Got (Clean) Milk? Transparency, Governance, and Incentives for Cleanliness in Indian Dairy Cooperatives

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August, 2020

Abstract

Much economic activity in developing countries takes place in production teams whose members are connected through a broader social network. We explore the effectiveness of team incentives among rural Indian dairy cooperatives. In a randomized evaluation, we find local cooperatives can solve internal collective action problems to respond to aggregate incentives for sanitation. However, in some cases, cooperative managers decline incentive payments when they cannot control information disclosure. Opting out of payment is prevalent among low social status managers, which we interpret in a model of elite capture with substitution between methods of rent extraction that have different efficiency implications.

JEL Codes: D23, Q13, P13, O13

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1 Introduction

Coase (1937) identifies a fundamental trade-off between decentralization of price signals and transaction costs that gives rise to the existence of the firm. In rural areas throughout the developing world, this trade-off manifests in the form of cooperative agriculture. Smallholder producers gain access to broader markets by organizing into cooperatives and similar arrangements that take advantage of economies of scale in purchasing inputs and selling outputs. This system generates a tension in which production is carried out by individual members, but market incentives are applied at the group level. However, cooperative organizations arise in the context of an existing community social structure that can address this misalignment of incentives through informal channels (e.g. Ostrom, 1990). Around the world, cooperative agriculture has been promoted as a means to achieve the dual goals of raising agricultural productivity by increasing the returns to investment and improving the livelihoods of poor rural households (see Bernard et al., 2008).

In this paper, we investigate how information interacts with the local social structure to affect production in a field experiment with Indian dairy cooperatives. Information asymmetries in this setting take two forms. First, there is decentralized information about individual milking practices that is inaccessible to the external market. We find evidence that changing incentives at the group level alters aggregate production outcomes, indicating that communities have the capacity for internal enforcement regarding milking practices. Second, there is centralized information about the group-level incentive that is known to local elites but may be unknown to individual cooperative members. Counter intuitively, we find that increasing the provision of information within a cooperative can actually undermine aggregate production goals and lower revenue. This finding highlights a trade-off between productive efficiency at the community level and the potential for elite capture within a community.

We study this question in the context of Karnataka Milk Federation (KMF). The KMF is a a quasi-governmental organization comprising over 2.4 million dairy producers in over 22,000 villages across the state of Karnataka, India. Production is organized through village-level cooperative societies that aggregate output from smallholder farmers each owning one or two producing cows. The pooled milk is then delivered to processing facilities for packaging and sale. Similar cooperative structures are present for milk production in many other Indian states and South Asian nations. Moreover, while the KMF is vertically integrated from rural production to retail sale, cooperatives in dairy and other agricultural sectors throughout the world have a comparable management structure at the village level.

In this setting we conduct a randomized evaluation of incentives to lower microbial contamination at the initial production stage. Contamination lowers the net profitability of the KMF by limiting the potential uses of raw milk. Due to different pasteurization methods, raw milk with a high microbial load is only suitable for sale as liquid milk while cleaner raw milk can be used in higher value-added products such as cheese, yogurt, and milk sweets. Despite the returns to cleanliness, logistical hurdles in the collection process prevent the KMF from tying incentives for cooperatives directly to the microbial load. Instead, the organization has invested heavily in infrastructure and technology to minimize the impact of contamination farther along the supply chain.

At the point of production, microbial contamination is mitigated by basic sanitary practices such as washing hands before milking and sterilizing both individual and cooperative collection equipment. The KMF cannot directly incentive these behaviors because dairy producers pour milk together into common cans for aggregate delivery to a processing plant, and hence contamination cannot be traced back to any single individual. The cooperative effectively constitutes a production team beyond which transaction costs prohibit the further decentralization of market signals. However, members of a cooperative belong to the same community and likely have better local information about each others' milking practices. Moreover, social ties in this type of setting have been show to sustain long-term collaboration (e.g. Chandrasekhar et al., 2018). Therefore there is reason to believe cooperatives have the tools to coordinate individual behavior to take advantage of a group reward. We investigate how the interplay between information and local governance affects the manner in which such coordination is achieved.

To address this question, we overcome a barrier to accurate measurement of milk quality that limits the KMF's ability to set appropriate incentives. Contamination proliferates with time as microbes reproduce, so variability in time to testing introduces noise into the testing procedure. Measuring the microbial load requires laboratory facilities with trained staff, and therefore must take place at a centralized location. The volume and highly decentralized nature of KMF milk production leads to uncertainty in transportation and laboratory wait times, drowning out the relationship between village effort and testing outcome. Our study isolates the issue of misalignment between individual production and group incentives by investing in a high-accuracy testing procedure. We design a protocol to sample milk at the time of village collection, immediately refrigerate it to arrest further microbial development, and deliver it to a local laboratory for prompt testing.

In a randomized evaluation with 51 village cooperative societies in northern Karnataka, we experimentally evaluate an incentive payment tied to high-quality measures of cleanliness, paid in the aggregate into the cooperative financial account. This intervention tests whether cooperatives can effectively monitor and enforce clean milking practices among their membership to benefit from collective payment. Among those offered incentives, we further randomize whether the incentive payment is announced privately to local elites who manage the cooperative or publicly to all cooperative members. This intervention tests whether the information environment affects bargaining, distribution of rents, and ultimate production outcomes within a cooperative.

We find that incentive payments for milk cleanliness led to a quantitatively large decrease in contamination of pooled cooperative milk. The incentive schedule offered the potential to increase cooperative revenue by 2.5 percent over a two-week period[1]. This opportunity generated an improvement in milk quality of up to 0.64 standard deviations, which corresponds to a 86% increase in the fraction of raw milk suitable for value-added processing into cheese, yogurt, or milk sweets. These relative magnitudes indicate that the potential gains from cleaner milking practices are large relative to the costs, and therefore the barrier to cleanliness is organizational rather than technological.

Among cooperatives offered incentives for cleanliness, public provision of information about the incentive schedule decreased the size of the treatment effect. This decrease was driven in large part by the remarkable fact that in the public information arm, almost a third of cooperative managers requested to opt out of receiving the incentive payment entirely rather than receive the payment with public knowledge. The decision to forego payment is perplexing because the cooperatives would have received positive payments had they maintained their current levels of cleanliness with absolutely no change to milking practices, and because the cooperatives that opted out of payment continued to consent to the somewhat disruptive testing protocol.

The decision to opt out of payment seems to be strongly linked to elites' control over information. All those requesting to opt out were assigned to the public information arm, and none of the cooperatives in the private information arm requested to opt out. Among managers foregoing payment, all initially requested to be switched to the private information arm, and only opted out when given the choice between public information and no payment. Furthermore, we observe that turning down payment is negatively correlated with the perceived social power and influence of cooperative managers. These facts suggest that local elites might privately oppose opportunities that would be welfare-enhancing in the aggregate. As a corollary, maximizing productive efficiency may involve structures that offer more opportunities for elite capture.

To formalize these intuitions, we develop a stylized model of production and information exchange between managers and workers; in the context of dairy cooperatives, as in many development settings, formal managerial authority coincides with elite status in the social hierarchy. We show that allowing managers to control the flow of information both distorts production away from its optimal level and shifts the distribution of rents towards managers. The model highlights the fact that elite capture can take multiple forms, some of which are more damaging than others. As a result, increasing managers' claim to economic surplus can improve production outcomes and, in some cases, can also be welfare-enhancing for workers. This latter result counterintuitively indicates that there are circumstances under which increasing the formal power of elites actually reduces elite capture in equilibrium.

This paper relates to several stands of literature. First, we provide evidence on the capacity for gains from decentralization of production processes (see Marschak, 1959). Decentralization

[1] Of course, not every cooperative earned the maximum incentive payment. Actual payouts amounted to a realized increase in cooperative revenue of one percent on average.

can better enable agents to incorporate local information (Aghion and Tirole, 1997; Acemoglu et al., 2007), but it may also generate unintended consequences that raise agents ability to shirk (Mookherjee, 2015; Shenoy, 2020). On the other hand, a centralized system enables economies of scale by ameliorating coordination problems and enabling greater market access (Markelova et al., 2009). This trade-off between local information and capacities of centralized agencies is seen in many development contexts (e.g. Bardhan, 2002; Besley and Coate, 2003). Notably, Alatas et al. (2012) and Hussam et al. (2020) demonstrate that local agents have private information on how to allocate funding to its intended targets. However, a large body work shows that decentralized decision-making authority can enable corruption and elite capture (e.g. Bardhan and Mookherjee, 2000; Reinikka and Svensson, 2004; Olken, 2007; Niehaus and Sukhtankar, 2013; Acemoglu et al., 2014; Anderson et al., 2015). Our results are consistent with a mode of capture where elites pass up opportunities that enhance social welfare at the cost of their private benefit.

Banerjee et al. (2012) note that the costs of corruption depend crucially on the incentives faced by agents in a position to be corrupt; if performance targets align with private returns, then allowing some corruption may actually improve outcomes (e.g. Weaver, 2019). In the context of cooperative agricultural production, Banerjee et al. (2001) and Casaburi and Macchiavello (2015) provide evidence on how private incentives can skew the behavior of cooperative leaders. While studies have shown information disclosure or technological barriers to leakage can reduce the extent of local capture (Ferraz and Finan, 2008; Muralidharan et al., 2016; Banerjee et al., 2020), our findings caution that such policies can backfire if they lead elites to shift towards more distortionary practices or seek out ways to circumvent these efforts entirely.

Second, we contribute to the empirical literature on the optimal design of incentives for team production.[2] There is a large body of empirical work evaluating incentive structures for individuals within teams (see Bandiera et al., 2011; Bloom and van Reenen, 2011). When individualized incentives are infeasible, team-level incentives have been shown to increase aggregate productivity (e.g. Bandiera et al., 2013; Friebel et al., 2017). We extend the study of team incentives to a setting where the hierarchy of authority within the production unit is reinforced by the social network outside the production unit.

Finally, our findings shed light on the potential role of agricultural cooperatives in economic development. As of 2008, 75% of the world's poor lived in rural areas and depended on agriculture for their livelihood (World Bank, 2007). Cooperative agriculture has been promoted as a potential pathway out of poverty for this population by connecting local producers to broader markets (e.g. Wanyama, 2014). Macchiavello and Miquel-Florensa (2019) confirm that revenue gains from connection to global value chains pass through to local production units, justifying a role for cooperatives in agricultural development. However, our work warns that cooperative agriculture faces the same dangers of corruption and elite capture that have derailed other development initiatives.

[2]See Marschak and Radner (1972) for a theoretical discussion.

The rest of the paper proceeds as follows. In Section 2, we describe the setting and production process in more detail. Section 3 outlines our experimental design, and Section 4 presents results. We place the results into a theoretical framework in Section 5, and Section 6 concludes.

2 Setting

The KMF, founded in 1974, is a quasi-governmental federation of village-level dairy cooperatives in the Indian state of Karnataka. In total, it collects, processes, and distributes 2 million gallons of milk per day from over 2.4 million dairy producers in over 22,000 villages across the state. Production is vertically integrated so that dairy products are processed and packaged for distribution nationally under the KMF brand name Nandini, with surplus profits nominally returned to the cooperative farmers.

Milk production is organized through village-level Dairy Cooperative Societies (DCSs) that aggregate output from smallholder farmers for delivery to processing plants. The typical DCS member farmer in the KMF owns between 1 and 2 producing cows, and earns from 20–30% of their income from dairy activities. The supply chain operates at an impressive scale, turning around milk from a large geographical area for national distribution in a matter of days. Similar cooperative structures are present for milk production in many other Indian states and South Asian nations.

Under the cooperative structure, raw milk production is highly decentralized into village-level units while processing, packaging, and retail are centralized through state-level facilities. The logistical complexity of the supply chain generates a disconnect between aggregate profitability and individual earnings. KMF revenue is a function of quantity produced and quality of raw milk—both composition and presence of microbes. However, payments to farmers are tied almost exclusively to quantity because it is prohibitively expensive to track and monitor quality at such a fine resolution. KMF efforts to improve quality center around technological upgrades in the supply chain rather than the incentive structure.

In this paper, we explore the potential to improve milk quality using incentives explicitly tied to the microbial load of raw milk. We deliver these incentives at the DCS level and test whether local institutions are strong enough to solve collective action problems and induce changes in individual production behavior. We further evaluate how local governance interacts with the provision of information about the incentive structure to influence production outcomes.

2.1 Supply Chain

Dairy production originates in rural villages by smallholder producers. Every village-level DCS, typically consisting of 50–100 producing members, coordinates on a common time for milking and collection. At the village collection center, each producer's milk is inspected by sight and smell for spoilage and tested for density to detect adulteration before being poured into common village cans. A single can typically holds milk from 5–10 different producers, and the quantity poured by each producer is recorded for later reimbursement. Village collection takes place early in the morning, with all producers delivering milk within a half-hour window. Once full, cans are sealed for immediate pickup and delivery to a state processing plant. Appendix A walks through the village-level milk collection process with pictures.

At the processing plant, milk from the DCS is rapidly chilled before being processed and packaged for sale. Samples from each can are withheld before pasteurization for testing to determine quality and suitability for various milk products. A portion is packaged directly as liquid milk, with a turnaround time of 1–3 days from receipt to retail sale. The remainder is creamed into butter or ghee, or cultured for higher value-added products such as cheese, yogurt, and milk sweets.

The final use of raw milk is determined by lab tests of quality that measure both milk components and microbial load. Milk components consist of fat and solid non-fats (SNF) such as lactose and protein, with higher quality milk being richer in each of these components. The composition of milk is affected by cow breed, time in the lactation cycle, feed quality, and overall cow health. Products marketed by the KMF each have specific requirements for fat and SNF percentages, so milks of different composition from different villages are blended together to reach the target for any given product.

In this study, we aim to raise profitability by improving the other main component of quality - microbial load. This is an important margin of adjustment because different products require different levels of cleanliness in their raw milk input due to pasteurization methods. Milk used in high-value production must be pasteurized at temperatures of 70–80°C. At this temperature, the USDA (2011) requires[3] that raw milk have no more than 500,000 colony-forming microbial units per milliliter (cfu/ml) to be used as an input for value-added milk products. Even below this threshold, variation in the bacterial content of raw milk produces noticeable differences in final product quality down to 10,000 cfu/ml (Murphy et al., 2016).

There is substantial room for improvement in the cleanliness of milk delivered to the KMF from village DCSs. Figure 1 presents a histogram of the microbial load by delivery can for villages in our study under the existing KMF incentive structure. Of 225 cans tested, only 37 contained microbial loads suitable for value-added processing. Raw milk with bacterial loads exceeding 500,000 cfm/ml requires ultra-high temperature pasteurization (UHT) that heats to around 135°C. Such high temperatures denature important dairy enzymes and proteins, and therefore UHT is only suitable for liquid milk. This process can accommodate bacterial contamination up to 5 million cfu/ml for shelf-stable packaging (Tetra Pak, 2014) and even greater levels if sold for immediate consumption.[4]

[3]To the best of our knowledge, the Food Safety and Standards Authority of India (FSSAI) sets standards for microbial load in final production but does not regulate raw milk inputs.

[4]Milk that is unsuitable even for UHT is usually detectable by sight or smell, and is therefore rejected before it reaches the processing plant.

[Figure 1 about here.]

The two primary determinants of microbial load in raw milk are cleanliness at the point of collection and time elapsed between collection and refrigeration. Initial cleanliness reflects how many microbial colonies are in the milk to start, and time to refrigeration governs their proliferation. Refrigeration effectively arrests microbial development until pasteurization, processing, and packaging. In the recent past, the KMF has invested significantly in reducing the time to refrigeration through initiatives such as optimizing the transportation routes of collection trucks and installing rural bulk refrigeration facilities.[5] In this paper we evaluate a pilot intervention to improve cleanliness at the point of collection.

Milk contamination at the point of collection is affected by both farmers' milking practices as well as the cleanliness of village equipment. Farmers can lower the microbial count in their own production with basic sanitation procedures such as regularly cleaning their cows' udders, maintaining a sanitary milking space, and washing their hands and equipment prior to milking. Because milk from each farmer is poured into common DCS delivery cans, regular sanitization of village equipment also contributes to milk cleanliness. Unfortunately, due to the small-scale, decentralized nature of dairy production, it would be prohibitively expensive for the KMF or any centralized body to monitor these types of activities. We investigate whether there is sufficient local monitoring and enforcement capacity to implement these practices given appropriate incentives.

We break down the potential for improvement in each of these two areas in Figure 2 by comparing samples taken from farmers immediately before pouring into village cans to samples taken from village cans immediately after pouring.[6] Panel A plots the distribution of cleanliness among individual producers. There is substantial variance, with only 14% of producers delivering milk that achieves the highest sanitation rating. Compressing this distribution by one standard deviation around the 95$^{\text{th}}$ percentile would raise this fraction by 16% (2 p.p.). Panel B of Figure 2 plots the distribution of sanitation at the DCS level measured before and after pouring into DCS cans. There is a large and statistically significant decline in the cleanliness of pooled milk samples from village cans from 4.26 to 3.52; a t-test rejects the equality of these two values with a t-statistic above 5 ($p < 0.01$). This contamination introduced by DCS equipment is equivalent to a 0.5 standard deviation decrease in individual producer quality. Improvements in both individual milking practices as well as sanitation of collective equipment could increase the cleanliness of milk delivered for processing.

[Figure 2 about here.]

[5] Shenoy (2020) studies the impacts of decentralized refrigeration facilities on the dairy supply chain.

[6] It was prohibitively expensive to conduct a plate count of microbial load on individual milk samples. Instead, we plot results from a dye reduction test designed to measure microbial contamination, which unfortunately does not directly translate to USDA safety measures. The relationship between these two measures is discussed in Section 3.

2.2 Production Incentives

The KMF makes payments for milk delivered to the DCS rather than to individual producers. This structure is in place because it would be logistically infeasible for a centralized body to track and directly reimburse individual production from multiple million producers each pouring small quantities daily. Instead, the KMF interacts with local DCS management, and the DCS is in charge of disbursing payments to individual farmers. During our period of study, KMF payments were delivered fortnightly into each DCS's bank account for milk supplied over the preceding two weeks. The DCS then paid its pouring members from this account according to their respective quantity of milk delivered.

DCSs are paid primarily for the quantity of milk delivered, with very slight adjustments for fat and SNF content. Importantly, there is no KMF incentive tied to milk cleanliness due to logistical constraints. Testing for microbial load requires laboratory facilities and specialized training, and the KMF lacks the personnel and appropriate facilities to achieve this in a decentralized fashion. Transportation to a central lab introduces a great degree of variance into the testing process because microbial load grows exponentially with time. With the high volume of milk produced daily, wait time at the laboratory introduces further noise. Linking incentives to milk cleanliness at large scales would require overcoming logistical hurdles to prevent the signal recovered by the test from being swamped by variance introduced in transportation. In our study we overcome this barrier by investing heavily in test accuracy. We investigate whether, given appropriate group-level incentives, the potential for greater DCS revenue can induce changes in individual constituent behavior.

The KMF imposes explicit requirements on the allocation of DCS revenue between cooperative members and the management. The majority of revenue is paid directly to farmers based on quantity delivered. However, there is a small wedge between the price received by the DCS from the KMF and that paid to producers, which generates a surplus over the course of the year. A portion of this annual surplus is used to pay for local facilities and maintenance, as well as salaries for local DCS staff. The remainder is intended to be distributed among farmers as a yearly bonus, pro-rated by production quantity. The KMF supplements this local surplus by returning a portion of its annual profits as a dividend to producers.

In practice, the use of DCS funds is murkier. In the three years leading up to our study, the KMF officially reported net surpluses for all DCSs participating in our study in every year, indicating that they should have paid bonuses to farmers. However, at baseline only 20% of farmers surveyed could remember ever receiving a bonus from the DCS, revealing a disconnect between official accounting and the actual use of funds.

2.3 DCS Governance

Each DCS is managed by elected president and secretary, who make administrative decisions and serve as the local points of contact for our study. Together they manage the cooperative financial account, which is held jointly in their names. In addition, the secretary is in charge of day-to-day operations, most notably managing daily milk collection. The president is elected to staggered ten-year terms, and they are overseen by a board of directors typically consisting of 9–10 cooperative members. The board is composed of local member producers and is intended to provide representation for the various communities within the DCS, though the election process varies idiosyncratically by village.

In Table 1, we present demographic characteristics of DCS producers, secretaries, board members, and presidents in our area of study. It is clear from this table that DCS presidents occupy traditional positions of high social status. They are wealthier and more educated on average than producers and directors, they are less likely to belong to a scheduled (i.e. low-status) caste or tribe, and they are more likely to have held a position as a member of the local elected government (Gram Panchayat).

DCS secretaries embody a second type of local elite. While their demographic characteristics are more in line with typical producers, the one notable exception is in education. Secretaries have on average twice as many years of education as the typical producer. The position of DCS secretary underscores an often overlooked channel through which people of historically lower social status with high education can participate in local administration.

Social perceptions of DCS presidents and secretaries relative to directors correspond to their position as elites. The second part of Table 1 presents cooperative members' and directors' subjective perceptions of each group. The columns correspond to beliefs about a group, and the rows correspond the group giving the evaluation. The table includes data on perceptions of social power/status, management capacity, and knowledge of dairy practices. Two facts stand out from the table. First, DCS management typically has a higher opinion of other managers than other producers' opinion of managers. Second, all groups evaluate secretaries and presidents higher than they evaluate members of the board of directors. In fact, secretaries are consistently rated slightly above presidents, even in questions of social standing.

These differences in the characteristics of cooperative managers demonstrate the potential for elite capture in this setting. In particular, the cooperative managers in charge of the DCS bank account—the president and the secretary—are also those that have the greatest education and social standing, and are seen to be the most capable and knowledgeable. Their position in the village social network may limit other stakeholders' ability to constrain their power within the cooperative.

[Table 1 about here.]

3 Experimental Design

We implement a randomized evaluation of incentives to pay dairy producers for lowering the microbial count in milk. The incentive is applied at the DCS level based on samples of pooled milk from village cans, and payments are made into the cooperative bank account. Each DCS in the study is randomly assigned to either receive incentive payments or not, and those assigned to receive payment are randomly selected into either having incentive payments announced publicly to a sample of cooperative dairy producers or privately to only the cooperative management. We evaluate milk cleanliness through two rounds of baseline testing and two rounds of testing during our intervention.

3.1 Timeline

The timeline of project activities was arranged around seasonality in dairy production. The two-year production cycle of a dairy cow starts with gestation, which lasts roughly nine months. Viable milk production begins in the week after calving, peaks around 2 months later, and remains high for another 6–7 months before tapering off, ending around one year after a calf is born. The cow then goes into a 2–3 month dry rehabilitation period before it is once again ready for insemination. In Karnataka during the time of study, the lean dairy season falls around January–April, with peak production in the months of May–December.

The baseline survey for this study took place in July–August, 2014, followed by two rounds of baseline milk testing in September–October. Program activities then paused through the subsequent dry season to limit any influence of baseline data collection on endline activities. Following the dry season, state-wide elections took place in June, 2015. Because the KMF is a state-run organization, all project activities were placed on hold in the run-up to elections. Milk testing resumed shortly after elections, with the two rounds of intervention milk testing in July–August, 2015, followed immediately by endline surveying at the end of August, 2015. A full timeline of project activities is given in Figure 3.

[Figure 3 about here.]

3.2 Intervention and Randomization

To promote clean practices in dairy production, we introduce financial incentives for cleaner milk among DCSs in the Dharwad district of Karnataka in India. Participating DCSs were recruited from the two subdistricts closest to the Dharwad processing plant. We contacted all 56 DCSs in the Hubballi and Dharwad subistricts, out of which 55 agreed to participate. Four dropped out before the intervention began, leaving a final sample of 51 cooperative societies with a total of 2,859 pouring members.

Randomization takes place at the DCS (effectively village) level. Each DCS is assigned randomly assigned to either receive incentive payments for clean milk or not. We follow the same quality testing procedure in all DCSs so the only experimental manipulation is the presence of payments. In treated DCSs, we further randomly vary whether incentive payments are announced privately or publicly. In the private treatment arm the existence of incentives is disclosed only to the DCS secretary and president, though they may choose to share this information with others at their discretion. In the public treatment arm, we also inform a subset of cooperative members about the incentive payments.

The intervention follows two rounds of incentivized milk collection with three village visits in each round. We first announce a two-week window during which we may return for testing. In this visit we also describe the incentive structure to DCS management in treated villages, and further share these details with 20 randomly selected producers that have poured milk on the day of our visit in the public information arm. We then pick a random day in the two-week window to return for milk testing. Following the regular DCS milk collection, we collect milk samples from each can, which we immediately refrigerate and send to a laboratory for testing. Finally, we return to announce the test results to the DCS secretary on the day following testing. During this third visit we make payments into the DCS account in treated villages, and disclose this payment to another 20 randomly selected pouring DCS members in the public treatment arm.

Incentive payments for treated DCSs range from Rs. 0 to Rs. 2,000, equivalent to roughly $40, depending on the quality of milk.[7] With average daily revenues of Rs. 5,600, producing the highest quality milk would generate a 36% increase in revenue for the day. The payment schedule is scaled so that the average payment from baseline data would be Rs. 500, or roughly $10, representing a 9% increase in typical DCS daily revenue. The high end of the payment scale is equivalent to just under one month's average salary for a DCS secretary, and just under 80% of a month's self-reported total earnings for the average dairy producer.

Because we test once in a two-week period, these values should be divided by 14 to interpret the size of the incentive on any given day. Payments are made to the cooperative financial account, and can subsequently be split among the management and producers in whatever way they decide.

Figure 3 shows the treatment assignment across the two rounds of intervention. In Round 1, there are 19 village assigned to control, 19 villages assigned to private payment, and 13 villages assigned to public payment. Between Rounds 1 and 2, 6 villages switch from control to public payment and 3 villages switch from private to public payment.[8] There are no villages that switch in the other direction because public announcement of payments is an absorbing state; we cannot credibly take back the knowledge that incentives will be paid.

Table 2 provides descriptive statistics for the treatment and control groups. The two groups

[7] Full details of the payment schedule are provided in Appendix B.

[8] Motivation for changing treatment assignment mid-intervention is discussed in Appendix C.

appear balanced on covariates; only the fraction of income earned from dairy differs significantly between the two. A joint test of significance for all survey outcomes fails to reject equality at the 10% level. Importantly, there are no statistically significant differences between treatment and control in average quantity poured, cleanliness, or number of livestock.

[Table 2 about here.]

3.3 Data Collection and Analysis

We collect four rounds of data on milk cleanliness, conduct baseline surveys with DCS management and a random sample of producers in each village, and conduct endline surveys of another random sample of producers. A preanalysis plan for this trial was submitted to the AEA RCT Registry prior to the start of any intervention. Appendix C discusses deviations from the prespecified design that arose during project implementation.

3.3.1 Milk Testing

The primary outcome of interest is the microbial load in raw milk produced by the DCS. We measure the average microbial load by collecting a samples during the morning dairy collection, and then taking the samples to a lab for testing. To limit the extent to which test results are influenced by transportation time to the lab, each collection team visited only one village per day and carried an insulated container full of ice to immediately chill milk samples. We collected samples from every can filled by the DCS during two visits in the baseline period and two visits during the intervention period, as well as from a subset of producers prior to pouring into village cans during the first baseline visit.

We employ two lab tests of bacterial load: the methylene blue reduction test (MBRT) and the standard plate count (SPC).

Methylene Blue Reduction Test (MBRT): MBRT involves adding a blue dye to the milk sample and measuring the time until the dye completely disappears. Reduction of the dye is accelerated by removal of dissolved oxygen, typically caused by microbes in milk. Test results are reported in hours, with a greater time to reduction indicating lower presence of bacteria. This test is cheap, fast, and requires little training to conduct. However, because different microbes produce different compounds as a byproduct of metabolism that may affect dye reduction, test results may vary by type of microbes rather than just their quantity. This test is most commonly used at KMF processing centers to determine the suitability of raw milk for various products.

Standard Plate Count (SPC): The SPC is performed by culturing a swab of liquid residue in a nutrient broth for 24 hours, and then counting the density of bacterial colonies under a microscope. Results are typically reported in colony-forming-units per milliliter (cfu/ml); in our analysis we take the negative log transformation of this measure so that increasing values are associated with cleaner milk. Unlike MBRT, SPC is not sensitive to different types of microbes as all colonies are counted on a slide. However, it is significantly more expensive, takes longer to implement, and requires a higher level of training from laboratory staff. This test is typically used by food safety regulators, and is similarly used internally by the KMF to verify sanitary standards.

MBRT and SPC can be considered two noisy measures of the underlying milk cleanliness. To maximize power, our primary outcome for analysis is a composite measure of milk quality that is the first principal component of these two variables.[9] We construct this index at the DCS level by averaging over individual can measurements. Details of the relationship between the two measures and the principal components analysis are provided in Appendix B.

For results on testing-related outcomes, we implement a difference-in-differences (DD) estimation strategy at the DCS level. The estimating equation is

$$Y_{jt} = \beta^{Pr} T_{jt}^{Pr} + \beta^{Pu} T_{jt}^{Pu} + \gamma_j + \delta_t + \epsilon_{jt} \tag{1}$$

where j indexes DCSs and t indexes testing rounds. The variables T^{Pr} and T^{Pu} are dummies representing assignment to either private or public incentive treatment arms in round t, and both dummies are 0 for all DCSs in the two baseline rounds of observation. γ and δ represent DCS and time fixed effects, respectively.

3.3.2 Survey Data

We supplement the milk quality tests with two rounds of survey data. At baseline, prior to any milk testing visits, we surveyed twenty producers at each DCS randomly selected from the population of cooperative farmers contributing milk on the day of the visit. Baseline questions include information on demographics, income, and dairy production practices. We also administered a baseline questionnaire to DCS secretaries, directors, and presidents covering their demographics, dairy involvement, and managerial practices. After the final round of testing during the intervention, we administered an endline questionnaire to another randomly sampled twenty producers per village covering demographics, dairy involvement, and knowledge about our experiment.

In both baseline surveys, we also elicit subjective beliefs about the knowledge, performance, and social status of DCS members and managers. Each respondent was asked about their perceptions of the DCS president, secretary, each member of the board of directors independently, and about DCS member producers collectively. Beliefs were scored on a scale of one to five. At endline reevaluate DCS members' subjective beliefs about secretary performance.

Survey data exist at the individual level, but do not constitute a panel because the sample of

[9]Incentive payments to treated DCSs were tied only to MBRT for transparency because it is the primary measure used for production decisions by the KMF. In focus group meetings we found that most cooperative members and secretaries were familiar with MBRT but not with SPC. It is highly unlikely that study participants could take actions specifically aimed to improve the MBRT measurement without increasing overall milk cleanliness.

respondents is drawn anew between baseline and endline. Therefore, analysis using outcomes from survey data employs a pseudo-DD strategy with DCS-level rather than individual fixed effects. The estimating equation is

$$Y_{ijt} = \beta^{Pr} T_{jt}^{Pr} + \beta^{Pu} T_{jt}^{Pu} + \gamma_j + \delta_t + \epsilon_{ijt} \tag{2}$$

where i indexes individual producers in village DCS j. When individuals belong to a DCS that switched treatment assignment between the two rounds of intervention, they are assigned $T^{Pu} = 1$ and $T^{Pr} = 0$ if their village was ever assigned to public incentives. For the subset of endline survey outcomes that were not asked at baseline, we drop the fixed effect terms and estimate the simple difference between treatment and control, which should be balanced under the null due to randomization.

4 Results

Results indicate that milk cleanliness improves substantially among DCSs that received incentive payments. We observe an increase in cleanliness of up to 0.64 standard deviations in response to incentives, which would generate an 81% increase in the fraction of raw milk suitable for higher-value processing. This gain was induced by an incentive payment amounting to only 1% of total DCS revenue over the two week measurement window. The relative magnitudes of these effects reveal large potential returns to broader uptake of sanitation practices at the time of village milk collection, though we lack the power and granularity to identify exactly which activities let to the greatest improvements.

The effect of treatment is weaker in the public information arm relative to the private information arm. Attenuation is driven in large part by an unexpected request among several DCS secretaries to opt out of receiving publicly announced payments. In the final intervention round, seven of twenty-two DCS managers chose to forego receiving payment altogether rather than allow the payment to be announced publicly. This decision is puzzling because all DCSs would have received positive payments had they remained in the incentive treatment arm without altering their behavior in any way. Opting out is predicted by weaker management at baseline, especially as perceived by DCS member producers. We explore the relationship between information, managerial authority, and the choice to forego potential revenue further in the next section.

4.1 Cleanliness

We find evidence that group incentives can induce improvements in milk cleanliness. This main result is presented in Table 3, which reports the effect of treatment assignment on milk quality.[10] Col. 1 presents estimates from the DD specification in equation (1) on the index of cleanliness. Assignment to the private information arm improved average cleanliness by 0.64 standard deviations, significant at the 10% level. The effect of treatment in the public information arm is also positive, but smaller in magnitude at 0.32 standard deviations. Given the limited size of the experiment, we can neither statistically distinguish this effect from zero nor can we rule out that it is equal to the effect of private information. Some of the diminished impact of public payments can be attributed to the fact that almost a third of DCSs assigned to this arm chose to forego payment, which we discuss in detail further below.

[Table 3 about here.]

We next decompose the treatment effect into its constituent components. Cols. 2 and 3 show the independent effect of treatment on SPC and MBRT test measures. The SPC microbial load decreased by 0.42 log(cfu/ml) and the time to MBRT reduction increased by 0.4 hours on average among DCSs in the private treatment arm. These values represent improvements of .37 and 0.7 standard deviations, respectively, which are in line with the magnitude of change in the quality index.

To quantify the economic importance of these effects, we use the maximum SPC threshold of 500,000 cfu/ml recommended by the USDA for raw milk inputs into value-added processing as a benchmark. Recall from Figure 1 that only 16 percent of cans tested at baseline satisfied this threshold. A 0.64 standard deviation improvement in the baseline distribution of SPC would correspond to an 81% increase in this number, to nearly 30 percent of cans acceptable for high-value production.[11]

4.2 Margins of Adjustment

Improvements in cleanliness can either come from better sanitation of village equipment or from DCS constituent members pouring cleaner milk. While we cannot independently measure changes

[10] Table 3 and all subsequent regression tables report both standard errors clustered at the DCS level and p-values generated by randomization inference using 10,000 iterations of a clustered bootstrap procedure following Bloom et al. (2012) and MacKinnon and Webb (2020). To estimate the significance of the coefficient on assignment to private incentives, we randomly re-draw 19 DCSs from 19 + 13 = 32 total private treatment and control DCSs in each iteration. For the public incentive, we redraw 22 DCSs from the 22+13 = 35 total public and control DCSs in each iteration.

[11] Regression analysis using a dummy for passing 500,000 cfu/ml on the left hand side estimates a comparable treatment effect magnitude of nine percentage points in the private information arm. However, such a coarsening of the outcome variable in an already small sample leads to very large standard errors for this exercise.

in these two outcomes, evidence points to both factors at work. During the intervention period, enumerators and producers frequently observed DCS staff washing collection equipment in incentivized villages; such sights were reportedly rare both prior to our involvement and in control villages during the intervention period. As reported in Figure 2, average time to MBRT reduction was 0.74 hours lower in pooled milk than in individual samples at baseline, indicating that sanitation of village equipment alone is large enough to account for the 0.4 hour treatment effect.

There is also indirect evidence of cleaner milking practices among producers in incentivized DCSs. Table 3 reports select results from the endline survey following the intervention period. In Col. 3, we show that producers' beliefs about others' cleanliness increase in the incentive arms. This change is not caused by the salience of testing because the table reports increases relative to control, where quality testing also takes place. It is similarly not caused by the salience of payments because it is present in the private information arm where there is little public knowledge about incentive payments (Col. 1). Thus, it is likely that perceptions track the observed behavior of other producers.

[Table 4 about here.]

The mechanism to induce behavior change is unclear as there are insignificant and quantitatively small differences in the frequency of DCS messaging about cleanliness between treatment and control (Col. 2), and DCS management doesn't explicitly notify producers about the potential return to cleanliness in the private information arm (Col. 1). These facts suggest that DCS managers may exert influence over production practices through informal channels that are more difficult to quantify.

While actual cleanliness improves most in the private treatment arm, perceptions of secretary cleanliness interestingly decrease in this arm. This fact, shown in Col. 4, may stem from increased visibility of cleaning activities. Without corresponding knowledge of an increase in returns to cleanliness, farmers may update to believe that secretaries had been inefficiently dirty before. Updating does not spill over into beliefs about managerial capacity (Col. 5). Other explanations are possible, but this dynamic hints at a reason why elites might sustain bad behavior to avoid revealing their past actions.

4.3 Payment

The gains described above were achieved with relatively low-powered incentives. The first two columns of Table 5 show the size of cleanliness payments to treated DCSs relative to the counterfactual payment the average control DCS would have earned in each intervention round. Greater sanitation among treated DCSs generates roughly an additional Rs. 100 per collection day for the cooperative in the private incentive arm. In total, treated DCSs earn around Rs. 800 per round in payments for cleanliness, equivalent to $16 at the time of study. Compared to the average DCS daily revenue of Rs. 5,600, this value amounts to only a 1% increase in revenue over the two-week testing window.

[Table 5 about here.]

Producers in the public incentive arm may have behaved strategically during the intervention period to secure a portion of this revenue. Almost all dairy-related payments in this setting are apportioned as a function of quantity poured: Producers and cooperatives are paid directly by volume, and any year-end bonuses or producer support schemes are awarded per liter. This fact gives context to the increase in quantity poured[12] in the public intervention arm, reported in Col. 4 of Table 3. A quantity increase of nearly 16% per producer is observed in the only intervention arm where producers knew the DCS would receive additional revenue.

Despite producers' efforts, we find no direct evidence that incentive payments were shared with cooperative members. There is no difference between treatment and control in the share of farmers that recall receiving bonus payments from the DCS post-intervention, reported in Col. 3 of Table 5. This calculation is made with the caveat that the overall share rose from 20% at baseline to 80% at endline due to a statewide support scheme delivered in early 2015, which might drown out any potential impacts from our intervention.

4.4 Foregone Payment

Some of the gap in treatment effects between the public and private incentive arms can be attributed to the unexpected fact that a substantial portion of DCSs assigned to public treatment declined to be paid. In the second round of intervention, seven out of twenty-two DCS secretaries opted to forego payments entirely rather than accept a publicly announced incentive payment (Table 5, Col.4). In all cases, the managers first requested that payment be made to the DCS account without public knowledge. Upon being denied, all seven consented to continue milk testing without payment, and allowed producers to participate in the subsequent endline survey.

We explore the relationship between opting out and cleanliness in Figure 4. Panel A plots the treatment effect in the two arms as the event study counterpart to Table 3 Col. 1. Panel B breaks down the public payment event study into DCSs that participate and those that opt out in the second round. The figure reveals two facts: First, DCSs that opted out start with ex ante lower milk quality than those that remain in the experiment. Therefore, there may be selection into opting out based on the anticipated size of payment. Second, the trend line for villages that stay in the experiment with public payments closely tracks that of private payments, while the trend line for those foregoing payment remains nearly flat.

[12] It is difficult to change quantity through number or quality of livestock over the short horizon of our study, so the most likely margin of adjustment is in the portion of milk delivered to the cooperative versus saved for home consumption.

[Figure 4 about here.]

Regression analysis reveals that opting out explains some, but likely not all, of the gap between treatment arms. In a two-stage least squares (2SLS) version of equation (1) using treatment assignment as an instrument for actually receiving incentives,[13] the estimated effect of public treatment increases from 0.32 (Table 3 Col. 1) to 0.39. Note that this latter value is still not directly comparable to the estimated 0.64 effect size in the private treatment arm because it is local to a selected subset of DCSs. It may be the case that DCSs remaining in the public information arm have lower potential for improvement.

DCSs that opt out of public payment appear to be negatively selected by managerial capacity. In Table 6 we report ex ante predictors of opting out in baseline data. Across all indicators of management quality, DCSs where the secretary declines payment perform consistently worse than those that remain in the public incentive arm. The board of directors meets less frequently, producers can identify fewer board members, and producers are less likely to recall having received bonuses. Moreover, producers rate all managers lower in both management quality as well as social status. An F-test confirms the joint significance of producers' negative beliefs about management quality at the 1% level. Interestingly, this trend does not appear in managers' reported beliefs about their own quality; a joint test fails to reject equality between opting out and not at the 10% level.

[Table 6 about here.]

5 Discussion

The decision by some managers to forego publicly disclosed payments is unexpected because cooperatives could have earned positive payment without making any changes to their milking behavior. Moreover, there must be a net return to some amount of cleaning because quality improved among cooperatives in both the private arm and those that remained in the public arm. We would expect this return to be, if anything, greater in the public information arm because information is typically thought to lower transactions costs, alleviate asymmetries, and facilitate exchange. Market failures arising from issues of collective action or hidden effort cannot explain the discrepancy in participation between treatment arms because they operate equally in both.

In this section, we present a stylized model of information exchange between a manager and a worker to better understand the role of public information.[14] The manager and worker constitute a production team with a fixed sharing rule to allocate the surplus they generate. Inefficiency

[13]The DD estimate can be thought of as an Intention to Treat (ITT), and the 2SLS as a Treatment on Treated (TOT).

[14]In the context of our experiment, the manager represents the cooperative secretary and president, and the worker represents member producers.

arises because the manager can hide a portion of surplus from the worker. Doing so distorts output relative to the efficient benchmark by skewing the worker's return to effort, but allows the manager to appropriate a greater share of the returns. The manager chooses a level of information disclosure that balances these two competing pressures. This model abstracts from issues of collective action, moral hazard, and managerial effort to isolate the role of information about returns; it is straightforward to introduce these further market failures to capture other features of the production environment.

The model highlights how elites can have multiple different avenues through which to influence their share of surplus, with different levels of market distortion. Economic efficiency and welfare for other participants depends on the way in which those in power substitute between these options. This substitution leads to the counterintuitive result that increasing formal elite control may actually improve welfare for non-elites, in both absolute and relative terms, by increasing total surplus. At the extreme, we observe evidence of this type of distortion in the decision to opt out of payment in our experiment, thereby foregoing all possible gains to all parties involved. We close this section with some qualitative evidence that suggests possible motivations for this decision to opt out.

5.1 Model Setup

Consider a team with one manager (M, she) and one worker (W, he) that share the surplus from production according to an agreed-upon rule. The manager first observes a production function, which she announces to the worker. The worker then chooses a level of effort based on the information he is provided.[15] Finally, the two parties split the surplus they generate according to the sharing rule.

Formally, let output y be a function of worker effort x such that $y = f(x)$ with a continuous, twice differentiable production function $f(\cdot)$ where $f(0) = 0$, $f'(\cdot) > 0$, $f''(\cdot) < 0$, and $\lim_{x\to\infty} f'(x) = 0$. These conditions guarantee there will be interior solutions to the optimal and equilibrium levels of effort.

The production function is initially observed only by the manager. She makes an announcement to the worker, but can choose how much to disclose by announcing

$$\hat{f}(x) = zf(x)$$

for some $z \in [0, 1]$ that governs the information communicated to the worker. $z = 1$ represents full disclosure and $z = 0$ represents no disclosure, effectively hiding the production opportunity from the worker entirely.

The worker then chooses a level of effort x given his information set. Effort has a linear cost so

[15] In the context of our experiment, private knowledge about the production function corresponds to the reimbursement for cleanliness and other details about the cooperative financial account.

the surplus generated from production is $f(x) - x$. However, the worker can only verify a portion of output $\hat{f}(\cdot)$, so he only has claims over $\hat{f}(x) - x$ of the total surplus. The remaining output is accessible to the manager alone.

The two parties split the public surplus, net of the worker's cost of effort, according to a sharing rule indexed by $\lambda \in (0, 1)$. We henceforth use the terms sharing rule and bargaining power interchangeably to refer to λ. The net value to the worker from the relationship is

$$\begin{aligned} V^W &= (1-\lambda)(\hat{f}(x) - x) \\ &= z(1-\lambda)f(x) - (1-\lambda)x \end{aligned}$$

where λ denotes the manager's bargaining power in the relationship. The manager keeps the remainder of the public surplus as well as the additional undisclosed output, so the value to the manager is

$$\begin{aligned} V^M &= \lambda(\hat{f}(x) - x) + (f(x) - \hat{f}(x)) \\ &= (1 - z(1-\lambda))f(x) - \lambda x \end{aligned}$$

In effect, the worker and the manager share the burden of effort according to the intended sharing rule, but the manager can skew the allocation of output in her favor by hiding some production.

Every Pareto optimal outcome of this production relationship maximizes total surplus, which is achieved when

$$\begin{aligned} & x^* = \arg\max_{x \geq 0} f(x) - x \\ \implies \quad & f'(x^*) = 1 \end{aligned}$$

Note that this condition only depends on z indirectly though its impact on x. The surplus-maximizing level of effort x^* and resulting output serve as benchmarks against which to compare equilibrium outcomes.

5.2 Equilibrium Production

Define an equilibrium conditional on the true production function $f(\cdot)$ to be a subgame-perfect set of strategies $(\tilde{z}, \tilde{x}(z))$, where tildes represent equilibrium quantities, such that neither the manager nor the worker can profitably deviate. That is, the manager chooses to announce a production function $\tilde{f}(\cdot)$ conditional on the anticipated level of worker effort. The worker chooses a profile of effort levels $\tilde{x}$ for every possible announcement of $\hat{f}(\cdot)$. Because $\hat{f}(\cdot)$ is fixed up to the choice of z, we represent strategy profiles as $(z, x(z))$ for ease of notation even though the worker does not directly observe z.

In a subgame perfect equilibrium, the worker optimizes his private return

$$\tilde{x} = \arg\max_{x \geq 0} (1-\lambda)(\hat{f}(x) - x)$$

for any given announcement $\hat{f}(\cdot)$. The worker's first order condition implies

$$\hat{f}'(\tilde{x}) = 1 \quad \Longrightarrow \quad f'(\tilde{x}(z)) = \frac{1}{z}$$

That is, the worker acts as though $\hat{f}(\cdot)$ is the true production function even if he suspects the manager is hiding information.[16]

It is clear from the worker's first order condition that effort is strictly increasing in information disclosure due to the concavity of $f(\cdot)$. The social optimum is reached only when there is full disclosure, i.e. $\tilde{x}(1) = x^*$. As long as the manager hides some portion of output, production will be inefficiently low. At the other extreme, if the manager hides all output then $\tilde{x}(0) = 0$ and the team passes up the production opportunity.

In equilibrium, the manager chooses z to maximize her return given the worker's effort response. She solves

$$\tilde{z} = \arg\max_{z \in [0,1]} (1 - z(1-\lambda))f(x) - \lambda x \quad \text{s.t.} \quad f'(x) = \frac{1}{z}$$

The first order condition to the manager's problem can be written as[17]

$$(1-\tilde{z})\frac{\partial \tilde{x}}{\partial z} - \tilde{z}(1-\lambda)f(\tilde{x}(\tilde{z})) = 0$$

This expression gives intuition for the two factors the manager balances. The first term represents worker effort, which determines the total surplus in the relationship, and the second term represents the manager's portion of that surplus. By increasing the amount of information disclosure, the manager induces more effort from the worker but must share more of the fruits of that effort.

Result 1. $0 < \tilde{z} < 1$. *In equilibrium the manager discloses a suboptimal level of information.*

This result follows directly from the first order condition. When $z = 0$, there is no surplus so the manager certainly prefers some production to no production. When $z = 1$, the first order condition reduces to $-(1-\lambda)f(x^*) < 0$. That is, at the social optimum, the first-order gain from hiding output exceeds the second-order decline in surplus. Therefore, the equilibrium $\tilde{z}$ must lie

[16] If we relax the requirement of subgame-perfection, there may be equilibria where the worker underperforms for low announcements of $\hat{f}(\cdot)$ in order to encourage more truth-telling when $f(\cdot)$ is high. Such a strategy could increase ex ante expected surplus given the distribution of possible $f(\cdot)$. It is sustainable as a subgame-perfect equilibrium in a repeated game where the production function evolves stochastically in each period if participants are sufficiently patient. This dynamic equilibrium, which is a special case of the class of repeated games with imperfect monitoring analyzed by Abreu et al. (1990), is beyond the scope of our discussion here.

[17] See Appendix D for a full derivation and proofs of all results.

between two extremes.

Inefficiency in this team stems from the rigidity of the sharing rule λ. In theory, the manager could propose a Pareto improving deviation by asking the worker to increase his effort from $\tilde{x}$ to x^* in exchange for an additional $x^* - \tilde{x} + \epsilon$ in compensation. This arrangement would be profitable for the manager, who could keep the rest of the output and end up with a share greater than λ of total surplus. Such deviation does not depend on the verifiability or contractability of $f(\cdot)$; the manager could propose it unilaterally to the benefit of both parties.[18] The equilibrium is only inefficient if this deviation is prohibited.

5.3 Comparative Statics

As a direct corollary of Result 1, output is suboptimally low when the manager controls information about the production function. Similarly, the distribution of surplus is skewed toward the manager relative to the full-information benchmark, and the worker derives less total value from the relationship. We next explore how these outcomes evolve with the bargaining power of the two parties. Recall that the manager's bargaining power is increasing in λ.

Result 2. *As long as the curvature of $f(\cdot)$ is not too great, $\frac{\partial \tilde{y}}{\partial \lambda} > 0$. Total output increases toward the efficient benchmark with the manager's bargaining power.*

Intuitively, as the manager's bargaining power grows, she receives a greater share of surplus. As long as the return to effort in the production function does not die out too quickly, then an increase in bargaining power induces her to prioritize incentivizing the worker over hiding output. See Appendix D for a precise condition regarding the curvature of the production function; this condition is guaranteed to be satisfied as λ approaches 1. As a corollary, increasing the manager's bargaining power may lower overall efficiency if the curvature in the production function is large. High curvature indicates the incentive effect of the return to effort rapidly decreases in the level of effort, offsetting any potential gains in production.

Result 3. $\frac{\partial V^M}{\partial \lambda} > 0$. *The manager's value from the production team is increasing in her bargaining power.*

This result is unsurprising. For any given choice of information disclosure z, the manager's value is strictly increasing in her share of surplus λ. Therefore, it must be the case that higher values of λ correspond to higher value for the manager after optimizing z.

Result 4. *The sign of $\frac{\partial V^F}{\partial \lambda}$ is ambiguous. The worker's value from the production team may be increasing or decreasing in his bargaining power.*

[18] Rigidity in the sharing rule is closely related to the issue of noncontractability that arises in typical models of hidden information. The manager initially hides a portion of output so that it is unverifiable and therefore excluded from surplus sharing, even if the worker suspects it exists. If proposing a deviation makes this additional output verifiable, e.g. by eliminating the plausible deniability of the manager, then the motivation to keep it hidden from contracts would preclude such a deviation.

This unintuitive result follows from the factors that determine the manager's information disclosure. When the manager's bargaining power increases, she may choose to disclose more information to the worker to induce more effort. If the gain in total surplus from this disclosure exceeds the loss in the worker's share from lower bargaining power by a large enough margin, then the worker will be better off in an environment with a more powerful manager who endogenously chooses to cede more control.[19] As a corollary, the worker's share of the total surplus may similarly increase or decrease with his bargaining power depending on the change in information disclosure relative to his claim on the surplus of production. Both of these values unambiguously fall to 0 as $\lambda \to 1$, but not necessarily monotonically so.

Taken together, these comparative statics highlight an important policy tradeoff in this production environment. Managers have two tools with which to manipulate their private returns: they can formally bargain over the surplus of production, characterized by λ, or they can informally appropriate output, characterized by z. Crucially, appropriation (z) distorts production incentives while formal bargaining (λ) does not. Intuitively, increasing the returns to formal bargaining will encourage the manager to prefer this tool, raising overall surplus as long as it is not too damaging to the worker's incentives. A less obvious implication is that this increase in the manager's formal bargaining power may induce enough of a shift from appropriation to bargaining that it is on net beneficial to the worker as well.

5.4 Relation to Experimental Results

This stylized model sheds light on how information disclosure affects manager incentives. In the context of the model, we can consider the manager to be the DCS secretary and president, who also make the decision to opt out of payment in the public treatment arm, and the worker to represent cooperative members. The "true" production function reflects the return to cleanliness induced by our experiment, and effort corresponds to clean milking practices. The public information arm fixes information disclosure at $z = 1$, the private information arm allows management to endogenously choose $\tilde{z}$, and the control arm and opting out both effectively set $z = 0$. This model abstracts from hidden information and collective action concerns in producer effort because these issues exist equally across treatment arms.

Our empirical findings indicate that transaction and renegotiation costs in the allocation of surplus within a village are economically significant. This implication follows from the differential rate of opt-out between public and private treatment arms. The net DCS-level return to cleanliness does not vary between these two arms, but the private return to management is evidently lower when information is public. Therefore, it must be the case that managers cannot easily renegotiate rents once information has been made public to achieve the same level of return as they would have

[19] Appendix D precisely defines the conditions under which this situation occurs. It depends on the third derivative of the production function, and is therefore difficult to interpret intuitively.

when information was private. Instead, public information disclosure forces managers to accept a lower net return, which in some cases they choose to decline.

The implication of high transaction costs is surprising given the fact that DCS jurisdiction coincides with village boundaries where members have substantial economic and social interaction outside of dairy production. Social networks have been shown to facilitate economic interaction both theoretically (e.g. Jackson et al., 2012) and empirically (e.g. Greif, 1993; Chandrasekhar et al., 2018) to improve economic efficiency. Our results suggest that norms over the allocation of rents in a network can lead to distortions away from the efficient outcome. In particular, a global norm regarding how surplus is shared across multiple contexts can lead individuals to take inefficient actions to circumvent that norm in each individual context.

Inefficiency caused by the the allocation of surplus reveals an unintuitive tradeoff in policy design. When local elites have multiple tools to exert control over economic surplus, some of which distort productive efficiency, then increasing elites' power in non-distortionary dimensions can lead them to substitute away from distortionary tactics. We report evidence of this mechanism at work in the predictors of opting out in the public treatment arm—managers are more likely to opt out of public payment where they have weaker social status and therefore less influence over the allocation of DCS profits. Our model predicts that in some cases, this tradeoff is so large that strengthening formal elite power can actually be welfare-enhancing for the rest of the population. In our setting, it is certainly the case that producers are worse off when managers opt out of the experiment and the DCS receives no payment.

Result 1 leads to the additional implication that, conditional on receiving incentives, full information should lead to greater output than private information. In fact we observe the reverse: incentives induce greater improvement in the private arm than the public arm, even after excluding DCSs that decline payment. This discrepancy may be reconciled by the fact that cleanliness is also improved through effort on the part of the secretary. The manager's incentive to contribute effort to the production relationship is exactly opposite that of the worker. She should like to work the hardest when information disclosure is low and she can keep a greater share of the profit. If the returns to managerial effort are large, then this effect may offset the gains from worker effort under full information, generating our experimental result.

While the model explains differences in manager surplus between the public and private arms as well as heterogeneity by social status of the manager, it does not fully justify opting out of payment because participation would generate positive returns for managers at every level of information disclosure. Opting out can only be rationalized if there is an additional cost to information disclosure outside of the production relationship. Secretaries who opted out hinted at such costs with statements such as, "farmers [will be] angry about why the monetary reward is going to the DCS when they were the ones who produced the milk" and "farmers will regularly start expecting payments."

Further qualitative investigation reveals two potential sources of burden that public information disclosure may place on DCS management. First, our method of disclosing information may induce disparate beliefs about the actual returns to cleanliness given the low-information environment. Producers may misunderstand or misinterpret our announcements about payment and conclude they are owed more than the DCS receives as surplus. In this case, managers would have to expend effort or social capital correcting producers' (incorrect) expectations, and might prefer a situation in which they can control the message DCS members receive.

Second, announcements about cleanliness payments may reveal undesirable information about DCS finances. Both focus group interviews as well as discrepancies between DCS accounting profits and member dividends suggest that DCS management has substantial private information and therefore de facto control over the cooperative financial account. If a public announcement of experiment incentives, paid into the financial account, reveals other financial information about this account, then it may weaken this control. Given the vast size of the DCS annual budget relative to our temporary incentive, some managers may have felt that even a small chance of this revelation would not be worth the risk. While we cannot quantitatively distinguish between these two explanations, both induce a negative relationship between public information and managerial returns that can justify the decision to opt out of payment.

6 Conclusion

In this paper, we evaluate the effectiveness of group incentives for a production team in the context of milk cleanliness among village dairy cooperatives in Karnataka, India. Cleanliness is determined by individual milking practices within the production unit. Cooperative members likely have local information about each others' behavior, but individual cleanliness is costly to measure for an outside observer. Team dynamics are complicated by the fact that the cooperative exists within a broader social structure, and formal managerial authority in the cooperative coincides with power in the social network. In this setting, we test whether the cooperative can effectively decentralize a group incentive to induce action among its constituent members.

We find that group incentives improve cleanliness on average. An incentive equaling one percent of cooperative revenue is enough to induce an increase in quality of up to 0.64 standard deviations, nearly doubling the fraction of production suitable for high-value processing. This increase indicates that within village economies, there is sufficient local information and enforcement capacity to solve collective action problems and take advantage of collective opportunities.

However, this potential is tempered by the interaction between local information and the cooperative governance structure. Incentives are more effective when communicated only to cooperative leadership rather than announced publicly to all cooperative members. This discrepancy is caused in large part by the decision among a subset of cooperative managers to forego payment entirely when faced with the prospect of public disclosure. The managers most likely to opt out of payment are those lower in social status within the village social network.

We interpret this unexpected outcome in the context of a model where local elites have multiple tools with which to exert control over social surplus. Some methods of control distort productive efficiency while others do not. Through this lens, opting out of payment can be considered an extremely distortionary method of preserving power. We show that limiting elite power in one dimension can have the unintended consequence of lowering welfare for non-elites by inducing elites to substitute towards more damaging alternatives.

This last result provides a cautionary message for technological approaches to limiting corruption. For instance, recent advances such as electronic banking and mobile money have enabled direct cash transfers intended to circumvent the possibility of elite capture. While such innovations hold promise, they will only deliver benefits if implemented in ways that are sensitive to alternative avenues of elite capture in local governance. It remains an open question how to balance aggregate efficiency with distributional goals, and the optimal design of group incentives in village economies paves the way for future work.

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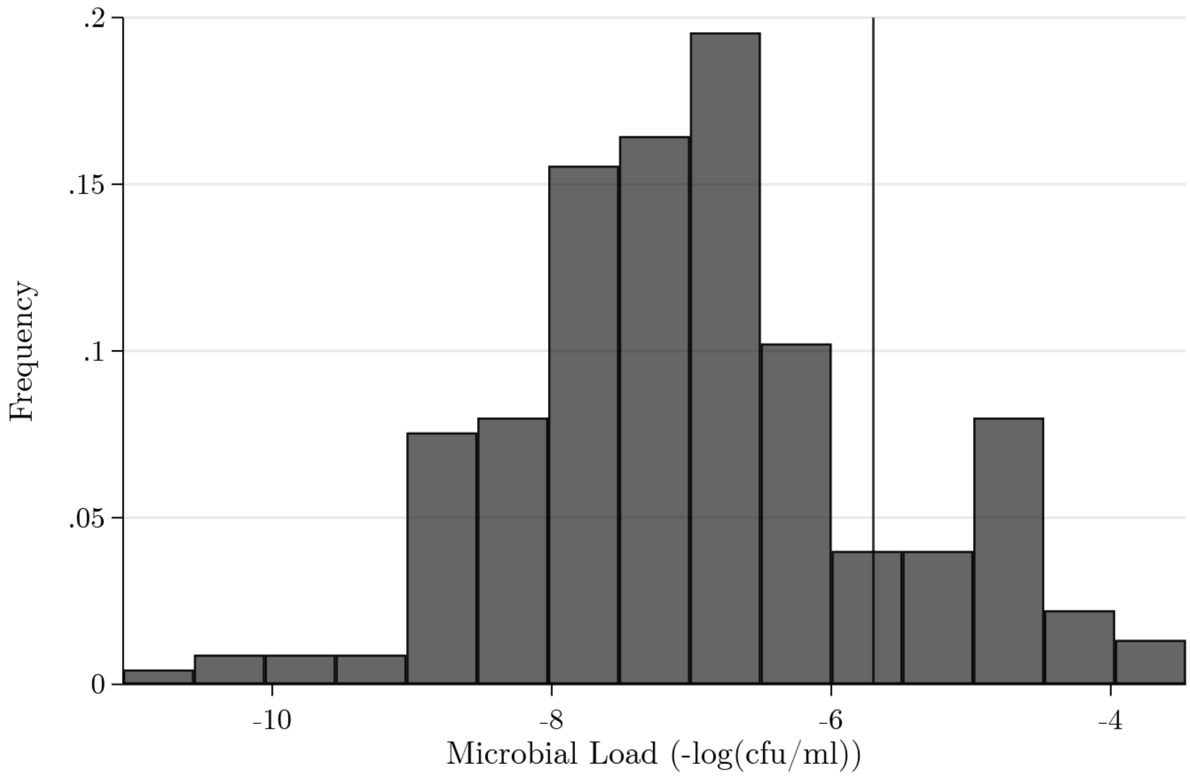
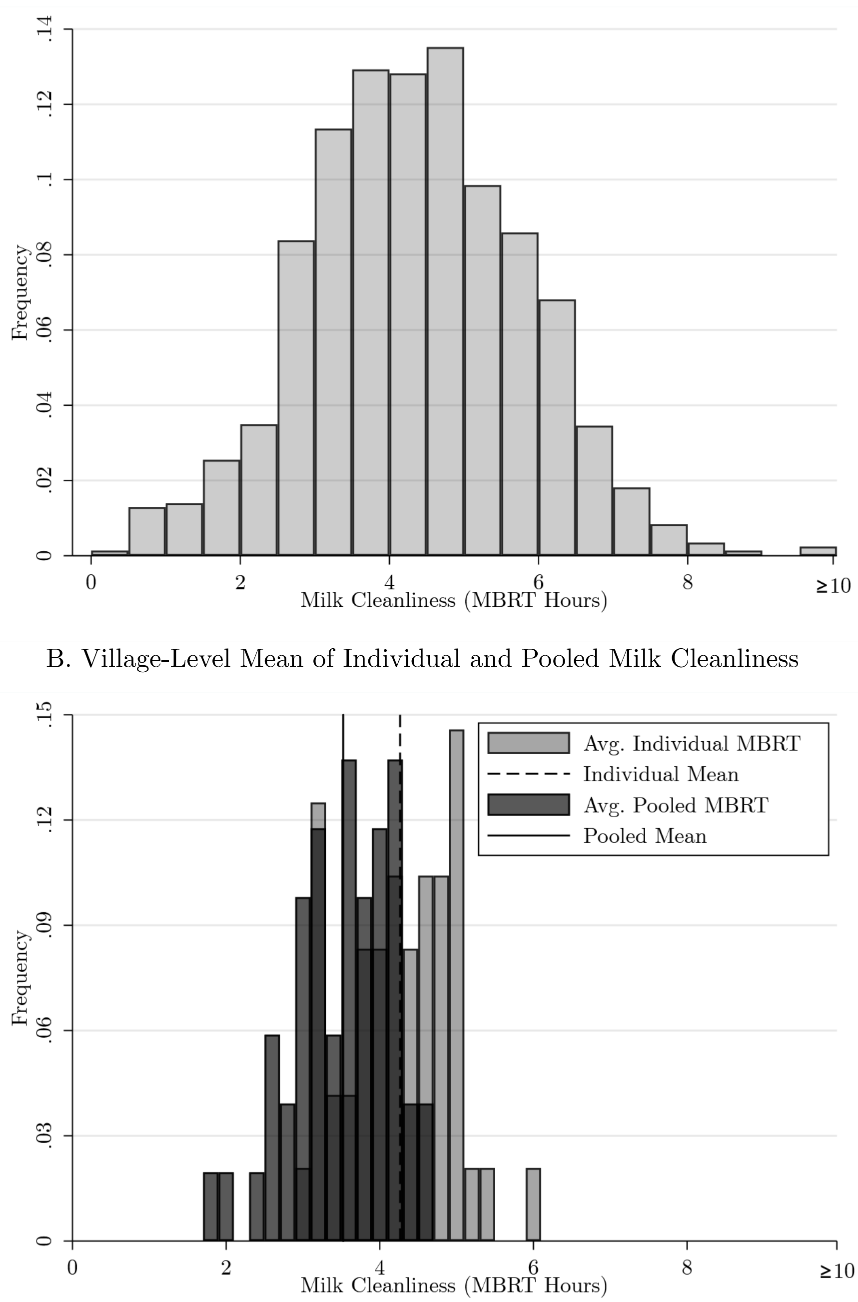
Figure 1: Microbial Load by Milk Can



Notes: The distribution of microbial load by delivery can among DCSs under the existing KMF payment structure. Samples are collected at the time of DCS milk collection and measurements are conducted using a standard plate count (SPC), reported in -log units so that higher values indicate cleaner milk. The vertical line represents the 500,000 cfu/ml threshold for use in value-added production. Only 37 of 225 cans tested (16%) satisfy this requirement.

Figure 2: Individual and Aggregate Distributions of Milk Quality

A. Distribution of Individual Cleanliness



Notes: Distributions of milk cleanliness at baseline. Samples are collected during DCS milk collection and measurements are conducted using a methylene blue reduction test (MBRT), reported in hours, so that higher values indicate cleaner milk. A. Distribution among samples from individual producers prior to contact with cooperative equipment. 14% of producers exceed the 6 hour threshold delineating high sanitation. B. Distribution of within-cooperative average of samples taken from individual producers immediately before pouring and from collective cans immediately after pouring. The dashed vertical line represents the mean among individual samples and the solid vertical line represents the mean among DCS cans. Reduction time declines by 0.74 hours from individual to pooled milk, and a t-test rejects equality with a t-statistic of 5.6 ($p < 0.01$).

Figure 3: Experiment Timeline and Randomization Design

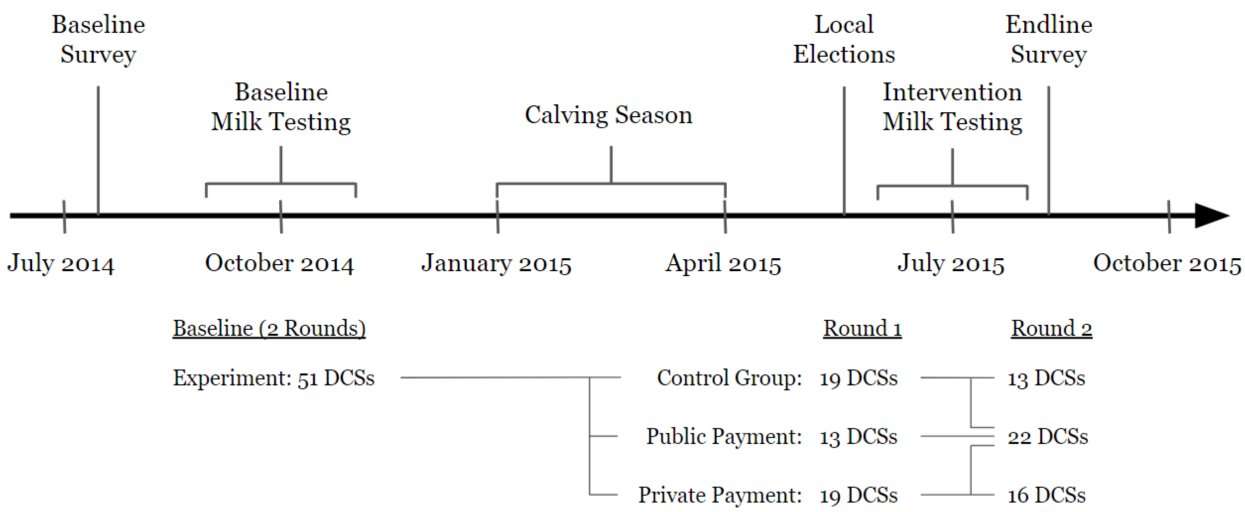
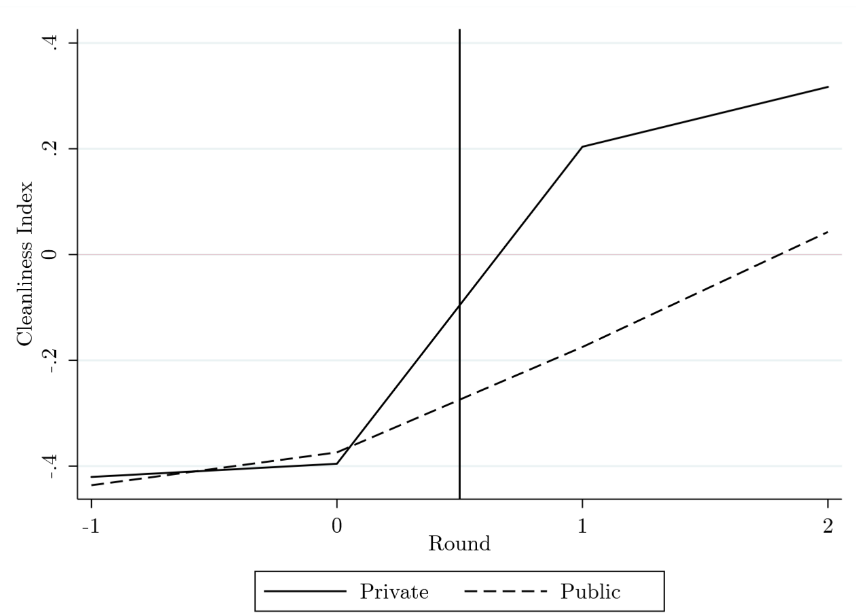
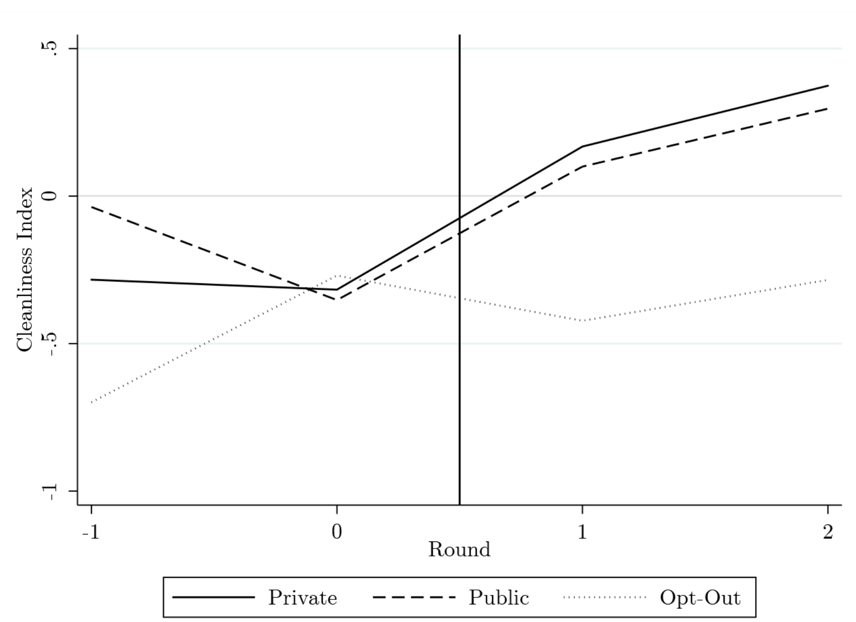


Figure 4: Event Study of Cleanliness by Treatment Assignment

A. Milk Cleanliness by Treatment Assignment



B. Milk Cleanliness by Treatment Status



Notes: Outcome is an index of milk quality constructed from principal components analysis of SPC and MBRT. A. Event study version of eqn. (1) by treatment assignment. B. Event study version of eqn. (1) splitting public incentive arm based on decision to opt out.

Table 1: Characteristics of DCS Members and Managers

	Producers	Directors	Secretary	President
Education	4.4	5.2	10.9	8.3
	(0.7)	(0.3)	(0.3)	(0.5)
Frac. SC/ST	0.29	0.30	0.24	0.08
	(0.02)	(0.03)	(0.06)	(0.04)
Land Owned	6.4	5.4	4.9	14.8
	(0.5)	(2.6)	(0.9)	(2.0)
Monthly Income	11,931	13,256	14,202	19,248
	(693)	(893)	(2,423)	(2,192)
Panchayat		0.06		0.21
		(0.01)		(0.06)
Observations	1,024	406	49	71
Social status as reported by:				
Producers		3.1	3.7	3.6
		(0.05)	(0.06)	(0.06)
Directors		3.4	4.1	4.0
		(0.06)	(0.07)	(0.08)
Management quality as reported by:				
Producers		3.0	3.7	3.5
		(0.05)	(0.07)	(0.06)
Directors		3.4	4.4	3.9
		(0.05)	(0.06)	(0.07)
Dairy knowledge as reported by:				
Producers		3.0	3.8	3.6
		(0.06)	(0.06)	(0.07)

Notes: Characteristics of and beliefs about DCS member producers, directors, secretaries, and presidents at baseline. Characteristics include years of education, fraction scheduled caste/schedule tribe, acres of land owned, monthly income, and fraction that has ever been elected to the local legislative assembly (Gram Panchayat). Beliefs include perceptions of social standing, managerial capacity, and knowledge about dairy practices on a scale of one to five. Each row represents a category of respondent stating their perceptions. Directors reported perception of every other director but not of own self. President includes both current and past DCS presidents. Standard errors clustered by DCS in parentheses.

Table 2: Descriptive Statistics by Treatment Status

	Control	Treated	Difference
HH Size	6.8	6.2	−0.60
	(0.30)	(0.23)	(0.38)
Education	5.4	4.1	−1.3
	(0.34)	(1.0)	(1.1)
Frac. SC/ST	0.31	0.28	−0.03
	(0.05)	(0.03)	(0.06)
Land Owned	7.4	6.0	−1.5
	(0.80)	(0.56)	(0.98)
Cows Owned	1.7	1.7	−0.05
	(0.11)	(0.04)	(0.11)
Monthly Income	13,894	11,114	−2,780*
	(1,218)	(800)	(1,458)
Frac. Dairy Income	0.28	0.33	0.05***
	(0.01)	(0.02)	(0.02)
Frac. Farmers	0.62	0.63	0.00
	(0.04)	(0.03)	(0.05)
Frac. Labor	0.12	0.17	0.05
	(0.02)	(0.02)	(0.03)
Milk Production	6.44	6.17	−0.27
	(0.38)	(0.23)	(0.45)
Milk Cleanliness	0.23	−0.17	−0.40
	(0.49)	(0.39)	(0.28)
Num. Villages	15	36	
Joint F-Statistic			1.5
[p-value]			[0.17]

Notes: Descriptive statistics at baseline for farmers in treated and control DCSs. The third column reports the differences between the two groups. Joint F-statistic excludes milk cleanliness, which was measured separately from survey responses. Standard errors clustered by DCS in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Impact of Treatment on Milk Cleanliness and Production

	(1) Cleanliness	(2) Cleanliness	(3) SPC	(4) MBRT	(5) Quantity
Private Incentive	0.64*	0.63**	0.47	0.36	−0.06
	(0.35)	(0.31)	(0.32)	(0.22)	(0.58)
	[0.1]		[0.32]	[0.11]	[0.94]
Public Incentive	0.32	0.39	0.38	0.17	1.0**
	(0.32)	(0.29)	(0.32)	(0.18)	(0.49)
	[0.32]		[0.41]	[0.43]	[0.14]
Control Mean	0.06	0.06	6.83	3.44	6.43
R-Squared	0.08		0.03	0.07	0.01
Wald-chi2		256.14			
Observations	204	204	204	204	2,006
DCS Fixed Effects	X	X	X	X	X
Round Fixed Effects	X	X	X	X	
Double-Post Lasso		X	X	X	

Notes: First four columns report DD estimates from eqn. (1). Columns 2-4 accounts for control variables using Double-Post Selection LASSO. Column 5 reports pseudo-DD estimates from eqn. (2). (1) Cleanliness is an index of milk quality constructed from principal components analysis of SPC and MBRT. (2) SPC is measured in -log(cfu/ml). (3) MBRT is hours to dye reduction. (4) Quantity is liters per day per producer surveyed; total DCS quantity is unavailable. Standard errors clustered by DCS in parentheses. p-values from randomization inference with clustered bootstrap in square brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Impact of Treatment on Endline Survey Responses

	(1) Know about Payments	(2) DCS Gave Information	(3) Believe Others Clean	(4) Believe Secy. Clean	(5) Believe Secy. Manager
Private Incentive	0.01	0.09	0.45***	−0.26**	0.07
	(0.01)	(0.07)	(0.11)	(0.12)	(0.21)
	[1.0]	[0.53]	[0.0]	[0.01]	[0.58]
Public Incentive	0.16***	0.09	0.30**	−0.08	0.24
	(0.04)	(0.07)	(0.12)	(0.13)	(0.21)
	[0.03]	[0.47]	[0.0]	[0.3]	[0.04]
Control Mean	0.008	1.37	4.31	4.53	4.09
Diff-in-Diff			X	X	X
R-Squared	0.08	0.004	0.06	0.03	0.05
Observations	982	982	1,918	1,990	1,983

Notes: First two columns report simple difference at endline; remaining three columns report pseudo-DD estimates from eqn. (2). (1) Fraction of respondents that know about cleanliness incentive payments. (2) Frequency with which DCS gives information on clean milking practices. (3) Avg. belief among producers about cleanliness of other producers. (4) Avg. belief among producers about cleanliness of secretary. (5) Avg. belief among producers about managerial quality of secretary. Standard errors clustered by DCS in parentheses. p-values from randomization inference with clustered bootstrap in square brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Impact of Treatment on Payment Received

	(1) Payment Round 1	(2) Payment Round 2	(3) Received Bonus	(4) Opted Out Round 2
Private Incentive	121.1	98.3	0.01	0
	(106.9)	(82.7)	(0.09)	(.)
	[0.33]	[0.26]	[0.84]	[.]
Public Incentive	−0.40	16.8	0.03	0.32***
	(85.4)	(81.1)	(0.08)	(0.10)
	[1.0]	[0.85]	[0.6]	[0.0]
Control Mean	715.8	676.9	0.81	0
R-Squared	0.05	0.05	0.48	0.21
Observations	153	153	2,006	51

Notes: First two columns report DD estimates from eqn. (1). Third column reports pseudo-DD estimates from eqn. (2). Fourth column reports simple difference in second intervention round. (1) and (2) report total payment received by DCS, and control mean reflects counterfactual payment that would have been received by DCSs in control arm. (3) Fraction of producers who report ever receiving a bonus payment. (4) Fraction of DCSs that opt out of payment in second intervention round. Standard errors clustered by DCS in parentheses. p-values from randomization inference with clustered bootstrap in square brackets. *** p<0.01, ** p<0.05, * p<0.1

Table 6: DCS Baseline Characteristics by Study Participation

	Treated	Opted Out	Difference
Ever Received Bonus	0.25	0.19	−0.06
	(0.07)	(0.06)	(0.09)
Frac. Directors Known	0.27	0.24	−0.03
	(0.03)	(0.03)	(0.04)
Directors Meetings	1.66	1.27	−0.39**
	(0.05)	(0.16)	(0.16)
Producers' opinions about:			
Dirs. Status	3.2	2.7	−0.42***
	(0.05)	(0.15)	(0.15)
Dirs. Management	3.1	2.7	−0.32**
	(0.07)	(0.15)	(0.17)
Secy. Status	3.7	3.5	−0.20
	(0.09)	(0.22)	(0.24)
Secy. Management	3.6	3.5	−0.10
	(0.13)	(0.11)	(0.17)
Pres. Status	3.63	3.29	−0.34
	(0.06)	(0.29)	(0.29)
Pres. Management	3.48	3.32	−0.16
	(0.09)	(0.18)	(0.2)
Joint F-Statistic			10.94
[p-value]			[0.00]
Directors' opinions about:			
Dirs. Status	3.4	3.3	−0.07
	(0.09)	(0.11)	(0.14)
Dirs. Management	3.4	3.3	−0.07
	(0.08)	(0.11)	(0.13)
Secy. Status	4.1	3.9	−0.25
	(0.10)	(0.18)	(0.20)
Secy. Management	4.3	4.4	0.04
	(0.09)	(0.13)	(0.16)
Pres. Status	3.87	3.87	−0.004
	(0.11)	(0.16)	(0.19)
Pres. Management	3.8	3.8	−0.001
	(0.07)	(0.09)	(0.12)
Joint F-Statistic			0.61
[p-value]			[0.72]
Num. Villages	15	7	

Table 7: Notes: Baseline measures of governance quality and perceptions of governors' social status and managerial capacity. Top three rows report fraction of producers that recall receiving a bonus, avg. fraction of directors that producers can name without prompting, and frequency of board meetings. Sample is limited to DCSs assigned to receive public payment in the second intervention, round split by decision to opt out of payment. The third column reports differences between the two groups. Standard errors clustered by DCS in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Supplementary Appendix for "Got (Clean) Milk"
For Online Publication Only

A Daily DCS Milk Collection

Figures A1–A5 depict the morning milk collection process at a typical DCS. Milk collection typically takes place between 5 and 7 AM, during which time each DCS has a half-hour collection window to when farmers deliver milk. Producers start milking shortly before this window so their milk is ready to deliver, shown in Figure A1. Potential contamination at this stage comes from bacteria on the outside of cows' udders, in farmers' containers, or on farmers' hands.

Producers deliver their milk to the DCS headquarters where it is pooled into common cans. Figure A2 shows a DCS secretary testing the density of milk to ensure it has not been diluted before pouring, and Figure A3 shows the milk being poured into the village can. Every producers' milk is density-tested before pouring, and in equilibrium milk is very rarely rejected due to excessive dilution. Tests for cleanliness require lab facilities and training, and therefore cannot be conducted at the time of pouring. Individual production quantity is recorded at this stage for later payment. Contamination can be introduced by unsanitary village testing equipment or improperly washed collection cans. Many DCSs engage in small-scale local sales of fresh milk before KMF collection, as depicted in Figure A4, which adds another potential source of contamination.

At the end of the collection window, a KMF truck arrives to deliver the filled DCS cans to the processing plant. Each truck follows a collection route that serves multiple villages; Figure A5 shows a typical collection truck, which is unrefrigerated. During transportation, existing bacterial colonies in the milk have time to proliferate. Differences in position along the route and uncertainty in transportation time add variance to the the cleanliness of milk as it reaches the processing facility, making it infeasible for the KMF to tie incentive payments to cleanliness as measured upon delivery. As soon as the milk reaches the processing plant, it is rapidly chilled to arrest further bacterial development.

[Figure 5 about here.]

[Figure 6 about here.]

[Figure 7 about here.]

[Figure 8 about here.]

[Figure 9 about here.]

B Supplemental Experiment Details

B.1 Incentive Payment Schedule

Table A1 lists the full incentive structure announced to treated DCSs. Payments are scaled so that the average DCS in the baseline testing rounds would receive Rs. 500, roughly $10 at the time of study. To encourage participation, the incentive was described as a base payment of Rs. 500 with a bonus for high quality and a penalty for low quality. All payments were made into the DCS financial account managed jointly by the DCS secretary and president.

[Table 7 about here.]

B.2 Construction of Cleanliness Outcome Measure

MBRT and SPC are each noisy measures of the true microbial load in a sample of milk. Figure A6 depicts the correlation between them at the can level. The positive slope verifies that they pick up the same signal on average, as cans with a greater time to dye reduction also have lower measured SPC microbial loads.

[Figure 10 about here.]

To increase precision in our quantification of cleanliness, we combine MBRT and SCP using principal components analysis (PCA). We construct an index of cleanliness using the first principal component between the two measures. Table A2 lists the loading factors and unexplained variance from index construction. The first component places positive loading on both time to MBRT dye reduction and -log(cfu/ml) from SPC. These measures both correspond to higher sanitation, indicating the component is picking up improvements in quality from the two variables.

[Table 8 about here.]

C Accordance with Pre-Analaysis Plan

This study was preregistered with the AEA RCT Registry under ID Number AEARCTR-0000700. Unanticipated conditions during implementation led to some deviations from the study as prespecified, which we discuss here.

C.1 Experimental Design

In the pre-analysis plan we specify three treatment arms, but two had to be merged due to communication difficulties at the time of implementation. We initially prespecified three variations on information provision—a fully private arm in which both the ex ante payment schedule and the ex post payment amount were disclosed privately to the DCS management, a second fully public arm in which both the ex ante schedule and ex post payment were disclosed publicly to a subset of farmers, and a third transitional arm in which the ex ante payment schedule was private but the ex post payment was subsequently made public. Communication and translation difficulties with DCS secretaries and with field implementation staff led to ex ante public disclosure of the payment schedule in most villages from the third transitional treatment arm during the first round of intervention. As a result, we chose to collapse both the second and third treatment arms into a single fully public disclosure arm during the second round of intervention.

The initially planned randomization had DCSs switch between treatment arms to maximize power. Because information once made public cannot subsequently be made private, DCSs in the transitional treatment arm with ex post public disclosure of payments in the first intervention round would have to be in the fully public treatment arm for the second intervention round. As a result, we initially planned the randomization to have a greater number of control and transitional DCSs in round one, with some of these switching to transitional and public information, respectively, in round two. Although this forced switching was no longer an issue after collapsing the transitional and public treatment arms, we chose to stay with the original randomization plan.

C.2 Analysis of Outcomes

We prespecify sampling milk from both individual producers and pooled DCS cans, and analyzing the samples using the MBRT test. However, because of the tight timing window, sampling milk from individuals proved to be too disruptive to the DCS milk collection and risked delaying the can truck. As a result, we have individual-level quality data for only one baseline round, and all subsequent rounds have only data on pooled can quality. Given the substantial decrease in the number of samples, we were able to devote the extra budget to add SPC testing to the lab analysis. We prefer analysis with the principal component quality index to reduce noise from measurement error, but report treatment effects from each individual test as well.

The remaining prespecified outcomes all depend on administrative data on DCS revenue and expenditures from financial accounts. Account details are maintained at local KMF offices and are audited annually. While we were initially optimistic about our ability to analyze these outcomes, it became clear over time that we would not have access to these accounts. The situation became worse after a change in KMF management following state-wide elections severely limited our administrative access. As a result, we have only the primary data we collected and are unable to report on any of the other prespecified outcomes.

In this paper we report additional unspecified outcomes related to DCS secretaries opting out of receiving payment. This was a wholly unanticipated result that we feel is critical in understanding barriers to collective production in village cooperatives, and added questions to the endline survey relating specifically to understand its determiants.

D Derivation of Theoretical Results

D.1 Result 1

The manager solves

$$\begin{aligned}
\tilde{z} &= \arg\max_{z\in[0,1]} (1 - z(1-\lambda))f(x) - \lambda x \quad \text{s.t.} \quad f'(x) = \frac{1}{z};\ x(0) = 0 \\
&= \arg\max_{z\in[0,1]} (1 - z(1-\lambda))f(\tilde{x}(z)) - \lambda \tilde{x}(z)
\end{aligned}$$

This is a continuous function on a compact space so an optimal $\tilde{z}$ must exist.

Totally differentiating the maximand with respect to z gives

$$\begin{aligned}
0 &= -(1-\lambda)f(\tilde{x}) + (1 - \tilde{z}(1-\lambda))f'(\tilde{x})\frac{\partial \tilde{x}}{\partial z} - \lambda\frac{\partial \tilde{x}}{\partial z} \\
&= -(1-\lambda)f(\tilde{x}) + \left[(1 - \tilde{z}(1-\lambda))f'(\tilde{x}) - \lambda\right]\frac{\partial \tilde{x}}{\partial z}
\end{aligned}$$

Substituting for $f'(\tilde{x})$ from the worker's first order condition gives

$$\begin{aligned} 0 &= -(1-\lambda)f(\tilde{x}) + \left[(1-\tilde{z}(1-\lambda))\frac{1}{\tilde{z}} - \lambda\right]\frac{\partial \tilde{x}}{\partial z} \\ &= \frac{(1-\tilde{z})}{\tilde{z}}\frac{\partial \tilde{x}}{\partial z} - (1-\lambda)f(\tilde{x}(\tilde{z})) \\ \iff 0 &= \frac{(1-\tilde{z})}{\tilde{z}}\frac{\partial \tilde{x}}{\partial z} - (1-\lambda)f(\tilde{x}(\tilde{z})) \equiv g(z) \end{aligned}$$

It is clear $g(1) = -(1-\lambda)f(x^*) < 0$ so $\tilde{z} \neq 1$. Moreover, $V^M(1) > V^M(0) = 0$ so $\tilde{z} \neq 0$. Therefore, there must be an interior solution to the manager's problem.

D.2 Result 2

Define the curvature of the production function to be

$$c(x) = \frac{f'(x)}{f''(x)}$$

Note that this function is closely related to the Coefficient of Absolute Risk Aversion in utility theory.

$$\begin{aligned} \frac{\partial z}{\partial \lambda} > 0 &\iff c'(\tilde{x}(z)) > -\frac{2-\lambda z}{1-z} \\ &\iff \frac{f'''(\tilde{x}(z))}{f''(\tilde{x}(z))^2} < \frac{(3-z+\lambda z)z}{1-z} \end{aligned}$$

These conditions follow from implicitly differentiating the manager's first order condition, and then substituting in the worker's first order condition. It is difficult to give an intuitive interpretation of $c'(x)$ because it depends on the third derivative of the production function. Note that as $z \to 1$, the denominator of the right hand side approaches 0 verifying that the condition is satisfied. As a result, $\tilde{z}$ continuously approaches 1 as $\lambda \to 1$. However, away from the optimum, information disclosure may not increase monotonically with the manager's bargaining power.

D.3 Result 3

Consider two values λ and $\lambda' > \lambda$. Further, let

$$\tilde{z} = \arg\max_{z\in[0,1]} (1 - z(1-\lambda))f(\tilde{x}(z)) - (1-\lambda)\tilde{x}(z)$$

It immediately follows that

$$(1-\tilde{z}(1-\lambda'))f(\tilde{x}(\tilde{z})) - \lambda'\tilde{x}(\tilde{z}) > (1-\tilde{z}(1-\lambda))f(\tilde{x}(\tilde{z})) - \lambda\tilde{x}(\tilde{z})$$

therefore

$$\begin{aligned}
V^M(\lambda') &= \max_{z\in[0,1]} (1 - z(1-\lambda'))f(\tilde{x}(z)) - \lambda'\tilde{x}(z) \\
&\geq (1 - \tilde{z}(1-\lambda'))f(\tilde{x}(\tilde{z})) - \lambda'\tilde{x}(\tilde{z}) \\
&> (1 - \tilde{z}(1-\lambda))f(\tilde{x}(\tilde{z})) - \lambda\tilde{x}(\tilde{z}) = V^M(\lambda)
\end{aligned}$$

D.4 Result 4

The worker's value from production is

$$V^W = (1 - \lambda\tilde{z})f(\tilde{x}(\tilde{z})) - (1-\lambda)\tilde{x}(\tilde{z})$$

Differentiating this with respect to λ and applying the envelope theorem gives

$$\frac{\partial V^W}{\partial \lambda} = \tilde{z}f(\tilde{x}(\tilde{z})) - \tilde{x}(\tilde{z}) + (1-\lambda)f(\tilde{x}(\tilde{z}))\frac{\partial \tilde{z}}{\partial \lambda}$$

Therefore,

$$\begin{aligned}
&\frac{\partial V^W}{\partial \lambda} > 0 \\
\iff &\frac{\partial \tilde{z}}{\partial \lambda} < \frac{\tilde{z}f(\tilde{x}(\tilde{z})) - \tilde{x}(\tilde{z})}{(1-\lambda)f(\tilde{x}(\tilde{z}))}
\end{aligned}$$

That is, when the social surplus from production grows relatively faster than the share the manager appropriates. This condition will not be satisfied as $\lambda \to 1$, but it may not evolve monotonically away from that extreme.

Figure A1: Morning Dairy Collection: A Couple Milking their Cow

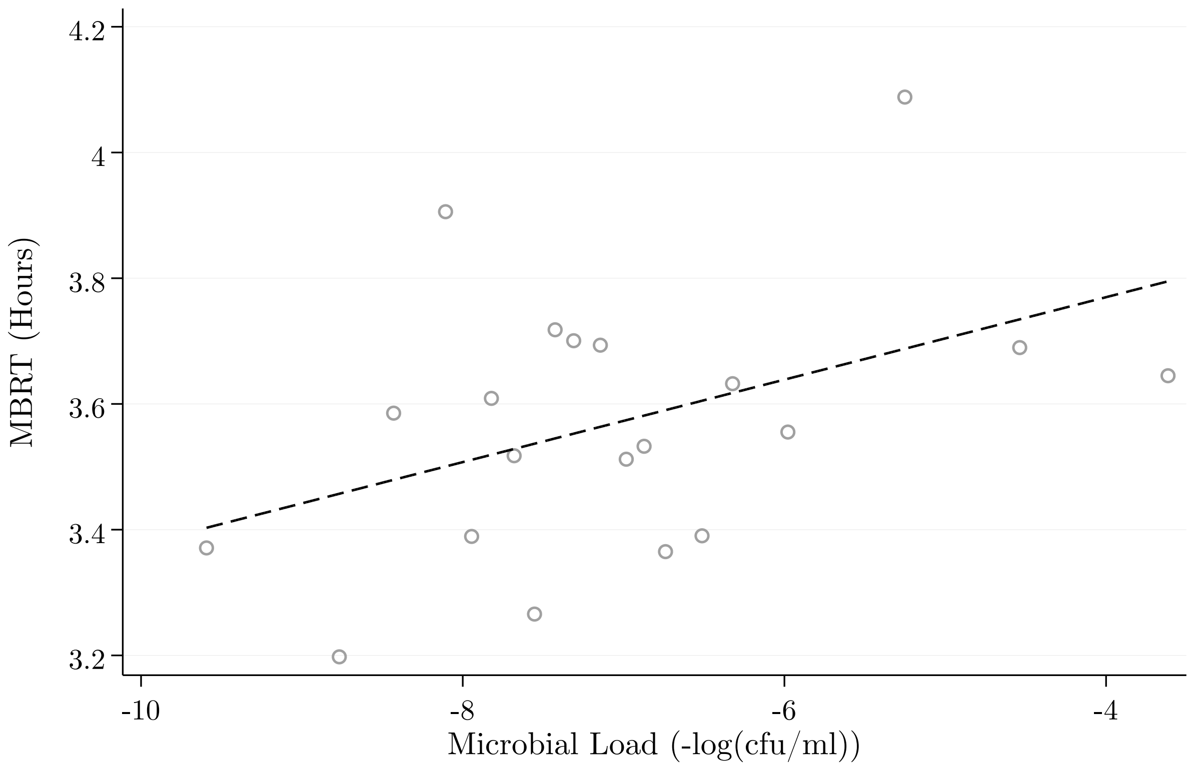
Figure A2: Morning Dairy Collection: Density Testing at the DCS Headquarters

Figure A3: Morning Dairy Collection: Milk Poured into a DCS Can

Figure A4: Morning Dairy Collection: Small-Scale Local Sales

Figure A5: Morning Dairy Collection: Can Truck for Delivery to Processing Plant

Figure A6: Correlation between MBRT and SPC



Notes: Binned scatterplot of MBRT and SPC measurements from 522 milk cans. MBRT is measured in time to dye reduction, and SPC is measured in –log(colony-forming-units per milliliter). The correlation coefficient between the two measures is 0.16, with a regression coefficient that is significant at the 5% level in the cross-section, and at the 10% level after accounting for serial correlation in samples from the same DCS.

Table A1: Payment Schedule for Incentive Structure

Structure:	Avg MBRT (hrs)	Base	Penalty/Bonus	Net Incentive
1	0–2 hrs	500	-500	0
2	2–3 hrs	500	-100	400
3	3–4 hrs	500	+200	700
4	4–5 hrs	500	+500	1000
5	5–6 hrs	500	+1100	1600
6	6+ hrs	500	+1500	2000

Notes: Size of incentive to DCS as a function of milk cleanliness measured by MBRT hours in treatment arms. Incentives were framed as a base payment of Rs. 500 with additional bonus (penalty) for high (low) quality milk.

Table A2: Principal Component Analysis for Cleanliness Index

Measure	Loading	Unexplained Variance
MBRT (hrs)	0.707	0.427
Log SPC (cfu/ml)	0.707	0.427

Notes: Loading weights on each measure of quality in the first principal component used to construct a quality index.