

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

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November 28, 2025

Abstract

In many agri-food supply chains, quality is hard to verify at first sale, and early aggregation of output from multiple suppliers makes it difficult to trace quality back to individual producers, weakening the link between effort and returns. These problems are amplified when actors hold divergent perceptions of what constitutes quality. We study whether making milk quality visible and traceable at collection, and aligning producers' knowledge with processors' quality standards, can support the emergence of quality-based incentives in Uganda's dairy sector. Working with 130 milk collection centers and 2,600 farmers, we implement a multi-level randomized controlled trial that installs digital milk analyzers and record-keeping tools at collection centers and provides farmers with targeted guidance and a complementary input to enable quality-enhancing practices. Increased testing at collection centers produces measurable improvements in quality, mainly through reductions in adulteration. However, neither the midstream nor upstream interventions affect prices or generate quality premia. The evidence shows that increased quality observability raises quality but does not affect the downstream price schedule, which remains unresponsive to compositional attributes.

JEL: O12, O14, Q13, D82, L15

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

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1 Introduction

Quality of commodities transacted within value chains, and the preservation of that quality throughout the chain, is central to value chain development. Higher-quality inputs improve efficiency by yielding more output per unit of input and 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 (Swinen 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; Macchiavello and Morjaria, 2020). 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 often 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 (Kembro, Näslund, and Olhager, 2017). 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 sub-sector. 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 dairy farmers to a growing cluster of processors. In dairy, quality is central: it determines processing yields for products such as cheese, casein, and infant formula, 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 mcs 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 mcs 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 installing milk analyzers at MCCs substantially increased the visibility, presence, and day-to-day use of quality-testing infrastructure, generating large and consistent increases in actual testing of both incoming and outgoing milk. Despite this operational uptake, neither the MCC-level intervention nor the farmer-level information treatment affected prices or the emergence of quality premia at any stage of the chain. At the farmer level, the information intervention improved recall, seed use, and some management practices, but these behavioral responses translated into measurable changes only when farmers were linked to MCCs equipped with analyzers, reflecting a clear complementarity between information and institutionalized quality visibility. Most importantly, analyzer installation improved milk quality itself—reducing added water and increasing butterfat—while leaving biologically determined components such as SNF and protein unchanged, consistent with adjustments in handling rather than deeper shifts in production. Together, the results show that the intervention made quality observable and improved milk composition through reduced adulteration, but without corresponding changes in price incentives or widespread upstream behavioral upgrading.

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

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

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

The rest of the paper is organized as follows. Section 2 describes Uganda’s dairy value chain and the institutional and technological constraints that motivate the intervention. Section 3 sets out the core market failures and develops the research hypotheses. Section 4 presents a simple conceptual framework linking observability, incentives, and farmer–MCC interactions to testable predictions. Section 5 details the two socio-technical innovation bundles and Section 6 outlines the multi-level experimental design. Section 7 discusses the estimation strategy. Section 8 describes our sample, data collection timeline, and randomization. Section 9 examines baseline balance, and Section 10 documents attrition and compliance. Section 11 reports the main results at the MCC, farmer, and milk-sample levels, as well as secondary outcomes along the proposed impact pathways. Section 12 concludes with implications for value-chain upgrading and the conditions under which markets for compositional quality can emerge.

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 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 or around 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 (SNF)—is often unavailable.¹

¹Most milk collection centers in Uganda rely on two low-cost diagnostic tests to assess basic milk quality: the lactometer test and the alcohol test. The lactometer test is a gravity based test that measures milk density using a floating hydrometer and is primarily employed to detect

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.

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 may be 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 supply, this may also strengthen their bargaining power vis-a-vis the MCC.²

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 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.³ A third hypothesis is thus

added water, since dilution lowers density, although readings are sensitive to temperature and cannot distinguish intentional adulteration from natural variation in fat or SNF. The alcohol test—typically using 68 to 75 percent ethanol—assesses protein stability as a proxy for freshness and acidity; milk that curdles upon contact with alcohol is rejected as sour. While both tests are inexpensive and easy to administer, neither provides information on compositional attributes such as butterfat, solids-not-fat, or protein, limiting their usefulness for enforcing or rewarding quality beyond basic adulteration and hygiene.

²As 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.

³Being a non-rival good, information is generally undersupplied by the private sector. Agri-

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

This section lays out a simple analytical framework that guides our interpretation of the mechanisms and generates testable predictions.

4.1 Environment and Timing

There is one processor, multiple MCCs 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 SNF.

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.

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:

$$q_i = \theta_i e_i + \varepsilon_i \tag{1}$$

cultural 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.

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

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

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

with $k_i > 0$.

4.3 Prices, Pass-Through, and Intermediation

Let the processor pay the MCC a unit price

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

where \bar{q}_m is average quality in MCC m and $\alpha \geq 0$ is the per-unit premium slope for verifiable quality. A key assumption we make is that, 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 farmers (p_i). Let the supplier-level price schedule be:

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

where p_0 is a base price, and $0 \leq \lambda_i \leq 1$ is the pass-through rate of the premium to farmer i .⁴ 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 q_{min} and $a_i = 0$ otherwise:

$$a_i = 1 \{q_i \geq q_{min}\} \quad (5)$$

Farmer i 's realized revenue is then

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

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

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

⁴In 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

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:

$$\frac{\partial \pi_i(e_i; q_{min})}{\partial e_i} > 0 \quad (8)$$

Farmer i 's expected revenue is therefore

$$E[r_i(e_i)] = \pi_i(e_i; q_{min}) [p_0 y_i + \lambda_i \alpha \theta_i e_i y_i] \quad (9)$$

The farmer chooses effort to maximize expected net returns:

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

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, $\pi_i(e_i; q_{min})$. 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

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

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

$$\frac{d}{de_i} E[r_i(e_i)] = \underbrace{\pi_i(e_i; q_{min}) \lambda_i \alpha \theta_i y_i}_{\text{intensive margin}} + \underbrace{\frac{\partial \pi_i(e_i; q_{min})}{\partial e_i} [p_0 y_i + \lambda_i \alpha \theta_i e_i y_i]}_{\text{extensive margin}}. \quad (12)$$

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 a weighted average of the quality of all accepted milk:

$$\bar{q}_m = \frac{\sum_i a_i y_i q_i}{\sum_i a_i y_i} \quad (13)$$

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:

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

Averaging over farmers, the expected margin per liter becomes:

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

where $\bar{\lambda}_m$ is the (volume-weighted) mean of the individual pass-through rates applied to accepted milk.

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 tighten 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

$$\frac{\partial \bar{q}_m}{\partial \alpha} > 0 \quad (16)$$

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.

$$\lambda_i > 0 \Rightarrow \frac{\partial e_i^*}{\partial \alpha} > 0 \text{ and } \frac{\partial q_i^*}{\partial \alpha} > 0 \quad (17)$$

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.

$$\frac{\partial e_i^*}{\partial \theta_i} > 0 \text{ and } \frac{\partial e_i^*}{\partial k_i} < 0 \quad (18)$$

4.6.4 Interaction

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

$$\frac{\partial^2 e_i^*}{\partial \alpha \partial (\theta_i/k_i)} > 0 \quad (19)$$

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

4.6.5 Intermediation

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 milk analyzers at MCCs. These machines assess milk quality based on a set of compositional parameters, such as butterfat content and solids-not-fat (SNF). 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 delivery.⁵ By providing immediate feedback, the milk analyzers help

⁵Generally milk was tested per (25 or 50 liter) milk can. Sometimes, if multiple cans of the same farmer were delivered, a composite sample of the different cans were tested.



Figure 1: Milk analyzer results during testing showing results for an exceptionally high quality milk sample

ensure 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 owners, 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 WhatsApp group and a telephone hotline. We also made sure that, over the course of the project, equipment was adequately

calibrated. We also made sure MCC managers had access to cleaning reagents. If milk analyzers malfunctioned, we fixed or replaced the machines.

2. **ICT-Mediated Record-Keeping System:** We developed an Android application for MCC managers to facilitate digital record-keeping. The app was designed to replace the paper notebooks that MCC managers generally use for keeping track 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. The app 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.⁶ 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.⁷ 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.

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 (or sometimes

⁶Farmers are typically paid on the 1st and the 15th of the month.

⁷The portal can be found [here](#).

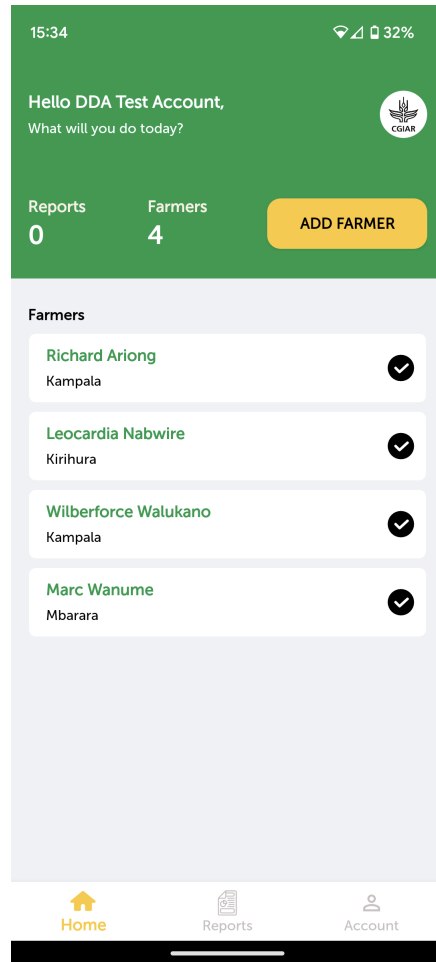


Figure 2: Dairy record keeping app

also as the *analyzer* treatment).

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.⁸ 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 videos such as the one we use 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 (or sometimes also as the *video* treatment), 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. The design is illustrated in Figure 3.

⁸To determine the content of the video, we first identified the top five practices and inputs that are known to raise butter fat and SNF 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.

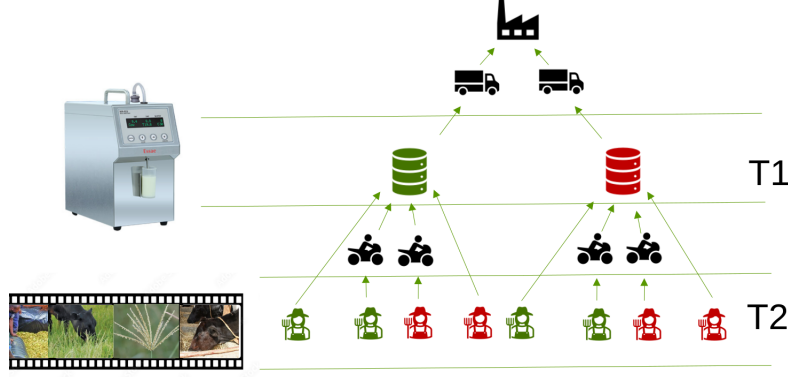


Figure 3: Design

The 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 T1 on outcomes at the MCC level. Because T1 is assigned downstream, we can also evaluate its upstream effects on farmers linked to those MCCs. In contrast, the farmer-level treatment T2 varies only within MCCs, so its effects can be identified exclusively from farmer-level outcomes.

In summary, and in reference to the estimating equations introduced 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 (T1) increases outcomes for the milk collection centers ($\beta_{H1} > 0$).
- Hypothesis 2: making quality visible at the MCC level (T1) increases outcomes for the farmers in the catchment areas of these MCCs ($\beta_{H2} > 0$).
- Hypothesis 3: providing information on what the desired milk quality parameters are and what affects these parameter (T2) increases outcomes

to farmers ($\beta_{H3} > 0$).

- Hypothesis 4: making quality visible at the MCC level (T1) and providing information on what the desired milk quality parameters are to farmers (YT2) 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) differs for farmers directly connected to an MCC and those supplying through traders ($\beta_{H2C} \neq \beta_{H2T}$).
- Hypothesis 6: The average treatment effect of the farmer-level information intervention (T2) differs for farmers directly connected to an MCC and those supplying through traders ($\beta_{H3C} \neq \beta_{H3T}$).
- Hypothesis 7: The average treatment effect of the combined intervention (T1 \times T2) differs for farmers directly connected to an MCC and those supplying through traders ($\beta_{H4C} \neq \beta_{H4T}$).

7 Estimation and Inference

To assess impact of the treatments, we estimate various specifications using Ordinary Least Squares. A first specification uses data at the MCC level. Denote milk collection centers by m , running from 1 to M . $T1_m$ is a treatment indicator at the MCC level that is one if the MCC was allocated to T1. y_m is the outcome of interest at the level of the milk collection center we 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 (y_m^b):

$$y_m = \alpha + \beta_{H1} \cdot T1_m + \beta_b \cdot y_m^b + \varepsilon_m \quad (20)$$

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 on farmers that are associated to that MCC. One way to do this is to estimate a fully interacted model such as:

$$y_{i,m} = \alpha + \beta_{H2}^* \cdot T1_{i,m} + \beta_{H3}^* \cdot T2_{i,m} + \beta_{H4}^* \cdot T1_{i,m} \cdot T2_{i,m} + \beta_b \cdot y_{i,m}^b + \varepsilon_{i,m} \quad (21)$$

Here, $T2_i$ is a treatment indicator at the farmer level that is one if the farmer was allocated to T2, with i indicating the farmer running from 1 to I , $y_{i,m}$ 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, $T1_{i,m}$ is a treatment indicator

that is one if the MCC (in who's catchment area farmer i resides) was allocated to T1, and zero otherwise. We also control for the lagged baseline outcome $y_{i,m}^b$. The parameter of interest in this equation is β_{H2}^* , which tests the impact of T1 on farmers, corresponding to Hypothesis 2 in Section 6.

Equation 21 can also be used to test 2 other hypotheses. 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 statistical power to estimate the effect of one treatment 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 23.⁹

$$y_{i,m} = \alpha + \beta_{H2} T1_{i,m} + \beta_{H3}^{T1} (T2_{i,m} - \bar{T}2) + \beta_{H4}^{T1} T1_{i,m} (T2_{i,m} - \bar{T}2) + \beta_b \cdot y_{i,m}^b + \varepsilon_{i,m} \quad (22)$$

$$y_{i,m} = \alpha + \beta_{H3} T2_{i,m} + \beta_{H2}^{T2} (T1_{i,m} - \bar{T}1) + \beta_{H4}^{T2} T2_{i,m} (T1_{i,m} - \bar{T}1) + \beta_b \cdot y_{i,m}^b + \varepsilon_{i,m} \quad (23)$$

Next, note that β_{H4}^* in equation 21 is estimated as an incremental effect to the main effects. In our analysis, we will also 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:

⁹It 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.

$$y_{i,m} = \alpha + \beta_{H4}.T1_{i,m}.T2_{i,m} + \beta_b.y_{i,m}^b + \varepsilon_{i,m} \quad (24)$$

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 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:

$$\begin{aligned} y_{i,m} = & \alpha + \alpha_C C_{i,m} + \beta_{H2T}.T1_{i,m} + \beta_{H3T}.T2_{i,m} + \beta_{H4T}.T2_{i,m}.T1_{i,m} \\ & + \beta_{H2C}.T1_{i,m}.C_{i,m} + \beta_{H3C}.T2_{i,m}.C_{i,m} + \beta_{H4C}.T2_{i,m}.T1_{i,m}.C_{i,m} + \beta_b.y_{i,m}^b + \varepsilon_{i,m} \end{aligned} \quad (25)$$

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 will combine primary outcomes into an index following [Anderson \(2008\)](#).

8 Sample and Timeline

Sample size was determined using a series of power simulations, details of which can be found in the pre-analysis plan. The primary outcome for these calculations was the price of milk, modeled at both the 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.¹⁰ 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

¹⁰Processors 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 $\rho \approx 0.20$.

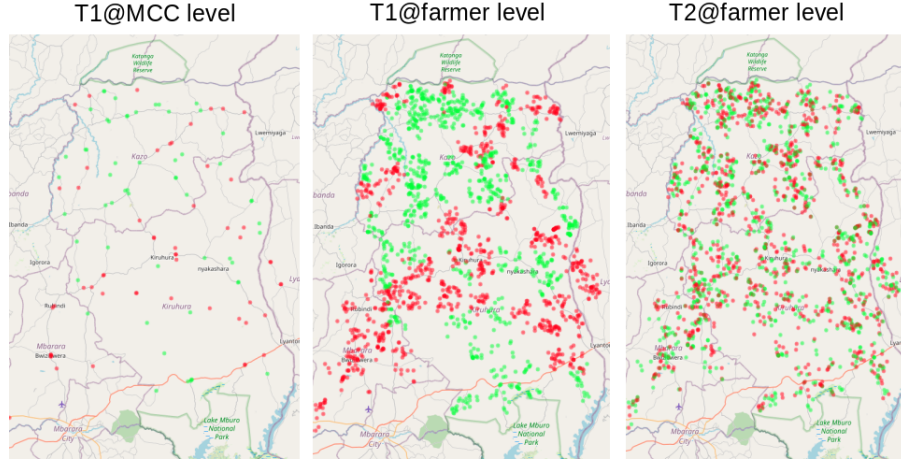


Figure 4: Sampling and Randomization

all hypotheses being true 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.¹¹ 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 an intermediary.

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

¹¹In some cases, more than one MCC were in a 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.

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 involved in-person surveys at the MCC level and at the farmer level. In addition, during endline we also measured quality of incoming milk. To do so, an enumerator equipped with a milk analyzer paid an unannounced visit to each MCC enrolled in the study and measured all incoming milk samples over the course of one full day.¹²

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 4,000 liters, and 27 percent reported paying a premium for higher quality milk to suppliers. The average MCCs has been in operation for just under 10 years, and 58 percent facilitated the supply of acaracides to supplying farmer.

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 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.

To assess pre-treatment balance across treatment arms, 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 (Total capacity of milk tanks). At the bottom of both tables we report results from an omnibus Wald test of joint balance across all

¹²This 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.

Table 1: Balance of Baseline Characteristics Between Treatment and Control Milk Collection Centers (MCCs)

	mean ctrl	analyzer	nobs
MCC is cooperative? (1=yes)	0.633 (0.486)	-0.086 (0.09)	124
Total Capacity of milk tanks (in liters)	4053.167 (1809.592)	1031.115* (433.343)	124
MCC pays quality premium (1=yes)	0.267 (0.446)	-0.029 (0.082)	123
MCC age in years of operation	9.325 (7.635)	0.235 (1.588)	123
Facilitates supply of acaracides? (1=yes)	0.583 (0.497)	-0.068 (0.093)	124
F-statistic		1.93	
p-value		0.113	

Note: This table reports baseline balance between MCCs assigned to the analyzer treatment and those in the control group. Column 1 presents control group means with standard deviations in parentheses. Column 2 shows the difference in means (treatment minus control) with robust standard errors in parentheses. Column 3 lists the number of non-missing observations. “Total tank capacity” is measured in liters and “MCC age” in years. The F-statistic and p-value correspond to a joint test of equality of all covariates. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 T1.

Table 2 reports baseline characteristics of dairy farmers across treatment groups. In the control group (corresponding to farmers that did not get the information on what quality parameters are important and are connected to an MCC that did not receive the milk testing and tracing bundle), household heads are on average 54 years old, with herds of about 62 animals, of which more than 90 percent are improved breeds.¹³ Farmers sell roughly 60 liters of milk per day during the rainy season, and they spend on average USD 66 per month on chemical purchases—primarily acaracides. Further characteristics 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.

¹³To 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.

Table 2: Baseline Balance Between Control Farmers and Farmers Assigned to Analyzer, Video, or Bundle Treatments

	mean ctrl	analyzer	video	bundle	nobs
Household Head Age (years)	54.469 (12.633)	-0.086 (1.148)	-0.584 (1.123)	-1.16 (1.503)	2261
Current Total herd size (number)	62.297 (54.007)	12.472 (7.702)	4.127 (4.356)	-9.378 (7.894)	1976
Number of improved animals in total herd (share)	0.932 (0.171)	-0.019 (0.015)	0.014 (0.012)	-0.002 (0.017)	1976
Liters milk sold per day (on average in the rainy season) (liters)	59.697 (56.325)	10.65 (7.679)	8.516 ⁺ (4.311)	-13.539 ⁺ (7.218)	2261
Average monthly expense (USD) on chemical purchases	65.551 (91.1)	33.097 ⁺ (18.869)	-0.896 (12.42)	-34.363 (22.723)	904
F-statistic		0.268	0.497	1.241	
p-value		0.927	0.776	0.314	

Note: This table reports baseline balance across farmers in the control group and the three treatment groups (analyzer, video, and bundle). Column 1 shows control group means with standard deviations in parentheses. Columns 2–4 report differences in means relative to the control group, with robust standard errors in parentheses. Column 5 gives the number of non-missing observations for each variable. The F-statistic and p-value correspond to joint tests of equality of all covariates across groups. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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). We find that farmers that are connected to a treatment MCC are somewhat less likely to be a member of a cooperative and more likely to be using steel cans or buckets. They also have a slightly higher expenditure on chemicals. However, F-tests do not reject joint orthogonality.

Second, we examine differences between farmers who received T2 and those who did not (corresponding to β_{H3T} ; see column with header *video*). Again, some significant difference are found between the two groups (treated farmer produce and sell slightly more milk, and are more likely to use steel cans or buckets), but the joint tests are not significant.

Third, we report the interaction effects at baseline (denoted as *bundle* in the table and corresponding to β_{H4T}), where we now find some evidence that farmers that received the full package were producing and selling less milk, and were less likely to use steel cans and buckets. However, also here, joint significance tests do not suggest imbalance.

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 were 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 randomly assigned to control condition and 64 to treatment condition 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 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. We revisit these issues in Section 11.2.

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 (and simultaneously consider multiple hypothesis testing concerns), we also construct a summary index following [Anderson \(2008\)](#). This index provides a single measure of how the intervention influenced the overall development of a market for quality at the MCC level.

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

The next two outcomes reflect how increased transparency affects prices. We measure the average price at which MCCs purchase milk from farmers during the seven days preceding the survey. We then ask about the average price MCCs received for sales to various buyers during the last transaction in the previous

Table 3: Primary Outcomes for Milk Collection Centers (MCCs)

	mean ctrl	analyzer	nobs
Tested incoming milk using MA (1=yes)	0.288 (0.457)	0.533** (0.078)	120
Testing outgoing milk using MA (1=yes)	0.203 (0.406)	0.285** (0.084)	120
Price at which milk was bought from farmers (UGX)	1075 (92.556)	-15.213 (14.704)	115
Price at which milk was sold (UGX)	1199.576 (106.327)	3.439 (19.243)	108
Does the MCC pay a quality premium to suppliers?	0.186 (0.393)	-0.032 (0.069)	119
Did the buyer pay a quality premium?	0.186 (0.393)	0.031 (0.074)	119
Index of primary MCC outcomes	-0.077 (0.477)	0.142 (0.099)	103

Note: Column 1 reports the mean of each outcome for the control group, with standard deviations in parentheses. Column 2 shows the estimated treatment effect of the analyzer intervention at the MCC level, with robust standard errors in parentheses. Column 3 lists the number of MCCs with non-missing observations. All prices are in Ugandan shillings (UGX). The “Index of primary MCC outcomes” is an Anderson (2008) index of the variables listed above. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 53 percentage points relative to a control group mean of 29 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.¹⁴

Turning to prices, we find no 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 2,200 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 (LATE), instrumenting the actual availability of a functioning milk analyzer with the randomized treatment assignment (See Appendix Table A4). The conclusions remain 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 is a composite in itself, and 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*, *Siratiro*, or *Desmodium*; (iii) adopting controlled or zero grazing during the last dry 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 as a result of the treatments (T2 in particular).

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

¹⁴These self-reported outcomes may raise concerns about experimenter bias. However, as shown in Table 6, we obtain similar results when using direct enumerator observations of analyzer use.

to the survey. The indicator is true if milk sold in the last 7 days was tested by at least one buyer.

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 shows parameter estimates from the fully interacted model of Equation 25 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 main treatment effect of T1 (corresponding to β_{H2C} in Equation 25, standard errors in parenthesis below) and in the third column, we provide an estimate of the farmer level main treatment effect of T2 (corresponding to β_{H3C} in Equation 25, standard errors in parenthesis below). The fourth column provides an estimate of the interaction between the MCC level treatment and the farmer level treatment (corresponding to β_{H4C} in Equation 25, standard errors in parenthesis below). Finally, below the standard errors, we also provide p-values for the null hypothesis that there is no difference 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 $\beta_{H2C} \neq \beta_{H2T}$ obtained from equation 25. Similar tests are reported for $\beta_{H3C} \neq \beta_{H3T}$ in column three and $\beta_{H4C} \neq \beta_{H4T}$ in column four.

In addition to the tables in the main text, we again provide various tables with additional estimates in the Appendix for robustness. In particular, we present tables with results from the pooled regressions corresponding to Equations 22 and 23 and the treatment bundle corresponding to Equation 24 (See Appendix Tables A5 and A7). Furthermore, in light of the compliance issues reported in Section 10, we also present LATE estimates where in addition to instrumenting actual presence of a milk analyzer with MCC level treatment assignment, we now also instrument the fact that farmers recall having seen the video with the farmer level treatment assignment (See Appendix Tables A6 and A7).

Looking at the main (fully interacted) specification in Table 4 and the pooled estimates in Table A5, we do not find evidence that the MCC-level intervention alone affected farmers’ production investments and management practices. The farmer-level information treatment also shows no significant effect in the fully interacted model. However, the pooled regression suggests a modest positive effect of the farmer-level intervention (significant at the 10 percent level). The significant interaction term in Table 4 indicates that this pooled effect is driven almost entirely by farmers whose MCCs were also equipped with an analyzer,

Table 4: Primary Outcomes for Farmers

	mean	analyzer	video	bundle	nobs
Production investment and management (Index)	0.014 (0.562)	-0.068 (0.051) [0.173]	-0.024 (0.036) [0.129]	0.135* (0.056) [0.005]	2054
Buyer checked for quality (1=yes)	0.157 (0.364)	0.058 (0.057) [0.436]	0.048 (0.039) [0.082]	0.028 (0.057) [0.882]	1337
Price received for milk sold	1019.292 (99.211)	13.674 (14.375) [0.691]	5.297 (11.359) [0.828]	-2.895 (15.037) [0.855]	1254
Get quality premium	0.081 (0.274)	-0.001 (0.036) [0.753]	0.042 (0.035) [0.127]	-0.054 (0.045) [0.176]	1281
Index of primary farmer outcomes	-0.036 (0.488)	0.092 (0.072) [0.452]	0.087 (0.071) [0.301]	0.013 (0.092) [0.757]	1202

Note: Column 1 reports mean outcomes for pure control farmers (those not receiving the information treatment and connected to control MCCs), with standard deviations in parentheses. Columns 2–4 present the pooled main treatment effects of the MCC-level intervention (T1), the farmer-level information intervention (T2), and their combined exposure, respectively; robust standard errors appear in parentheses. Numbers in square brackets report p-values for tests of whether the treatment effect differs by the farmer's connection type (directly to an MCC versus through a small trader). Column 5 shows the number of non-missing observations. Prices are in Ugandan shillings (UGX). The "Index of primary farmer outcomes" is an Anderson (2008) index of the outcomes listed above. Standard errors are clustered at the catchment-area level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ (Benjamini-Krieger-Yekutieli sharpened q-values).

suggesting that information only translates into improved management practices when quality is made observable and salient at the MCC level. This pattern is consistent with complementarities in the theory of change: farmers have little incentive to act on information in environments where quality is not measured, but respond when improved knowledge is paired with an institutional setting that demands or rewards higher quality. Finally, we find significant heterogeneity with respect to intermediation for the interaction effect: As expected, the significant increase in investment and effort is driven by directly connected farmers.

Among pure control farmers, approximately 16 percent report that their milk was tested using an analyzer. Farmers linked to treatment MCCs report slightly higher testing rates—by roughly 6 to 7 percentage points in both the fully interacted and pooled specifications—although these differences are not statistically distinguishable from zero.¹⁵ The coefficient on the farmer-level information treatment is likewise positive but imprecisely estimated. At the same time, the fully interacted model indicates heterogeneity by connection type: the information treatment reduces the likelihood of being tested among farmers who supply through traders. We detect no statistically significant interaction between the MCC-level and farmer-level interventions.

Across all specifications, we find no evidence that either intervention affected the prices farmers receive for milk. Control farmers report an average price of UGX 1,019 per liter—a level consistent with MCC-level data once accounting for sales to alternative buyers such as traders or direct consumers, who typically pay slightly less. Prices received by farmers in both treatment arms are statistically indistinguishable from those of control farmers, and this holds for the interaction term as well as for pooled, fully interacted, and instrumented models. Similarly, the likelihood that a farmer reports receiving an explicit quality premium does not differ across groups, mirroring the null effects observed for prices. Taken together, these results point to no detectable impact of the interventions on the price dimension of farmers’ marketing outcomes.

Taken together, these weak and null effects translate into an overall insignificant impact on the composite index of primary farmer outcomes. Nonetheless, the pooled specification does provide some suggestive evidence that the MCC-level intervention modestly improves the combined index, and a direct comparison between pure control farmers and those exposed to the full bundle of interventions points to a small but positive shift in behavior (See Appendix Table A5).

¹⁵Although these effects are generally small and imprecise, they are consistent with qualitative reports from MCC managers who stated that analyzers were typically used only in suspected cases of adulteration rather than on every single delivery. Our outcome measure captures self-reported testing across all potential offtakers, not just MCCs, and therefore may not fully reflect this selective-use pattern. Even so, selective but credible testing can still shift behavior: the possibility of being tested may be sufficient to induce farmers to upgrade milk quality, a mechanism supported by the compositional improvements documented in the sample-based analysis below (Section 11.1.3).

11.1.3 Milk samples

To obtain objective measures of compositional milk quality, enumerators conducted supervised testing at both treatment and control MCCs. For one full day at each site, all incoming milk was analyzed using milk analyzers, yielding high-quality measures of key quality parameters: added water, butterfat, solids-not-fat (SNF), protein, and density (corrected lactometer reading). These variables are also combined into an index of overall quality.

It is important to note that the compositional quality measures obtained through supervised testing at MCCs are farmer-level outcomes, but they need not correspond to the same individuals who appear in the farmer survey. The universe of suppliers observed in the testing data reflects the set of farmers who delivered milk on the specific day of supervised measurement, which may include new entrants who began supplying after analyzers were introduced, as well as exclude farmers who had previously supplied but stopped delivering. Conversely, the survey sample includes baseline suppliers regardless of whether they continued or ceased deliveries by endline. Each data source therefore captures a different margin of adjustment. The MCC testing data reveal changes in the composition and quality of actual incoming supply, incorporating potential selection effects induced by the technology. The survey-based outcomes capture how the intervention affected the behaviors and perceptions of a fixed cohort of farmers. Both perspectives are essential for identifying the mechanisms at play: selection into supplying higher-quality milk is itself part of the theory of change, and observing it requires precisely this dual use of administrative-style testing data and survey follow-up.

Table 5 reports the results obtained from the analysis of supervised testing data. Average butterfat content of milk samples delivered to control MCCs was 3.88 percent; this increased to approximately 4.00 percent in MCCs equipped with analyzers. SNF shows a similar directional increase, but the estimate is not statistically distinguishable from zero with the current sample size. Protein—which is a component of SNF—shows no detectable change, consistent with the null finding for SNF.

In contrast, we observe clear improvements in adulteration-related measures. Milk delivered to treated MCCs contains significantly less added water, with a reduction of nearly half a percentage point relative to the control mean of 1.63 percent. Density (CLR) rises by 0.44 units, consistent with lower dilution and greater compositional integrity.

The composite index combining all five components mirrors these patterns, indicating a significant improvement of 0.21 standard deviations in overall milk quality. Taken together, these results suggest that the introduction of analyzers reduced adulteration and improved observable fat content, but had more limited effects on biologically determined components such as SNF and protein. This pattern is consistent with adjustments driven by changes in handling practices—such as reduced skimming or dilution—rather than by deeper shifts in feeding or production management, in line with the comparatively weak farmer-level behavioral responses documented in the previous subsection.

Table 5: Milk quality

	mean ctrl	analyzer	nobs
Butter fat (%)	3.881 (0.539)	0.114** (0.036)	2518
SNF (%)	8.579 (0.49)	0.081 (0.05)	2518
Added Water (%)	1.626 (3.682)	-0.488* (0.213)	2518
Protein (%)	3.163 (0.194)	0.029 (0.022)	2518
Density (CLR)	27.93 (2.31)	0.435* (0.197)	2518
Index	-0.103 (0.817)	0.209** (0.054)	2518

Note: Column 1 reports mean milk quality measures for the control group, with standard deviations in parentheses. Column 2 presents the average treatment effect of the MCC-level analyzer intervention, with robust standard errors in parentheses. Column 3 shows the number of non-missing observations. The index is an Anderson (2008) index of the five quality components, with added water entering with a negative sign. Standard errors are clustered at the catchment-area level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The treatment-on-the-treated estimates, presented in Appendix Table A8 for completeness, are generally less precisely estimated than the intention-to-treat (ITT) effects. The instrument only shifts the probability that an MCC consistently uses the analyzer, and the first stage is mechanically weaker than the underlying ITT assignment. As a result, the 2SLS estimator inflates sampling variability because it attributes all treatment effects to the subset of MCCs that actually complied with analyzer use. Moreover, if assignment affects outcomes partly through channels other than actual machine use—such as expectations, monitoring incentives, or changes in manager behavior—then the instrument captures only a fraction of the relevant variation, further reducing precision. Together, these factors imply wider confidence intervals for the LATE relative to the more precise ITT estimates.

11.2 Secondary outcomes

11.2.1 MCC level

A key question in understanding the effects of the MCC-level intervention is whether the treatment actually changed the visibility, availability, and operational use of the milk analyzers. These intermediate outcomes form the core impact pathway through which the intervention could influence milk quality, rejection practices, and price formation. Table 6 therefore reports several secondary measures intended to capture the uptake and functioning of the tech-

nology as observed by enumerators during the endline visit. Because these outcomes rely on direct observation and on-the-spot demonstrations, they offer an objective assessment of whether the treatment altered day-to-day practices at MCCs.

The first outcome captures whether the enumerator observed the project posters publicizing the milk analyzers and encouraging farmers to request their milk to be tested. This variable reflects both the visibility of the intervention to suppliers and the extent to which MCCs engaged in basic communication around quality measurement. The second outcome indicates whether a milk analyzer was physically observed at the MCC during the visit. A related variable distinguishes analyzers distributed through the project from machines obtained through alternative channels, thereby providing a direct measure of compliance with treatment assignment.

Functionality is assessed through an indicator based on the enumerator witnessing a successful real-time demonstration of the machine. This corresponds to the manager performing an on-the-spot test and the machine producing a result without technical failure. Finally, a last outcome variable captures whether the MCC used the digital record-keeping in the form of an application (including but not limited to the one developed as part of the project) or a file on a computer (generally an excel sheet).

The results show clear and sizable treatment effects on the visibility and presence of the technology. Treated MCCs are significantly more likely to display the poster, suggesting that assignment increased the outward communication of quality testing. The presence of a milk analyzer increases by roughly 53 percentage points, and the increase is even larger when restricting attention to analyzers supplied directly through the project. These effects confirm both compliance and the persistence of the physical hardware at the treatment sites.

The intervention also increased the likelihood that MCCs used digital tools to record quality and quantity traded. This reinforces the idea that the project induced complementary behavioral changes rather than simple adoption of a single physical asset. Because digital record-keeping addresses traceability and transparency—capabilities that are central to creating enforceable quality-linked transactions—this result is critical for understanding why some downstream outcomes (such as improved milk composition or reduced adulteration) are detectable despite relatively modest price adjustments.

11.2.2 Farmer level:

To understand whether the farmer-level components of the intervention were implemented as intended, and to assess the earliest steps along the behavioral impact pathway, we also examine a set of secondary outcomes capturing farmers' treatment exposure, compliance, and basic conceptual understanding of compositional quality. Table 7 reports these outcomes.

A first outcome simply asks whether the farmer recalls having been shown the informational video on milk quality during baseline. This directly captures exposure with the information treatment. A second outcome records whether

Table 6: Uptake and Operational Use of Milk Analyzers at MCCs

	mean ctrl	analyzer	nobs
Poster is visible (1=yes)	0.034 (0.183)	0.343** (0.068)	120
Milk Analyzer present (1=yes)	0.237 (0.429)	0.533** (0.078)	120
Project Milk Analyzer is present (1=yes)	0.085 (0.281)	0.637** (0.069)	120
Milk analyzer operational (1=yes)	0.237 (0.429)	0.369** (0.084)	120
MCC uses digital record-keeping (1=yes)	0.237 (0.429)	0.369** (0.084)	120
Index of uptake	-0.436 (0.44)	0.858** (0.108)	120

Note: column 1 reports the mean of each outcome for the control group, with standard deviations in parentheses. Column 2 shows the estimated treatment effect of the analyzer intervention at the MCC level, with robust standard errors in parentheses. Column 3 lists the number of MCCs with non-missing observations. All prices are in Ugandan shillings (UGX). The “Index of uptake” is an Anderson (2008) index of the variables listed above. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the farmer recalls the distribution of the pasture seed pack, which served as a simple extension-style nudge toward improved feeding practices. We also have an indicator variable for farmers actually planting the seed. This allows us to study exposure, recall, and behavioral follow-through.

The final outcome tests whether farmers can correctly identify practices that increase the compositional quality of milk. Farmers were presented with three pairs of options—each contrasting a hygiene-focused practice (such as washing hands or using clean containers) with a compositional-quality-focused practice (such as controlled grazing or using feed supplements). The individual answers are aggregated again using an Anderson (2008) index. This measure provides an objective assessment of whether the interventions shifted farmers’ understanding of what determines higher-quality milk.

The MCC-level intervention generates no detectable effects on any of the farmer-level outcomes. It does not increase recall of the video or seed, nor does it increase seed usage or improve farmers’ understanding of compositional quality. This is consistent with the intervention design: the MCC treatment targeted technology adoption and testing behavior at collection centers, not farmer education. The results therefore suggest limited spillover from improved analyzer use at MCCs toward farmer knowledge or practice, reinforcing the need for direct engagement when targeting farmer behavior.

In contrast, the video treatment produces clear and statistically precise effects on all but one outcome. Farmers assigned to the video intervention are

significantly more likely to recall both the video and the seed distribution. The video treatment also raises the probability of using the distributed seed, though not universally so, likely due to the fact that the season was exceptionally dry and some farmers decided planting the seed would be a waste.

We do not find that the farmer level intervention increased knowledge in the fully interacted model in Table 7. Results from the pooled model, reported in Table A9, are somewhat more encouraging. If we remove from the index the multiple choice questions we deem to be the most difficult, the coefficient does become significantly positive.

The composite index, which aggregates all farmer-level outcomes into a single measure, reinforces this conclusion. The video treatment leads to a substantial and statistically significant increase in overall uptake, while the MCC treatment shows no effect. Taken together, these results show that farmer-level behavioral change depends critically on direct information provision, whereas changes in practices at MCCs do not automatically trickle down to farmers without explicit communication or incentives.

12 Conclusion

Quality upgrading in smallholder-dominated value chains is often constrained by two interlinked problems: quality is difficult to observe at the point of aggregation, and actors along the chain hold misaligned perceptions of what “quality” actually means. In Uganda’s dairy sector, where raw milk from many farmers is quickly aggregated and tested only downstream, farmers face little incentive to invest in compositional quality, while processors lack the tools to reward higher-quality supply. As a result, markets for quality fail to emerge even in rapidly modernizing chains. This study examines whether reducing information frictions and making compositional quality visible earlier in the chain can shift behavior and support such a market’s development.

To answer this question, we implemented a multi-level field experiment introducing coordinated innovations at two nodes of the dairy value chain. At the midstream level, milk collection centers received digital milk analyzers, record-keeping tools, and farmer-facing information displays to make quality measurable, transparent, and traceable in real time. Upstream, farmers received an information intervention and a small complementary input designed to correct misperceptions about the determinants of compositional quality and to nudge adoption of quality-enhancing practices. This design allowed us to test whether technology-enabled monitoring (a pull factor) and improved producer knowledge (a push factor) can independently—or jointly—stimulate quality upgrading and reshape incentives throughout the chain.

Uganda’s dairy sector provided a particularly relevant context for examining these dynamics. The rapid expansion of cooling infrastructure, rising private investment, and growing processor demand have created the appearance of a modernizing value chain, yet quality assurance systems remains rudimentary. Most MCCs routinely assess only freshness and adulteration, while composi-

Table 7: Secondary outcomes at farmer level - uptake

	mean	analyzer	video	bundle	nobs
Remembers video	0.209 (0.407)	-0.022 (0.04) [0.367]	0.3** (0.04) [0.005]	0.012 (0.056) [0.538]	2059
Remembers receiving seed	0.251 (0.434)	-0.002 (0.046) [0.929]	0.32** (0.043) [0.038]	0.056 (0.054) [0.26]	2059
Used seed	0.171 (0.377)	-0.01 (0.043) [0.632]	0.213** (0.043) [0.22]	0.016 (0.056) [0.485]	2059
Knows compositional quality matters	-0.037 (0.767)	0.064 (0.086) [0.285]	0.029 (0.055) [0.915]	-0.027 (0.087) [0.373]	2059
Index of uptake	-0.211 (0.571)	0.017 (0.057) [0.813]	0.345** (0.05) [0.031]	0.011 (0.07) [0.888]	2059

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.

tional attributes such as butterfat, solids-not-fat, and protein are rarely measured at the point of aggregation. Farmers, for their part, associate “good quality” with cleanliness and hygiene rather than the compositional traits that processors value most and that determine processing yields. At the same time, prices are typically fixed, with little differentiation by quality and very limited traceability, weakening incentives for both farmers and intermediaries to invest in upgrading. These structural features — rapid commercialization without corresponding improvements in information flow, testing capacity, or aligned incentives — makes the Ugandan dairy value chain an ideal setting to test whether better measurement, communication, and farmer awareness could help overcome the longstanding barriers preventing the emergence of a functioning market for quality.

The interventions produced a mixed pattern of results. At the MCC level, the introduction of milk analyzers markedly increased the visibility, availability, and day-to-day use of quality-testing infrastructure, leading to substantial growth in both incoming and outgoing testing activity. This uptake was accompanied by clear improvements in objectively measured milk quality: treated MCCs received milk with higher butterfat content and significantly less added water, yielding a meaningful gain in overall quality. However, the intervention did not influence MCC buying or selling prices. The improvements in quality seem to reflected changes in handling and reduced adulteration rather than price-driven incentives or broader shifts in market structure.

A key insight that emerges when we map the empirical results back to the conceptual framework is that the per-unit quality premium α appears to be structurally zero in this setting. The model predicted that once quality becomes observable, $\alpha > 0$ would trigger both stricter screening at MCCs and stronger farmer responses. While we do observe the predicted adjustments in screening and a modest improvement in delivered quality, prices do not move at any stage of the chain. This pattern suggests that the downstream slope of the price schedule is fixed by market structure and contracting norms rather than by information frictions. In other words, the experiment made quality measurable and salient, but it did not activate the incentive channel that the model requires. The results therefore highlight that technological visibility is necessary but not sufficient, and that the binding constraint now lies in the rigidity of α rather than in the ability of upstream actors to respond to it.

There are different reasons for the rigidity of α . A first structural explanation relates to the pricing norms and governance practices of cooperatives. In many dairy cooperatives, including those operating in our study area, farmers are paid a uniform price per liter regardless of compositional quality. These uniform-price policies are often defended as preserving solidarity and minimizing conflict among members, but they also remove the possibility of transmitting individual-level incentives for quality upgrading. However, cooperatives could still respond to downstream quality premia at the collective level, even without differentiating prices internally, provided they are able to establish credible mechanisms for managing the free-rider and common-pool resources problems inherent in jointly supplied quality (Winfrey and McCluskey, 2005; Bonroy et al.,

2019). In practice, only cooperatives with strong internal governance, enforceable rules for monitoring and sanctioning members, and a shared understanding of the importance of compositional quality are likely to overcome these coordination frictions.

A second explanation concerns the way prices are set and revised in Ugandan dairy value chains. In our study area, processors typically operate with biweekly payment cycles, and purchase prices are fixed for the full 14-day period. This creates a built-in intertemporal rigidity: once prices are locked in for two weeks, buyers cannot immediately reward or penalize day-to-day variation in compositional quality, even when new information from analyzers becomes available. Such contractual arrangements limit the short-run pass-through of improved information into prices. This pattern is consistent with a broader literature showing that in agricultural markets characterized by repeated relationships, limited competition, and high search or coordination costs, prices are revised infrequently and adjust sluggishly to new signals (Macchiavello and Morjaria, 2015; Renner and Tyran, 2004).

A third reason relates to market structure and the potential for coordinated price setting among processors. The southwestern Ugandan dairy sector is highly concentrated, with a small number of processors purchasing the bulk of raw milk. If processors implicitly or explicitly coordinate on uniform base prices, individual MCCs have little incentive—or even room—to differentiate based on compositional quality, because doing so would erode already thin margins without guaranteed corresponding increases in the price they receive. This dynamic can suppress the emergence of quality premia even when reliable testing becomes available. There are, however, signs that this may evolve: a new large processor specializing in infant formula production has recently entered the market and has begun approaching MCCs to explore supplying under a quality-based payment scheme. Increased competition of this kind may weaken existing pricing coordination and create the conditions under which quality improvements would translate into higher farmgate prices in the future.

A fourth explanation concerns issues of scale and perceived system-wide capacity. Even if individual MCCs adopt testing technology and demonstrate improvements in compositional quality, processors may remain hesitant to introduce quality-differentiated pricing if they believe that too few suppliers can reliably participate. From a processor’s perspective, a quality-based payment system requires coordination, traceability, and consistent measurement across a broad supplier base; if only a small share of MCCs can test accurately and routinely, the administrative costs of implementing such a scheme may outweigh its benefits. Processors may also worry that offering premia to a subset of MCCs could create supply fragmentation or increase tensions with non-participating suppliers. As a result, processors may strategically delay the introduction of quality premia until testing capacity reaches a critical threshold in the supply base and the system acquires enough scale to function smoothly. In our context—where analyzer coverage was intentionally limited by the research design—processors may have viewed the improvements as too localized to warrant immediate changes in their pricing policies.

Looking ahead, the key challenge is to demonstrate to processors that paying for quality is privately profitable. Carefully designed pilots that vary the structure and magnitude of quality premia across seasons, combined with transparent cost–benefit calculations, can help reveal where and when such schemes generate net gains for downstream actors. Policy also has a role to play: clearer regulatory standards for testing capacity, traceability, and eligibility to supply the formal dairy sector could reduce processor concerns about scale and ensure that quality-differentiated pricing can be implemented system-wide. Continued investment and entry in processing—already visible in the region—may further increase competition and weaken the implicit coordination that currently sustains uniform pricing. Together, these developments could provide the final push needed for a transition toward quality-based payments of the kind observed in more mature dairy markets such as India.

13 Acknowledgments

During the preparation of this work the author(s) used OpenAI’s chatGPT in order to obtain editorial suggestions to improve clarity and readability and explore alternative phrasing for technical terms. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article. We would like to thank all funders who supported this research through their contributions to the CGIAR Trust Fund: <https://www.cgiar.org/funders/>. In particular, funding from the CGIAR Rethinking Food Markets Initiative and the CGIAR Science program on Better Diets and Nutrition is greatly appreciated. We want to thank Leocardia Nabwire, Wilberfoce Walukano and Marc Charles Wanume for field support. This research received clearance from 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).

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Online Appendix

Table A1: Balance of Baseline Characteristics Between Treatment and Control Milk Collection Centers (MCCs)

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

Note: This table reports baseline balance between MCCs assigned to the analyzer treatment and those in the control group. Column 1 presents control group means with standard deviations in parentheses. Column 2 shows the difference in means (treatment minus control) with robust standard errors in parentheses. Column 3 lists the number of non-missing observations. “Total tank capacity” is measured in liters and “MCC age” in years. The F-statistic and p-value correspond to a joint test of equality of all covariates. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Baseline Balance Between Control Farmers and Farmers Assigned to Analyzer, Video, or Bundle Treatments

	mean ctrl	analyzer	video	bundle	nobs
Household Members (number)	9.754 (4.687)	-0.122 (0.436)	-0.004 (0.31)	0.654 (0.478)	2261
Liters Produced Total Per Day (average during rainy season) (liters)	70.053 (61.477)	11.774 (8.554)	9.381 ⁺ (4.91)	-14.316 ⁺ (7.845)	2261
Normally during the rainy season sells most of its milk to a milk collection center? (1=yes)	0.793 (0.405)	0.01 (0.039)	0.001 (0.018)	0.017 (0.033)	2261
Uses only steel can/bucket during sales transactions in the last 7 days before survey? (1=yes)	0.752 (0.432)	0.1 [*] (0.049)	0.049 ⁺ (0.028)	-0.078 ⁺ (0.045)	2261
Member of dairy cooperative? (1=yes)	0.757 (0.429)	-0.104 [*] (0.051)	0 (0.022)	0.003 (0.038)	2261
F-statistic		1.283	0.605	1.322	
p-value		0.288	0.696	0.273	

Note: This table reports baseline balance across farmers in the control group and the three treatment groups (analyzer, video, and bundle). Column 1 shows control group means with standard deviations in parentheses. Columns 2–4 report differences in means relative to the control group, with robust standard errors in parentheses. Column 5 gives the number of non-missing observations for each variable. The F-statistic and p-value correspond to joint tests of equality of all covariates across groups. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Baseline Balance Between Control Farmers and Farmers Assigned to Analyzer, Video, or Bundle Treatments (pooled)

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

Note: The first column reports means for the pure control group, with standard deviations in parentheses. The remaining columns report differences in means for each treatment arm relative to its appropriate control group in the pooled sample, with robust standard errors in parentheses. Standard errors are clustered at the catchment-area level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Primary Outcomes for Milk Collection Centers (MCCs) – LATE

	mean ctrl	analyzer	nobs
Tested incoming milk using MA (1=yes)	0.288 (0.457)	1.445** (0.245)	120
Testing outgoing milk using MA (1=yes)	0.203 (0.406)	0.775** (0.22)	120
Price at which milk was bought from farmers (UGX)	1075 (92.556)	-42.06 (42.863)	115
Price at which milk was sold (UGX)	1199.576 (106.327)	9.892 (55.34)	108
Does the MCC pay a quality premium to suppliers?	0.186 (0.393)	-0.086 (0.194)	119
Did the buyer pay a quality premium?	0.186 (0.393)	0.084 (0.202)	119
Index of primary MCC outcomes	-0.077 (0.477)	0.429 (0.27)	103

Column 1 reports the mean of each outcome for the control group, with standard deviations in parentheses. Column 2 shows the estimated treatment effect of the analyzer intervention at the MCC level, with robust standard errors in parentheses. Column 3 lists the number of MCCs with non-missing observations. All prices are in Ugandan shillings (UGX). The “Index of primary MCC outcomes” is an Anderson (2008) index of the variables listed above. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Primary outcomes for farmers (pooled)

	mean	analyzer	video	bundle	nobs
Production investment and management	0.014 (0.562)	-0.02 (0.039)	0.044 ⁺ (0.024)	0.024 (0.048)	2054
Buyer checks for quality	0.157 (0.364)	0.07 (0.047)	0.016 (0.021)	0.086 (0.052)	1337
Price received for milk sold	1019.292 (99.211)	11.308 (9.852)	1.44 (5.104)	12.293 (11.954)	1254
Get quality premium	0.081 (0.274)	-0.016 (0.023)	-0.006 (0.014)	-0.022 (0.028)	1281
Index of primary farmer outcomes	-0.036 (0.488)	0.079 ⁺ (0.047)	0.038 (0.028)	0.119* (0.059)	1202

Note: Column 1 reports mean outcomes for pure control farmers (those not receiving the information treatment and linked to control MCCs), with standard deviations in parentheses. Columns 2–4 report pooled average treatment effects for the MCC-level intervention (T1), the farmer-level information intervention (T2), and their joint exposure, respectively. Each estimate is calculated relative to its appropriate control group in the pooled sample; robust standard errors are shown in parentheses. Square-bracketed values report p-values for tests of whether each treatment effect differs by connection type (directly to an MCC versus through a small trader). Column 5 gives the number of non-missing observations. Prices are in Ugandan shillings (UGX). The “Index of primary farmer outcomes” is an Anderson (2008) index of the outcomes listed. Standard errors are clustered at the catchment-area level. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A6: Primary outcomes for farmers — LATE

	mean	analyzer	video	bundle	nobs
Production investment and management (Index)	0.014 (0.562)	-0.204 (0.159) [0.185]	-0.122 (0.082) [0.053]	0.396* (0.173) [0.015]	2054
Buyer checked for quality (1=yes)	0.157 (0.364)	0.184 (0.18) [0.402]	0.021 (0.081) [0.573]	0.098 (0.19) [0.752]	1337
Price received for milk sold	1019.292 (99.211)	45.984 (49.426) [0.608]	7.568 (24.249) [0.982]	-9.206 (52.071) [0.886]	1254
Get quality premium	0.081 (0.274)	-0.002 (0.113) [0.798]	0.082 (0.072) [0.168]	-0.16 (0.157) [0.246]	1281
Index of primary farmer outcomes	-0.036 (0.488)	0.311 (0.256) [0.399]	0.085 (0.138) [0.653]	0.014 (0.3) [0.828]	1202

Note: Column 1 reports mean outcomes for pure control farmers (those not receiving the information treatment and connected to control MCCs), with standard deviations in parentheses. Columns 2–4 present the pooled main treatment effects of the MCC-level intervention (T1), the farmer-level information intervention (T2), and their combined exposure, respectively; robust standard errors appear in parentheses. Numbers in square brackets report p-values for tests of whether the treatment effect differs by the farmer's connection type (directly to an MCC versus through a small trader). Column 5 shows the number of non-missing observations. Prices are in Ugandan shillings (UGX). The "Index of primary farmer outcomes" is an Anderson (2008) index of the outcomes listed above. Standard errors are clustered at the catchment-area level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Primary outcomes for farmers (pooled LATE)

	mean	analyzer	video	bundle	nobs
Production investment and management	0.014 (0.562)	-0.057 (0.113)	0.043 ⁺ (0.024)	0.071 (0.137)	2054
Buyer checks for quality	0.157 (0.364)	0.195 (0.131)	0.02 (0.022)	0.256 (0.158)	1337
Price received for milk sold	1019.292 (99.211)	32.99 (29.183)	1.725 (5.311)	36.705 (36.979)	1254
Get quality premium	0.081 (0.274)	-0.042 (0.063)	-0.007 (0.014)	-0.062 (0.083)	1281
Index of primary farmer outcomes	-0.036 (0.488)	0.22 ⁺ (0.131)	0.039 (0.03)	0.338 ⁺ (0.173)	1202

Note: Column 1 reports mean outcomes for pure control farmers (those not receiving the information treatment and linked to control MCCs), with standard deviations in parentheses. Columns 2–4 report pooled average treatment effects for the MCC-level intervention (T1), the farmer-level information intervention (T2), and their joint exposure, respectively. Each estimate is calculated relative to its appropriate control group in the pooled sample; robust standard errors are shown in parentheses. Square-bracketed values report p-values for tests of whether each treatment effect differs by connection type (directly to an MCC versus through a small trader). Column 5 gives the number of non-missing observations. Prices are in Ugandan shillings (UGX). The “Index of primary farmer outcomes” is an Anderson (2008) index of the outcomes listed. Standard errors are clustered at the catchment-area level. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01 .

Table A8: Milk quality - LATE

	mean ctrl	analyzer	nobs
Butter fat (%)	3.881 (0.539)	0.395 ⁺ (0.204)	2491
SNF (%)	8.579 (0.49)	0.247 (0.171)	2491
Added Water (%)	1.626 (3.682)	-1.533 (1.045)	2491
Protein (%)	3.163 (0.194)	0.091 (0.072)	2491
Density (CLR)	27.93 (2.31)	1.289 ⁺ (0.737)	2491
Index	-0.103 (0.817)	0.675* (0.204)	2491

Note: Column 1 reports mean milk quality measures for the control group, with standard deviations in parentheses. Column 2 presents the average treatment effect of the MCC-level analyzer intervention, with robust standard errors in parentheses. Column 3 shows the number of non-missing observations. The index is an Anderson (2008) index of the five quality components, with added water entering with a negative sign. Standard errors are clustered at the catchment-area level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Secondary outcomes at farmer level (pooled) - Uptake

	mean	analyzer	video	bundle	nobs
Remembers video	0.209 (0.407)	-0.006 (0.031)	0.326** (0.021)	0.29** (0.05)	2059
Remembers seed	0.251 (0.434)	0.003 (0.029)	0.391** (0.02)	0.374** (0.047)	2059
Used seed	0.171 (0.377)	-0.004 (0.028)	0.25** (0.019)	0.22** (0.052)	2059
Knows compositional quality matters	-0.037 (0.767)	0.039 (0.069)	0.057 (0.035)	0.065 (0.091)	2059
Index of uptake	-0.211 (0.571)	0.016 (0.041)	0.405** (0.028)	0.372** (0.066)	2059

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.