# Technology, Transparency, and the Emergence of Markets for Quality: Evidence from Ugandan Dairy Supply Chains

Richard Ariong,* Jordan Chamberlin[†], Sarah Wairimu Kariuki[†],
Bjorn Van Campenhout[‡]

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**Abstract**

In many agri-food supply chains, products from multiple suppliers are aggregated at several stages, breaking the link between individual effort and product quality. This problem is compounded when assessing quality is costly and occurs only downstream, after aggregation has already taken place. A further challenge arises when actors along the chain hold different conceptions of what constitutes quality, such that producers' efforts may not focus on quality attributes buyers value most. We use a multilevel randomized controlled trial to test a coordinated intervention that aligns perceptions of quality and makes quality visible and traceable at key points in Uganda's dairy supply chains: At the farmer level, an information campaign paired with small incentives addresses the misalignment between producers' and processors' perceptions of milk quality, shifting attention from hygiene to compositional attributes such as butterfat and solids-not-fat. At milk collection centers, we install digital milk analyzers and introduce digital record-keeping tools. We evaluate both interventions at the farmer and milk collection center levels, examining effects on milk quality, prices, and volumes.

JEL: O12, O14, Q13, D82, L15

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## 1   Introduction

Quality of commodities transacted within value chains, and the preservation of that quality throughout the chain, is central to value chain development. Higher-quality inputs improve efficiency by yielding more output per unit of input and

*Innovation Policy and Scaling Unit, International Food Policy Research Institute, Kampala, Uganda

[†]CIMMYT, Nairobi, Kenia

[‡]Innovation Policy and Scaling Unit, International Food Policy Research Institute, Leuven, Belgium

reducing waste. Maintaining quality during aggregation, storage, transport and processing is also critical for food safety and consumer health. Beyond these direct effects, consistent quality fosters trust and reputation, supports compliance with domestic and export standards, and facilitates access to higher-value markets. As a result, the transformation of value chains is often accompanied by substantial quality upgrading, reshaping incentives and market structures.

For quality to become an important driver of behavior, actors must be properly incentivized to produce and preserve it. In many markets, such incentives take the form of price premiums for higher-quality products, which reward the additional effort or investment required to meet quality standards (Swinnen and Maertens, 2007). When buyers are willing and able to pay more for quality, producers have stronger incentives to adopt better inputs and practices, while intermediaries are more likely to safeguard quality during aggregation, storage, and transport (Reardon and Barrett, 2000; Minten, Randrianarison, and Swinnen, 2009). In the absence of such premiums, quality improvements may not be financially viable, and actors may instead prioritize volume over quality.

The emergence of quality premia is often hindered by difficulties in observing and verifying quality at the point of transaction. When quality attributes are not directly visible and are costly to discover, buyers face a classic problem of asymmetric information. Without a credible verification mechanisms, high- and low-quality products trade at similar prices, eroding incentives to invest in quality and potentially leading to adverse selection equilibria (Akerlof, 1970). Aggregation across suppliers further weakens the connection between individual performance and observed quality, undermining incentives for improvement: Even when buyers wish to pay for quality, the absence of traceability prevents quality-enhancing investments from translating into higher returns. Further constraints arise from the coordination and investment required to establish quality-based payment systems, including grading, certification, and monitoring infrastructure.

Another fundamental constraint to value chain upgrading lies in the imperfect transmission of information across chain nodes, with the quality signal attenuating as the distance between actors increases (Van Campenhout, 2022). In the absence of shared standards or explicit product specifications, upstream producers and downstream processors often develop divergent conceptions of quality. Producers tend to focus on easily observable attributes—such as cleanliness or appearance—that are only weakly correlated with processing outcomes, while overlooking compositional traits that buyers value more highly. This misalignment of quality perceptions leads to inefficient allocation of effort and investment toward attributes that have limited influence on market returns. Establishing common reference points for quality and mechanisms to credibly measure and communicate these attributes can help align incentives along the chain, thereby facilitating the emergence of quality premia and promoting sustained upgrading (Ponte and Gibbon, 2005; Gereffi, Humphrey, and Sturgeon, 2005).

The structure of the value chain itself can exacerbate these challenges. When producers and processors are linked only indirectly through layers of traders or

informal intermediaries, the likelihood of traceability breaking down increases substantially. At the same time, intermediated chains may further limit information flows: traders may not transmit, or may even distort, processors' signals about which quality attributes matter most, leaving producers with little guidance for aligning practices with downstream demand. By contrast, in chains where producers are more directly connected to processors, opportunities for credible testing, traceability, and clearer communication of standards are greater, increasing the scope for effective quality-based incentives to emerge.

These challenges are particularly salient in Uganda's emerging dairy subsector. Over the past decade, the industry has undergone rapid transformation, especially in the southwestern milk shed around the city of Mbarara, where foreign direct investment has spurred the development of modern value chains (Van Campenhout, Minten, and Swinnen, 2021). A dense network of milk cooling and collection centers (mccs) now connects smallholder farmers to a growing cluster of processors. In dairy, quality is central: it determines processing yields for products such as cheese, casein, and milk powder, and maintaining sanitary conditions is essential given the perishability of raw milk. Yet, unlike in more developed dairy markets, there is generally no functioning market for quality in Uganda; Prices are typically fixed per liter, irrespective of butterfat, solids-not-fat, or protein content.

Part of the problem lies in divergent understandings of quality. Dairy farmers often associate quality with hygiene—clean containers, washed udders—while processors prioritize compositional parameters, which are driven largely by feeding practices and breed. Another part lies in the lack of technological capacity to measure and communicate compositional quality at the point of aggregation: Most mccs limit testing to freshness and basic adulteration checks, primarily for added water, and farmers rarely have access to test results. Together, these factors weaken the link between effort and reward, suppressing incentives for quality upgrading.

We use this setting to test whether strengthening quality observability and aligning perceptions of what constitutes quality can enable the emergence of quality premia in Uganda's dairy sector. Our experimental design addresses these mechanisms at different points along the value chain. At the midstream level, we work with 130 mccs to make quality observable and recordable in real time through compositional milk testing, digital record-keeping, and farmer-facing information campaigns. At the upstream level, we work with 2,600 farmers to align their understanding of quality with processor priorities through targeted information, visual reinforcement, and provision of improved pasture seeds to enable quality-enhancing practices. By implementing these interventions both upstream and midstream, the experiment tests whether reducing information frictions and making quality visible can shift behavior, improve milk quality, and ultimately foster the conditions for a functioning market for quality in the Ugandan dairy value chain.

We find that

The paper builds on a large literature that studies how incentives and organizational structures shape quality upgrading in value chains. Rao and Shenoy

(2023) demonstrate that group-level incentives in Indian dairy cooperatives can overcome free-rider problems and improve cleanliness, though distributional frictions emerge when elites resist transparency. Treurniet (2021) provides complementary evidence from Indonesia, where individual incentives introduced by processors quickly improved both compositional and hygienic quality of milk, particularly when paired with inputs and training. Saenger et al. (2013) show in the Vietnamese dairy sector that both penalties for low quality and bonuses for high quality increase farmers' investment in quality-enhancing inputs, with bonuses inducing the strongest improvements. Together, these studies highlight the importance of incentive design, the complementarities between price signals and capacity-building, and the risks that organizational frictions pose for sustainability.

This micro-level evidence connects to a broader literature on value chain transformation and quality upgrading in low- and middle-income countries. Bold et al. (2022) show across four field experiments that easing smallholder access to high-quality inputs can promote upgrading, though adoption depends critically on downstream incentives. Fieler, Eslava, and Xu (2018) highlight theoretically and empirically that input-output linkages shape quality upgrading decisions, while Antràs and Chor (2013) emphasizes how the organization of global value chains determines incentives for suppliers to invest in quality. Barrett et al. (2022) situate these findings within the "agrifood value chain revolution," arguing that the spread of modern procurement systems in developing countries fundamentally reorders incentives, contracting arrangements, and standards.

Our study contributes by examining how technology-enabled monitoring alters the feasibility and credibility of incentive schemes in smallholder-dominated value chains. Whereas Rao and Shenoy (2023) focus on the ability of social networks to enforce group incentives, we test whether digital feedback mechanisms can substitute for or complement such informal enforcement. Unlike Treurniet (2021) and Saenger et al. (2013), who study incentive contracts designed and implemented by processors, we evaluate how introducing quality analyzers at the level of mccs reshapes the space of possible contracts and accountability structures. In doing so, we highlight how technological innovations interact with organizational frictions and market power in ways that may unlock sustained quality upgrading where traditional incentive schemes have struggled.

## 2 Background: dairy supply chains in Uganda

The Ugandan dairy subsector is a dynamic and rapidly growing sector, with its development closely linked to significant policy reforms. Notably, the privatization of the National Dairy Corporation and the enactment of the Dairy Industry Act of 1998 marked critical turning points for the industry. These reforms also led to the establishment of the Dairy Development Authority (DDA), a statutory body under the Ministry of Agriculture, Animal Industry, and Fisheries. The DDA has a dual mandate to regulate and promote the dairy sector, ensuring

compliance with quality standards while supporting farmers and stakeholders through training, improved technologies, and market development initiatives.

The policy changes spurred an influx of foreign direct investment, particularly in Mbarara, a key town in southwestern Uganda often referred to as the country's "milk shed" (Van Campenhout, Minten, and Swinnen, 2021). This investment fostered the emergence of a cluster of milk processors in the region, enhancing value addition and market access. Additionally, productivity in the sector has been bolstered by the widespread adoption of improved dairy breeds, such as Holstein Friesians and Jersey cows, significantly increasing milk yields and overall sector efficiency. Today, the dairy subsector is one of the main export earners of the country.

Although dairy value chains in Uganda differ in their organizational form—from fully integrated systems led by large processors to fragmented structures of small cooperatives—a typical chain comprises five main actors, each with a distinct role in milk production, transport, and processing:

1. Dairy farmers: At the upstream end of the chain are farmer households, who are the primary producers of milk. These farmers deliver milk daily to milk collection centers (MCCs) either personally or by relying on intermediaries such as small traders or transporters.

2. Transporters and Traders: Transporters collect milk directly from farms and deliver it to MCCs for a fee, thus providing a service. Traders purchase milk from farmers with the intent to sell it at MCCs or to other traders for profit, thus functioning as commercial intermediaries within the chain.

3. Milk Collection Centers (mccs): Mccs are critical nodes in the value chain. Their primary role is to bulk and chill milk, marking the start of the cold chain essential for maintaining milk quality. These centers are strategically distributed across rural areas, facilitating access for farmers, traders and transporters.

4. Large Traders: Once milk is chilled and bulked at mccs, large traders transport it to processing facilities. This step often involves the use of specialized milk tankers to preserve quality during transit.

5. Processors: Processors, concentrated in key towns such as Mbarara—Uganda's dairy hub—convert raw milk into value-added products with extended shelf lives, such as ultra-heat-treated (UHT) milk, powdered milk, and infant formula. These processors play a pivotal role in integrating Uganda's dairy sector into both domestic and export markets.

This layered and dynamic structure enables the participation of diverse stakeholders while presenting opportunities for efficiency improvements at various points along the chain.

# Hypotheses and impact pathways

A key reason a market for quality fails to emerge is that raw milk of unknown quality from many farmers is aggregated at various points in the supply chain, making it impossible to trace quality back to individual suppliers. At the start of the cold chain, milk collection centers (MCCs) typically conduct only basic tests for freshness or adulteration, while equipment to measure compositional attributes—such as butterfat and solids-not-fat—is often unavailable. As a result, quality is only revealed downstream at the processor level, long after aggregation has taken place. This makes it impossible to use incentives like quality premia to reward individual effort and transmit market signals upstream to producers. We hypothesize that introducing milk testing and digital record-keeping at MCCs can make quality observable earlier in the chain, strengthening the link between effort and reward.

In a first hypothesis, we expect that reducing the cost of quality discovery at the collection stage will improve outcomes at this level for several reasons. First, it enables MCCs to identify and selectively purchase higher-quality milk, thereby increasing the average quality of aggregated milk in their tanks. Second, with verifiable quality data, MCCs can more effectively match supply to processor demand—for example, channeling high-fat milk to cheese producers and high-SNF milk to processors focusing on casein extraction. Such early market segmentation within the supply chain can improve overall efficiency by ensuring that milk is allocated to its most value-appropriate use. Third, better information strengthens MCCs' bargaining power with buyers. Collectively, these mechanisms are expected to enhance efficiency and value transmission along the chain, aligning incentives for quality upgrading among all actors.

In a second hypothesis, we expect that farmers will also benefit indirectly from improved quality measurement at the milk collection center. Making quality visible at this midstream level enables MCCs to reward farmers for supplying higher-quality milk, thereby strengthening incentives for quality-enhancing practices at the farm level. When farmers are aware that their milk can be tested accurately and transparently, they are more likely to invest in better feeding and handling practices, knowing that superior quality will be recognized and compensated. Moreover, the availability of reliable testing equipment may empower farmers to request verification in cases of disagreement over quality, promoting greater trust and accountability in farmer–MCC transactions. Indeed, as is the case for mccs, if farmers know the quality of the milk they receive, they may also strengthen their bargaining power vis-a-vis the cooperative.[1]

Another potential reason why a market for quality does not develop may be related to the fact that farmers do not have adequate knowledge about what is meant by milk quality. In particular, farmers seem to focus most on food safety related quality aspects of milk, and less on the compositional aspect. As a result, even when the technology to assess quality is available, farmers may not be able

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[1] As will be explained below, this is the reason why we paired the milk analyzer with an information intervention raising awareness with farmers that the mcc is now able to test milk quality if each incoming sample for free at the simple request of the farmer.

to improve without additional knowledge on what parameters to improve upon. Furthermore, it may be that farmers do not have a good understanding of how these compositional parameters can be affected.[2] A third hypothesis is thus that providing information on what the desired milk quality parameters are, and what affects these parameters, increases outcomes for farmers.

In value chains, it is not always clear whether upgrading is driven by push (eg a productivity increasing technological innovation at the farm level) or pull factors (eg in increase in demand due to opening up of export markets). Often, it is a combination of both, and push and pull factors endogenously reinforce each other in a virtuous cycle (Van Campenhout, Minten, and Swinnen, 2021). In a final hypothesis, we thus also test if making quality visible at the milk collection center level (a pull factor) and at the same time providing information on what the desired milk quality parameters are (a push factor) increases outcomes for farmers.

# 3 Conceptual framework and simple model

## 3.1 Environment and timing

There is one processor, many milk collection centers $m$, and farmers $i$ in each MCC catchment. The quantity of milk supplied by farmer i, denoted $y_i$, is assumed to be fixed in the short run, as it primarily depends on the farmer's herd size, which does not adjust quickly. Milk quality is $q_i \in [0, 1]$ and processors pay MCCs a premium for quality when it is verifiable. Our model also distinguishes between short and long value chains. Some farmers within the MCC are directly connected to the MCC as they bring the milk themselves. Other farmers use traders, who may capture part of the quality premium.

## 3.2 Technology and costs at the farmer level

Farmer $i$ chooses effort $e_i \geq 0$ that increases quality:

$$q_i = \theta_i e_i + \varepsilon_i$$

with $\theta_i \geq 0$ the productivity of effort and $\varepsilon_i$ a mean-zero shock. Effort cost is convex: $c(e_i) = \frac{k_i}{2} e_i^2$ with $k_i > 0$.

## 3.3 Prices, pass-through, and trader intermediation

Let the processor pay the MCC a unit price

$$p_m = \bar{p} + \alpha \, \bar{q}_m \tag{1}$$

where $\bar{q}_m$ is average quality in MCC $m$ and $\alpha \geq 0$ is the per-unit premium slope for verifiable quality. Without verifiable measurement, $\alpha = 0$, when quality becomes observable, we assume that $\alpha > 0$.

The MCC offers farmer $i$ a price schedule

$$p_i = p_0 + \lambda_i \alpha\, q_i \tag{2}$$

where $0 \leq \lambda_i \leq 1$ is the pass-through rate of the premium to farmer $i$. Pass-through depends on local contracting frictions and transparency. We assume $\lambda_i = \lambda_C$ if the farmer is directly connected to the MCC and $\lambda_i = \lambda_T$ if the farmer sells via a trader, with $0 \leq \lambda_T \leq \lambda_C \leq 1$.

## 3.4 Farmer problem and comparative statics

Farmer $i$ chooses effort to maximize:

$$\pi_i = \left(p_0 + \lambda_i \alpha q_i\right) y_i - \tfrac{k_i}{2} e_i^2 \tag{3}$$

Substituting $q_i = \theta_i e_i$ and ignoring $\varepsilon_i$ for the choice, the first-order condition yields optimal farmer effort and associated quality:

$$e_i^* = \frac{\lambda_i \alpha \theta_i y_i}{k_i} \tag{4}$$

$$q_i^* = \theta_i e_i^* = \frac{\lambda_i \alpha \theta_i^2 y_i}{k_i} \tag{5}$$

A stronger link between price and quality ($\alpha$) leads to more effort:

$$\frac{\partial e_i^*}{\partial \alpha} = \frac{\lambda_i \theta_i y_i}{k_i} > 0 \tag{6}$$

Stronger responsiveness of price schedule to quality in the form of a higher pass-through ($\lambda_i$) also leads to more effort:

$$\frac{\partial e_i^*}{\partial \lambda_i} = \frac{\alpha \theta_i y_i}{k_i} > 0 \tag{7}$$

The farmer's ability to translate effort in into quality also positively affects effort levels:

$$\frac{\partial e_i^*}{\partial \theta_i} = \frac{\lambda_i \alpha y_i}{k_i} > 0 \tag{8}$$

Finally, a higher marginal cost of effort leads to less effort:

$$\frac{\partial e_i^*}{\partial k_i} = -\frac{\lambda_i \alpha \theta_i^2 y_i}{k_i^2} < 0 \tag{9}$$

The model also predicts positive complementarities: making quality visible increases the return to effort for high $\theta_i$ farmers more, leading them to respond

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mores strongly. Or, it becomes easier to translate effort at the farmer level into quality, the returns to testing become higher (irrespective of pass-through).

$$\frac{\partial^2 e_i^*}{\partial \alpha \, \partial \theta_i} = \frac{\lambda_i y_i}{k_i} > 0 \qquad (10)$$

The reverse holds for an increase in $k_i$.

$$\frac{\partial^2 e_i^*}{\partial \alpha \, \partial k_i} = -\frac{\lambda_i \theta_i y_i}{k_i^2} > 0 \qquad (11)$$

Heterogeneity by connection comes from $\lambda_C > \lambda_T$:

$$e_{i,C}^* - e_{i,T}^* = \frac{(\lambda_C - \lambda_T)\alpha \theta_i y_i}{k_i} \geq 0 \qquad (12)$$

so for any given $\alpha, \theta_i, k_i, y_i$, optimal effort level will be larger for directly connected farmers.

## 3.5 MCC level outcomes

The MCCs aggregate milk and sell to the processor. Its per-unit margin per farmer is:

$$\underbrace{\bar{p} + \alpha \bar{q}_m}_{\text{revenue from processor}} - \underbrace{\left(p_0 + \lambda_i \alpha q_i\right)}_{\text{payment to farmer}} \qquad (13)$$

Averaging over suppliers, the expected margin per liter becomes:

$$\mu_m = \bar{p} - p_0 + \alpha(1 - \bar{\lambda}_m)\,\bar{q}_m \qquad (14)$$

where $\bar{\lambda}_m$ is the average pass-through in the catchment.

An increase in $\alpha$ raises $\bar{q}_m$ through increased farmer effort (Equation 6), increasing margins at the mcc level. If transparency also increases $\bar{\lambda}_m$, the MCC retains a smaller share per unit but benefits from higher volumes of quality and reduced disputes. Net effects on MCC outcomes remain non-negative under mild conditions because both $\alpha$ and $\bar{q}_m$ rise.

# 4 Experimental design

We use a field experiment to test the predictions in Section 6. In particular we use a split plot trial design with interventions at two levels of the value chain. The design is illustrated in Figure 1.

The design follows the value chain structure previously outlined, where the first treatment (T1) is implemented at the MCC level. Within each MCC, the second treatment (T2) is randomized at the individual farmer level. Specifically, half of the farmers are assigned to receive the video treatment, while the other half are randomized into the control group. Additionally, within each milk collection center, half of the farmers connected to that MCC receive the video
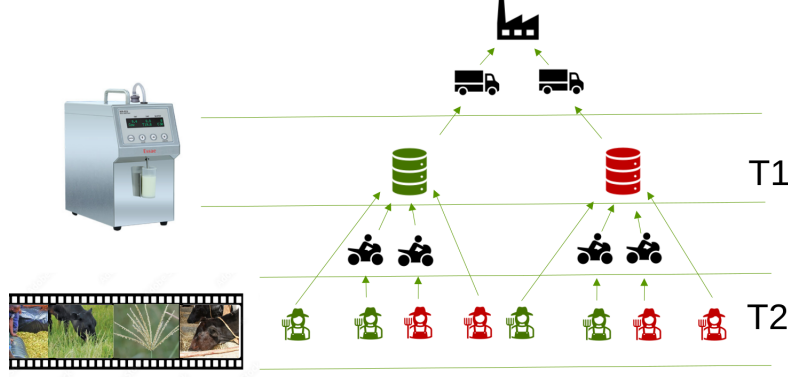
Figure 1: Design

treatment, while the other half are in the control group. To explore heterogeneity in treatment effects, we also stratify by the manner in which farmers are connected to the MCC—either directly or via a trader.

This design allows us to examine outcomes at different levels of the value chain. At the MCC level, we can assess the impact of the T1 intervention on MCC-level outcomes. Furthermore, we can analyze the effect of the second treatment (T2) on farmers connected to the MCC, either directly or through a trader. However, the impact of the farmer-level treatment (T2) can only be evaluated by examining outcomes at the individual farmer level.

In sum, and in reference to the equation we will estimate in the next section, the four main hypotheses that we will test with this design are:

- Hypothesis 1: making quality visible at the MCC level increases outcomes for the milk collection centers ($\beta_{H1} > 0$).

- Hypothesis 2: making quality visible at the MCC level increases outcomes for the farmers in the catchment areas of these MCCs ($\beta_{H2} > 0$).

- Hypothesis 3: providing information on what the desired milk quality parameters are and what affects this parameter increases outcomes for farmers ($\beta_{H3} > 0$).

- Hypothesis 4: making quality visible at the MCC level and providing information on what the desired milk quality parameters to farmers increases outcomes for farmers ($\beta_{H4} > 0$).

Additional research questions, based on the stratification, tests for equality in average treatment effects between farmers that are connected to milk collection centers versus those that are not. Testing for this treatment heterogeneity allows us to explore if the interventions only strengthen existing value chains or whether they can also draw in actors from informal value chains.

- Does the MCC level intervention affect farmers that are already connected to the milk collection center similarly than farmers that are not already connected to an MCC ($\beta_{H2C} = \beta_{H2T}$).

- Does the information treatment affect farmers that are connected to an MCC similarly than farmers that are not connected to an MCC ($\beta_{H3C} = \beta_{H3T}$)

- Does the combined treatment (making quality visible at the MCC level and providing farmers with information on the desired quality dimension) affect farmers that are connected to an MCC similarly than farmers that are not connected to an MCC ($\beta_{H4C} = \beta_{H4T}$)

# 5 Treatments: Innovation Bundles for Addressing Milk Quality Challenges

In response to the challenge of unobservable milk quality in the Ugandan dairy value chain, we designed an innovation bundle targeting Milk Collection Centers (MCCs). This bundle aims to enhance transparency, improve record-keeping, and empower both MCC managers and farmers by making milk quality measurable and visible. The bundle, developed after extensive consultations with stakeholders and implemented together with the DDA, consists of three key components:

1. Milk Analyzer: A central component of the innovation bundle is the installation of a milk analyzer at MCCs. This machine assesses milk quality based on a set of compositional parameters, such as butterfat content and solids-not-fat. The testing process is non-destructive and takes less than one minute per sample, enabling rapid and accurate quality evaluation of all milk collected. By providing immediate feedback, the milk analyzer helps ensure that quality standards are met and maintained. More information on the milk analyzer can be obtained from the manufacturer's website. Figure 2 shows a milk analyzer during piloting.

The milk analyzers were delivered with clear Standard Operating Procedures. Two separate trainings were organized. One training targeted MCC managers, where the focus was mostly on generating buy-in by pointing out the benefits of measuring and tracking milk quality. A second training was geared toward MCC managers and focused more on use and maintanance of the milk analyzers ans

We collaborate with the DDA to set up a system to monitor the milk analyzers and its use. In particular, DDA technicians will visit treatment MCCs at set periods. We also set up a hotline that MCCs can contact in case of problems with the milk analyzers. We also make sure that, over the course of the project, equipment is adequately cleaned and calibrated.

2. IT-Mediated Record-Keeping System: We developed an Android application for MCC managers to facilitate digital record-keeping. The app replaces

Figure 2: Milk analyzer

the traditional paper notebooks used for tracking milk deliveries and payments. In addition to recording quantities and prices, the app allows MCC managers to store and monitor quality parameters obtained from the milk analyzer. It can provide MCC managers with simple reports, such as the average butter fat (weighted by quantities supplied) over a different period (today, yesterday, last week, last two weeks and custom data range). Reports by farmer are also possible, such that MCC managers can determine the total sum to be paid to a farmer for milk delivered over a particular time frame, such as in the last 14 days. [3] In addition to the app, we also developed different online portals that can be used to obtain data for different stakeholders. For instance, one portal was geared towards MCC owners, such that they can always monitor key parameters in the MCCs. Another portal aggregated information from all MCCs, enabling government officials such as the DDA to monitor quality parameters, prices and quantities in real time.[4] This digital system enhances efficiency and transparency, providing both MCC managers and farmers with reliable records that integrate milk quality metrics. The android app can be downloaded from google play store; A screenshot of the application can be found in Figure 3.

Milk collection centers were provided with Samsung Galaxy Tab A7 Android tablet computers on which the application was pre-installed. Each tablet contained a SIM card with a prepaid data bundle to enable cloud-based synchronization of records. The application was developed following offline-first design principles, ensuring that all core functionalities remained accessible without an active internet connection and that data were uploaded automatically once connectivity was restored. Data bundles were topped up by us on a monthly basis throughout the course of the project.

3. Farmer Engagement through Advertisements: To address potential power imbalances emerging from the installation of milk analyzers and ensure farmers are equally informed, we introduced a poster campaign at MCCs. The poster, designed by a local artist, advertises the availability of free milk quality testing for farmers. By making this service widely known, the campaign aims to empower farmers with knowledge about their product quality, fostering trust and collaboration between farmers and MCC managers.

Together, these three components form a comprehensive strategy to make milk quality observable and actionable, creating incentives for improved practices throughout the dairy value chain. This first package will constitute our first treatment in the field experiment below and will be referred to as T1.

To bridge the gap in how milk quality is understood between farmers and processors, we designed an intervention aimed at improving farmers' knowledge of compositional quality and its importance in the dairy value chain. This treatment combines information dissemination, practical advice, and tangible support to drive behavioral changes. It consists of three components:

1. Educational Video: The use of video has been found to increase technology adoption in different settings, although the effectiveness also depends on

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[3]Farmers are typically paid after 14 days of milk delivery.
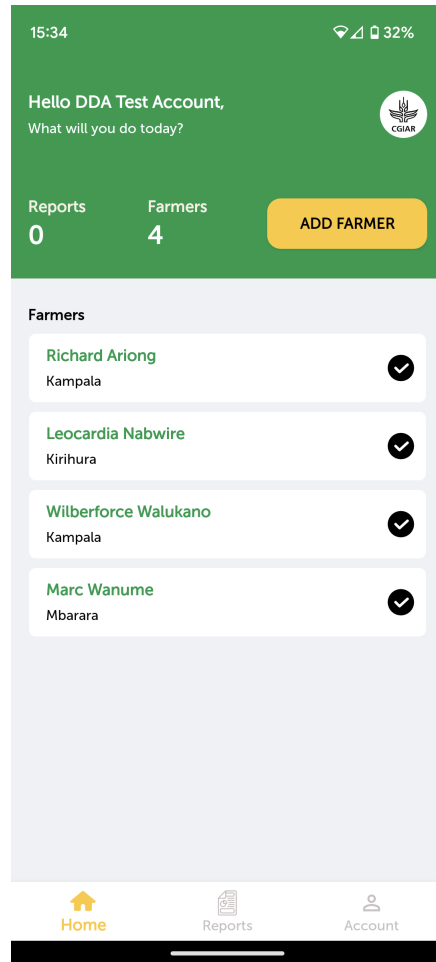[4]The portal can be found here.

Figure 3: Application

a range of design attributes (Spielman et al., 2021). The ability to depict role models in videos seems important to increase both aspirations of the person targeted, as well as creating an enabling environment for adoption in that it may challenge world views and stereotypical thinking (Riley, 2019; Lecoutere, Spielman, and Van Campenhout, 2023). As such, a short, engaging video was developed to explain the concept of compositional milk quality (parameters such as butterfat and protein content) and why it matters for both farmers and processors. The video also highlights practical management practices and inputs that farmers can adopt to improve milk quality, mostly focusing on feeding strategies.[5] The video is designed to be accessible and appealing, ensuring key messages resonate with the target audience. The video was shown to treatment farmers twice: once during baseline data collection in December 2022 and once at the time of installation of the milk analyzers in October 2023.

2. Cartoon Handout: To reinforce the information provided in the video, we created a handout in the form of a cartoon summary. The cartoons provide a visual, easy-to-understand recap of the key points, serving as a quick reference for farmers after watching the video. This format ensures the information remains accessible even to farmers with limited literacy.

3. Improved Pasture Seeds: To make the knowledge actionable, each participating farmer received a free bag of improved pasture seeds (1 kg of *Chloris Gayana*, also known as Rhodes grass). By planting these seeds, farmers can enhance the nutritional value of their pastures, a critical factor in increasing the compositional quality of milk. This practical input complements the educational components, enabling farmers to directly apply the recommendations provided.

This treatment, henceforth referred to as T2, aims to align the understanding of milk quality between farmers and processors while equipping farmers with the tools and knowledge to improve milk quality in a sustainable manner.

# 6  Mapping to hypotheses

**Hypothesis 1 (T1 at MCC level).**  We expect that *T1* increases $\alpha$ and induces higher $q_i^*$, which raises $\bar{q}_m$ and MCC outcomes that are increasing in realized quality or quality-linked revenue.

$$\text{Prediction: } \beta_{H1} > 0$$

**Hypothesis 2 (T1 at farmer level).**  With $\lambda_i > 0$, the increase in $\alpha$ from *T1* raises $e_i^*$ and $q_i^*$, and also raises the quality-linked component of the price

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[5]To determine the content of the video, we first identified the top five practices and inputs that are known to raise butter fat and Solid Non Fats in milk. This was done through consultations of experts. We found the top 5 practices and inputs were: selection of breed and genetic potential, selection of grasses for high-quality forage, best practice in silage and hay making, correct mixing and dosage of feed, and feed supplements like Methionine and Lysine. As selection of breed and genetic potential is unlikely to change sufficiently fast give the length of our research project, we decided to focus on feeding practices.

received. Farmer outcomes that are increasing in quality or in the quality premium rise.

$$\text{Prediction: } \beta_{H2} > 0$$

**Hypothesis 3 (T2 at farmer level).** Treatment T2 affects the farmer problem in two ways. First, it improves knowledge about how actions map into quality, which we capture as an increase in effective $\theta_i$. Second, it provides inputs that reduce the marginal cost of effort, captured as a decrease in $k_i$. In short, treatment T2 raises $\theta_i$ and lowers $k_i$, which raises $e_i^*$, $q_i^*$, and quality-linked revenues.

$$\text{Prediction: } \beta_{H3} > 0$$

**Hypothesis 4 (T1 x T2 at farmer level).** Because $e_i^*$ is multiplicative in $\alpha$ and $\theta_i/k_i$, the cross-partial is positive (Equation 10). The effect of $T2$ is larger when $T1$ is in place and vice versa.

$$\text{Prediction: } \beta_{H4} > 0$$

**Heterogeneity by connection (C vs. not C).** Since $\lambda_C > \lambda_T$, any treatment that works through $\alpha$ has a larger impact for directly connected farmers. Formally, P

$$\text{Prediction: } \Delta e_{T1|C}^* > \Delta e_{T1|T}^*$$

and similarly for the combined treatments. This delivers the tests $\beta_{H2C} = \beta_{H2}$, $\beta_{H3C} = \beta_{H3}$, and $\beta_{H4C} = \beta_{H4}$ as equality checks when pass-through is complete within connection type, and suggests treatment effects are larger for connected farmers when $\lambda_C > \lambda_T$.

# 7   Estimation and inference

We will estimate two equations using Ordinary Least Squares. One equation is at level of the milk collection centers, the second equation is at the level of the dairy farmers.

For the equation that measures impact at the MCC level, denote milk collection centers by $m$, running from 1 to $M$. $T_m^T$ is a treatment indicator at the MCC level that is one if the MCC was allocated to the test and tracing treatment. $y_m$ is the outcome at the level of the milk collection center you want to estimate the treatment effect for and $\varepsilon_m$ is an error term. We then estimate the following equation using Ordinary Least Squares. In all equations we also control for baseline outcome if information was collected at that time $\left(y_m^b\right)$.

$$y_m = \alpha + \beta_{H1}.T_m^T + \beta_b.y_m^b + \varepsilon_m \tag{15}$$

The parameter of interest in this equation is $\beta_{H1}$, which tests Hypothesis 1.

All other equations use farmer level data. We start by estimating the main treatment effect for T1, the installation of a milk analyzer, on farmers that are

associated to the MCC where the milk analyzer was installed. One way to do this is to estimate a fully interacted model such as the one given in Equation 16. Here, $T_i^I$ is a treatment indicator at the farmer level that is one if the farmer was allocated to the information treatment that informs farmers about what quality parameters are important for processors (with $i$ indicating the farmer running from 1 to $I$).

$$y_{i,m} = \alpha + \beta_{H2}^* . T_{i,m}^T + \beta_{H3}^* . T_{i,m}^I + \beta_{H4}^* . T_{i,m}^T . T_{i,m}^I + \beta_b . y_{i,m}^b + \varepsilon_{i,m} \qquad (16)$$

$y_{i,m}$ is the outcome of interest at the level of the individual farmer living in the catchment area of milk collection center $m$ and $\varepsilon_{i,m}$ is an error term (which may be correlated within catchment area). As above, $T_{i,m}^T$ is a treatment indicator that is one if the MCC (in who's catchment area farmer $i$ resides) was allocated to the milk analyzer treatment and we also control for the lagged baseline outcome $y_{i,m}^b$, again in deviations from its mean. The parameter of interest in this equation would be $\beta_{H2}^*$, which tests Hypothesis 2, $\beta_{H3}^*$, which tests Hypothesis 3 and $\beta_{H4}^*$, which tests for the interaction effect.

While our power calculations relied on models that include the full set of interactions (and we will likewise estimate such a fully interacted specification in Equation 20), an important feature of split-plot (factorial) designs is that power can be increased by pooling observations across the orthogonal treatment. In our case, this means that the effect of the farmer-level intervention can be estimated by pooling across MCC-level treatment arms, and conversely the effect of the MCC-level intervention can be estimated by pooling across farmer-level treatment arms. At the same time, a recent article points out the dangers of pooling treatment cells if there are potential interaction effects between the treatments (Muralidharan, Romero, and Wüthrich, 2023). One way to recover the pooled main treatment effect is to consider the orthogonal treatment as a co-variate and adjust for it, entering it in the regression demeanded and fully intereacted as in equations 17 and 18. This give a more robust version of the treatment estimate that corresponds to the coefficient estimate of the treatment of interest after dropping the interaction with orthogonal treatment.

$$y_{i,m} = \alpha + \beta_{H2} T_{i,m}^T + \beta_{H3}^I \left( T_{i,m}^I - \bar{T}^I \right) + \beta_{H4}^I T_{i,m}^T \left( T_{i,m}^I - \bar{T}^I \right) + \beta_b . y_{i,m}^b + \varepsilon_{i,m} \qquad (17)$$

$$y_{i,m} = \alpha + \beta_{H3} T_{i,m}^I + \beta_{H2}^T \left( T_{i,m}^T - \bar{T}^T \right) + \beta_{H4}^T T_{i,m}^I \left( T_{i,m}^T - \bar{T}^T \right) + \beta_b . y_{i,m}^b + \varepsilon_{i,m} \qquad (18)$$

Next, note that $\beta_{H4}^*$ in equation 16 is estimated as an incremental effect on top of the main effects. In our analysis, we will test hypothesis 4 by directly comparing farmers that received the training and are connected to an MCC that received a milk analyzer to farmers that did not get the training and are connected to a control MCC. In other words, we will estimate:

$$y_{i,m} = \alpha + \beta_{H4}.T_{i,m}^T.T_{i,m}^I + \beta_b.y_{i,m}^b + \varepsilon_{i,m} \tag{19}$$

after dropping from our data farmers that were exposed to only a single treatment.

Finally, we will also look at treatment heterogeneity, exploiting the fact that we stratified farmers on their link to the MCC. In particular, $C_{i,m}$ is an indicator variable at the farmer level that is one if the farmer $i$ is directly connected to MCC $m$ (and zero if the farmer is connected through a trader). We also add a full set of interactions with this connection indicator and run the following model:

$$y_{i,m} = \alpha + \alpha_C C_{i,m} + \beta_{H2T}.T_{i,m}^T + \beta_{H3T}T_{i,m}^I + \beta_{H4T}T_{i.m}^I.T_{i,m}^T$$

$$+ \beta_{H2C}.T_{i,m}^T.C_{i,m} + \beta_{H3C}T_i^I.C_{i,m} + \beta_{H4C}T_i^I.T_{i,m}^T.C_{i,m} + \beta_b.y_{i,m}^b + \varepsilon_{i,m} \tag{20}$$

The parameter of interest in this equation is $\beta_{H2}$, which tests Hypothesis 2, $\beta_{H3}$, which tests Hypothesis 3 and $\beta_{H4}$, which tests for the interaction effect. In all regressions, we apply a cluster-robust variance estimator with the bias-reduced linearization (CR2) small-sample correction (Imbens and Kolesár, 2016), with standard errors clustered at the level of randomization (MCC catchment area level).

To account for multiple comparisons, we will us the two methods illustrated in Anderson (2008). The first consists of computing the Benjamini-Krieger-Yekutieli (2006) sharpened q-values for a vector of p-values We will also combine primary outcomes into an index following Anderson (2008), which also guards against the dangers of multiple comparisons (See Section 11.1).

# 8  Sample and Timeline

Sample size was determined using a series of power simulations detailed in the pre-analysis plan. The primary outcome for these calculations was the price of milk, modeled at both the milk collection center (MCC) and farmer level. At the MCC level, prices were assumed normally distributed with mean 1000 UGX/liter and standard deviation 50, while farmer-level prices were drawn with the MCC mean and a higher variance (SD = 100) to capture greater dispersion. We assumed the intervention would increase MCC prices by 30 UGX/liter (medium to large effect size), translate into a 40 UGX/liter increase for farmers (small to medium effect), and that the individual-level information treatment would generate a 25 UGX/liter increase (small effect), with a large interaction effect of 50 UGX/liter. Power was calculated for the joint test of all hypotheses at the 5 percent significance level using 1,000 simulations across varying combinations of clusters (100–130 MCCs) and farmers per cluster (10–40). Results showed that with about 125 MCCs and 20 farmers per MCC (total sample of about 2,500

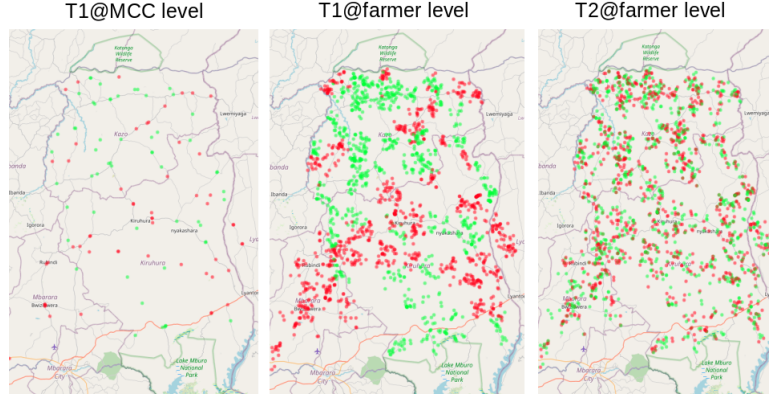| T1@MCC level | T1@farmer level | T2@farmer level |

Figure 4: Sampling

farmers), power was just above 0.80 for a joint significance test, while power for individual hypotheses was substantially higher, ranging from 0.87 to 0.99. At the design stage, we decided to target 130 MCCs to account for attrition.

The field experiment was conducted in four districts of Southwestern Uganda: Ntungamo, Mbarara, Kazo, and Kirihura. The study began with a comprehensive census of all milk collection centers (MCCs) in the region, from which we sampled 130 MCCs. Half of these were randomly selected to receive T1, while the other half served as the control. In each of the 130 MCCs, we then randomly selected 20 farmers who deliver milk to the center. Of these 20 farmers, 10 were randomly assigned to the video treatment (T2), while the remaining 10 served as the control group.

Figure 4 shows randomization in three of the four districts for T1 and T2 at both the MCC and farmer level. The first map to the left of the figure shows the locations of the MCCs and their treatment status for T1. The second panel shows the treatment status for T1 for the farmers that are connected to the MCCs, which is clustered at the MCC level as T1 is implemented at that level. The third panel shows treatment allocation of T2 among farmers linked to MCCs, which is at the individual level.

Baseline data from both MCCs and associated farmers was collected towards the end of 2022 using in person surveys. At this time, the intervention at the farmer level (T2) was implemented. In the second half of 2023 milk analyzers were installed and MCC managers were trained on the use of the analyzers and the digital record-keeping system. Towards the end of this project, in October 2023, we reinforced T2 by showing the video again to T2 farmers. Next, during the course of one year, together with the DDA we supported T1 MCCs with regular visits to make sure the equipment was operational, including recalibration after 6 months. In december 2024, endline data was collected. This involded in-person surveys at the MCC level and at the farmer level. In addition, during endline we also measured quality of incoming milk. To do so,

an enumerator equipped with a milk analyzer paid an unannounced visit to each MCC enrolled in the study and measures all incoming milk samples over the course of one full day.[6] After all data was collected, all equipment was donated to the MCCs.[7]

# 9   Descriptive Statistics and Baseline Balance

We pre-registered 10 variables at each level to demonstrate balance. Results for five variables measured at each level (MCC and farmer) are in Table 1; five more variables for each level are in Appendix Table 12 to conserve space (this was also pre-registered). The top panel of Table 1 shows that among MCCs in the control group (i.e., those that did not receive a milk analyzer), 63 percent are organized as cooperatives, reflecting how collective institutions continue to play a central role in the organization of Uganda's dairy value chain. Their average total storage capacity is about 4000 liters, and 27 percent reported paying a premium for higher quality milk. The average MCCs has been in operation for just under 10 years, and 58 percent facilitated the supply of acaracides to their farmer members. The top panel of Appendix Table 12 further shows that among MCCs in the control group, the average number of full-time employees is about three, and a typical MCC receives milk from about 56 farmers or traders on an average day during the rainy season. On average, MCCs use 38 percent of their processing or cooling capacity during the dry season, which is indicative of significant seasonality affecting the sector. MCCs report they own 21 milk cans and the vast majority indicate that they provide credit or loans to cooperative members and regular suppliers.

Both tables further show treatment–control differences for each baseline variable for T1 in the second column. Only one of the individual differences is statistically significant at the 5 percent level (capacity). At the bottom of the top panels of both tables we report results from an omnibus Wald test of joint balance across all covariates (F-statistic and p-values below). These tests do not reject the null of joint equality, indicating that treatment assignment is not systematically predicted by observed baseline characteristics. Overall, the tables suggest that randomization achieved reasonably balanced treatment and control groups along key baseline characteristics of MCCs for the treatment at that level.

The bottom panel of Table 1 reports baseline characteristics of dairy farmers across treatment groups. In the control group (corresponding to farmers that did no see the video and are connected to an MCC that did not receive the milk analyzer), household heads are on average 54 years old, with herds of about

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[6]This exercise posed logistical challenges, as MCCs opened early (usually at 7:00 am) and were often in remote areas. Enumerators frequently stayed overnight nearby to set up equipment before deliveries and carried generators for use where power was unavailable. To limit information spillovers, the testing was conducted over a short period with as many enumerators deployed simultaneously as possible.

[7]The milk analyzers used by enumerators for supervised testing were donated to control MCCs, which also received tablets and training after the project to ensure fairness.

Table 1: Balance table

| | mean ctrl | analyzer | video | bundle | nobs |
|---|---|---|---|---|---|
| *milk collection centers* | | | | | |
| Is this milk collection center (part of a) cooperative? (1=yes) | 0.633 | -0.086 | | | 124 |
| | (0.486) | (0.09) | | | |
| Total Capacity of milk tanks (in liters) | 4053.167 | 1031.115* | | | 124 |
| | (1809.592) | (433.343) | | | |
| Does the MCC pay a premium for quality (1=yes) | 0.267 | -0.029 | | | 123 |
| | (0.446) | (0.082) | | | |
| MCC age in years of operation | 9.325 | 0.235 | | | 123 |
| | (7.635) | (1.588) | | | |
| Facilitates supply of acaracides? (1=yes) | 0.583 | -0.068 | | | 124 |
| | (0.497) | (0.093) | | | |
| F-statistic | | 1.93 | | | |
| p-value | | 0.113 | | | |
| *dairy farmers* | | | | | |
| Household Head Age (years) | 54.469 | -0.052 | 0.213 | -1.562 | 2261 |
| | (12.633) | (0.819) | (0.745) | (1.032) | |
| Current Total herd size (number) | 62.297 | 4.983 | 5.787 | -4.691 | 1976 |
| | (54.007) | (6.127) | (3.812) | (5.589) | |
| Number of improved animals in total herd (share) | 0.932 | -0.007 | 0.009 | -0.014 | 1976 |
| | (0.171) | (0.012) | (0.011) | (0.014) | |
| Liters milk sold per day (on average in the rainy season) (liters) | 59.697 | 5.821 | 7.306* | -7.741 | 2261 |
| | (56.325) | (6.051) | (3.568) | (4.877) | |
| Average monthly expense (USD) on chemical purchases | 65.551 | 12.076 | 15.349+ | -29.131* | 904 |
| | (91.1) | (11.481) | (7.922) | (13.696) | |
| F-statistic | | 0.268 | 0.497 | 1.241 | |
| p-value | | 0.927 | 0.776 | 0.314 | |

Note: First column reports control group means (and standard deviations below); **, * and + denote significance at the 1, 5 and 10 percent levels.

62 animals, of which more than 90 percent are improved breeds.[8] Farmers sell roughly 60 liters of milk per day during the rainy season, and they spend on average USD 66 per month on chemical purchases—primarily acaracides. Further characteristics in the bottom panel of Appendix Table 12 shows that the average household counts nearly ten members and produces about 70 liters of milk per day during the rainy season. Roughly 79 percent of farmers sell most of their milk to a collection center, three-quarters report using only steel containers when transacting, and a similarly high share are members of a dairy cooperative.

The farmer-level balance tables report three different sets of comparisons. First, we test for pre-treatment differences between farmers connected to MCCs that received a milk analyzer and those connected to control MCCs. With the exception of a modest difference in cooperative membership (significant at the 10 percent level in Appendix Table 12), no systematic imbalance is observed. Second, we examine differences between farmers who received the video-and-seed intervention and those who did not. Here we find some evidence of higher milk production ($p < 0.1$), higher sales volumes ($p < 0.05$), and slightly higher acaracide expenditures among treated farmers. Third, we report the interaction effects at baseline, where two variables are significant at the 5 percent level and one at the 1 percent level. While these individual differences suggest some imbalance across treatment arms, the omnibus F-tests are consistently insignificant.

## 10    Attrition

Meeting sample size targets within the available budget proved challenging at baseline, largely because dairy farmers are geographically dispersed. In the end, we surveyed 2,261 farmers across 124 MCCs, corresponding to 87 and 95 percent of our planned farmer and MCC samples, and 90 and 99 percent of the required sizes from the power calculations. Of these 124 MCCs, 60 were assigned to control condition and 64 to treatment condition of T1.

By endline, we managed to re-contact 122 MCCs, of which 2 MCCs refused to cooperate, leaving us with data for 120 MCCs. We further managed to contact 2,139, from which 6 refused to be interviewed, leading to an effective sample of 2,133. Further restricting farmers to the subset of farmers connected to an MCC that we were able to interview at endline, we get 2,059.

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[8]To calculate herd, we did not simply ask total numbers but asked 6 separate questions: we ask how many local cows; local heifers; and local calves the farmer has, and ask the same 3 categories for improved animals. Farmers were allowed to indicate that they did not know for a particular category, which were treated as missing in our analysis leading to the reduction in the number of observations.

# 11 Results

## 11.1 Primary outcomes

### 11.1.1 MCC level

We pre-registered six primary outcomes at the level of the MCC. All six are hypothesized to move in a positive direction in response to our intervention, which was designed to make milk quality more transparent and salient in transactions. To capture the aggregate effect across these outcomes, we also construct a summary index following Anderson (2008). This index provides a single measure of how the intervention influenced the overall development of a market for quality at the MCC level.

Our first two outcomes measure the extent to which quality testing becomes embedded in routine operations at the MCC. Specifically, we record whether MCCs used a milk analyzer to measure butter fat and solid-non-fat content of incoming milk samples in the last 7 days. In addition, we asked whether MCCs test outgoing milk deliveries destined for buyers. This measure is based on more detailed sales transaction data, and is true if for any buyer (eg processor, other trader, etc) butter fat or SNF was tested using a milk analyzer. Together, these indicators capture the degree to which the analyzers are used as intended, and whether testing shapes quality assurance both upstream and downstream.

The next two outcomes reflect how increased transparency affects pricing behavior. We measure the average price at which MCCs purchase milk from farmers during the seven days preceding the survey. We then ask the average price MCCs received for sales to various buyers during the last transaction in the previous week, and take a (weighted) average of these. These outcomes allow us to assess whether improved quality monitoring translates into higher farm-gate prices and whether MCCs are able to cash in on quality improvements through higher sales prices.

Finally, two outcomes directly capture whether price differentiation by quality emerges. We ask whether the MCC pays explicit quality premiums to its suppliers, and whether downstream buyers pay a premium for higher-quality milk. Together, these indicators provide evidence on whether the intervention helped overcome the central coordination problem in quality upgrading: aligning incentives on both sides of the market so that producers and intermediaries are rewarded for investing in quality.

Results are in Table 2. The results show that many MCCs saw the merits of milk analyzers. In particular, MCCs in the treatment group were substantially more likely to test incoming deliveries: the probability of testing rose by 34 percentage points relative to a control group mean of 20 percent, a large and highly significant increase. We also observe a large and significant increase in the probability of testing outgoing deliveries to buyers. These results suggest that the analyzers were effectively used for monitoring both milk supplied by farmers and deliveries to downstream buyers.[9]

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[9]These self-reported outcomes may raise concerns about bias. However, as shown in Table

Table 2: Primary outcomes at MCC level

|  | mean ctrl | analyzer | nobs |
|---|---|---|---|
| Tested incoming milk using MA (1=yes) | 0.203 | 0.342** | 120 |
|  | (0.406) | (0.084) |  |
| Testing outgoing milk using MA (1=yes) | 0.203 | 0.285** | 120 |
|  | (0.406) | (0.084) |  |
| Price at which milk was bought from farmers (UGX) | 1075 | -15.213 | 115 |
|  | (92.556) | (14.704) |  |
| Price at which milk was sold (UGX) | 1199.576 | 3.439 | 108 |
|  | (106.327) | (19.243) |  |
| Does the MCC pay a quality premium to suppliers? | 0.186 | -0.032 | 119 |
|  | (0.393) | (0.069) |  |
| Did the buyer pay a quality premium? | 0.186 | 0.031 | 119 |
|  | (0.393) | (0.074) |  |
|  |  |  |  |
| Index of primary MCC outcomes | -0.06 | 0.114 | 103 |
|  | (0.465) | (0.096) |  |

Note: First column reports control group means (and standard deviations below); Second column shows average treatment effect of the MCC level intervention (and standard error of coefficient estimate below); **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

Turning to prices, we find little evidence that the intervention affected transaction terms at MCCs. In the control group, the average farm-gate price paid to suppliers was about UGX 1,075 per liter, and we detect no significant increase in the treatment group. Similarly, the average price MCCs received from buyers was about UGX 2,000 per liter in the control group, with no evidence that treatment raised buyer offers. These results suggest that while the intervention influenced testing practices, it did not translate into higher prices on either side of the market.

In addition, about 20 percent of MCCs in the control group reported paying a quality premium to suppliers, and the same share (11 out of 59) reported receiving a premium from buyers. Consistent with the price outcomes, we do not find that making quality more visible in the value chain increased the likelihood of such premiums being paid.

Taken together, data recorded at the MCC level suggests that the intervention led to a substantial and consistent increase in testing behavior, but no evidence of quality-based price differentiation. Judged by the composite index of pre-registered MCC-level outcomes, we conclude that T1 had no effect.

### 11.1.2   Farmer level

We also define four primary outcomes at the farmer level and combine them into an index to assess overall impact of the interventions on farmers level outcomes.

The first outcome measures production investment and management practices that are expected to improve milk quality. We construct an Anderson (2008) index from farmer reports on six recommended practices undertaken in the past year: (i) over-sowing new fields with improved forage grasses such as *Napier*, *Brachiaria*, or *Rhodes* grasses; (ii) using legume pastures such as *Centro*, *Siratro*, or *Desmodium*; (iii) adopting controlled or zero grazing during both the last dry and wet season; (iv) practicing pasture conservation through hay, silage, or haylage; and (v) using feed supplements such as maize bran, crop residues (for example banana peelings), or mineral licks. This index summarizes the extent to which farmers adjusted production strategies, particularly in response to the farmer-level information treatment.

The second outcome captures whether buyers actively checked milk quality at the point of transaction. Here, we distinguish between different categories of buyers (eg. MCCs, processor, trader, etc.) and ask if milk was tested using a milk analyzer if the farmer sold milk to this particular buyer in the 7 days prior to the survey. The indicator is true if milk sold in the last 7 days was tested by at least one buyer.[10]

The third outcome is the price received for milk sold. Specifically, we record the average price per liter obtained in the farmer's most recent sale during the

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6, we obtain similar results when using direct enumerator observations of analyzer use.

[10]We restrict this outcome to farmers who reported selling milk in the last seven days. Roughly 20 percent did not sell during this period. While such a restriction could introduce selection bias if treatments also affected market participation, Table 8 shows no evidence of differential participation across treatment groups.

past seven days, inclusive of any quality premiums. Farmers reported prices by buyer category, and we construct a weighted average across categories using transaction volumes as weights. We also directly ask whether the buyer pays a higher price for higher-quality milk. This question was posed in general terms, without reference to a specific time frame. These outcomes capture whether quality improvements translate into tangible financial benefits for farmers.

Table 2 reports treatment effects on our four primary outcomes at the farmer level, as well as the index. The table combines parameter estimates from the different equations discussed in section 7. In the first column, we show mean outcome for pure control farmers (that did not get the information treatment and are connected to control MCCs); standard deviations are in parenthesis below. In the second column, we provide an estimate of the farmer level pooled main treatment effect of T1 (corresponding to $\beta_{H2}$ in Equation 17, standard errors in parenthesis below) and in the third column, we provide an estimate of the farmer level pooled main treatment effect of T2 (corresponding to $\beta_{H3}$ in Equation 18, standard errors in parenthesis below). The fourth column provides an estimate of the difference in outcomes between farmers that are exposed to both treatments and pure control farmers (corresponding to $\beta_{H4}$ in Equation 19, standard errors in parenthesis below). Finally, below the standard errors, we also provide p-values for the hypothesis that there is no different in the estimated effect depending on how the farmer is connected to the MCC (directly or through a small trader). More in particular, the number in square brackets in column two is the p-value for the hypothesis $\beta_{H2C} = \beta_{H2T}$ obtained from equation 20. Similar tests are reported for $\beta_{H3C} = \beta_{H3T}$ in column three and $\beta_{H4C} = \beta_{H4T}$ in column four.

The index of production investments and management practices designed to improve milk quality shows a positive treatment effect for the farmer level information treatment, but after controlling for multiple hypothesis testing, the difference is not significant. This suggests that farmers did not systematically adjust their production strategies in response to either the analyzer at the MCC or the farmer-focused intervention bundle.

We find that among pure control farmers, about 19 percent report that their milk was tested using a milk analyzer. This is about 7 percentage points higher when the farmer was connected to a treatment MCC. However, the coefficient is not significantly different from zero. We find no impact video, but we again find a substantial (though insignificant) difference in being tested between control farmers and farmers that were exposed to both treatments. Interestingly, for the bundle, we also reject the null that that the effects are equal irrespective of how farmers are connected to the MCC. This is because, in line with expectations, while the interaction effect $\beta_{H3C}$ in 20 is positive, the additional interaction with the trader indicator $\beta_{H3T}$ is negative.

Farmers report receiving on average UGX 1,022 per liter, which is consistent with MCC-level data in Table 2. Some farmers sell to alternative buyers such as traders or directly to consumers, typically at slightly lower prices than those offered by MCCs. Prices received by farmers in both treatment arms are statistically indistinguishable from those obtained by control farmers, and

Table 3: Primary outcomes at farmer level

| | mean | analyzer | video | bundle | nobs |
|---|---|---|---|---|---|
| Production investment and management (Index) | 0 | -0.02 | 0.045 | 0.044 | 2054 |
| | (0.56) | (0.038) | (0.024) | (0.052) | |
| | | [0.924] | [0.93] | [0.324] | |
| Buyer checked for quality (1=yes) | 0.186 | 0.07 | 0.016 | 0.108 | 1337 |
| | (0.39) | (0.046) | (0.021) | (0.057) | |
| | | [0.61] | [0.968] | [0.072] | |
| Price received for milk sold | 1021.887 | 11.308 | 1.44 | 21.011 | 1254 |
| | (104.146) | (9.678) | (5.037) | (12.849) | |
| | | [0.544] | [0.189] | [0.059] | |
| Get quality premium | 0.072 | -0.016 | -0.006 | -0.006 | 1281 |
| | (0.259) | (0.022) | (0.014) | (0.028) | |
| | | [0.368] | [0.108] | [0.392] | |
| Index of primary farmer outcomes | -0.002 | $0.079^{+}$ | 0.038 | $0.181^{**}$ | 1202 |
| | (0.533) | (0.046) | (0.028) | (0.066) | |
| | | [0.286] | [0.167] | [0.007] | |

Note: First column reports control group means (and standard deviations below); the second column shows average treatment effect of MCC level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; the third column shows average treatment effect of the farmer level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; the third column shows average treatment effect of the interaction of the MCC level and farmer level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; Standard errors are clustered at the catchment area level, $^{**}$, $^{*}$ and $+$ denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

the likelihood of receiving an explicit quality premium does not differ across groups. Farmers exposed to both treatments received about 20 shillings more per liter, but this effect is small and statistically insignificant. We also find evidence of heterogeneity by farmers' mode of connection to the MCC, with results suggesting that traders capture part of the price increase.

Overall, the index suggests that the analyzer, particularly when combined with the video treatment, did improve farmer-level outcomes. While individual coefficients rarely attain conventional significance, the consistent direction of effects across multiple indicators points to meaningful gains for treated farmers. This pattern is unlikely to arise by chance alone and is suggestive of broad though modest improvements in milk marketing conditions. The evidence indicates that making quality information more visible and understandable helped farmers secure outcomes more in line with the potential benefits of quality upgrading, even if the impact on any single dimension is difficult to isolate with precision. The coherence of the results across outcomes therefore provides encouraging evidence that the intervention bundle generated tangible though diffuse benefits at the farmer level.

### 11.1.3   Milk samples

To obtain objective measures of compositional quality, enumerators conducted a supervised testing exercise at both treatment and control MCCs. During a full day of collection, all incoming milk was analyzed on-site using milk analyzers. While logistically demanding, this exercise generated high-quality data on several key parameters that are routinely recorded in the app and can be measured with the analyzers: added water, butterfat, solids-not-fat (SNF), protein, and density (corrected lactometer reading). The supervised testing also allows us to construct alternative outcome measures. Since prices were collected alongside the quality tests, we are able to examine the relationship between compositional quality and farm-gate prices. In addition, we can directly measure rejection rates, providing another indicator of whether quality standards were enforced.

Before the supervised data collection began, all analyzers were verified against a reference device calibrated using the ISO 2442 approved method. This verification ensured that the analyzers produced accurate readings across MCCs and that any observed differences in milk quality reflected underlying variation rather than measurement error.

Table 4 presents treatment effects on objective measures of milk compositional quality obtained from the supervised testing exercise. Across several key parameters, we observe consistent improvements in the quality of milk delivered to MCCs in the treatment group.

Milk from treatment MCCs contained significantly higher levels of butterfat and solids-not-fat (SNF), with increases of 0.11 and 0.08 percentage points respectively relative to control group means of 3.88 and 8.58. Protein content also rose by 0.03 percentage points. While these magnitudes are small in absolute terms, they are meaningful given the tight variation in compositional parameters

Table 4: Milk quality

|  | mean ctrl | analyzer | nobs |
|---|---|---|---|
| Butter fat | 3.881 | 0.114* | 2518 |
|  | (0.539) | (0.035) |  |
| SNF | 8.579 | 0.081$^{+}$ | 2518 |
|  | (0.49) | (0.049) |  |
| Added Water | 1.626 | -0.488$^{+}$ | 2518 |
|  | (3.682) | (0.211) |  |
| Protein | 3.163 | 0.029$^{+}$ | 2518 |
|  | (0.194) | (0.021) |  |
| Density (CLR) | 27.93 | 0.435$^{+}$ | 2518 |
|  | (2.31) | (0.193) |  |
| Index | -0.103 | 0.209** | 2518 |
|  | (0.817) | (0.053) |  |

Note: First column reports control group means (and standard deviations below); Second column shows average treatment effect of the MCC level intervention (and standard error of coefficient estimate below); **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values. Added water enters negatively in the Anderson index.

and the importance of butterfat and protein in determining milk value.

At the same time, the prevalence of adulteration declined. Milk in the treatment group contained significantly less added water, with a reduction of nearly half a percentage point relative to the control mean of 1.63. Density (CLR) increased by 0.44, consistent with lower dilution and higher compositional integrity.

The composite index aggregating all five parameters confirms these patterns: overall milk quality improved significantly in the treatment group, with an index effect of 0.21 standard deviations. Taken together, these results suggest that the introduction of milk analyzers not only increased testing behavior at MCCs but also translated into measurable improvements in the quality of milk supplied, reducing adulteration and enhancing key compositional traits.

## 11.2 Impact on Freshness

Qualitative explorations during the course of the project suggests an interesting side effect of introducing milk analyzers: an increase in freshness. This is because skimming of milk becomes easier to detect and so farmers will abolish this. To fat from milk, milk has to rest a bit after milking as the fat floats on top. If skimming is discouraged, farmers are likely to take milk to MCCs faster, leading to fresher milk.

We test this hypothesis by looking at the distribution of the time at which samples are brought in. We expect that in treatment MCCs, milk is brought in earlier than in control MCCs. In other words, the difference between the time when a sample is brought in and the closing time of the MCC (fixed at 14:00
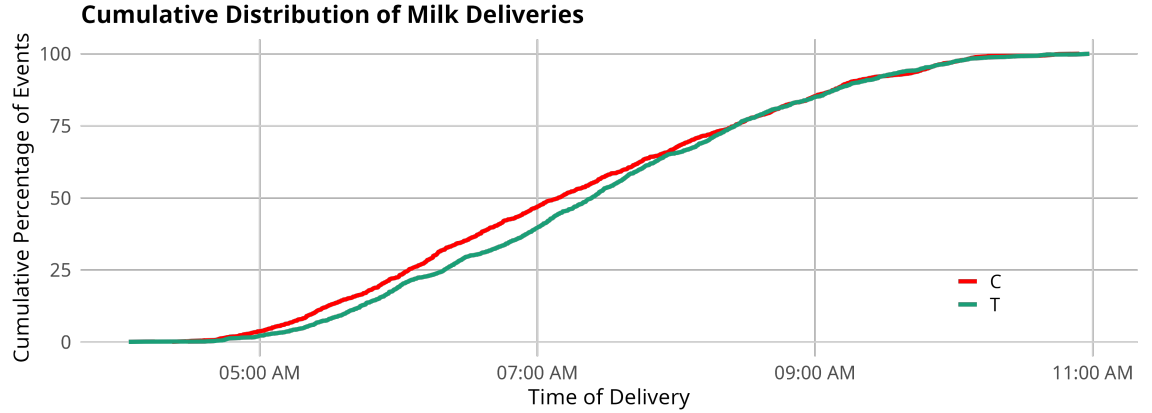
Figure 5: Timing of deliveries

in our analysis) is likely to increase as a result of the treatment. We investigate this graphically (Figure 5) but also test if distributions are different using a KS-test (test statistic: $9.6503718 \times 10^{-4}$, p-value: 1) as well as tests for a shift in the distribution using a t-test (test statistic: 2.6599864, p-value: 0.0078727) and a Mann-Whitney test (test statistic: $8.08393 \times 10^5$, p-value: 0.0050529). Finally, we test for first and second order stochastic dominance. A second way in which we will look at freshness is by the alcohol test.

## Secondary outcomes

Secondary outcomes at the milk collection center level include:

1. Enumerator: Do you see the poster advertizing the milk analyzer? - poster

2. Enumerator: Do you see a milk analyzer? - machine

3. Enumerator: Is this the machine that was provided through the project? Make ESSAE - machine_project

4. Enumerator: ask the manager to demonstrate the use of the milk analyzer on the fly and indicate what best maches what transpired machine_in_use==1 or 2

5. How do you keep track of the milk delivered by farmers? record_keeping

6. treatment uptake:

    (a) use of milk analyzer - q16c and q16cc - Information on milk analyzer use (for ITT-TOT analysis). - q16

c("tot_sales_q","test_MA","MCC_decides","MCC_got_premium","avg_prem_received")

Table 5: Secondary outcomes at MCC level - quantities collected

|  | mean ctrl | analyzer | nobs |
| --- | --- | --- | --- |
| Customers wet season | 53.966 | 4.352 | 110 |
|  | (59.45) | (8.385) |  |
| Customers dry season | 48.831 | -0.913 | 116 |
|  | (56.549) | (9.881) |  |
| Customers last week | 53.102 | 0.402 | 118 |
|  | (60.21) | (6.472) |  |
| Volumes dry season | 1428.814 | 157.408 | 120 |
|  | (980.508) | (183.545) |  |
| Volumes wet season | 2597.119 | -347.905 | 120 |
|  | (1625.096) | (244.984) |  |
| Volumes last week | 2345.881 | -315.412 | 120 |
|  | (1633.783) | (233.945) |  |
|  |  |  |  |
| Index of secondary MCC outcomes | -0.018 | -0.07 | 108 |
|  | (0.814) | (0.106) |  |

Note: First column reports control group means (and standard deviations below); Second column shows average treatment effect of the MCC level intervention (and standard error of coefficient estimate below); **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

1. local sales - previous research found that milk collection centers are also important for local milk supply, often doubling as milk shops. Does the intervention crowd out the local market? - q32 == 4X Sold to top 5 processors (Pearl, Amos, Lakeside, GBK, Vital tomosi) (in last 7 days) - q32==2 & q33!=6

2. Xvolumes sold - q35, q48, q58, q68, q78

3. Impact pathway:

   (a) did MCC measure quality of aggregated milk before selling? q37/q50/q60/q70/q80

   (b) XIn particular butter fat and SNF using a milk analyzer? What equipment was used? q38/q51/q61/q71/q81-q39/q52d/q62d/q72d/q82d

4. Who decided on the price? 1. buyer made offer and MCC accepted, 2. MCC made offer and buyer accepted, 3. negotiation - q40/q53q63/q73/q83 == 2

5. Quality:

   (a) XDid the buyer pay a quality premium? q44/q54/q64/q74/q84 == 1

Table 6: Secondary outcomes at MCC level - uptake

|  | mean ctrl | analyzer | nobs |
|---|---|---|---|
| Poster is visible | 0.034 | 0.343** | 120 |
|  | (0.183) | (0.068) |  |
| Milk Analyzer present | 0.237 | 0.533** | 120 |
|  | (0.429) | (0.078) |  |
| Project Milk Analyzer is present | 0.085 | 0.637** | 120 |
|  | (0.281) | (0.069) |  |
| Milk analyzer works | 0.237 | 0.369** | 120 |
|  | (0.429) | (0.084) |  |
| Milk Analyzer used for almost all incoming samples | 0.169 | 0.388** | 120 |
|  | (0.378) | (0.081) |  |
| MCC uses App | 0.237 | 0.369** | 120 |
|  | (0.429) | (0.084) |  |
|  |  |  |  |
| Index of MCC uptake | -0.432 | 0.85** | 120 |
|  | (0.392) | (0.104) |  |

Note: First column reports control group means (and standard deviations below); Second column shows average treatment effect of the MCC level intervention (and standard error of coefficient estimate below); **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

Table 7: Secondary outcomes at MCC level - sales

|  | mean ctrl | analyzer | nobs |
|---|---|---|---|
| Quantity sold | 2727.085 | -247.552 | 120 |
|  | (2086.725) | (376.422) |  |
| Tested Fat and SNF using MA | 0.288 | 0.328** | 120 |
|  | (0.457) | (0.086) |  |
| MCC decides | 0.068 | 0.039 | 120 |
|  | (0.254) | (0.051) |  |
| MCC got premium | 0.186 | 0.028 | 120 |
|  | (0.393) | (0.073) |  |
| Average premium received | 70.364 | -10 | 7 |
|  | (79.915) | (12.472) |  |
|  |  |  |  |
| Index of MCC sales | 0.403 | 0.113 | 7 |
|  | (0.532) | (0.171) |  |

Note: First column reports control group means (and standard deviations below); Second column shows average treatment effect of the MCC level intervention (and standard error of coefficient estimate below); **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

(b) How much was the quality premium (UGX per liter)? - q46/q56/q66/q76/q86

(c) How much passes through to farmers? q31d - share

(d) How is it distributed to farmers? - distribution

(e) Does the MCC pay a quality premium to suppliers? - q29

(f) What was it based on? - q30

6. Does market for quality lead to additional investment in quality preservation - milk cans, etc - q14a-n

7. Does the development of a market for quality lead to more formalization (eg written contracts)

(a) Between farmer and MCC? (q31)

(b) Between MCC and buyer? q47/q57/q67/q77/q87

8. Changes in mid-stream service provision: Does the MCC provide services related to

(a) credit? q17

(b) Access to acaracides? q18

(c) Artificial Insemination? q19

(d) transport? q20

(e) Training on milk sanitation? q21

(f) Training on feeding practices? q22

9. product differentiation: do MCCs collect milk in different takers based on quality (eg high protein milk is marketed separately from low protein milk)? - differentiate

10. Buyer changed since start of project? same_buyer

## Secondary outcomes at the farmer level:

A first family of secondary outcomes we consider are related to sales by farmers. Results are in Table 8. We asked out average quantities sold on a typical day during the last dry season and during the last rainy season. We also have a binary variable indicating if they sold at any point in the last week. To assess changes at the intensive margin, we also ask about quantities sold during the last sales transactions with each buyer.

Additional family of outcomes looks at choice of buyer:

1. Buyer type sold to on average day in rainy and dry season - q51 and q51x

2. Sold to milk to collection center in the week preceding the survey? (1=yes) - q53==2

Table 8: Secondary outcomes at farmer level - Quantities

| | mean | analyzer | video | bundle | nobs |
|---|---|---|---|---|---|
| Quantity sold in last dry season | 4.281 | -0.04 | 0.05 | -0.072 | 2035 |
| | (1.081) | (0.064) | (0.053) | (0.073) | |
| | | [0.943] | [0.466] | [0.172] | |
| Qantity sold in current season | 3.701 | 0.018 | 0.067 | -0.121 | 2019 |
| | (1.111) | (0.079) | (0.056) | (0.08) | |
| | | [0.46] | [0.313] | [0.856] | |
| Sold last week? | 0.797 | -0.038 | 0.013 | 0.011 | 2031 |
| | (0.402) | (0.037) | (0.023) | (0.041) | |
| | | [0.543] | [0.787] | [0.544] | |
| Quantity sold in last week | 3.309 | -0.274 | -0.001 | 0.128 | 1601 |
| | (1.938) | (0.185) | (0.143) | (0.195) | |
| | | [0.186] | [0.641] | [0.346] | |
| Index of sales | 0.005 | -0.06 | 0.018 | 0.004 | 1579 |
| | (0.657) | (0.053) | (0.039) | (0.066) | |
| | | [0.713] | [0.559] | [0.366] | |

Note: First column reports control group means (and standard deviations below); the second column shows average treatment effect of MCC level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; the third column shows average treatment effect of the farmer level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; the third column shows average treatment effect of the interaction of the MCC level and farmer level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; Standard errors are clustered at the catchment area level, **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

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3. While we already looked at price received during during transactions is the 7 days prior to endline interview, we also collected data on prices received during the dry and rainy seasons - q51a and q51ax

To assess treatment take-up and compliance, a second family asks weather farmers remember having been shown a video. We also ask if they remember having been given pasture seed and if they do, whether they used it. Finally, we also test of the interventions changed if farmers now start seeing the importance of compositional quality. To do so, we present farmers with three sets of options by asking "If an MCC or processor complains about poor quality milk, which of the 2 options is most important to increase milk quality?" and present two options, one option that focuses on improving milk sanitation (eg washing hands and using milk cans) and one that focuses on compositional quality. (eg using controlled grazing or using feed supplements). The 3 sets of options are then combined and get scored one if the farmer indicates the practice that focuses on compositional quality for all three sets.

A third family of outcomes looks at production, starting with

1. Production (liters) on average day in last wet season - q44 and in the last dry season - q45 and in the last 7 days - q46

2. Home consumption of dairy products (liters (q48), and who consumes diary products - children, calves (q49, q49a)) - test if the development of a market for quality milk crowds out animal sourced food intake within the family or milk as a productive factor

3. Does the intervention affect ghee processing? q66 q68-q69 Does this have gendered effects? q70-q71

4. Main reason for selling to buyer (in particular: because they offer testing, pays premium for quality, payment modalities,...) - q56/qx3/qx15/qx27/qx39/qx51

5. Number of dairy animals (improved/local) - does a market for quality lead to technology adoption for intensification? Is this stronger for the subgroup of farmers that receives the training video, where we explicitly mention that genetics also affect quality parameters? q24-q37

6. Price of dairy animals (improved/local) - test if the development of a market for quality has an impact on the price of animals. q25/q27/q29/q31/q33/q35

7. Gendered decision making outcomes - test if the development of a market for milk impacts who within the household makes the decisions to sell to a particular buyer. q62/qx9/qx21/qx33/qx45/qx57

8. Does the development of a market for quality lead to more formalization and less relational contracting? q63/qx10/qx22/qx34/qx46/qx58

Table 9: Secondary outcomes at farmer level - Sales

| | mean | analyzer | video | bundle | nobs |
|---|---|---|---|---|---|
| Sold to MCC in wet season | 0.743 | -0.07 | 0.006 | 0.047 | 2058 |
| | (0.437) | (0.042) | (0.027) | (0.039) | |
| | | [0.883] | [0.227] | [0.49] | |
| Sold to MCC in dry season | 0.735 | -0.061 | 0.016 | 0.034 | 2058 |
| | (0.441) | (0.043) | (0.028) | (0.041) | |
| | | [0.919] | [0.119] | [0.592] | |
| Sold to MCC in last week | 0.588 | -0.097 | 0.014 | 0.058 | 2058 |
| | (0.492) | (0.053) | (0.033) | (0.049) | |
| | | [0.479] | [0.371] | [0.603] | |
| Price received in wet season | 990.566 | 11.592 | 1.954 | -20.465 | 1994 |
| | (153.302) | (14.157) | (8.993) | (13.338) | |
| | | [0.409] | [0.492] | [0.287] | |
| Price received in dry season | 1225.851 | 9.895 | 3.887 | -9.879 | 1958 |
| | (173.874) | (14.988) | (13.072) | (16.405) | |
| | | [0.747] | [0.772] | [0.49] | |
| Index of farmer sales | 0.021 | -0.048 | 0.015 | 0.013 | 1929 |
| | (0.625) | (0.062) | (0.04) | (0.055) | |
| | | [0.771] | [0.33] | [0.708] | |

Note: First column reports control group means (and standard deviations below); the second column shows average treatment effect of MCC level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; the third column shows average treatment effect of the farmer level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; the third column shows average treatment effect of the interaction of the MCC level and farmer level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]. Standard errors are clustered at the catchment area level, **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

Table 10: Secondary outcomes at farmer level - uptake

| | mean | analyzer | video | bundle | nobs |
|---|---|---|---|---|---|
| Remembers video | 0.376 | 0.002 | 0.326** | 0.008 | 2058 |
| | (0.484) | (0.037) | (0.033) | (0.063) | |
| | | [0.942] | [0.001] | [0.528] | |
| Remembers receiving seed | 0.446 | -0.018 | 0.353** | 0.039 | 2058 |
| | (0.497) | (0.044) | (0.036) | (0.068) | |
| | | [0.567] | [0.01] | [0.676] | |
| Used seed | 0.3 | -0.001 | 0.235** | 0.019 | 2058 |
| | (0.458) | (0.036) | (0.034) | (0.046) | |
| | | [0.783] | [0.096] | [0.901] | |
| Knows compositional quality matters | 0.222 | 0.048 | 0.024+ | -0.029 | 2058 |
| | (0.416) | (0.042) | (0.024) | (0.071) | |
| | | [0.398] | [0.396] | [0.977] | |
| Index of uptake | 0 | 0.045 | 0.382** | -0.008 | 2058 |
| | (0.63) | (0.049) | (0.044) | (0.082) | |
| | | [0.632] | [0.007] | [0.809] | |

Note: First column reports control group means (and standard deviations below); the second column shows average treatment effect of MCC level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; the third column shows average treatment effect of the farmer level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; the third column shows average treatment effect of the interaction of the MCC level and farmer level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; Standard errors are clustered at the catchment area level; **, *, and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

9. Does the intervention also increases milk sanitation (use of milk cans)? q60/qx7/qx19/qx31/qx43/qx55

10. Gendered labour outcomes (milking, marketing, feeding and herding or cleaning)

11. Are farmers aware about the premium offered by buyers? knows_price_downstream/price_downstream

12. Buyer switching behavior. (still_connected==1, q51, q51_prev, q51_name, q51_name_prev) or during dry season (q51x, q51_prevx, q51_namex, q51_name_prevx)?

**Secondary outcomes at the transaction level:**

We should also look at prices here!

# 12 Heterogeneity with respect to chain length

Our model predicts potential differences in the treatment effect depending on how farmers are connected to MCCs. To test this, we stratified our farmer sample on how they are connected to MCCs: within each MCC, half of the farmers are directly connected, while the other half is connected through an intermediary (see also Figure 1).

To do so, enumerators were required to obtain the list of farmers that actively deliver to the MCC. The list is then split into those that deliver directly, and those that deliver through a trader (either against a fee or a trader working for his/her own account). Systematic sampling was then used to select 10 farmers in each of these two groups: each $n$-th farmer on the list within each group was interviewed with $n$ being the total number of farmers in the group divided by 10.

Unfortunately, this procedure did not always work in practice. Particularly in MCCs that take a coopertive form, it was often difficult to find sufficient traders, and so proportionally more directly collected farmers were selected. In particular,

# 13 Conclusion

This study explored the potential of targeted interventions to accelerate quality upgrading in Uganda's dairy value chain. Using a field experiment, we introduced innovations at the MCC and farmer levels, including milk analyzers, digital record-keeping tools, and farmer training. The interventions aimed to address persistent challenges related to milk quality by making it observable, actionable, and incentivized. This comprehensive design allowed us to assess impacts at multiple levels of the value chain, providing robust insights into what drives—or limits—quality improvements.

Table 11: Secondary outcomes at farmer level - switching

| | mean | analyzer | video | bundle | nobs |
|---|---|---|---|---|---|
| Buyer still connected to baseline MCC? | 0.765 | -0.065 | 0.007 | 0.033 | 2052 |
| | (0.424) | (0.04) | (0.023) | (0.035) | |
| | | [0.193] | [0.946] | [0.443] | |
| Still supplying wet | 0.807 | -0.081 | -0.008 | 0.054 | 1692 |
| | (0.394) | (0.039) | (0.023) | (0.034) | |
| | | [0.065] | [0.438] | [0.558] | |
| Still supplying dry | 0.807 | -0.044 | 0.002 | 0.031 | 1685 |
| | (0.395) | (0.041) | (0.024) | (0.034) | |
| | | [0.351] | [0.075] | [0.612] | |
| Index of switching | 0.049 | -0.163+ | -0.011 | 0.115 | 1663 |
| | (0.882) | (0.091) | (0.048) | (0.074) | |
| | | [0.132] | [0.271] | [0.668] | |

Note: First column reports control group means (and standard deviations below); the second column shows average treatment effect of MCC level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; the third column shows average treatment effect of the farmer level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; the third column shows average treatment effect of the interaction of the MCC level and farmer level intervention, (standard error of coefficient estimate below) and [p-value for the hypothesis of no treatment heterogeneity with respect to connection type below]; Standard errors are clustered at the catchment area level, **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

Findings:

- analyzers were effectively used for monitoring both milk supplied by farmers and deliveries to downstream buyers - at least that is what MCCs told us - secondary outcomes also suggest MAs are used, a good share of MAs also put up the posters and used the app.

- very weak effects at farmer levels - farmers do not only sell to MCCs. Is the result different if we only consider sales to MCCs

- No clear price effects - which of the following explanations are most plausible

    - Thin margins at MCCs: MCCs typically operate on tight margins, with their sales price closely tied to what processors or other downstream buyers pay them. If buyers did not pay more for higher quality milk, MCCs had little scope to pass quality information through prices. - this seems consistent with the

    - Contracts and price stickiness: Prices may be set in advance or negotiated infrequently (daily/weekly/monthly), making them less responsive to changes in quality testing over the study period. - this is also plausible in the context, where prices are typically fixed for 14 days

    - Market structure: If competition among MCCs is limited, or if buyers wield monopsony power, MCCs may be unable to raise prices for farmers even if quality improves.

    - Heterogeneous effects masked in averages: Rather than raising the average price, quality testing may have led to more price differentiation: better-quality suppliers receiving a premium, but lower-quality suppliers being rejected or paid less. This could leave the mean unchanged even if underlying incentives shifted. - this does not seem to be the reason but we can investigate this using the testing data.

    - Adjustment margins other than price: MCCs may have used testing results to enforce non-price mechanisms such as rejecting adulterated milk, reducing disputes, or strengthening supplier relationships.

    - Short time horizon: It may take time for buyers to recognize and reward systematic improvements in quality. The intervention might influence quality assurance practices first, with price effects emerging later.

The current price-setting mechanism is a critical bottleneck. Processors continue to publish uniform prices for milk, undermining the alignment of quality improvements with financial rewards. However, recent developments indicate potential shifts in the market. Two of Uganda's largest processors are piloting quality-based payment systems, directly rewarding farmers for higher-quality

milk. One MCC SUMPCArecently started selling milk to one of the large processors through their quality based milk payment system. Additionally, a large new processor specializing in infant formula production that is entering the market has already started contacting MCCs to gauge their interest in supplying milk under a quality based payment system.

These findings highlight both the progress made and the challenges that remain. While the interventions successfully improved milk quality and increased transparency, systemic changes—particularly in pricing mechanisms—are essential to sustain and scale these improvements. Future efforts should focus on supporting emerging market trends, addressing adoption barriers, and ensuring that economic incentives align with quality-based practices, ultimately benefiting all stakeholders across the dairy value chain.

# Ethical clearance

This research received clearance form Makerere's School of Social Sciences Research Ethics Committee (MAKSSREC-10.2022.594/AR) as well as from IFPRI IRB (DSGD-22-1057). The research was also registered at the Ugandan National Commission for Science and Technology (SS1520ES).

# Transparency and replicability

To maximize transparency and allow for replicabiliy, we use the following strategies:

- pre-analysis plan: the current document provides an ex-ante step-by-step plan setting out the hypothesis we will test, the intervention we will implement to test these hypotheses, the data that will be collected and specifications we will run to bring the hypotheses to the data. This pre-analysis plan will be pre-registered at the AEA RCT registry.

- revision control: the entire project will be under revision control (that is time stamped track changes) and committed regularly to a public repository (github).

- mock report: After baseline data is collected, a pre-registered report will be produced and added to the AEA RCT registry and GitHub. This report will differ from the pre-analyisis plan in that it already has the tables filled with simulated data (drawn from the baseline). The idea is that after the endline, only minimal changes are necessary (basically connecting a different dataset) to obtain the final result, further reducing the opportunity of specification search.

# 14    Acknowledgments

# References

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# Online Appendix

Table 12: Balance table

| | mean ctrl | analyzer | video | bundle | nobs |
|---|---|---|---|---|---|
| | *milk collection centers* | | | | |
| Number of people employed (full-time) at this MCC? (number) | 2.967 (1.886) | 0.346 (0.337) | | | 124 |
| Number of farmers/traders that supply on an average day during the rainy season (number) | 55.923 (64.037) | -6.573 (10.032) | | | 112 |
| Capacity use during dry season (share) | 37.978 (20.991) | -4.564 (3.718) | | | 119 |
| Number of milk cans owned by the MCC | 21.05 (52.963) | 0.716 (7.877) | | | 124 |
| Supplies credit/loans to cooperative members and regularly supplying farmers? (1=yes) | 0.833 (0.376) | 0.057 (0.07) | | | 124 |
| F-statistic | | 1.604 | | | |
| p-value | | 0.269 | | | |
| | *dairy farmers* | | | | |
| Household Members (number) | 9.754 (4.687) | -0.512 (0.342) | -0.314 (0.252) | 0.925* (0.357) | 2261 |
| Liters Produced Total Per Day (average during rainy season) (liters) | 70.053 (61.477) | 9.438 (7.614) | 7.726+ (4.051) | -10.447+ (6.076) | 2261 |
| Normally during the rainy season sells most of its milk to a milk collection center? (1=yes) | 0.793 (0.405) | -0.023 (0.049) | 0.006 (0.015) | 0.025 (0.028) | 2261 |
| Uses only steel can/bucket during sales transactions in the last 7 days before survey? (1=yes) | 0.752 (0.432) | 0.046 (0.039) | 0.029 (0.019) | -0.046 (0.03) | 2261 |
| Member of dairy cooperative? (1=yes) | 0.757 (0.429) | -0.084+ (0.048) | 0.004 (0.017) | -0.009 (0.028) | 2261 |
| F-statistic | | 1.283 | 0.605 | 1.322 | |
| p-value | | 0.288 | 0.696 | 0.273 | |

Note: First column reports control group means (and standard deviations below); **, * and + denote significance at the 1, 5 and 10 percent levels.

Table 13: Primary outcomes at farmer level (pooled)

| | mean | analyzer | video | nobs |
|---|---|---|---|---|
| Production investment and management | 0 | -0.02 | 0.045 | 2054 |
| | (0.56) | (0.038) | (0.024) | |
| Buyer checks for quality | 0.186 | 0.07 | 0.016 | 1337 |
| | (0.39) | (0.046) | (0.021) | |
| Price received for milk sold | 1021.887 | 11.308 | 1.44 | 1254 |
| | (104.146) | (9.678) | (5.037) | |
| Get quality premium | 0.072 | -0.016 | -0.006 | 1281 |
| | (0.259) | (0.022) | (0.014) | |
| Index of primary farmer outcomes | -0.002 | $0.079^{NA}$ | $0.038^{NA}$ | 1202 |
| | (0.533) | (0.046) | (0.028) | |

Note: First column reports control group means (and standard deviations below); the second column shows average treatment effect of MCC level intervention, (standard error of coefficient estimate below); the third column shows average treatment effect of the farmer level intervention, (standard error of coefficient estimate below); Standard errors are clustered at the catchment area level, **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

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Table 14: Secondary outcomes at farmer level (pooled) - Quantities

|  | mean | analyzer | video | nobs |
|---|---|---|---|---|
| Quantity sold in last dry season | 4.281 | -0.072 | 0.069 | 2035 |
|  | (1.081) | (0.101) | (0.045) |  |
| Quantity sold in current season | 3.701 | -0.059 | 0.037 | 2019 |
|  | (1.111) | (0.093) | (0.046) |  |
| Sold last week? | 0.797 | -0.035 | 0.01 | 2031 |
|  | (0.402) | (0.028) | (0.015) |  |
| Quantity sold last week | 3.309 | -0.139 | 0.114 | 1601 |
|  | (1.938) | (0.165) | (0.072) |  |
| Index of secondary outcomes | 0.005 | -0.079 | 0.026 | 1579 |
|  | (0.657) | (0.049) | (0.025) |  |

Note: First column reports control group means (and standard deviations below); the second column shows average treatment effect of MCC level intervention, (standard error of coefficient estimate below); the third column shows average treatment effect of the farmer level intervention, (standard error of coefficient estimate below); Standard errors are clustered at the catchment area level, **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

Table 15: Secondary outcomes at farmer level (pooled) - Sales

| | mean | analyzer | video | nobs |
|---|---|---|---|---|
| Sold to MCC in wet season | 0.743 | -0.074 | 0.007 | 2058 |
| | (0.437) | (0.038) | (0.019) | |
| Sold to MCC in dry season | 0.735 | -0.07 | 0.007 | 2058 |
| | (0.441) | (0.037) | (0.018) | |
| Sold to MCC in last week | 0.588 | -0.07 | 0.026 | 2058 |
| | (0.492) | (0.045) | (0.02) | |
| Price received in wet season | 990.566 | -1.213 | -10.037 | 1994 |
| | (153.302) | (12.319) | (5.907) | |
| Price received in dry season | 1225.851 | 3.156 | -3.15 | 1958 |
| | (173.874) | (13.633) | (7.466) | |
| Index of sales outcomes | 0.021 | -0.059 | -0.006 | 1929 |
| | (0.625) | (0.062) | (0.023) | |

Note: First column reports control group means (and standard deviations below); the second column shows average treatment effect of MCC level intervention, (standard error of coefficient estimate below); the third column shows average treatment effect of the farmer level intervention, (standard error of coefficient estimate below); Standard errors are clustered at the catchment area level, **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

Table 16: Secondary outcomes at farmer level (pooled) - Uptake

| | mean | analyzer | video | nobs |
|---|---|---|---|---|
| Remembers video | 0.376 | -0.005 | 0.325 | 2058 |
| | (0.484) | (0.03) | (0.021) | |
| Remembers seed | 0.446 | 0.003 | 0.391 | 2058 |
| | (0.497) | (0.028) | (0.02) | |
| Used seed | 0.3 | -0.005 | 0.25 | 2058 |
| | (0.458) | (0.028) | (0.019) | |
| Knows compositional quality matters | 0.222 | 0.036 | 0.01 | 2058 |
| | (0.416) | (0.037) | (0.017) | |
| Index of uptake | 0 | 0.031 | 0.381** | 2058 |
| | (0.63) | (0.04) | (0.027) | |

Note: First column reports control group means (and standard deviations below); the second column shows average treatment effect of MCC level intervention, (standard error of coefficient estimate below); the third column shows average treatment effect of the farmer level intervention, (standard error of coefficient estimate below); Standard errors are clustered at the catchment area level, **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.

Table 17: Secondary outcomes at farmer level (pooled) - Switching

| | mean | analyzer | video | nobs |
|---|---|---|---|---|
| Buyer still connected to baseline MCC | 0.765 | -0.037 | 0.02 | 2052 |
| | (0.424) | (0.033) | (0.017) | |
| Still supplying wet | 0.807 | -0.029 | -0.001 | 1692 |
| | (0.394) | (0.034) | (0.018) | |
| Still supplying dry | 0.807 | -0.007 | -0.008 | 1685 |
| | (0.395) | (0.034) | (0.018) | |
| Index of switching | 0.049 | -0.062 | -0.003 | 1663 |
| | (0.882) | (0.081) | (0.039) | |

Note: First column reports control group means (and standard deviations below); the second column shows average treatment effect of MCC level intervention, (standard error of coefficient estimate below); the third column shows average treatment effect of the farmer level intervention, (standard error of coefficient estimate below); Standard errors are clustered at the catchment area level, **, * and + denote significance at the 1, 5 and 10 percent Benjamini-Krieger-Yekutieli sharpened q-values.