Signed, Sealed, Delivered: Digital Receipts in the Ugandan Dairy Chain*

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Abstract

Based on a randomized experiment with dairy cooperatives in western Uganda, we provide causal evidence that SMS-based digital receipts for daily milk deliveries improve accountability, product quality, and delivery frequency. In a context of weak monitoring and imperfect transaction information, these messages allow smallholder farmers to better observe the behavior of intermediaries in the supply chain. The intervention effects vary with the intensity of information frictions. Among farmers facing a high level of information friction (i.e., those relying on intermediaries to transport the product), the intervention increased their detection of discrepancies and encouraged switching from dishonest intermediaries. Farmers in low-friction settings (those who deliver their own product) delivered milk more frequently; the likely mechanism was the nudge provided to these farmers when they received messages both on days that they made deliveries and days that they did not. We also found that the intervention increased milk quality for both self-deliverers and farmers using transporters. Overall, we provide evidence that simple digital tools can reduce information asymmetry and strengthen accountability in smallholder supply chains.

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1 Introduction

In many agricultural markets, especially in low- and middle-income countries (LMICs), high levels of fragmentation generate multiple frictions from the large number of small transactions. These frictions make it difficult for markets to function effectively, affecting productivity, revenues, and profitability. As a result, smallholder farmers often struggle to access larger markets at reasonable costs and to receive fair compensation for their products.

Cooperatives have emerged as a common response to the fragmentation in agricultural value chains, allowing farmers to pool their output and sell collectively to increase their bargaining power and reach larger markets. However, many frictions remain even within the cooperative structure. Because cooperatives serve small farmers, they rely on large membership bases and a high volume of small transactions to stay in business. This structure generates substantial transaction costs, including measurement, transportation, and monitoring costs, which make it difficult for cooperatives to operate efficiently, even as they help address market failures from fragmentation.

Depending on distance and transportation options, some farmers deliver their products themselves, while others rely on informal service providers to transport and sell their goods, often without visibility into what happens after collection. These information frictions open the door to inefficiencies and opportunistic behavior. While these issues might be more severe for small agricultural producers, similar dynamics arise in several other markets where producers depend on intermediaries. For example, Bai (2021) shows how watermelon intermediaries exploit asymmetric information to pass off low-quality produce as higher-quality. Likewise, in input markets, local agents may adulterate fertilizer or seed, reducing trust and efficiency (Bold et al., 2017). In Uganda's coffee sector, Bai et al. (2025) show that premiums for quality dissipate before reaching farmers, as buyer power and layers of intermediation remove incentives for high-quality production. Beyond agriculture, Björkman et al. (2022) document how information frictions allow low-quality and counterfeit antimalarial drugs to enter and persist in the market. In each case, hidden actions, combined with weak monitoring and limited enforcement, create scope for opportunistic behavior by intermediaries, undermining both trust and efficiency in these markets.

This paper examines these dynamics in Uganda's dairy sector, where smallholder farmers deliver their milk to cooperatives. Farmers in this context face two options for delivery: they can use transporters, who are usually hired informally and may engage in opportunistic behavior, or they can self-deliver, which requires time that could otherwise be spent on production or other tasks. For those who rely on transporters, these intermediaries typically hold important informational advantages. They observe what happens to the milk after collection, including any dilution that affects quality and the actual quantity delivered at the cooperative. Such asymmetries create opportunities for strategic behavior and misreporting, ultimately undermining farmers' earnings and weakening trust in the supply chain.

For instance, transporters may under-report milk volumes, reducing the amount credited to farmers. They may also siphon off milk from containers and deliver it to whichever collection center offers cash payments in the spot market. Additionally, transporters may dilute milk with water to artificially inflate volumes, profiting from the additional liters by siphoning them off. This can have substantial impacts on milk quality, and can harm farmers' reputations and revenues. Prices change daily and farmers are paid biweekly[1] in lump sums without timely data on deliveries, making discrepancies difficult to detect and harder to punish. As a result, formal contract enforcement is largely ineffective.

Even though farmers make the delivery decision, timing differs fundamentally depending on how farmers deliver their milk. Farmers who self-deliver make an active decision each day about whether to deliver and how much to deliver, taking into account their own transportation constraints; most of these farmers rely on bicycles or walking. In contrast, farmers who rely on transporters face two key constraints. First, the decision to deliver must be made in advance, since pick-up frequency and timing need to be coordinated and scheduled with the transporter ahead of time. Second, the volume that can be sent is limited by the transporter's available capacity at the time of pick-up. Although both types of farmers ultimately make the decision on whether and how much to deliver, the timing of the decision differs. Because farmers who use transporters schedule pick-ups in advance, their delivery behavior is stickier than those who self-deliver.

Building on Holmström (1979) and Levin (2003), this paper examines whether improving transparency in post-harvest transactions through a digital tool can mitigate information frictions in a context of relational contracts—those based on ongoing relationships—under low monitoring. We study the introduction of a digital receipt system that sends farmers SMS messages reporting the daily quantities of milk that were delivered and recorded at the cooperative on their behalf. The intervention was designed to improve farmers' ability to monitor transporter behavior, adjust delivery arrangements if needed, potentially increase milk deliveries, and reduce opportunities for quality-related misconduct by transporters. Most of the literature about this type of intervention focuses on information frictions between farmers and buyers; we shift the focus to a key component of agricultural firms' production function (transportation) by addressing frictions between farmers and transporters, who facilitate the movement of goods without taking ownership. Moreover, while SMS interventions typically target information frictions during pro-

[1] We refer to two-week periods as a biweek.

duction, we target post-harvest frictions through a monitoring mechanism designed to make transactions at cooperatives observable and transparent to farmers. Lastly, we are able to explore whether the impact of the digital receipt is different depending on the intensity of the information frictions. To do so, we compare the outcomes for farmers using transporters (i.e., those with high information frictions) to those for self-delivery farmers (those with low information frictions) in order to understand how technology can enhance accountability along the value chain. The dairy sector provides a particularly useful setting to answer these questions, because the perishability of milk means that post-harvest transactions occur daily. This offers a unique opportunity to study how improved transparency shapes behavior with rich high-frequency data.

We collected high-frequency administrative data from cooperatives, including daily milk prices, volume of milk sold by each farmer, farmer revenues, and the transporters used. We complemented these records with farmer and transporter surveys, as well as random visits to cooperatives to collect milk quality data. The intervention linked cooperative records to a digital SMS platform. Each time a farmer's milk was delivered, whether directly or through a transporter, the cooperative manager recorded the transaction in the receipt book, as was standard practice. Treated farmers received an SMS with a daily breakdown of their deliveries, including days when they did not deliver milk. In other words, if no delivery occurred, the cooperative recorded a zero, and the system sent an SMS reflecting this to the farmer. Our team digitized these records, and the system then generated and sent an SMS to the farmer confirming the date, quantity, and cooperative of delivery. In this way, paper-based records were transformed into verifiable digital receipts, providing farmers with near-real-time information about their deliveries.

We find that the intervention worked differently depending on the presence of information frictions. Among farmers with high frictions—those relying on transporters—treated farmers were almost 20 percentage points more likely to detect discrepancies and 14 percentage points more likely to switch their baseline transporter, relative to non-treated peers. They were also less likely to report trust in their current transporter. In addition, digital receipts improved milk quality, with treated farmers delivering less diluted milk, particularly among transporter users.

By contrast, among farmers with low frictions—those who self-deliver—the effects were concentrated on participation and moderate quality improvements. Treated self-deliverers were significantly more likely to deliver, both during and after the intervention, and showed modest gains in milk quality. However, the average volume of self-deliverers did not change.

Overall, these findings show that improving observability through digital receipts can shift farmer behavior along several margins, even without price premiums or formal enforcement. Even in low-friction settings, a tool aimed at reducing information frictions increased farmers' delivery frequency through a behavioral nudge. The intervention helped farmers monitor transporter behavior more closely, increased accountability, and led many to adjust their delivery decisions. Changes in delivery frequency, product quality, and transporter switching, despite relatively constant volumes, suggest that better information makes it easier for farmers to navigate these markets.

This study contributes to three strands of literature. The first is the literature on information frictions in agricultural value chains and rural markets (Anagol, 2017; Bai, 2021; Bergquist & Dinerstein, 2020; Bernard & Spielman, 2009; Bold et al., 2017, 2022; Mitra et al., 2018; Neupane et al., 2023; Roba et al., 2018, Saitone et al., 2018). We contribute to this literature by focusing on information frictions between actors in the middle of the value chain, such as transporters and other intermediaries, who facilitate the movement of goods without assuming ownership. This paper also provides insights into the behavioral responses of both farmers and transporters to the erosion of transporters' informational advantages. Analyzing the response of both farmers and transporters to the digital receipts allows us to understand how promoting transparency and observability affects the entire market.

Second, this study contributes to a growing literature on how digital technologies can reduce information frictions and improve market functioning in agriculture (Aker & Mbiti, 2010; Fabregas et al., 2019; Jensen, 2007). While previous work has primarily emphasized digital tools that support farmer decisions at the production stage, our study focuses on improving observability and accountability in post-harvest transactions. By evaluating a simple intervention, we show how digital tools can improve transparency in settings where monitoring is limited and formal enforcement mechanisms are weak.

Lastly, due to the contract structure, this study also relates to the recent literature on relational contracts (Blouin & Macchiavello, 2019; Levin, 2003; Macchiavello, 2022; Morjaria & Macchiavello, 2015, 2020; Startz, 2019). The dairy supply chain in Uganda features informal, repeated interactions between farmers and transporters, making it a natural setting for relational contracting. These relationships are largely trust-based, and information asymmetries within them create space for opportunistic behavior. Our evidence shows that when one party detects misbehavior by the other, trust breaks down and relationships are often terminated or replaced. We contribute to this literature by investigating how the behavior of each actor and the structure of the relational contract shift when one party gains access to verifiable information about the other's actions. More broadly, we identify causal impacts of improved observability on product quality in an agricultural supply chain with informal, trust-based contracts, and document how greater transparency alters the dynamics of trust, misbehavior, and relationship turnover in these relational contracts.

This paper is organized as follows. Section 2 describes the study context, including the structure of Uganda's dairy sector, seasonal production patterns, and the milk delivery process. Section 3 describes the digital receipts intervention. Section 4 presents the conceptual framework and outlines predictions about the effects of the digital receipt intervention across different types of farmers. Section 5 details the experimental design, randomization strategy, timeline of the intervention, and data sources, and provides descriptive statistics. Section 6 outlines the empirical strategy used to estimate treatment effects across different margins. Section 7 presents the main results, including effects on delivery volumes, milk quality, and the mechanisms driving these outcomes. Section 8 concludes with broader implications, policy recommendations, and directions for future research.

2 Study Context: Uganda's Dairy Sector

Uganda's dairy sector accounted for about 7% of the country's agricultural GDP in 2023 (DDA, 2023), with roughly 2.3 million households engaged in dairy farming as of 2021 (UBOS, 2024). The sector is highly fragmented, as millions of smallholder farmers sell only a few liters each day to local milk collection centers or dairy cooperatives (Van Campenhout et al., 2021, 2022). Cooperatives play a central role in this fragmented market by aggregating supply, enabling smallholder farmers to collectively access larger buyers and negotiate better prices. However, prices fluctuate daily depending on market conditions and overall supply, and cooperatives do not guarantee prices to farmers until the milk is sold. Farmers are typically paid every two weeks in a lump sum without a detailed breakdown of daily deliveries or prices, limiting their ability to track volumes and revenues over time. Beyond market access, cooperatives often provide additional services such as veterinary care, livestock drugs, and financial services, making them a critical institution for rural livelihoods and an essential component of Uganda's agricultural landscape.

2.1 Seasonality and Dairy Production in Uganda

Dairy production in Uganda is highly influenced by seasonal variation, particularly the alternation between rainy and dry periods. During the rainy season, pasture and water are more abundant, leading to better nutrition and higher milk yields. Cows have more access to quality forage, and the temperature is less stressful for them, both of which contribute to increased milk production. Conversely, during the dry season, pasture quality is lower, water sources become scarce, and cows often suffer from heat stress and nutritional deficits, leading to a decline in milk productivity.

Uganda experiences a bimodal rainfall pattern, with two rainy seasons and two dry seasons. In the western region of Uganda, the first rainy season typically spans from March to May, peaking in April, and the second occurs from September to November, with a peak in October and November. The driest months are June and July, with another relatively dry period in January and February. The crop calendar is aligned with these patterns. Seasonal factors directly affect livestock productivity through the availability of forage and pasture.

These seasonal dynamics are particularly consequential for small-scale farmers, many of whom operate with limited resources and small herds, primarily composed of a local breed: Ankole cows. While this breed is well-adapted to local climatic conditions, it is less productive than others in terms of milk output. A subset of these farmers—whom we refer to as *seasonal farmers*—either deliver only sporadic quantities of milk or stop delivering altogether during the dry season. In these months, the combination of pasture scarcity and limited water access leads to milk yields so low that market participation is not viable. Some farmers may instead use the little milk they produce for home consumption rather than sale.

As a result, pronounced seasonal fluctuations in milk deliveries to cooperatives are common in our setting, underscoring the importance of accounting for farmer heterogeneity when designing and evaluating interventions in the dairy value chain.

2.2 Milk Delivery Process

Milk delivery to the cooperative in Uganda follows a process that involves several steps. First, farmers (or transporters) bring fresh milk to the cooperative, where it is unloaded and prepared for inspection. Upon arrival, the milk goes through a quality and volume check; each batch is tested to ensure it meets the cooperative's quality standards. To discourage practices such as dilution with water, which artificially inflates volume while compromising quality, most cooperatives enforce a minimum specific gravity threshold to test for quality, typically measured using a lactometer[2]. In this setting, a reading of at least 26 degrees is often required to qualify for acceptance. Milk below this quality threshold is rejected by the cooperative. This quality control mechanism ensures that the milk collected and sold by the cooperative aligns with the standards demanded by downstream buyers, such as processors and traders.

Only milk that passes this quality threshold is accepted and formally recorded by the cooperative. Once accepted, the transaction enters a biweekly (two-week) payment cycle. During this period, milk deliveries are recorded daily, and payments are disbursed as a lump sum at the end of the cycle. Farmers

[2]As cooperatives grow, they often adopt milk analyzers, which provide additional quality metrics such as fat content.

are paid a uniform price per liter, regardless of milk quality; the price can vary daily to reflect changes in market conditions or cooperative policies. Transporters typically receive a fixed rate of 100 Ugandan shillings (UGX) (about 0.03 USD) per liter. If the transporter is hired independently by the farmer, the farmer pays the transporter directly. If the transporter is contracted by the cooperative board, the cooperative pays the transporter by deducting transportation costs from the farmer's earnings.

2.3 Mobile Phone Usage

As noted by Fabregas et al. (2019), the rapid spread of mobile phones in developing countries has created new opportunities to deliver timely and customized agricultural extension services at scale. In our study, the intervention was delivered via text messages (SMS), making access to a functional mobile phone a necessary condition to be treated. According to the 2023 Annual Communications Sector Report by the Uganda Communication Commission, the penetration of mobile phones in the country is 81%. In other words, 8 out of every 10 Ugandans have a mobile phone. To ensure that all farmers in our sample were able to receive digital receipts, we conducted a phone validation census in August 2024. Through this exercise, we successfully validated phone numbers for 688 out of the 766 farmers, representing about 90% of our sample.

3 Digital Receipts Intervention

The intervention introduced an SMS-based digital receipts system to improve record keeping and transparency in milk transactions between farmers and dairy cooperatives. Each time a farmer delivered milk, either directly or through a transporter, the cooperative recorded the quantity and ran the quality tests. These records were then entered on a digital platform by our team. This information was then sent via SMS to the farmer's phone twice a week—every Monday and Thursday. The Monday message covered deliveries from the previous Thursday through Sunday, and the Thursday message covered deliveries from the previous Monday through Wednesday. It is important to note that all treated farmers received a message on each *message* day, even if they made no deliveries; in such cases, the message explicitly indicated zero deliveries.

The content of the digital receipts included a personalized breakdown of delivery volumes and the name of the cooperative. For example:

> *"Your milk was delivered to [COOP NAME]. Here is a breakdown of your deliveries:*
>
> *2-SEPT: 24 L*

3-SEPT: 0 L

4-SEPT: 19 L.

Thank you!"

The idea behind the digital receipts was simple: reduce information frictions in the supply chain. Without them, farmers get paid every two weeks in a lump sum, with no breakdown of daily deliveries or prices. Combined with price fluctuations, this makes it hard for farmers to verify how much milk was recorded or to detect discrepancies, especially when using a transporter. By giving farmers timely, itemized information, the digital receipts aimed to increase transparency, strengthen accountability, and change the way farmers interact with both transporters and cooperatives.

4 Conceptual Framework

Our study evaluates whether introducing digital receipts—SMS messages reporting the quantity and date of each delivery—can reduce information frictions at the early stage of the dairy value chain. In Uganda, most farmers (whether they self-deliver or rely on transporters) use cooperative payments as the main signal of whether deliveries were accurately recorded. Conceptually, digital receipts serve as a monitoring technology that enhances transparency among farmers, transporters, and cooperatives by improving the quality and timeliness of the information. This makes it easier for farmers to spot potential discrepancies, identify dishonest behavior, and take corrective action. By transforming previously unobservable actions into verifiable outcomes, digital receipts improve the signal associated with delivery behavior at the cooperative. This reduces moral hazard, strengthens accountability, enhances observability, and shifts the equilibrium of repeated farmer–transporter interactions toward more honest behavior.

We model farmer–transporter relationships as repeated games under two scenarios: high information frictions for transporter users and low frictions for self-deliverers. For transporter users, cheating may yield short-term gains for the transporter but risks future punishment (e.g., losing the client or being fired). Without monitoring, discrepancies are difficult to detect, weakening punishment strategies. Digital receipts raise both the probability of detection and the potential benefits of switching away from dishonest transporters in a competitive environment with low switching costs. As a result, digital receipts make honest behavior by transporters incentive-compatible.

On the other hand, for self-deliverers, where information frictions are minimal, digital receipts might alleviate concerns about potential under-reporting by cooperative staff. While such concerns are likely minimal for most self-delivery farmers, they may still arise because farmers do not have access to the cooperative's records, even when making their own deliveries. More importantly, self-deliverers decide each day whether to deliver (extensive margin) and how much to deliver (intensive margin). By contrast, transporter users typically pre-arrange pickups. As a result, their day-to-day decisions are limited to the intensive margin (how much to deliver, if anything), since the extensive margin decision (whether to deliver) has been made in advance.

4.1 Hypothesis

Under the high information frictions scenario (among farmers who use transporters), we expect a reduction in under-deliveries, because digital receipts increase the likelihood that cheating, such as volume skimming, is detected. In other words, we expect a greater volume of milk to be delivered on behalf of treated farmers, reflecting an improvement along the intensive margin. Additionally, treated farmers in this group should be more likely to detect discrepancies between what was picked up and what was delivered; as a result, they should be more likely to switch away from dishonest transporters, especially when switching costs are low and transporter competition is high. The effect on milk quality remains an empirical question. It depends on two factors: how transporters respond to the increased transparency introduced by digital receipts and who holds the upper hand in terms of bargaining power and enforcement capacity within the relational contract between farmers and transporters.

Finally, under the low information frictions scenario, for farmers who deliver milk themselves, we expect that improved transparency may lead to changes on both the extensive and intensive margins. In other words, we expect an increase in the likelihood of delivering on a given day, as well as greater quantities delivered when they do. That said, the transportation constraints faced by most self-delivering farmers may limit their ability to make large changes on the intensive margin. Therefore, we primarily expect to observe effects along the extensive margin.

We also expect treatment effects to materialize gradually, rather than immediately, due to a learning process. Farmers must first validate the accuracy of the digital receipts and confirm that the information they receive matches cooperative records. This verification process is likely to take between one and two payment cycles (roughly two to four weeks), depending on the frequency with which farmers deliver milk early in the intervention period.

5 Experimental Design

We partnered with the Ugandan Dairy Development Authority (DDA) to implement the SMS intervention as a randomized controlled trial (RCT) across 13 dairy cooperatives in Western Uganda. The study covers about 150 villages across four districts and includes 766 dairy farmers who regularly sell milk to their cooperative. Each farmer sells milk to a specific cooperative.

Farmers were randomly assigned to one of two groups:

- **Treatment Group** (378 farmers): Farmers received digital receipts (via SMS) detailing the volumes of milk recorded at the cooperative. Messages were delivered in RuNyankore—the local language—from a consistent caller ID[3].

- **Control Group** (388 farmers): Farmers continued under the status quo and did not receive any digital receipts.

Randomization was carried out at the farmer level and was stratified by:

1. Cooperative size

2. Whether the farmer was a *seasonal farmer*. As mentioned in Section 2, *seasonal farmers* are those who deliver only sporadic quantities of milk or stop delivering altogether during the dry season

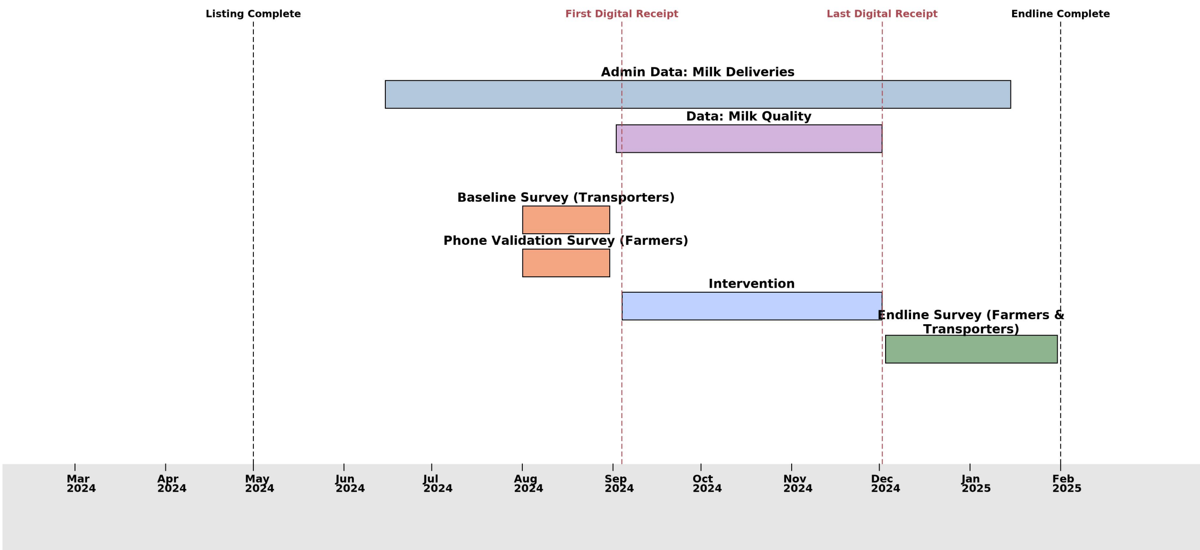
3. Average daily milk volume delivered to the cooperative during the last payment period, conditional on delivering a positive amount

5.1 Data Collection and Treatment Rollout

Baseline data collection took place in August 2024. These activities included a phone validation survey (completed for 688 farmers) and a baseline survey with 74 transporters. Treated farmers received an introductory message on September 4, 2024, informing them that they would begin receiving digital receipts twice per week. The first digital receipt was sent to treated farmers on Thursday, September 5, 2024, covering the deliveries done from Monday, September 2, through Wednesday, September 4, 2024. The last digital receipt was sent on December 2, 2024.

In collaboration with the cooperatives in our sample and the Uganda Dairy Development Authority, we assembled a rich dataset combining administrative records, market prices, and survey data:

[3] We acquired a caller ID through Uganda's two largest mobile service providers, Airtel and MTN, allowing all digital receipts to be sent from a unified sender ID labeled `DAIRY`, regardless of the service provider used by farmers.



- **Administrative data** from cooperatives, include daily volumes delivered, prices, payments, and the transporter associated with each delivery. These data span the pre-treatment, treatment, and post-treatment periods. To ensure accuracy, an enumerator visited each cooperative daily to verify that the digital records matched the cooperatives' records.

- **Survey data** include a phone validation survey and baseline in August 2024, and endline surveys in December 2024.

5.2 Data

We collected three main types of data. First, high-frequency administrative data was obtained from the cooperatives. These records include every delivery made by the farmers in our sample over a seven-month period, from June 15, 2024, to January 15, 2025. Additionally, using administrative data from the cooperatives, we identified the farmers who used transporters and the farmers who delivered their own milk. Second, during the treatment period, an enumerator visited one randomly selected cooperative from our sample each day and collected milk quality data using a lactometer for all farmers who delivered milk on that day. We use these enumerator-reported lactometer scores to examine whether the digital receipt intervention had any effect on milk quality. Lastly, we collected survey data from both farmers and transporters. Baseline surveys were conducted in August 2024. The farmer phone validation survey was conducted by phone, with the primary goal of confirming the phone numbers of farmers in our sample. Once the team confirmed that a phone number belonged to a participating farmer, a short survey was administered. The survey covered questions on distance to the cooperative, transporter use, and milk production, in order to complement the administrative data used for randomization. The baseline survey of transporters was conducted in person at the cooperative where each transporter regularly makes deliveries. The primary objective of this survey was to better understand each transporter's client base, daily delivery routes, socioeconomic background, and any additional income-generating activities in which they engage. Lastly, we conducted in-person endline surveys with all transporters serving the cooperatives in our sample, as well as with a randomly selected subset of farmers across groups. These endline surveys captured changes in behavior and perceptions related to milk delivery, milk quality, transporter trustworthiness, and the use of digital receipts.

5.3 Descriptive Statistics

We begin by describing the key characteristics of both agents (transporters) and principals (farmers). The data combines information from our baseline transporter survey, administrative records from dairy cooperatives, and an endline survey of farmers.

5.3.1 Transporter Characteristics

Table 1 presents descriptive statistics from the baseline survey of 74 transporters operating across 13 cooperatives. About 32% of transporters in our sample are also dairy farmers. Transporters in our sample are, on average, 33 years old, with ages ranging from 18 to 74. Each transporter serves approximately 8.5 farmers, though this varies significantly, with some working with as few as one and others with up to 29 farmers. Transporters report making just over two trips per day[4], and 77% of them own their own motorcycle. On average, each cooperative works with 4.7 transporters. These statistics highlight the heterogeneity in characteristics and the operational scale of milk transporters.

5.3.2 Farmer Sample and Baseline Balance

Our study includes 766 farmers randomly assigned at the individual level to treatment ($n = 378$) or control ($n = 388$), stratified by cooperative size, delivery volumes in the last payment period, and seasonal farmer status. Table 2 shows baseline balance checks using both administrative data and phone survey responses. There are no statistically significant differences between treatment and control groups in key baseline characteristics, including validation of phone number, distance to the cooperative, average

[4] A trip is defined as a single drop-off at the cooperative, which may follow one or multiple farmer pickups. In other words, each delivery to the cooperative constitutes one trip, regardless of how many farmers were visited.

daily liters delivered, use of a transporter, or whether the transporter was hired by the cooperative. A joint F-test across these variables yields a p-value of 0.962, confirming that treatment and control groups are statistically comparable at baseline.

5.3.3 Farmer Demographics and Milk Production

Table 3 shows descriptive statistics from the endline survey of 396 farmers who were randomly selected from our sample and illustrates the socioeconomic and production characteristics of our sample. The average farmer is approximately 53 years old and lives in a household with about 7 members. They own an average of 10 productive cows and produce approximately 45 liters of milk per day. Of this, about 27 liters are sold to the cooperative, while the rest is either consumed at home or sold to other buyers, such as private collection centers, traders, or restaurants and other local small businesses.

On average, farmers sell to 1.2 buyers, indicating relatively limited marketing channels. About 62% of farmers report using a transporter to deliver milk to the cooperative. This figure is consistent with baseline administrative records and underscores the prevalence of transporter use in the dairy supply chain.

Together, these statistics offer a detailed snapshot of the key actors in our study and underscore the central role played by transporters in shaping farmer access to cooperative markets.

5.4 Milk Quality Data

During the treatment period, an enumerator visited one randomly selected cooperative from our study sample each day. At each visit, the enumerator recorded milk quality using a lactometer for every farmer who delivered milk to the cooperative that day. These measurements allow us to construct a consistent measure of milk quality over time. We use the enumerator-reported lactometer scores to estimate the effect of the digital receipt treatment on milk quality.

There are a couple of limitations to collecting milk quality data at the point of delivery rather than at the farm level. First, we are unable to observe milk quality when it left the farm, meaning our measure reflects quality after any tampering by the transporter may have occurred. Second, small-scale farmers often share transportation containers. To reduce costs, transporters typically collect and mix milk from multiple farmers at the farm level until the container is full. In such cases, only one lactometer reading was taken for the shared container, and this value was assigned to all farmers contributing to that delivery, which could potentially attenuate the estimated treatment effect on milk quality.

6 Empirical Strategy

6.1 Analysis of Digital Receipts and Information Frictions

First, to assess whether digital receipts helped reduce information frictions for transporter users, we use survey data and implement the following empirical strategies:

$$Y_i = \rho_1 \cdot Treat_i + \tau_s + \varepsilon_i \tag{1}$$

In this specification, Y_i represents the outcome for individual i. We focus on the following outcomes: (i) the farmer's ability to detect discrepancies between what they sent to the cooperative and what was actually delivered and recorded at the cooperative, (ii) whether the farmer switched from their baseline transporter after the intervention, and (iii) the level of trust the farmer has in their transporter after the intervention. $Treat_i$ is a binary indicator for whether the individual was assigned to the treatment group. The model includes strata fixed effects τ_s to account for the stratified randomization design. Standard errors are clustered at the individual level, because treatment was randomized at that level.

Together, these strategies allow us to estimate both average and dynamic treatment effects on milk deliveries, quality, delivery likelihood, and potential mechanisms. In the next section, we present the main empirical results from this analysis.

6.2 Milk Quality Analysis

To examine both the overall treatment effect on milk quality and how it varies with the intensity of information frictions, we use the following empirical strategies:

$$Y_{it} = \beta_1 \cdot Treat_i + \tau_s + \rho_t + \varepsilon_{it} \tag{2}$$

$$Y_{it} = \beta_1 \cdot Treat_i + \beta_2 \cdot Treat_i \cdot SelfDeliver_i + \tau_s + \rho_t + \varepsilon_{it} \tag{3}$$

In this specification, Y_{it} represents the outcome for individual i at time t, and $Treat_i$ is a binary indicator for whether the individual was assigned to the treatment group. The variable $SelfDeliver_i$ is a binary indicator equal to one for farmers who delivered their own milk at baseline (i.e., did not use a transporter). The model includes strata fixed effects τ_s to account for the stratified randomization design and month fixed effects ρ_t to control for temporal shocks common across cooperatives. Although treatment is randomized at the farmer level, milk quality was measured at cooperative visits where the enumerator recorded lactometer readings for all farmers delivering that day. To account for this design, the standard errors are clustered at the cooperative level using wild bootstrapping, following Cameron et al. (2008).

6.3 Extensive Margin Analysis: Delivery Likelihood

To estimate the effect of the intervention on deliveries, we explore dynamic treatment effects on the extensive margin, measured by the likelihood of making a delivery. The outcome variable is defined as a binary indicator equal to one if a farmer made a delivery on a given day, and zero otherwise. This design takes advantage of the seven months of administrative panel data we collected on milk deliveries, allowing us to examine both pre-trends and dynamic treatment effects. In addition to estimating the overall treatment effect, we also test whether these effects differ by the intensity of information frictions by comparing self-delivering farmers (low frictions) with farmers who rely on transporters (high frictions). We estimate an event-study model using the following specifications:

$$Y_{it} = \sum_{\substack{j=-7 \\ j\neq -1}}^{7} \mathbb{1}(t - t_i^* = j) \cdot \tau_j \cdot Treat_i + \alpha_i + \psi_t + \varepsilon_{it} \tag{4}$$

$$\begin{aligned} Y_{it} = & \sum_{\substack{j=-7 \\ j\neq -1}}^{7} \mathbb{1}(t - t_i^* = j) \cdot \tau_j \cdot Treat_i \\ & + \sum_{\substack{j=-7 \\ j\neq -1}}^{7} \mathbb{1}(t - t_i^* = j) \cdot \omega_j \cdot Treat_i \cdot SelfDeliver_i \\ & + \alpha_i + \psi_t + \sum_{\substack{j=-7 \\ j\neq -1}}^{7} \mathbb{1}(t - t_i^* = j) \cdot \lambda_j \cdot SelfDeliver_i + \varepsilon_{it} \end{aligned} \tag{5}$$

where Y_{it} denotes the outcome variable—whether or not they deliver—for individual i at time t, $\mathbb{1}\{t - t_i^* = j\}$ is an indicator for time relative to the last biweek prior to the intervention t_i^*, and $Treat_i$ is a binary indicator equal to one if individual i was part of the treatment group. The variable $SelfDeliver_i$ is a binary indicator equal to one for farmers who delivered their own milk at baseline. The omitted group is $j = -1$, corresponding to the biweek immediately before the introduction of the digital receipts technology. The model includes individual fixed effects α_i and time fixed effects ψ_t, as well as an interaction between time and self-delivery status ($\sum_{\substack{j=-7\\j\neq-1}}^{7} \mathbb{1}(t - t_i^* = j) \cdot \lambda_j \cdot SelfDeliver_i$) to allow for differential time trends. Standard errors are clustered at the individual level, as treatment was randomized at that level.

6.4 Intensive Margin Analysis: Average Volumes Delivered to Cooperative

Similarly to the extensive margin analysis, we implement an event study approach to explore how treatment effects on delivered volumes (intensive margin) evolve over time. This analysis also allows us to test whether effects differ by the intensity of information frictions, comparing farmers who self-deliver (low frictions) with those who rely on transporters (high frictions). Our identification strategy is as follows:

$$Y_{it} = \sum_{\substack{j=-7\\j\neq-1}}^{7} \mathbb{1}(t - t_i^* = j) \cdot \tau_j \cdot Treat_i + \alpha_i + \psi_t + \varepsilon_{it} \tag{6}$$

$$\begin{aligned} Y_{it} = & \sum_{\substack{j=-7\\j\neq-1}}^{7} \mathbb{1}(t - t_i^* = j) \cdot \tau_j \cdot Treat_i \\ & + \sum_{\substack{j=-7\\j\neq-1}}^{7} \mathbb{1}(t - t_i^* = j) \cdot \omega_j \cdot Treat_i \cdot SelfDeliver_i \\ & + \alpha_i + \psi_t + \sum_{\substack{j=-7\\j\neq-1}}^{7} \mathbb{1}(t - t_i^* = j) \cdot \lambda_j \cdot SelfDeliver_i + \varepsilon_{it} \end{aligned} \tag{7}$$

where Y_{it} denotes the outcome variable—average volumes delivered—for individual i at time t, $\mathbb{1}\{t - t_i^* = j\}$ is an indicator for time relative to the last biweek prior to the intervention t_i^*. $Treat_i$ is a binary indicator equal to one if individual i was part of the treatment group. The variable $SelfDeliver_i$ is a binary indicator equal to one for farmers who delivered their own milk at baseline. The omitted group is $j = -1$, corresponding to the biweek immediately before the introduction of the digital receipts technology. The model includes individual fixed effects α_i and time fixed effects ψ_t, as well as an interaction between time and self-delivery status ($\sum_{\substack{j=-7\\j\neq-1}}^{7} \mathbb{1}(t - t_i^* = j) \cdot \lambda_j \cdot SelfDeliver_i$) to allow for differential time trends. Standard errors are clustered at the individual level, as treatment was randomized at that level.

7 Results

This section presents the main results. We begin by examining whether the intervention reduced information frictions between farmers and transporters, the central mechanism through which digital receipts were expected to operate. We then turn to effects on milk quality, followed by an analysis of milk deliveries at both the extensive and intensive margins for transporter users and self-deliverers. Throughout, we test whether impacts differ depending on the intensity of information frictions, comparing farmers who self-deliver with those who rely on transporters.

7.1 Do Digital Receipts Reduce Information Frictions?

We begin by examining whether the intervention achieved its intended purpose of reducing information frictions between farmers and transporters. To assess whether the digital receipts reduced frictions, we draw on survey evidence and identify three key channels through which the intervention operated.

7.1.1 Discrepancy Detection

Table 4 shows that treated farmers using transporters were significantly more likely to detect discrepancies between the volumes picked up and those recorded at the cooperative. Among farmers who relied on transporters, those in the treatment group were almost 20 percentage points more likely to report inconsistencies in delivery records. This suggests that digital receipts enhanced observability, allowing farmers to cross-check cooperative records against their own or the volumes they handed off. This improved ability to monitor deliveries likely increased the perceived risk of misreporting and siphoning by transporters.

7.1.2 Transporter Switching

Table 5 shows that treated farmers using transporters were 14 percentage points more likely to switch transporters over the course of the intervention. Access to verifiable information reduced the cost of assessing transporter performance and increased the perceived benefit of moving away from under-performing or dishonest transporters. This points to a disciplining mechanism: as farmers gained timely and more accurate information, they were better positioned to respond strategically to misconduct, using the threat of switching to a different transporter as a tool to enforce accountability and deter misconduct.

7.1.3 Trust Decline

Table 6 shows that treated farmers using transporters expressed lower levels of trust in their current transporter relative to untreated farmers. This reduction in trust may reflect increased awareness of misbehavior that was previously hidden by information frictions. This reinforces the interpretation that the intervention made misconduct more visible, prompting farmers to reassess the reliability of their transporters and adjust their behavior accordingly.

7.2 Milk Quality Improvements among Transporter Users

In this section, we examine whether the treatment impacted the quality of milk delivered to cooperatives, as measured by lactometer readings. Higher readings indicate greater density and thus lower water content, serving as a proxy for reduced dilution.

For this outcome, as shown in Table 7, we estimate an OLS specification leveraging the randomized design. In Table 8, we also examine heterogeneity by delivery method to assess whether the treatment had differential effects based on farmers' reliance on transporters. This heterogeneity analysis helps identify whether the change in milk quality is due to behavioral changes (i.e., changes in milk dilution) by farmers or by transporters.

We find that the treatment led to a statistically significant improvement in milk quality. On average, treated farmers delivered milk with lactometer readings that were 0.1 degrees higher than those of control farmers. While this may appear modest in magnitude, it represents a significant improvement given the market conditions of the Ugandan dairy sector. To put this in context, the average positive effect of the rainy season on milk quality in our data is 0.78. Framed relative to seasonal variation, the intervention's impact amounts to nearly 13% of the average quality gain observed during the rainy season. Moreover, Table 8 shows a positive and statistically significant effect of 0.145 degrees in the third month of the treatment among farmers using transporters.

By increasing the cost of dishonest behavior, the treatment seems to have encouraged higher-quality deliveries. These gains are concentrated among farmers who use transporters, reinforcing the idea that the intervention helped farmers identify misbehaving transporters and limited opportunities for tampering with milk during transport by making transporters' actions more observable.

7.3 Extensive Margin Effects: Likelihood of Delivery among Transporter Users

In this section, we examine whether the treatment affected the frequency of milk deliveries, focusing on the decision whether to deliver and thus capturing effects along the extensive margin. As described in Section 6, we used an event study approach using seven months of farmer-level delivery data. Figure 1 shows no statistically significant effect of the treatment on deliveries at the extensive margin for transporter users. In other words, treated farmers who used transporters at baseline did not, on average, deliver more frequently than control farmers who also used transporters at baseline during the study period.

One reason we may see no effect on delivery frequency for transporter users is that pick-up frequency and timing must be coordinated and scheduled with the transporter in advance. In other words, the decision of whether to deliver on a given day is typically made during scheduling, rather than on a day-to-day basis, making delivery behavior among farmers who use transporters somewhat stickier.

7.4 Intensive Margin Effects: Volumes Delivered by Transporter Users

We now examine whether the treatment affected the volume of milk delivered to cooperatives for transporter users, focusing on how much farmers delivered and thus capturing effects along the intensive margin. As with the analysis of extensive margin effects, we implement an event study approach using seven months of farmer-level delivery data. Figure 2 shows no statistically significant effect of the treatment on delivery volumes at the intensive margin, regardless of farmers' baseline delivery method. In other words, treated farmers did not, on average, deliver more milk than control farmers during the study period, whether they self-delivered or used a transporter at baseline.

One reason we may see no effect on volumes delivered is the presence of transportation constraints faced by transporters. The volumes that transporter users send to the cooperative must be arranged in advance, and increases are possible only if the transporter has the capacity to carry the additional liters. In Figure 8, we observe *bunching* at different levels. These patterns highlight potential transportation constraints that may limit farmers' ability to increase volumes delivered to cooperatives.

7.5 Potential Spillovers

We anticipate two key channels through which spillover effects may occur, both of which could bias our treatment estimates downward. The first channel is on the demand side, through farmer-to-farmer information sharing. Treated farmers who receive digital receipts may become aware of discrepancies between what they sent and what was delivered (and reported) at the cooperative, revealing dishonest behavior by their transporter. Because farmers often rely on shared transporters and maintain strong social ties within their communities, treated individuals may share their experiences with peers, especially when trust or misconduct is at stake. As a result, untreated farmers who use the same transporter could be indirectly affected by the treatment, either by gaining information about the transporter's behavior or by adjusting their own delivery practices in response to concerns about potential misconduct.

The second channel is on the supply side, due to changes in transporter behavior after the treatment started. Transporters may become aware that some farmers are receiving digital receipts but may not know exactly who is treated. In response, they could choose to adjust their behavior toward all farmers in order to minimize the risk of detection. This uncertainty could induce more honest behavior across the board, even among untreated farmer–transporter pairs.

These mechanisms allow control farmers to benefit indirectly from the treatment, either through increased information or improved intermediary behavior. As a result, the estimated treatment effects will likely understate the true impact of the treatment. In addition, because only one lactometer reading was collected for each shared container and assigned to all contributing farmers, the estimated treatment effect on milk quality is likely biased downward. Overall, these factors suggest that our estimates should be interpreted as a lower bound of the true treatment effect on farmer outcomes.

7.6 Milk Quality Improvements among Self-deliverers

In this section, we examine whether the treatment impacted the quality of milk delivered to cooperatives by self-deliverers. Once again, higher lactometer readings indicate greater density and thus lower water content, serving as a proxy for reduced dilution.

For this outcome, we return to Table 7, where we estimate an OLS specification leveraging the randomized design. As mentioned before, we find that the treatment led to a statistically significant improvement in milk quality across our entire sample. On average, treated farmers delivered milk with lactometer readings that were 0.1 degrees higher than those of control farmers. When exploring potential heterogeneous effects of the treatment (Table 8), we do not find evidence of differential impacts among self-deliverers. We interpret these two tables as the treatment having a moderate effect on milk quality for self-deliverers in relation to the quality improvements coming from farmers using transporters.

7.7 Extensive Margin Effects: Likelihood of Delivery by Self-deliverers

In this section, we examine whether the treatment affected the frequency of milk deliveries by self-deliverers, focusing on whether to deliver and thus capturing effects along the extensive margin. As described in Section 6, we used an event study approach using seven months of farmer-level delivery data. Figure 3 shows a statistically significant effect of the treatment on deliveries at the extensive margin for self-delivering farmers. On average during the study period, treated farmers who self-delivered at baseline were more likely to deliver milk than control farmers who self-delivered at baseline. In terms of magnitude, treated self-delivering farmers were 5–9 percentage points more likely to deliver to the cooperative after the first biweek following the start of the treatment. Consistent with our hypothesis that treatment effects would emerge gradually through a learning process, we find effects within the first month of implementation. This pattern suggests that digital receipts increased participation by improving transparency at the point of delivery. By enhancing trust in the accuracy of recorded transactions, the receipts may have mitigated perceived risks at the cooperative level, encouraging more consistent engagement among self-delivering farmers.

Taken together with our extensive margin results for transporter users, these patterns show that the intervention works differently depending on the intensity of information frictions. For self-deliverers, who already have full observability over their deliveries, impacts are concentrated on participation. In contrast, for transporter users, where observability is limited, impacts are concentrated on detecting discrepancies and moving away from baseline intermediaries. An additional explanation is that, for self-deliverers, the digital receipts functioned as a behavioral nudge encouraging consistent delivery behavior.

7.8 Intensive Margin Effects: Volumes Delivered by Self-deliverers

In this section, we examine whether the treatment affected the volume of milk delivered to cooperatives for self-deliverers, focusing on how much farmers delivered and thus capturing effects along the intensive margin. As with the analysis for transporter users, we implement an event study approach using seven months of farmer-level delivery data. Figure 4 shows no statistically significant effect of the treatment on delivery volumes at the intensive margin for self-deliverers. In other words, treated self-deliverers did not, on average, deliver more milk than control self-deliverers during the study period.

One reason we may see no effect on volumes delivered is transportation constraints for this group. Farmers who self-deliver typically transport milk by walking or bicycle, which physically limits how much they can carry. In Figure 7, we observe *bunching* at different levels, as we observed for transporter users.

Taken together with the findings at the intensive margin for transporter users, these patterns highlight potential transportation constraints that may limit farmers' ability to increase volumes delivered to cooperatives, regardless of the farmer's delivery method.

7.9 Individual Behavior and Market Dynamics

Because we identify effects at the extensive margin of deliveries for self-delivery farmers, but not at the intensive margin, our results suggest that the treatment acted more as a behavioral nudge than as a tool to reduce information frictions, which are minimal for these farmers.

We also find a modest increase in the share of farmers using transporters at endline compared to baseline. At the start of the intervention, approximately 63% of farmers in our sample relied on transporters to deliver their milk to cooperatives. By the end of the intervention, that share had risen to nearly 66%. This change reflects underlying dynamics: 46 farmers stopped using transporters, while 68 began using them. At the same time, the number of transporters offering services to the cooperatives in our sample increased from 74 to 81. While this is not a large increase, the fact that such a shift occurred over a relatively short period suggests that farmers may adjust their delivery method by leveraging the information provided by digital receipts to reassess the costs and benefits of using transporters.

Together, the evidence suggests that digital receipts shifted behavior primarily by increasing the visibility of transactions and empowering farmers to act on that information. The effects were concentrated in relationships with high information frictions, such as transactions involving transporters, where accountability and transparency were weakest. In contrast, for relationships with low information friction, such as self-delivery, the intervention functioned more as a behavioral nudge than as a tool for monitoring. These results highlight that the effectiveness of digital interventions depends critically on the structure of market relationships and the intensity of existing information frictions. Even simple, low-cost digital tools that improve information flow can lead to meaningful changes in behavior by making it easier to monitor transactions or by helping farmers observe what was previously hidden. Additionally, we provide evidence that making misbehavior observable in relational contracts can erode trust and ultimately lead to contract breakdowns. This highlights that trust is an essential feature of such contracts, and that information frictions allow opportunistic behavior to persist in this context.

8 Discussion and Conclusion

This paper provides causal evidence that simple digital technologies can reduce information frictions and improve outcomes in agricultural markets, though the effects depend on the intensity of those frictions. We study a randomized intervention in western Uganda that sent digital receipts via SMS to farmers, reporting the quantity of milk delivered on their behalf to the cooperative each day.

For farmers facing high information frictions (those relying on transporters), the intervention increased accountability. Treated farmers were more likely to detect discrepancies, switch away from dishonest transporters, and ultimately deliver higher-quality milk. While farmers do not receive higher prices for better quality milk, the reduction in dilution may carry important public health benefits, especially in contexts where the water used to dilute milk is unsafe, as is often the case in rural Uganda. Anderson et al. (2022) document that milk inspections in late 19th-century U.S. cities reduced mortality from waterborne diseases by 12–19%. In rural Uganda, where access to potable water is limited, water used for dilution is likely drawn from natural sources or untreated tap water. This raises concerns about introducing parasites and pathogens into the milk supply, particularly for vulnerable populations such as children and immunocompromised individuals (Sente et al., 2023). These risks are especially important given that cooperatives in our study area are key suppliers of milk to households and small businesses in nearby rural villages. More broadly, quality upgrading is key for economic growth, especially in low- and middle-income countries (Verhoogen, 2023), making our findings relevant not only for farmer welfare and public health, but also for longer-term development.

For farmers with low information frictions (those who self-deliver), the effects were different. Treated self-deliverers were more likely to deliver during the treatment period and continued to do so even after the intervention ended, including during the dry season when delivery volumes typically decline. This has important implications for market access and sustainability, especially for small dairy cooperatives in Uganda. These cooperatives often depend on small-scale farmers with limited productive capacity and operate with thin margins. During the dry season, when milk yields drop, cooperatives frequently struggle to meet buyer demand. In this sense, digital receipts functioned not only as a monitoring tool but also as a behavioral nudge, encouraging more regular participation by smallholder farmers and supporting the viability of smallholder cooperatives.

These results show that digital receipts address different problems depending on the presence and intensity of information frictions. They can discipline intermediaries, help farmers navigate this market more efficiently in high-friction settings, and increase farmers' participation in low-friction settings. More broadly, the findings highlight how even low-cost technologies can improve observability and accountability, reduce strategic behavior, and support more consistent engagement in cooperative markets. As digital infrastructure expands in rural areas, tools such as SMS receipts may offer a scalable way to strengthen smallholder supply chains, especially in settings with limited enforcement and high monitoring costs.

At the same time, our results highlight the importance of physical and logistical constraints that may limit how farmers respond to improved monitoring. Farmers who rely on transporters depend on the transporter's carrying capacity and pre-arranged schedules, while self-delivering farmers are constrained by how much they can carry on foot or by bicycle. These limitations may partially explain why we do not observe changes at the intensive margin in delivered volumes, even as observability and accountability improved.

Future research could examine how digital receipts interact not only with price incentives or alternative contracts, such as premiums for higher-quality deliveries, but also with efforts to alleviate transportation constraints. Pairing these approaches could strengthen observability and accountability while aligning incentives among farmers, transporters, and cooperatives. Another open question is the long-term adoption and sustainability of digital receipt systems, particularly when implemented by cooperatives or processors themselves.

Overall, our results suggest that digital receipts did more than just provide information. By improving transparency and making transactions observable in near real time, they reshaped incentives within the farmer–transporter relationship. Farmers gained a greater ability to monitor and discipline intermediaries, reducing opportunistic behavior and strengthening the relational contracts that sustain cooperation. More broadly, these findings highlight the potential of simple, low-cost digital technologies to improve accountability, strengthen farmer engagement, and shift behavior in fragmented agricultural markets. As digital infrastructure continues to expand across Sub-Saharan Africa, tools such as SMS receipts offer a scalable and cost-effective way to improve supply chain integrity and strengthen smallholder-oriented institutions, even in settings with limited enforcement and high monitoring costs.

9 Figures

Figure 1: Event Study on Delivery Likelihood – Transporter Users

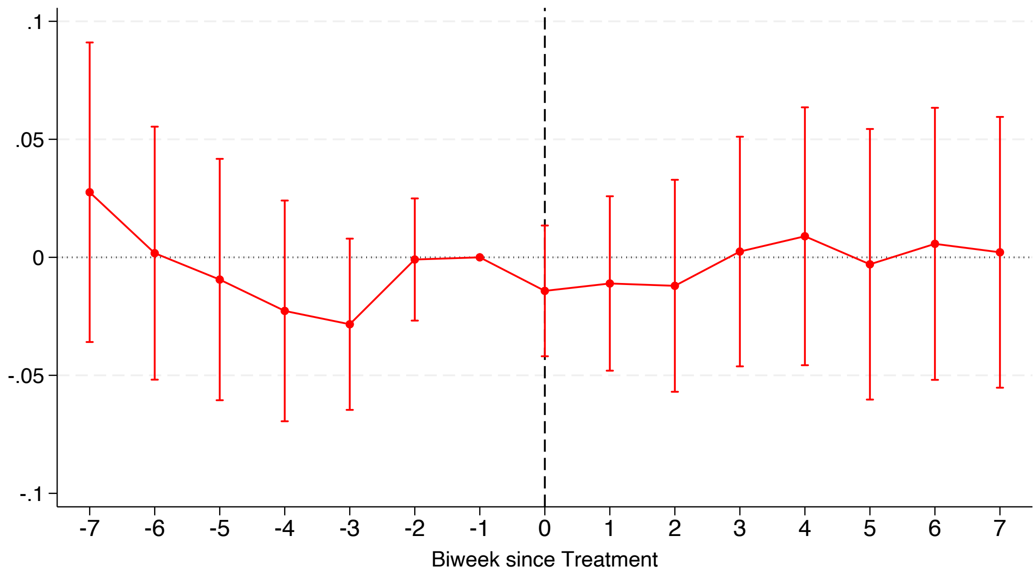


Figure 2: Event Study on Average Volumes Delivered – Transporter Users

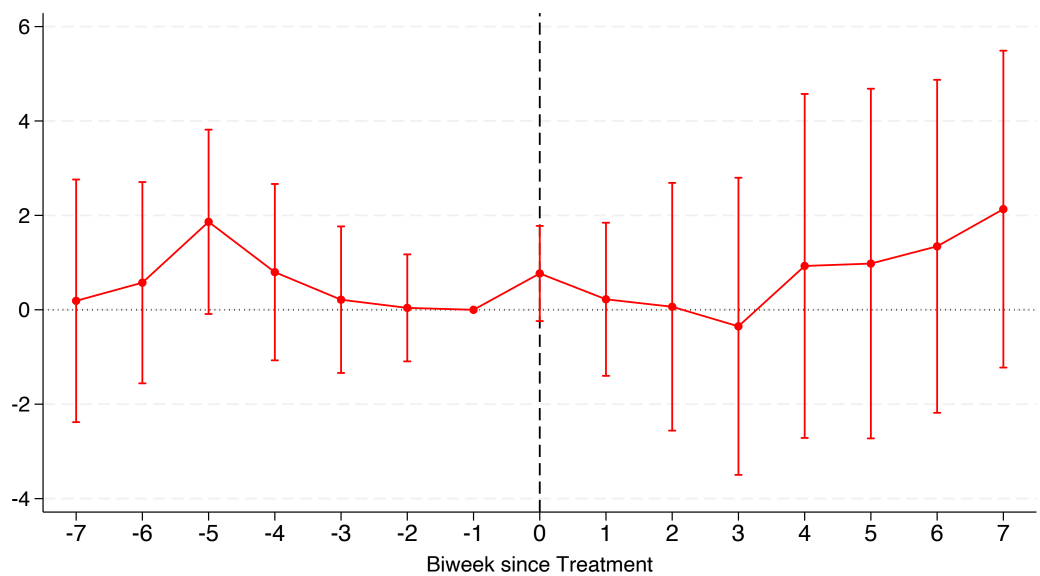


Figure 3: Event Study on Delivery Likelihood – Self-deliverers

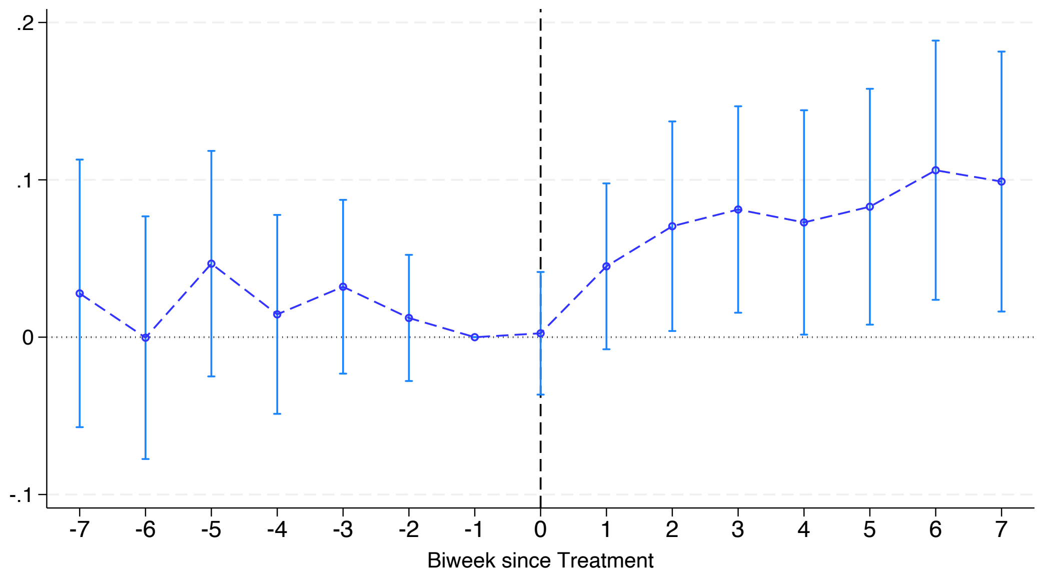


Figure 4: Event Study on Average Volumes Delivered – Self-deliverers

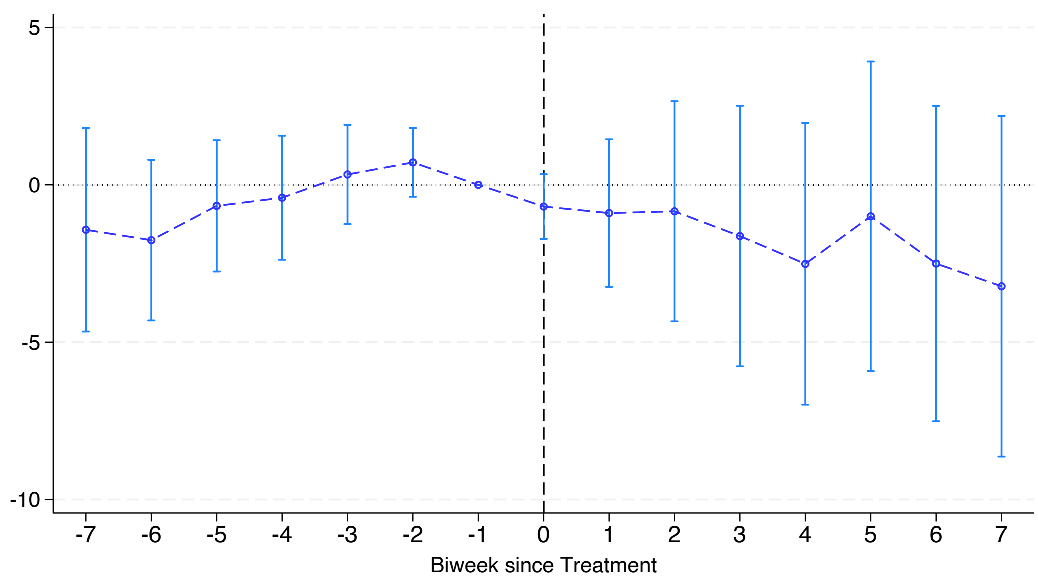


Figure 5: Event Study on Delivery Likelihood

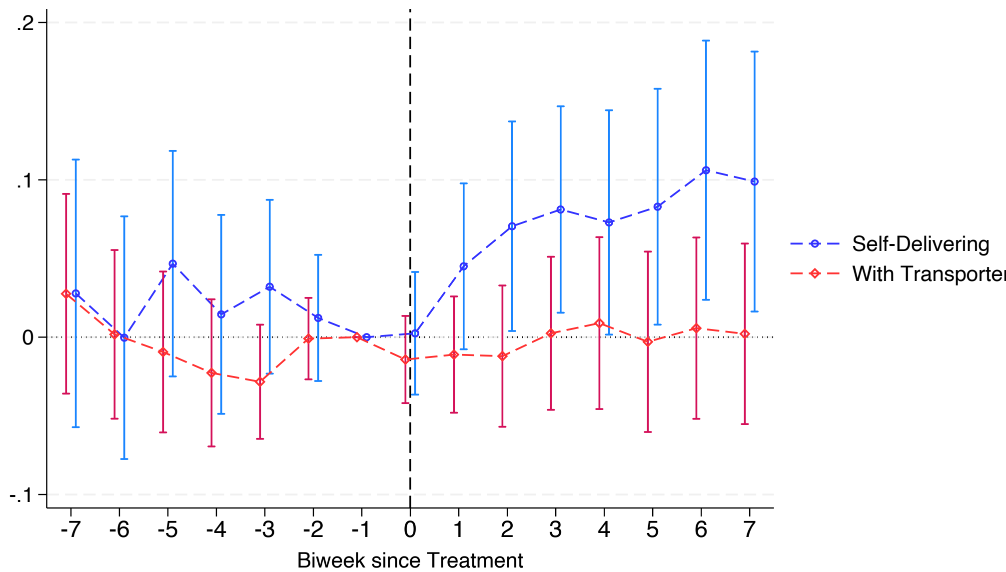


Figure 6: Event Study on Average Volumes Delivered

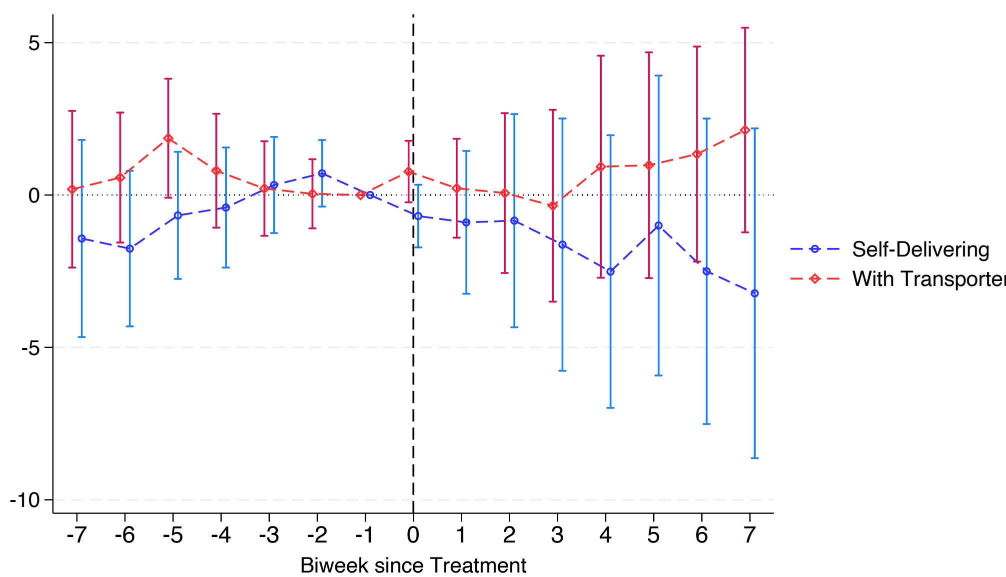


Figure 7: Histogram on Administrative Deliveries – Self-Delivering Farmers

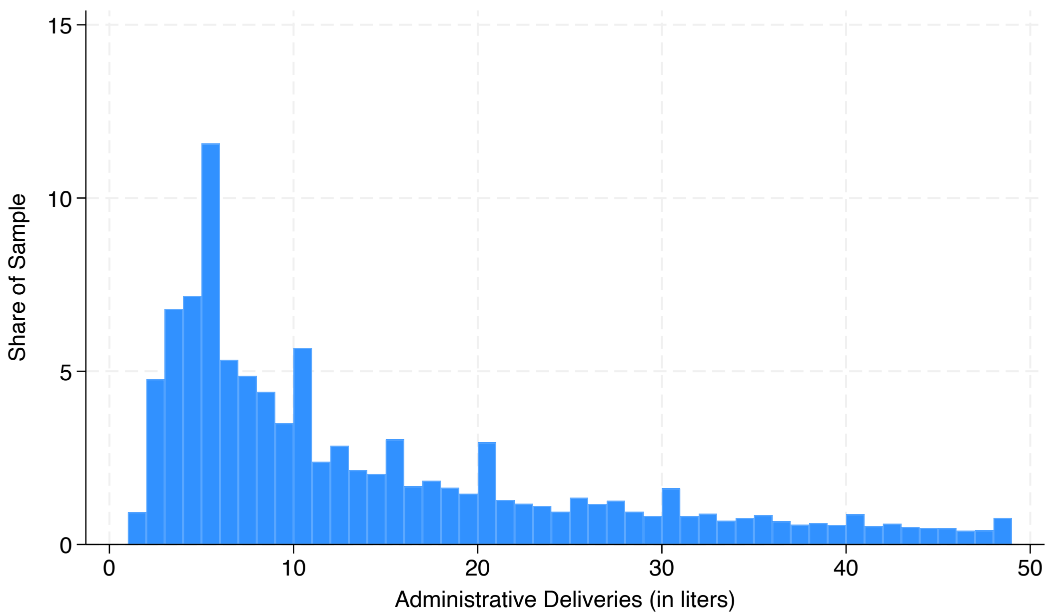


Figure 8: Histogram on Administrative Deliveries – Farmers using Transporters

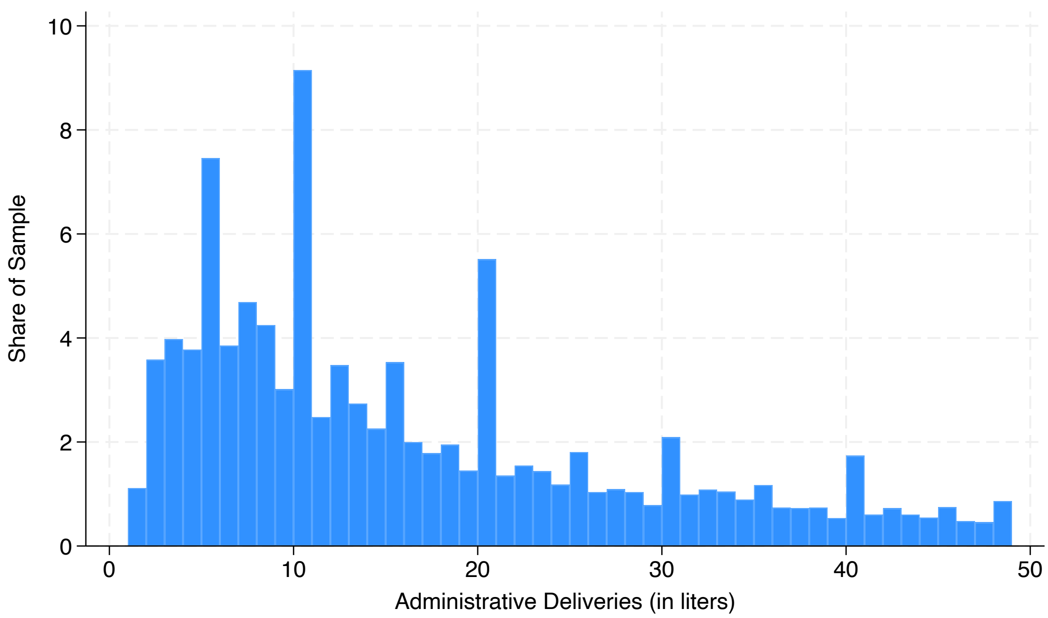


Figure 9: Kernel on Milk Quality – Full Sample

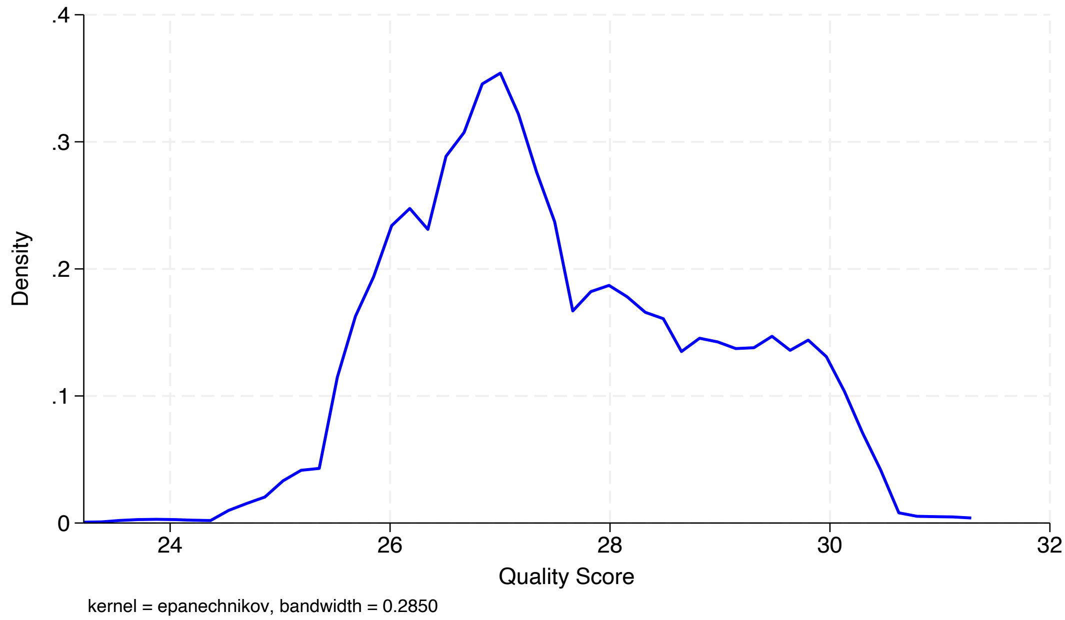
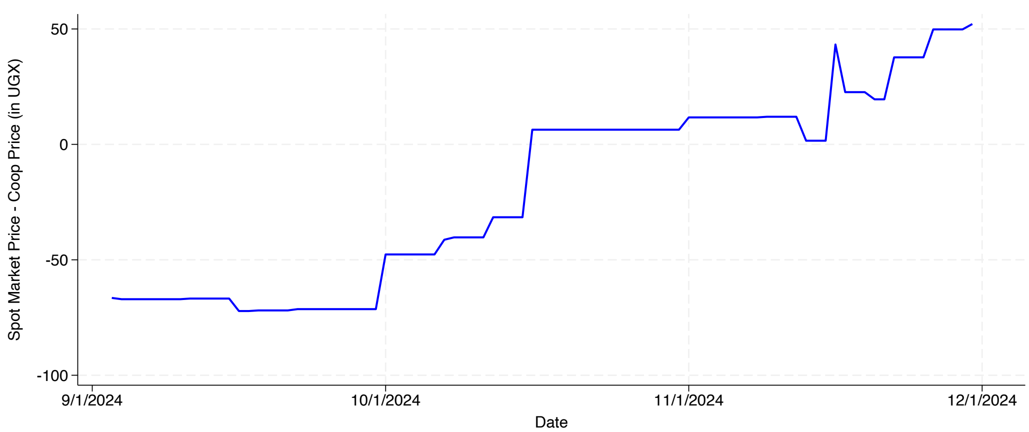


Figure 10: Average Spot Market Price vs Average Coop Price (in UGX)



10 Tables

Table 1: Transporter Baseline Characteristics

Variable	Mean	Min	Max	N
Age	33.44	18	74	74
Farmers per transporter	8.46	1	29	74
Trips per day	2.19	1	8	74
Own motorcycle (1=yes)	0.77	0	1	74
Transporters per cooperative	4.71	1	13	74

Table 2: Baseline Characteristics and Balance

	Control		Treatment vs Control		Farmers
	Mean	Std. dev.	Coeff.	Std. err.	N
	(1)	(2)	(3)	(4)	(5)
Validate phone number	0.894	(0.308)	0.008	(0.022)	766
Distance to coop (minutes)	18.320	(10.493)	0.399	(0.746)	766
Number of liters delivered	16.577	(28.562)	0.050	(2.005)	766
Uses transporter	0.619	(0.486)	0.019	(0.035)	766
Coop hires transporter	0.571	(0.496)	-0.009	(0.045)	484
P-value (joint F-test)				0.962	

Table 3: Farmer Endline Characteristics

Variable	Mean	SD	Min	P25	P75	Max
Age	52.90	15.02	19	42	63	94
Household members	7.29	3.52	1	5	9	20
Productive cows	10.42	9.01	0	4	15	60
Milk production (L/day)	44.71	45.81	2	16	55	400
Liters sold to coop (L/day)	26.57	29.69	0	8	35	202
Number of buyers	1.24	0.63	0	1	1	9
Uses transporter service (1=yes)	0.62	—	—	—	—	—

Table 4: Effect of Treatment on Spot Discrepancy (LPM)

	(1) LPM: Spot Disc.
Treatment	0.196***
	(0.055)
Strata FE	Yes
Observations	245
Control mean	0.181
R^2	0.215

Only farmers using transporters. Standard errors are clustered at the farmer level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect of Treatment on Transporter Switching (LPM)

	(1) LPM: Switch
Treatment	0.141***
	(0.037)
Strata FE	Yes
Observations	246
Control mean	0.034
R^2	0.248

Only farmers using transporters. Standard errors are clustered at the farmer level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effect of Treatment on Trust in Transporters (LPM)

	(1) LPM: Trust
Treatment	-0.118*
	(0.063)
Strata FE	Yes
Observations	246
Control mean	0.698
R^2	0.154

Only farmers using transporters. Standard errors are clustered at the farmer level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Effect of Treatment on Average Quality

	Overall	Month 1	Month 2	Month 3
Treatment	0.100*	0.108	0.091	0.121**
	(0.053)	(0.105)	(0.093)	(0.052)
Strata FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	No	No
Observations	1419	472	498	449
Control mean	27.535	27.180	27.492	27.957
R^2	0.459	0.284	0.518	0.708

Standard errors are clustered at the cooperative level.
Computed using wild cluster bootstrapping.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Effect of Treatment on Average Quality, by Delivery Method

	Overall	Month 1	Month 2	Month 3
Treatment	0.054	-0.028	0.081	0.145***
	(0.076)	(0.146)	(0.138)	(0.036)
Self-deliver	0.150	0.186	0.144	0.112
	(0.094)	(0.227)	(0.091)	(0.078)
Treatment × Self-deliver	0.128	0.387	0.024	-0.100
	(0.159)	(0.241)	(0.223)	(0.152)
Strata FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	No	No
Observations	1419	472	498	449
Control mean	27.535	27.180	27.492	27.957
R^2	0.462	0.297	0.519	0.707

Standard errors are clustered at the cooperative level.
Computed using wild cluster bootstrapping.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Effect of Treatment on Average Quality, Switchers versus Keepers I

	Overall	Month 1	Month 2	Month 3
Switcher	0.063	0.025	0.115	0.032
	(0.089)	(0.193)	(0.149)	(0.058)
Strata FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	No	No
Observations	907	290	306	311
Control mean	27.578	27.100	27.523	28.078
R^2	0.538	0.381	0.546	0.742

Standard errors are clustered at the cooperative level.
Computed using wild cluster bootstrapping.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Effect of Treatment on Average Quality, Switchers versus Keepers II

	Overall	Month 1	Month 2	Month 3
Switcher	0.006	0.055	-0.054	0.053
	(0.105)	(0.214)	(0.178)	(0.088)
Treatment	0.022	0.036	-0.047	0.163***
	(0.089)	(0.185)	(0.107)	(0.038)
Switcher × Treatment	0.122	-0.059	0.347*	-0.035
	(0.101)	(0.214)	(0.180)	(0.120)
Strata FE	Yes	Yes	Yes	Yes
Month FE	Yes	No	No	No
Observations	907	290	306	311
Control mean	27.578	27.100	27.523	28.078
R^2	0.538	0.377	0.548	0.744

Standard errors are clustered at the cooperative level.

Computed using wild cluster bootstrapping.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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11 Appendix

Figure 11: Diagram of Farmers by Delivery Method

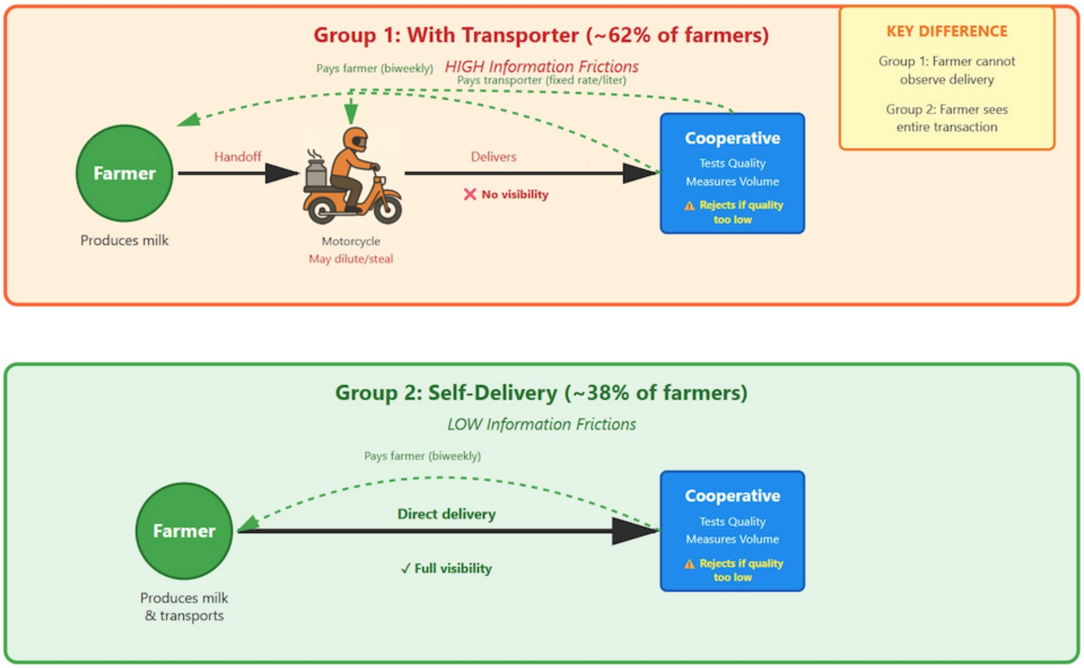

Figure 12: Uganda—Geographical Location of the Study I

Figure 13: Uganda—Geographical Location of the Study II

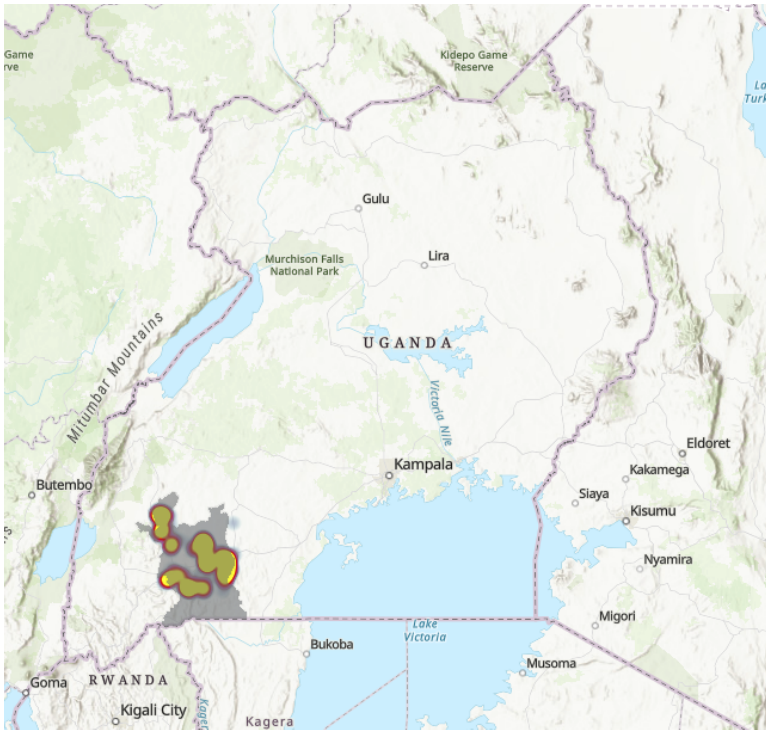

Figure 14: Western Region—Geographical Location of the Study I

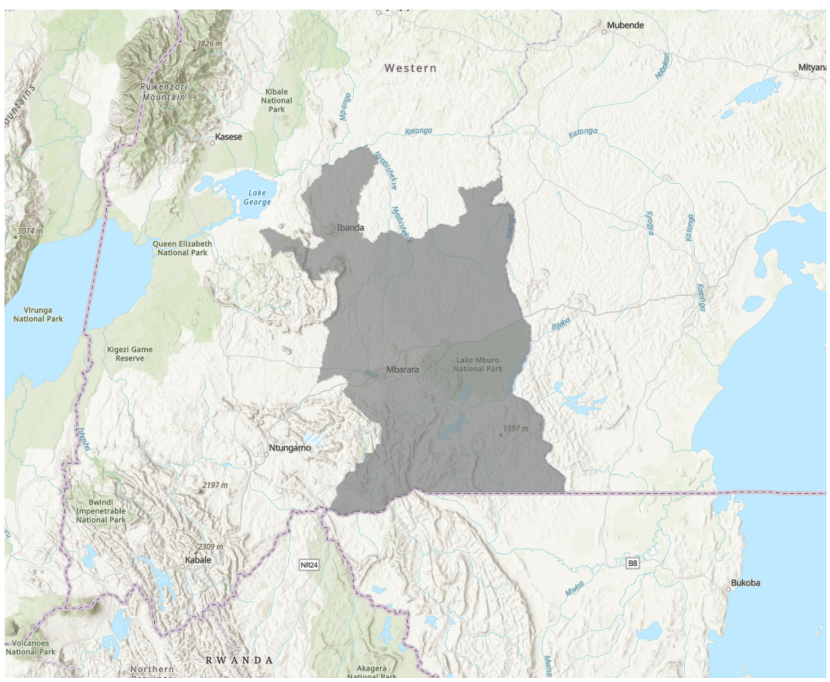

Figure 15: Western Region—Geographical Location of the Study II

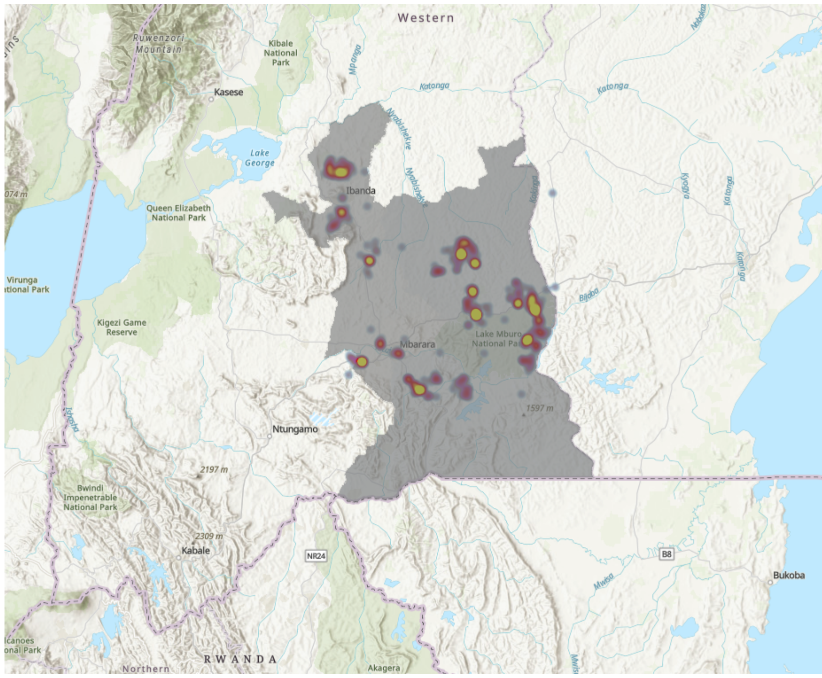

Figure 16: Average Volumes Delivered per Group (Monthly)

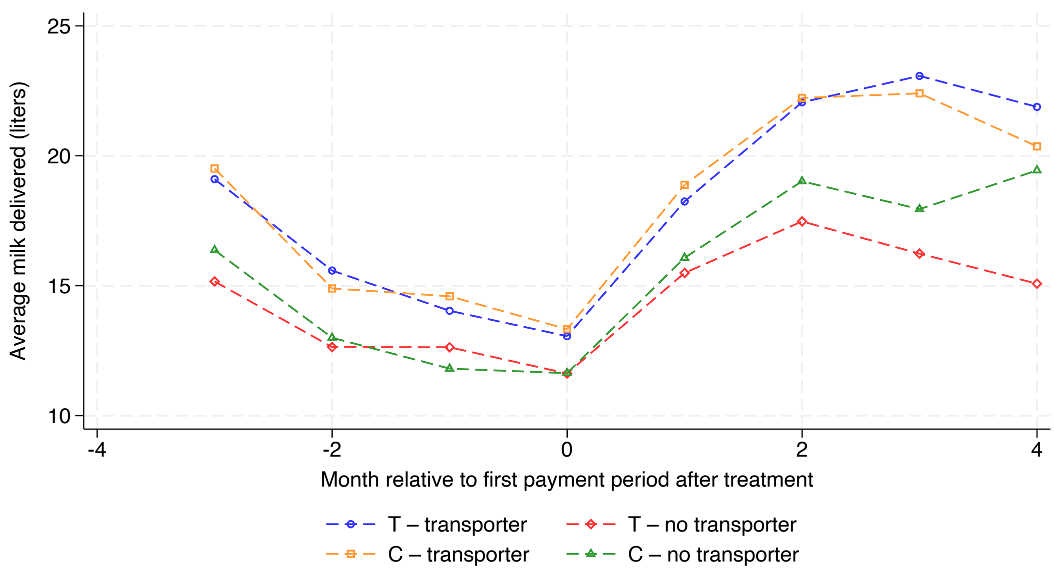

Figure 17: Average Log Volumes Delivered per Group (Monthly)

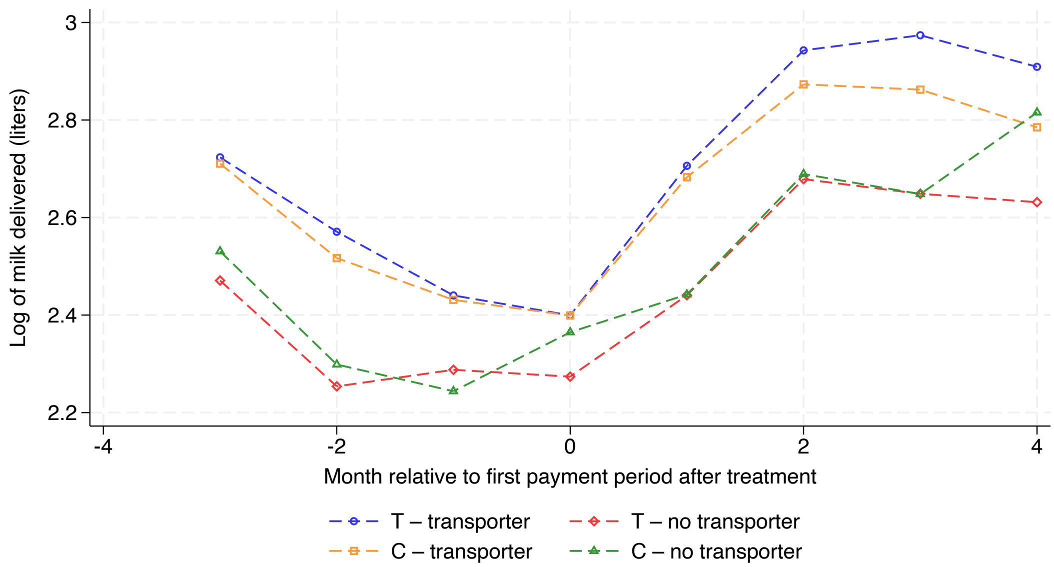

Figure 18: Probability of Delivery per Group (Monthly)