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

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November 19, 2025

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 multi-level 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

Keywords: value chain upgrading, dairy, quality assurance, information

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

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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

3

(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.

3 Problem Statement and Research Hypotheses

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.

4 Conceptual Framework and Testable Predictions

4.1 Environment and Timing

There is one processor, multiple milk collection centers indexed by m, and, within each MCC catchment, multiple farmers indexed by i that deliver milk to the MCC. 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 expressed on a continuum ($q_i \in [0,1]$) and reflects compositional attributes such as butterfat and solids-not-fat.

After observing delivered quantities and a (possibly noisy) signal of quality for each farmer, the MCC decides whether to accept or reject each delivery. Accepted milk is aggregated and sold to the processor, who pays a premium for verifiable compositional quality. The downstream price received by the MCC therefore depends on average quality of accepted milk.

Farmers differ in how they are connected to the MCC: some deliver directly; others deliver through intermediaries. Because these intermediaries may retain part of any quality premium, farmers connected through traders face lower pass-through of downstream incentives.

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[2]Being a non-rival good, information is generally undersuplied by the private sector. Agricultural extension and advisory services are therefore often organized by governments or non-governmental organizations who tend to prioritize food safety concerns over profitability. As a result, farmers are mostly trained on how to maintain milk sanitary standards and less on ways to improve quality in terms of butter fat and Solid Non-Fat.

4.2 Production of Quality at the Farm

Each farmer i supplies a fixed quantity of milk y_i in the short run and chooses effort $e_i \geq 0$ that affects the compositional quality of milk:

$$q_i = \theta_i e_i + \varepsilon_i \qquad (1)$$

with $\theta_i \geq 0$ captures how effectively effort is translated into quality, and ε_i a mean-zero shock.

Effort assumed to be costly, which we model as a quadratic function:

$$c_i(e_i) = \frac{k_i}{2} e_i^2 \qquad (2)$$

with $k_i > 0$.

4.3 Prices, Pass-Through, and Intermediation

Let the processor pay the MCC a unit price

$$p_m = \bar{p} + \alpha\, \bar{q}_m \qquad (3)$$

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 posts a pricing rule that links observed quality (q_i) to price paid to suppliers (p_i). Let the supplier-level price schedule be:

$$p_i = p_0 + \lambda_i \alpha\, q_i \qquad (4)$$

where p_0 is a base price, $\alpha \geq 0$ is the per-unit premium slope for verifiable quality, and $0 \leq \lambda_i \leq 1$ is the pass-through rate of the premium to farmer i.[3] 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 $0 \leq \lambda_T \leq \lambda_C \leq 1$.

4.4 Farmer Optimization

The MCC may reject milk that does not meet a minimum quality standard. Let $a_i \in \{0, 1\}$ be an acceptance indicator, where $a_i = 1$ if farmer i's milk meets a minimum quality threshold $\bar{q}$ and $a_i = 0$ otherwise:

$$a_i = 1\left\{q_i \geq \bar{q}\right\} \qquad (5)$$

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[3]In principle, the extent to which the MCC passes through the quality premium to farmers is the outcome of a profit-maximization problem: the MCC would optimally choose a pass-through rate that balances retaining a share of the downstream premium against inducing higher farmer effort and thus higher average quality. For tractability and to keep the conceptual model focused on testable predictions, we treat λ_i as a reduced-form parameter summarizing institutional frictions, bargaining power, and local contracting norms

Farmer i's realized revenue is then

$$r_i(e_i) = a_i p_i(q_i) y_i \qquad (6)$$

Because observed quality includes noise (Equation 1), acceptance is uncertain from the farmer's perspective. Let

$$\pi_i(e_i; \bar{q}) = Pr(a_i = 1|e_i) \qquad (7)$$

denote the acceptance probability for farmer i. Since higher effort raises quality $q_i = \theta_i e_i$, the acceptance probability is increasing in effort:

$$\frac{\partial \pi_i(e_i; \bar{q})}{\partial e_i} > 0 \qquad (8)$$

Farmer i's expected revenue is therefore

$$E[r_i(e_i)] = \pi_i(e_i; \bar{q})[p_0 y_i + \lambda_i \alpha \theta_i e_i y_i] \qquad (9)$$

The farmer chooses effort to maximize expected net returns:

$$e_i^* = \arg\max_{e_i \geq 0}\{E[r_i(e_i)] - c_i(e_i)\} \qquad (10)$$

This decision problem highlights two distinct channels through which effort affects expected payoffs:

1. Intensive margin (price effect): When pass-through is positive ($\lambda_i > 0$), higher effort raises quality q_i and therefore the quality-linked component of the price $\lambda_i \alpha q_i$ conditional on acceptance. Holding the acceptance probability fixed, the marginal return to effort comes from a steeper price–quality gradient.

2. Extensive margin (acceptance effect): Even absent pass-through on the price (for example when $\lambda_i = 0$), higher effort increases the probability that milk meets the MCC's standard and is accepted, $\pi_i(e_i; \bar{q})$. If rejected milk receives a strictly lower payoff than accepted milk (for example zero or a low salvage value), this acceptance channel generates its own incentive to exert effort.

The first-order condition, which implicitly defines optimal effort is

$$\frac{\mathrm{d}}{\mathrm{d}e_i} E[r_i(e_i)] = k_i e_i, \qquad (11)$$

where the left-hand side collects both intensive and extensive margin effects:

$$\frac{\mathrm{d}}{\mathrm{d}e_i} E[r_i(e_i)] = \underbrace{\pi_i(e_i; \bar{q})\lambda_i \alpha \theta_i y_i}_{\text{intensive margin}} + \underbrace{\frac{\partial \pi_i(e_i; \bar{q})}{\partial e_i}[p_0 y_i + \lambda_i \alpha \theta_i e_i y_i]}_{\text{extensive margin}}. \qquad (12)$$

9

The model therefore implies that stronger quality-based incentives at the MCC level (higher α), higher pass-through λ_i, more effective technology θ_i, and lower effort cost k_i, all increase optimal effort e_i^*, realized quality $q_i^* = \theta_i e_i^*$, and the likelihood of supplying accepted milk.

4.5 MCC Pricing, Screening, and Outcomes

The MCC observes a (possibly noisy) measure of individual quality and decides whether to accept each farmer's delivery. Aggregate quality at the MCC is then the quality of accepted milk:

$$\bar{q}_m = \frac{\sum_i a_i y_i p_i}{\sum_i a_i y_i} \tag{13}$$

The MCC chooses a quality standard (acceptance rule) that trades off higher average quality against the loss of volume from rejected milk. A higher weight on quality in the downstream price schedule, α, makes it optimal for the MCC to tighten this standard, rejecting more low-quality milk and thereby directly increasing $\bar{q}_m$, even holding farmer effort fixed.

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

$$\underbrace{\bar{p} + \alpha \bar{q}_m}_{\text{revenue from processor}} - \underbrace{\left(p_0 + \lambda_i \alpha q_i\right)}_{\text{payment to farmer}} \tag{14}$$

Averaging over suppliers, the expected margin per liter becomes:

$$\mu_m = \bar{p} - p_0 + \alpha(1 - \bar{\lambda}_m) \bar{q}_m \tag{15}$$

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

An increase in α raises $\bar{q}_m$ both directly (through stricter acceptance), and, at least if $\lambda_i > 0$, through increased effort of the farmer.

4.6 Model predictions

4.6.1 Stronger Quality-based Incentives at the Aggregation Stage

A higher α increases the value of quality for the MCC. As a result, MCCs may tightens acceptance standard, rejecting more low-quality milk and thereby increasing average quality $\bar{q}_m$ among accepted deliveries. Second, when pass-through is positive ($\lambda_i > 0$), higher α also raises farmer effort and individual quality q_i^*, further increasing $\bar{q}_m$ and any intermediary outcome that is increasing in realized quality or quality-linked revenue

$$\frac{\partial \bar{q}_m}{\partial \alpha} > 0 \tag{16}$$

4.6.2 Farmer Responses to Stronger Downstream Incentives

With $\lambda_i > 0$, an increase in α raises farmers' optimal effort e_i^* and quality q_i^*, and also raises the quality-linked component of the price received.

$$\lambda_i > 0 \Rightarrow \frac{\partial e_i^*}{\partial \alpha} > 0 \; and \; \frac{\partial q_i^*}{\partial \alpha} > 0 \tag{17}$$

4.6.3 Efficiency and Cost-effectiveness of Producing Quality

An increase in the ability to translate effort into quality ($\theta_i \uparrow$) or a reduction in the marginal cost of effort ($k_i \downarrow$) both increase optimal effort, realized quality, and quality-linked revenues.

$$\frac{\partial e_i^*}{\partial \theta_i} > 0 \; and \; \frac{\partial e_i^*}{\partial k_i} < 0 \tag{18}$$

4.6.4 Interaction

Because e_i^* is multiplicative in α and θ_i/k_i, the cross-partial derivatice is positive:

$$\frac{\partial^2 e_i^*}{\partial \alpha \, \partial \left(\theta_i / k_i \right)} > 0 \tag{19}$$

Hence, stronger incentives (α) have larger effects on effort when the cost-effectivenss of producing quality (θ_i/k_i) is higher , and vice-versa.

4.6.5 Intermedation

When suppliers differ in the extent to which intermediary incentives are transmitted to them, those with direct linkages ($\lambda_C > \lambda_T$) respond more strongly to changes in α

$$\Delta e_i^*(\alpha | \lambda_C) > \Delta e_i^*(\alpha | \lambda_T)$$

5 Innovation Bundles for Addressing Milk Quality Challenges

In response to the challenge of unobservable milk quality in the Ugandan dairy value chain, we designed a first socio-technical 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

Figure 1: Milk analyzer

based on a set of compositional parameters, such as butterfat content and solids-not-fat. Another important parameter is the amount of added water, providing a more accurate assessment of what MCC managers usually test using gravity based methods. The testing process is non-destructive and takes less than one minute per sample, enabling rapid and accurate quality evaluation of each milk can that is delivered. By providing immediate feedback, the milk analyzer helps ensuring that quality standards are met and maintained. More information on the milk analyzer can be obtained from the manufacturer's website. Figure 1 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 maintenance of the milk analyzers.

We collaborated with the DDA to set up a system to monitor the milk analyzers and its use. In particular, DDA technicians visited treatment MCCs at set periods. We also provided various ways in which MCC managers could request assistance if needed, including a WhatAapp group and a telephone hotline. We also make sure that, over the course of the project, equipment is adequately calibrated. We also made sure MCC managers had access to cleaning reagents. If milk analyzers malfunctioned, we fixed or replaced the machine.

2. IT-Mediated Record-Keeping System: We developed an Android application for MCC managers to facilitate digital record-keeping. The app replaces 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 certain 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.[4] 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 targeted MCC owners, such that they can monitor key parameters in the MCCs they own. Another portal aggregated information from all MCCs, enabling government officials such as the DDA to monitor quality parameters, prices and quantities in real time.[5] 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 2.

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. Increasing Farmer Awareness of Midstream Testing Capacity: To mitigate potential power imbalances that could arise once MCCs adopt milk analyzers and to ensure farmers are equally informed, we implemented a farmer-facing information campaign using posters displayed at MCCs. Designed by a local artist, the posters publicized the new testing capacity and encouraged farmers to request free quality tests for their milk. By making this service visible and widely known, the campaign aimed to equip farmers with accurate information about their product quality and strengthen trust and cooperation between farmers and MCC managers.

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[4]Farmers are typically paid on the 1st and the 15th of the month.

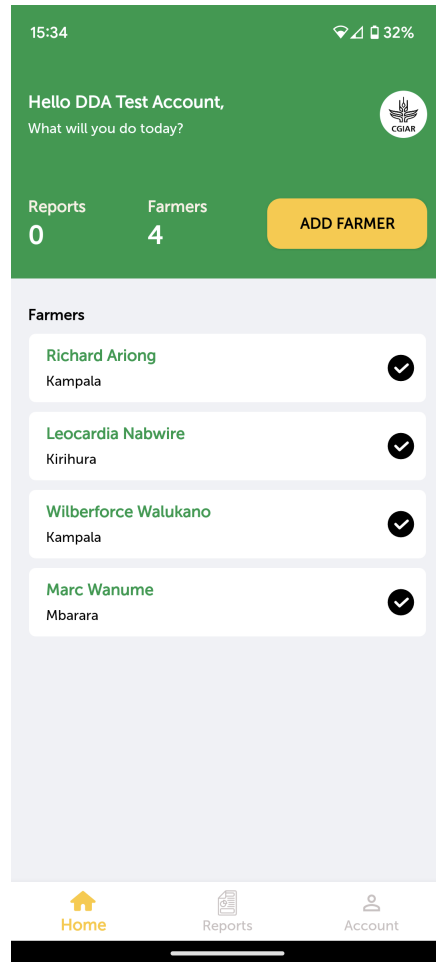[5]The portal can be found here.

Figure 2: Dairy record keeping app

Together, these three components form an integrated strategy to make milk quality observable and actionable, improving information flows and incentive structures throughout the dairy value chain. This bundle constitutes the first treatment arm in the field experiment and is referred to as T1.

To address the mismatch between how farmers and processors perceive milk quality, we designed an intervention to improve farmers' understanding of compositional quality and its role in the dairy value chain. The treatment combines targeted information, practical guidance, and modest material support. It consists of three components:

1. Educational Video: 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.[6] 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. The use of video has been found to increase technology adoption in different settings (Spielman et al., 2021).

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 from the video, 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 socio-technical innovation bundle, referred to as T2, seeks to narrow perception gaps around milk quality and strengthen farmers' capacity to supply higher compositional quality on a sustained basis.

6 Experiment

We use a field experiment to test the predictions in Section 4.6. In particular we use a split-plot design with interventions at two levels of the value chain.

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[6]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.
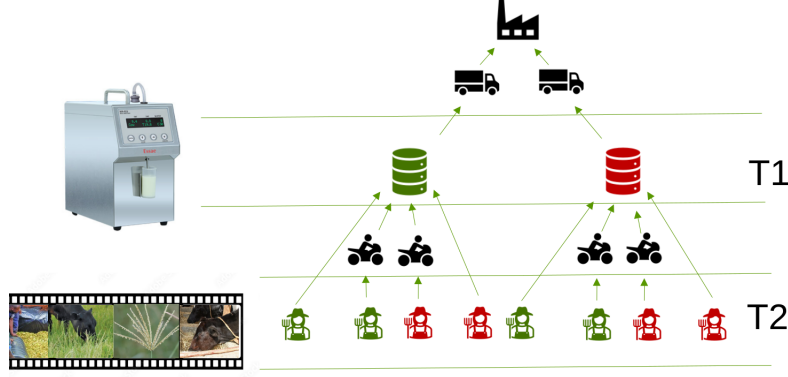
Figure 3: Design

The design is illustrated in Figure 3.

The experimental design mirrors the structure of the dairy value chain and involves randomization at two levels. First, at the MCC level, we assign half of the MCCs to receive the first socio-technical innovation bundle (T1), with the remaining MCCs serving as controls. Second, within each MCC—regardless of its assignment to T1—we randomize the second innovation bundle (T2) at the farmer level. For each MCC, half of its supplying farmers are assigned to T2 and the remainder to the farmer-level control. This yields a nested, multi-level design in which T1 varies across MCCs and T2 varies within MCCs. To examine heterogeneous effects, we further stratify the farmer-level randomization by the nature of the farmer's linkage to the MCC (direct delivery versus delivery through a trader).

This multi-level design enables us to estimate impacts at different nodes of the value chain. At the MCC level, we can assess the effect of the T1 intervention on outcomes aggregated at the MCC. Because T1 is assigned upstream, we can also evaluate its downstream effects on farmers linked to those MCCs, whether they supply directly or through traders. In contrast, the farmer-level treatment T2 varies only within MCCs, so its effects can be identified exclusively from farmer-level outcomes.

In sum, and in reference to the equation we will estimate in the next section (Section 7), the research questions posed in Section 3, and the predictions made in Subsection 4.6, 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 ($\beta_{H2} > 0$).

16

- Hypothesis 3: providing information on what the desired milk quality parameters are and what affects these 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 hypotheses, based on the stratification, tests for equality in average treatment effects between farmers that are directly connected to mccs and that are using traders.

- Hypothesis 5: The average treatment effect of the MCC-level intervention (T1) is equal for farmers directly connected to an MCC and those supplying through traders ($\beta_{H2C} = \beta_{H2T}$).

- Hypothesis 6: The average treatment effect of the farmer-level information intervention (T2) is the same for farmers directly connected to an MCC and those supplying through traders ($\beta_{H3C} = \beta_{H3T}$).

- Hypothesis 7: The average treatment effect of the combined intervention (T1 × T2) is the same for farmers directly connected to an MCC and those supplying through traders ($\beta_{H4C} = \beta_{H4T}$).

7 Estimation and Inference

To assess impact of the treatments, we estimate various specifications using Ordinary Least Squares. A first specification is at the level of the milk collection centers 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 of interest at the level of the milk collection center you want to estimate the treatment effect for and ε_m is an error term. In all equations we also control for baseline outcome if information was collected at that time $\left(y_m^b\right)$:

$$y_m = \alpha + \beta_{H1}.T_m^T + \beta_b.y_m^b + \varepsilon_m \tag{20}$$

The parameter of interest in this equation is β_{H1}, which tests Hypothesis 1 in Section 6.

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 that MCC. One way to do this is to estimate a fully interacted model such as the one given in Equation 21. 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 (T2) with i indicating the farmer running from 1 to I:

$$y_{i,m} = \alpha + \beta^*_{H2}.T^T_{i,m} + \beta^*_{H3}.T^I_{i,m} + \beta^*_{H4}.T^T_{i,m}.T^I_{i,m} + \beta_b.y^b_{i,m} + \varepsilon_{i,m} \qquad (21)$$

$y_{i,m}$ 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, $T^T_{i,m}$ 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 zero otherwise. We also control for the lagged baseline outcome $y^b_{i,m}$. The parameter of interest in this equation is β^*_{H2}, which tests the impact of T1 om farmers, corresponding to Hypothesis 2 in Section 6.

Equation 21 can also be used to test 2 other hypothesis. First, β^*_{H3}, provides and estimate of the farmer level impact of T2, which tests Hypothesis 3 from Section 6. Second, in a fully saturated model such as the one in Equation 21, β^*_{H4} also allows us to tests for the interaction effect, corresponding to Hypothesis 4 in Section 6.

While our power calculations relied on models that include the full set of interactions, an important feature of split-plot (factorial) designs is that power can be increased by pooling observations across the orthogonal treatment List, Sadoff, and Wagner (2011). 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, Muralidharan, Romero, and Wüthrich (2023) cautions against indiscriminate pooling of treatment cells when the underlying interventions may exhibit interaction effects. The authors note that, in the presence of even modest complementarities or antagonisms between treatment components, pooling can lead to biased or misleading estimates of marginal treatment effects. Consequently, they argue that a more rigorous and defensible approach is to estimate fully interacted specifications, which allow each treatment combination to have its own effect and thereby avoid imposing potentially unwarranted additivity assumptions. One way to recover an unbiased estimate of the pooled main treatment effect is to consider the orthogonal treatment as a co-variate and adjust for it, entering it in the regression demeaned and fully interacted as in equations 22 and 23.[7]

$$y_{i,m} = \alpha + \beta_{H2}T^T_{i,m} + \beta^I_{H3}\left(T^I_{i,m} - \bar{T}^I\right) + \beta^I_{H4}T^T_{i,m}\left(T^I_{i,m} - \bar{T}^I\right) + \beta_b.y^b_{i,m} + \varepsilon_{i,m}$$
$$(22)$$

$$y_{i,m} = \alpha + \beta_{H3}T^I_{i,m} + \beta^T_{H2}\left(T^T_{i,m} - \bar{T}^T\right) + \beta^T_{H4}T^I_{i,m}\left(T^T_{i,m} - \bar{T}^T\right) + \beta_b.y^b_{i,m} + \varepsilon_{i,m}$$
$$(23)$$

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[7]It is important to note that the estimand of the respective treatments in Equations 22 and 23 changes. For instance, while the estimand for the MCC-level treatment (T1) in Equation 21 is the effect of the treatment in and of itself, the estimand in Equation 22 is a weighted average of the pure effect of the MCC-level treatment (T1) and the effect of the T1 in the presence of T2.

Next, note that β_{H4}^* in equation 21 is estimated as an incremental effect to 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:

$$y_{i,m} = \alpha + \beta_{H4}.T_{i,m}^T.T_{i,m}^I + \beta_b.y_{i,m}^b + \varepsilon_{i,m} \tag{24}$$

after dropping from our data farmers that were exposed to only a single treatment. This specification recovers the effect of the intervention as an integrated package that addresses quality upgrading through both supply-side (push) and demand-side (pull) channels.

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 an intermediary). We also add a full set of interactions with this connection indicator, resulting in the the following model:

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

$$+ \beta_{H2C}.T_{i,m}^T.C_{i,m} + \beta_{H3C}T_i^I.C_{i,m} + \beta_{H4C}T_i^I.T_{i,m}^T.C_{i,m} + \beta_b.y_{i,m}^b + \varepsilon_{i,m} \tag{25}$$

This specification is used to test Hypotheses 5-7 outlined in Section 6.

In all farmer level regressions (Equations 21 to 25), 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 use 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.

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

at that level.[8] 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 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.[9] In each of the 130 MCCs, we then randomly selected 20 farmers who deliver milk to the center, half of which were taking the milk themselves and the other half using a trader or transported to get the milk to the MCC. Of these 20 farmers, 10 were randomly assigned to the video treatment (T2), while the remaining 10 served as the control group. With again in each group half directly connected and the other half connected through a mediator.

Figure 4 illustrates the randomization of T1 and T2 in three of the four study districts at both the MCC and farmer levels. The leftmost panel displays the spatial distribution of MCCs and their assigned T1 status. The middle panel shows the corresponding T1 assignment for farmers connected to those MCCs, reflecting the fact that T1 was clustered at the MCC level. The rightmost panel depicts the allocation of T2 among farmers linked to MCCs, which was randomized at the individual level.

Baseline data from both MCCs and associated farmers was collected towards the end of 2022 using in person surveys. At that 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 the installation of the analyzers, 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

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[8] Processors set fairly stable procurement prices and MCCs adjust tightly around those. The nested nature of the sampling and variance parameters imply an intra-cluster correlation of approximately $\rho \approx 0.20$.

[9] In some cases, more than one MCC were in particular location (eg. in a trading center). In such cases, MCCs were pooled in the same treatment group, as a result, the number of clusters was slightly lower than the number of MCCs.

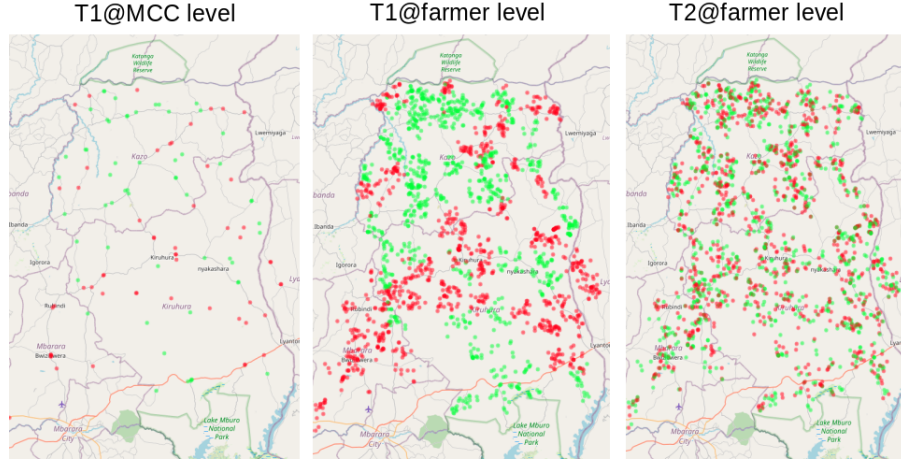| T1@MCC level | T1@farmer level | T2@farmer level |

Figure 4: Sampling and Randomization

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.[10] After all data was collected, all equipment was donated to the MCCs.[11]

9   Descriptive Statistics and Baseline Balance

We pre-registered 10 variables at each level to demonstrate balance. Results for five variables measured at the MCC level are in Table 1; five more variables are in Appendix Table A1 to conserve space. Table 1 shows that among MCCs in the control group, 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.

Appendix Table A1 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

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[10]This exercise posed logistical challenges, as MCCs opened early (usually at 8:00 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.

[11]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: MCC level

	mean ctrl	analyzer	nobs
MCC is 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)	
MCC pays quality premium (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	

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

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 balanced treatment and control groups along key baseline characteristics of MCCs for the treatment at that level.

Table 2 reports baseline characteristics of dairy farmers across treatment groups. In the control group (corresponding to farmers that did not get the information what quality parameters are important and are connected to an MCC that did not receive the milk testing and tracing infrastructure), household heads are on average 54 years old, with herds of about 62 animals, of which more than 90 percent are improved breeds.[12] Farmers sell roughly 60 liters of milk per day during the rainy season, and they spend on average USD 66

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[12]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.

per month on chemical purchases—primarily acaracides. Further characteristics are in Appendix Table A2 and 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 (Table 2 and Appendix Table A2) report six different sets of comparisons (corresponding to the six β_{H} coefficients in Equation 25). First, we test for pre-treatment differences between farmers connected to MCCs that received a milk analyzer and those connected to control MCCs (corresponding to β_{H2T} and indicated as *analyzer* in the table heading). No systematic imbalance is observed. Second, we examine differences between farmers who received the video-and-seed intervention and those who did not (corresponding to β_{H3T}; see column with header *video*). Again, no significant difference is found between the two groups. Third, we report the interaction effects at baseline (denoted as *bundle* in the table and corresponding to β_{H4T}), where again there is not evidence of pre-treatment imbalance. The tables also report p-values (in square brackets) that test whether each treatment effect differs between farmers connected to an MCC and those not connected. For example, in Table 2, the heterogeneity test for herd size shows a statistically significant difference in treatment effects across the two groups (p = 0.043). Additional pre-treatment differences in analyzer-treatment effects are observed for expenditures on chemicals (Table 2) and the use of steel cans or buckets (Appendix Table A2). Finally, the omnibus F-tests confirm overall balance.

In the appendix, partly for consistency with results reporting below, we add a few more comparisons. In particular, in Table A3 we report on pre-treatment differences based on the pooled models (with the column named *analyzer* corresponding to β_{H2} in Equation 22 and the column named *video* corresponding to β_{H3} in Equation 23) for the 10 preregistered farmer level characteristics. In the last column, we test pre-treatment differences for the bundled intervention by directly comparing pure control farmers to those that we exposed to both T1 and T2, corresponding to β_{H4} in Equation 24. These additional models confirm good overall balance.

10   Attrition and Compliance

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. One of the 4 attrited MCCs was originally assigned to the control arm of the mcc level treatment; 3 were from

Table 2: Balance table: farmer level

	mean ctrl	analyzer	video	bundle	nobs
Household Head Age (years)	54.469	-0.086	-0.584	-1.16	2261
	(12.633)	(1.148)	(1.123)	(1.503)	
		[0.944]	[0.381]	[0.923]	
Current Total herd size (number)	62.297	12.472	4.127	-9.378	1976
	(54.007)	(7.702)	(4.356)	(7.894)	
		[0.043]	[0.944]	[0.268]	
Number of improved animals in total herd (share)	0.932	-0.019	0.014	-0.002	1976
	(0.171)	(0.015)	(0.012)	(0.017)	
		[0.196]	[0.389]	[0.591]	
Liters milk sold per day (on average in the rainy season) (liters)	59.697	10.65	8.516	-13.539	2261
	(56.325)	(7.679)	(4.311)	(7.218)	
		[0.164]	[0.197]	[0.119]	
Average monthly expense (USD) on chemical purchases	65.551	33.097	-0.896	-34.363	904
	(91.1)	(18.869)	(12.42)	(22.723)	
		[0.065]	[0.24]	[0.409]	
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.

the treatment group. A chi-square test confirms that attrition was unrelated to the treatment. 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. Also at the farmer level, attrition is unrelated to the treatments and any interaction thereof.

We also documented several compliance challenges. In some cases, analyzers were moved to control MCCs, and in others, treatment MCCs did not use or retain the machines. At endline, we observed that 14 of the 59 control MCCs had a milk analyzer on site, and 14 of the 61 treatment MCCs did not have a machine readily available. Among the 14 analyzers found in control MCCs, five were devices originally provided through the project. In the treatment group, we identified 47 analyzers across MCCs, but only 37 were operational or could be used for immediate testing at the time of the visit; the remaining units were non-functional or lacked an available operator.

Similar compliance concerns arise at the farmer level. Although the information treatment was delivered in a controlled manner and the video was shown twice, only 54 percent of farmers in the control group reported having been shown a video, suggesting substantial recall error. At the same time, more than one in five control-group farmers stated that they had seen a video explaining how to improve compositional quality, indicating potential contamination. Among treated farmers, only 42 percent reported using the seed provided by the project, a rate that is plausibly affected by drought conditions during the season.

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 designed to make milk quality more transparent and traceable. 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

Table 3: 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.

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 prices. 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 3. 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.[13]

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 the mcc level 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.

In light of the compliance issues discussed in the previous section, we also estimated local average treatment effects, instrumenting the actual availability of a functioning milk analyzer with the randomized treatment assignment. The conclusions remained largely unchanged. Overall, MCC-level data indicate that the intervention produced a sizable and consistent increase in testing activity, yet we find no evidence that it generated quality-based price differentiation. When we consider the composite index of pre-registered MCC-level outcomes, the data indicate that T1 did not lead to measurable improvements at the MCC level.

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

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[13]These self-reported outcomes may raise concerns about bias. However, as shown in Table 7, we obtain similar results when using direct enumerator observations of analyzer use.

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.[14]

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 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 3 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 β_{H2} in Equation 22, 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 β_{H3} in Equation 23, 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 β_{H4} in Equation 24, 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 25. 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

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[14]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 9 shows no evidence of differential participation across treatment groups.

Table 4: Primary outcomes at farmer level

	mean	analyzer	video	bundle	nobs
Production investment and management (Index)	0	-0.02	0.045	0.047	2054
	(0.56)	(0.039)	(0.024)	(0.058)	
		[0.196]	[0.174]	[0.408]	
Buyer checked for quality (1=yes)	0.186	0.07	0.016	0.134$^+$	1337
	(0.39)	(0.047)	(0.021)	(0.056)	
		[0.436]	[0.082]	[0.012]	
Price received for milk sold	1021.887	11.308	1.44	15.67	1254
	(104.146)	(9.852)	(5.104)	(14.609)	
		[0.691]	[0.828]	[0.421]	
Get quality premium	0.072	-0.016	-0.006	-0.012	1281
	(0.259)	(0.023)	(0.014)	(0.037)	
		[0.753]	[0.127]	[0.932]	
Index of primary farmer outcomes	-0.002	0.079$^+$	0.038	0.196*	1202
	(0.533)	(0.047)	(0.028)	(0.074)	
		[0.427]	[0.267]	[0.013]	

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.

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 β_{H3C} in 25 is positive, the additional interaction with the trader indicator β_{H3T} is negative.

Farmers report receiving on average UGX 1,022 per liter, which is consistent with MCC-level data in Table 3. 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 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

Table 5: 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.

rather than measurement error.

Table 5 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 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.
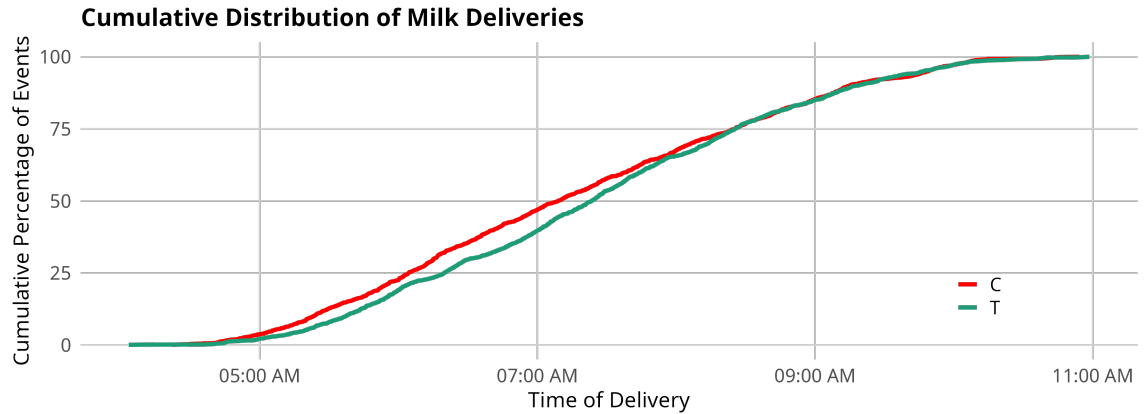
Cumulative Distribution of Milk Deliveries

Figure 5: Timing of deliveries

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 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: 9.6503718×10^{-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: 8.08393×10^{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

Table 6: 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.

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")

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

Table 7: 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 8: 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) XIn particular butter fat and SNF using a milk ana-
        lyzer? 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 ac-
   cepted, 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

    (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 preserva-
   tion - 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 9. 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

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

Table 9: Secondary outcomes at farmer level - Quantities

	mean	analyzer	video	bundle	nobs
Quantity sold in last dry season	4.281	0.023	0.096	-0.124	2035
	(1.081)	(0.08)	(0.066)	(0.091)	
		[0.354]	[0.118]	[0.129]	
Qantity sold in current season	3.701	0.08	0.01	-0.157	2019
	(1.111)	(0.087)	(0.07)	(0.094)	
		[0.529]	[0.641]	[0.566]	
Sold last week?	0.797	-0.002	0.016	0	2031
	(0.402)	(0.043)	(0.031)	(0.047)	
		[0.513]	[0.723]	[0.937]	
Quantity sold in last week	3.309	-0.051	-0.056	0.136	1601
	(1.938)	(0.217)	(0.206)	(0.26)	
		[0.633]	[0.605]	[0.563]	
Index of sales	0.005	-0.001	0.025	-0.043	1579
	(0.657)	(0.064)	(0.05)	(0.085)	
		[0.434]	[0.984]	[0.824]	

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 - Sales

	mean	analyzer	video	bundle	nobs
Sold to MCC in wet season	0.743	-0.08	-0.009	0.041	2058
	(0.437)	(0.049)	(0.032)	(0.053)	
		[0.522]	[0.963]	[0.664]	
Sold to MCC in dry season	0.735	-0.071	0.013	0.017	2058
	(0.441)	(0.048)	(0.032)	(0.053)	
		[0.563]	[0.497]	[0.994]	
Sold to MCC in last week	0.588	-0.105	-0.003	0.08	2058
	(0.492)	(0.059)	(0.037)	(0.057)	
		[0.306]	[0.95]	[0.291]	
Price received in wet season	990.566	9.387	-4.531	-17.597	1994
	(153.302)	(15.578)	(11.414)	(15.829)	
		[0.656]	[0.663]	[0.596]	
Price received in dry season	1225.851	27.95	11.321	-31.73	1958
	(173.874)	(15.685)	(13.821)	(17.433)	
		[0.111]	[0.516]	[0.664]	
Index of farmer sales	0.021	-0.038	-0.003	0.009	1929
	(0.625)	(0.065)	(0.046)	(0.062)	
		[0.853]	[0.982]	[0.872]	

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 11: Secondary outcomes at farmer level - uptake

	mean	analyzer	video	bundle	nobs
Remembers video	0.376	-0.022	0.3**	0.051	2059
	(0.484)	(0.04)	(0.04)	(0.051)	
		[0.367]	[0.005]	[0.538]	
Remembers receiving seed	0.446	-0.002	0.32**	-0.009	2059
	(0.497)	(0.046)	(0.043)	(0.05)	
		[0.929]	[0.038]	[0.26]	
Used seed	0.3	-0.01	0.213**	0.03	2059
	(0.458)	(0.043)	(0.043)	(0.048)	
		[0.632]	[0.22]	[0.485]	
Knows compositional quality matters	0.222	0.045	0.02	-0.009	2059
	(0.416)	(0.047)	(0.027)	(0.047)	
		[0.498]	[0.615]	[0.065]	
Index of uptake	0	0.028	0.347**	0.032	2059
	(0.63)	(0.057)	(0.048)	(0.065)	
		[0.968]	[0.014]	[0.629]	

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) 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.

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

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 3).

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.

Table 12: Secondary outcomes at farmer level - switching

	mean	analyzer	video	bundle	nobs
Buyer still connected to baseline MCC?	0.765	-0.053	-0.006	0.007	2053
	(0.424)	(0.045)	(0.033)	(0.047)	
		[0.456]	[0.559]	[0.892]	
Still supplying wet	0.807	-0.079	-0.018	0.031	1693
	(0.394)	(0.043)	(0.031)	(0.046)	
		[0.127]	[0.869]	[0.93]	
Still supplying dry	0.807	-0.048	-0.001	0.014	1686
	(0.395)	(0.045)	(0.034)	(0.049)	
		[0.323]	[0.48]	[0.575]	
Index of switching	0.049	-0.176	-0.034	0.086	1664
	(0.882)	(0.108)	(0.069)	(0.11)	
		[0.141]	[0.978]	[0.947]	

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.

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.

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.

42

- 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

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Online Appendix

Table A1: Balance table: MCC level

	mean ctrl	analyzer	nobs
Number of people employed at MCC?	2.967	0.346	124
	(1.886)	(0.337)	
Nr farmers that supply to MCC	55.923	-6.573	112
	(64.037)	(10.032)	
Capacity use during dry season (%)	37.978	-4.564	119
	(20.991)	(3.718)	
Number of milk cans owned by MCC	21.05	0.716	124
	(52.963)	(7.877)	
Supplies credit/loans (1=yes)	0.833	0.057	124
	(0.376)	(0.07)	
F-statistic		1.604	
p-value		0.269	

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

Table A2: Balance table: farmer level

	mean ctrl	analyzer	video	bundle	nobs
Household Members (number)	9.754	-0.122	-0.004	0.654	2261
	(4.687)	(0.436)	(0.31)	(0.478)	
		[0.464]	[0.354]	[0.895]	
Liters Produced Total Per Day (average during rainy season) (liters)	70.053	11.774	9.381	-14.316	2261
	(61.477)	(8.554)	(4.91)	(7.845)	
		[0.35]	[0.194]	[0.266]	
Normally during the rainy season sells most of its milk to a milk collection center? (1=yes)	0.793	0.01	0.001	0.017	2261
	(0.405)	(0.039)	(0.018)	(0.033)	
		[0.378]	[0.842]	[0.902]	
Uses only steel can/bucket during sales transactions in the last 7 days before survey? (1=yes)	0.752	0.1	0.049	-0.078	2261
	(0.432)	(0.049)	(0.028)	(0.045)	
		[0.028]	[0.174]	[0.16]	
Member of dairy cooperative? (1=yes)	0.757	-0.104	0	0.003	2261
	(0.429)	(0.051)	(0.022)	(0.038)	
		[0.181]	[0.883]	[0.711]	
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 A3: Baseline balance (pooled)

	mean ctrl	analyzer	video	bundle	nobs
Household Head Age (years)	54.469	-0.835	-0.592	-1.83	2261
	(12.633)	(0.762)	(0.516)	(1.23)	
Current Total herd size (number)	62.297	2.63	3.37	7.221	1976
	(54.007)	(5.641)	(2.802)	(8.236)	
Number of improved animals in total herd (share)	0.932	-0.014	0.002	-0.006	1976
	(0.171)	(0.011)	(0.007)	(0.015)	
Liters milk sold per day (on average in the rainy season) (liters)	59.697	1.938	3.317	5.627	2261
	(56.325)	(5.626)	(2.434)	(7.371)	
Average monthly expense (USD) on chemical purchases	65.551	-2.534	0.339	-2.161	904
	(91.1)	(9.446)	(6.92)	(13.732)	
Household Members (number)	9.754	-0.048	0.162	0.528	2261
	(4.687)	(0.298)	(0.178)	(0.446)	
Liters Produced Total Per Day (average during rainy season) (liters)	70.053	4.198	2.343	6.84	2261
	(61.477)	(6.653)	(3.05)	(8.011)	
Normally during the rainy season sells most of its milk to a milk collection center? (1=yes)	0.793	-0.01	0.019	0.029	2261
	(0.405)	(0.043)	(0.014)	(0.036)	
Uses only steel can/bucket during sales transactions in the last 7 days before survey? (1=yes)	0.752	0.023	0.006	0.071	2261
	(0.432)	(0.036)	(0.015)	(0.05)	
Member of dairy cooperative? (1=yes)	0.757	-0.089	-0.001	-0.1	2261
	(0.429)	(0.045)	(0.014)	(0.053)	

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.

3

Table A4: Primary outcomes at farmer level (pooled)

	mean	analyzer	video	nobs
Production investment and management	0	-0.02	0.045	2054
	(0.56)	(0.039)	(0.024)	
Buyer checks for quality	0.186	0.07	0.016	1337
	(0.39)	(0.047)	(0.021)	
Price received for milk sold	1021.887	11.308	1.44	1254
	(104.146)	(9.852)	(5.104)	
Get quality premium	0.072	-0.016	-0.006	1281
	(0.259)	(0.023)	(0.014)	
Index of primary farmer outcomes	-0.002	0.079^{NA}	0.038^{NA}	1202
	(0.533)	(0.047)	(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.

Table A5: Secondary outcomes at farmer level (pooled) - Quantities

	mean	analyzer	video	nobs
Quantity sold in last dry season	4.281	-0.074	0.072	2035
	(1.081)	(0.105)	(0.044)	
Quantity sold in current season	3.701	-0.062	0.039	2019
	(1.111)	(0.097)	(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)	(0.169)	(0.073)	
Index of secondary outcomes	0.005	-0.079	0.026	1579
	(0.657)	(0.051)	(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 A6: Secondary outcomes at farmer level (pooled) - Sales

	mean	analyzer	video	nobs
Sold to MCC in wet season	0.743	-0.077	0.01	2058
	(0.437)	(0.043)	(0.02)	
Sold to MCC in dry season	0.735	-0.073	0.01	2058
	(0.441)	(0.041)	(0.02)	
Sold to MCC in last week	0.588	-0.073	0.029	2058
	(0.492)	(0.049)	(0.021)	
Price received in wet season	990.566	-1.398	-9.79	1994
	(153.302)	(12.842)	(5.917)	
Price received in dry season	1225.851	3.822	-3.705	1958
	(173.874)	(14.225)	(7.75)	
Index of sales outcomes	0.021	-0.06	-0.002	1929
	(0.625)	(0.069)	(0.024)	

Table A7: Secondary outcomes at farmer level (pooled) - Uptake

	mean	analyzer	video	nobs
Remembers video	0.376	-0.006	0.326	2059
	(0.484)	(0.031)	(0.021)	
Remembers seed	0.446	0.003	0.391	2059
	(0.497)	(0.029)	(0.02)	
Used seed	0.3	-0.004	0.25	2059
	(0.458)	(0.028)	(0.019)	
Knows compositional quality matters	0.222	0.037	0.01	2059
	(0.416)	(0.037)	(0.017)	
Index of uptake	0	0.032	0.381**	2059
	(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.

7

Table A8: Secondary outcomes at farmer level (pooled) - Switching

	mean	analyzer	video	nobs
Buyer still connected to baseline MCC	0.765	-0.039	0.022	2053
	(0.424)	(0.034)	(0.017)	
Still supplying wet	0.807	-0.031	0.005	1693
	(0.394)	(0.034)	(0.018)	
Still supplying dry	0.807	-0.008	-0.002	1686
	(0.395)	(0.034)	(0.018)	
Index of switching	0.049	-0.062	0.013	1664
	(0.882)	(0.082)	(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.