evidence that WFP activities have general equilibrium effects, increasing prices not just for farmers that sell directly to WFP but also for farmers that sell to other traders. Farmers are typically both sellers and buyers of maize, and so whether higher prices are good or bad for farmers depends on whether they are net sellers or net buyers at that point in time (Deaton, 1989). Seasonality in maize transactions results in seaonality in prices, with farmers being net sellers early in the season and becoming net buyers later in the season. It is important that WFP is aware of this and plans the timing of its procurement activities to increase counter cyclical effects, increasing demand for maize early in the season to drive up prices and increasing benefits for farmers, and reducing purchased (or even selling to the market) of maize later in the season to reduce upward price pressure. This will also benefit WFP because it allows them to buy when maize is cheapest. Systems need to be in place to avoid delays in approvals etc. We get the impression from our data that WFP is generally too late with their procurement.

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