Got (Clean) Milk? Governance, Incentives, and Collective Action in Indian Dairy Cooperatives

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Abstract

Much economic activity in developing countries takes place in groups whose members are associated through social networks. Group sales can connect small-scale producers to broader markets, but introduce opportunities for free-riding. We explore the effect of collective incentives on group production among rural Indian dairy cooperatives. In a randomized evaluation, we find village-level cooperatives can solve internal collective action problems to improve production quality. However, some village elites decline payments when they cannot control information disclosure. Opting out reflects frictions in allocating surplus within a social network, and suggests some transparency-based efforts to limit elite capture may undermine policy goals.

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1 Introduction

Coase (1937) identifies a fundamental trade-off between transaction costs and decentralization of price signals 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 (Markelova et al., 2009). 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. These systems generate a tension in which production is carried out by individual members, but market incentives are applied at the group level leading to potential frictions in collective action. However, cooperative organizations arise in the context of a community social structure that can address this misalignment of incentives between individual producers and collective profits through informal channels (e.g. Ostrom, 1990).

In this paper, we investigate how information relates to the capacity of local social structures to solve collective action problems in production through a field experiment among Indian dairy cooperatives. Around the world, cooperative agriculture has been promoted as a means to achieve the dual goals of raising productivity by increasing the returns to investment and improving the livelihoods of the rural poor (see Bernard et al., 2008). These institutions tend to organize around pre-existing communities wherein members have extensive social connections that can facilitate cooperation. However, managerial authority frequently reinforces social hierarchies and may therefore allow for institutional capture by elites. Given the prevalence of agricultural cooperatives in developing economies, they provide a valuable setting to examine how social networks address tensions between group-level incentives and individual input into production.

Our study experimentally introduces production incentives that deliver collective returns in response to individual effort. Information plays two roles in this environment. First, there is decentralized information about individual production behavior that is inaccessible to the external market but may be observable within the cooperative. We find evidence that incentives at the group level improve aggregate production outcomes, indicating that communities have the capacity for internal enforcement regarding peers' level of effort. Second, there is centralized information about the group-level incentive that is known to local elites but may be unknown to individual members. Counterintuitively, we find that increasing the provision of this latter type of information within a cooperative can undermine production goals and lower revenue. This second finding highlights a trade-off between productive efficiency at the cooperative level and the potential for elite capture.

We study this question in the context of dairy cooperatives in Karnataka, India. The state's dairy sector encompasses more than 2.4 million dairy producers in over 22,000 villages. Production is organized through village-level cooperative societies that aggregate output from smallholder farmers who pool their milk for delivery to processing facilities for packaging and sale. Dairy is an important source of income for smallholder farmers throughout the developing world, and similar cooperative structures exist at the local level in the agricultural sector worldwide.

In this setting we conduct a randomized evaluation of incentives to lower microbial contamination at the initial production site. Lowering contamination can increase profitability farther down the supply chain by expanding 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 high returns to cleanliness, microbial load has little bearing on the direct compensation for cooperatives at the production stage. Instead, the sector has invested heavily in infrastructure and technology to minimize the impact of contamination along the supply chain.

We examine the role of incentives for cleanliness at the cooperative level, which generates a local collective action problem with the potential for free-riding. At the point of production, contamination is mitigated by sanitary practices such as washing hands and sterilizing equipment. Since incentives and quality measurement take place at the cooperative level, contamination cannot be traced back to any single individual. Each producer has an incentive to minimize private effort and rely on the cleanliness of their peers. The cooperative effectively constitutes a production team beyond which transaction costs prohibit further decentralization of the incentives.

There is reason to believe cooperatives can internally mitigate free-riding because members belong to an existing village social network. Even though individual quality is neither observed by the market nor by local producers, members of a cooperative likely have local information about each others' effort. Moreover, social ties in these types of communities have been show to sustain long-term collaboration (e.g. Chandrasekhar et al., 2018). Therefore cooperatives may have the tools to coordinate private behavior to take advantage of a group reward. We investigate how the interplay between information and local social structure affects the extent and manner in which such coordination is achieved.

We study village-level incentives for cleanliness via a randomized control trial in 51 village dairy cooperative societies in northern Karnataka. Specifically, we introduce two sources of random variation: First, we experimentally offer a group incentive payment tied to aggregate measures of cleanliness. This intervention tests whether cooperatives can effectively monitor effort and prevent free-riding among their membership to benefit from collective payment. Second, 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 members. The public payment intervention tests whether the potential for elites to extract information rents affects bargaining, distribution of surplus, and production outcomes.

Our first main finding is that bacterial contamination decreases among cooperatives that were offered financial incentives. This result indicates that local social ties are strong enough for cooperative members to both collect information on peers' milking practices and to enforce a norm of collective action based purely on observed effort. We present suggestive evidence that both dairy farmers and local elites adjust their practices to improve sanitation. However, we find little evidence of direct financial remuneration to farmers from the cooperative, implying that collective action might be sustained using alternative social mechanisms.

The increase in cleanliness is quantitatively large relative to the cost of the incentives. The incentive schedule offers the potential to raise cooperative revenue by up to 2.5 percent over a two-week period[1]. This modest opportunity generates an improvement in milk quality of up to 0.64 standard deviations, which corresponds to an 81% increase in the fraction of raw milk suitable for value-added processing into cheese, yogurt, or milk sweets. The collective response to such a small incentive indicates that local social networks are strong. Furthermore, the potential gains from cleaner milking practices are large, and thus, the barrier to cleanliness at this stage is organizational rather than technological.

Our second main finding is that among cooperatives offered incentives for cleanliness, public provision of information about the incentive schedule decreases the size of the treatment effect. This result is unexpected because alleviating information asymmetries facilitates cooperation in most multi-agent models, especially in cases where the information pertains to higher returns to effort (e.g. Teoh, 1997). Prior work has found providing decentralized information about market prices to increase production (Goyal, 2010) or, at worst, have no effect on production outcomes

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

(Fafchamps and Minten, 2012; Mitra et al., 2018). In our setting, this type of information can actually have deleterious consequences.

We find the decreased treatment effect to be driven in large part by the fact that in the public payment arm, almost a third of cooperative managers—i.e. local elites—request 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 the status quo with absolutely no change to production practices, and because the cooperatives that opted out of payment continue to consent to the somewhat disruptive testing protocol.

Opting out of payment appears to be strongly linked to elites' control over information. All those requesting to opt out were assigned to the public payment arm, and none in the private payment arm request to opt out. Among managers foregoing payment, all initially request to be reassigned to the private payment arm, and only opt out when given the choice between public information and no payment. Furthermore, turning down payment is negatively correlated with the perceived social power and influence of cooperative managers. These facts along with interviews post-intervention suggest that local elites might privately resist activities that would be welfare-enhancing in the aggregate, especially in cases where their capacity for rent extraction is constrained. As a corollary, maximizing productive efficiency might involve structures that offer some opportunity for elite capture.

Together, these two findings paint a nuanced picture of the capacity for social networks to alleviate market frictions. Improvements in cleanliness on average indicate that networks facilitate enforcement of norms regarding individual behavior, which contributes to solving collective action problems. Since both treatment arms offer the same level of aggregate incentive, differences between them can be attributed to the allocation of surplus. The fact that some elites choose to opt out at the prospect of public payment indicates that there are frictions in reallocation. As a result of these frictions, collective incentives to rural communities cannot be viewed as separate from the method of incentive delivery.

This paper relates to several stands of literature. First, 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

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

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 formal authority within the production unit is less important than informal status in the social network outside the production unit.

Second, we provide evidence on the capacity for gains from decentralization of production processes (see Marschak, 1959). Decentralization 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). This trade-off is seen in many development contexts (e.g. Bardhan, 2002; Besley and Coate, 2003). Notably, local agents have been shown to have private information on how to allocate funding to (Alatas et al., 2012; Hussam et al., 2020) and collect taxes from (Balán et al., 2020) intended targets. We demonstrate that local agents also have knowledge about private behaviors as well as the capacity to limit shirking.

Third, we contribute to research on the role of information in the distribution of rents. A large body of 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). In the context of cooperative agricultural production, Banerjee et al. (2001) and Casaburi and Macchiavello (2015) provide evidence on how private incentives skew the behavior of cooperative leaders. Our results indicate that private returns generated by information rents may be substantial given the level of return elites are willing to forego to protect private information.

Studies have shown that information disclosure or technological barriers to leakage may discipline elites and reduce the extent of local capture (Ferraz and Finan, 2008; Muralidharan et al., 2016; Banerjee et al., 2020). However, as Banerjee et al. (2016) note, the costs of rent extraction depend crucially on the incentives faced by agents in a position to extract rents; if performance targets align with private returns, then allowing some corruption may actually improve outcomes (e.g. Weaver, 2019). Our findings similarly caution that policies to constrain elite power may backfire if they lead elites to shift towards more distortionary practices or seek out ways to circumvent these efforts entirely.

Finally, our research sheds 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. We demonstrate that cooperatives based around existing social structures can internally solve contracting problems in the absence of formal institutions. However, our work also warns that cooperative agriculture faces the same threats from corruption and elite capture that have derailed other development initiatives in the past.

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 discuss the findings in Section 5, and Section 6 concludes.

2 Setting

We study collective action among production teams within an existing social structure in the context of dairy cooperatives in Karnataka, India. The cooperative infrastructure of the state is managed by the Karnataka Milk Federation (KMF), a quasi-governmental federation of village-level dairy cooperatives founded in 1974. 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 20–30% of their total 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 organizations 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 both quantity and quality of raw milk, but, payments to farmers are based almost exclusively on quantity alone 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 cleanliness of raw milk. We deliver these incentives through the existing financial system at the DCS-level, which introduces the possibility for free-riding by individual member producers. We test whether local institutions are strong enough to solve the collective action problem and induce changes in production behavior, and we further evaluate how local governance interacts with the provision of information about the incentive structure to influence production outcomes.

2.1 Supply Chain and Cleanliness

Dairy production originates in rural villages with smallholder producers. Each village-level DCS, typically consisting of 50–100 producers, collects milk from pouring members into common cans during a brief daily window. A single can holds milk from 5–10 different producers, and once full, cans are sealed for immediate pickup and delivery to a KMF processing plant. Appendix A walks through the village-level milk collection process with photographs.

At the processing plant, milk from the DCS is rapidly chilled before being processed and packaged for sale. Samples from each can are tested for quality before processing to determine suitability for various dairy products. Low-quality milk is packaged directly as liquid milk, while higher-quality milk is creamed into butter or ghee or cultured for higher value-added products such as cheese, yogurt, and milk sweets.

In this study, we aim to raise profitability by improving one main component of quality: microbial load. This is an important margin of adjustment because different retail 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

[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.

threshold, variation in the bacterial content of raw milk produces noticeable differences in flavor 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 at baseline, only 37 were suitable for value-added processing. The remaining milk, with bacterial loads exceeding 500,000 cfm/ml requires ultra-high temperature (UHT) pasteurization at 135°C. This process denatures certain enzymes and proteins, meaning the product is only suitable for sale as liquid milk. UHT 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]

[Figure 1 about here.]

Microbial contamination in raw milk is a function of 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. 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.

Cleanliness at the point of collection is affected by both farmers' milking practices as well as the cleanliness of DCS 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.

We break down the potential for improvement in each of these areas by comparing samples taken from farmers immediately before pouring into village cans to samples taken from village cans immediately after pouring in Figure 2.[6] Panel A plots the distribution of cleanliness among

[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.

[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

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 percentage points). Panel B 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 raw milk delivered for processing.

[Figure 2 about here.]

Measuring microbial load requires lab equipment, training, and time. It is therefore logistically infeasible to regularly measure individual producers' milk at the point of collection beyond a basic sight and smell check for spoilage. In the supply chain, the most decentralized unit that could reasonably be tested is the delivery can, which contains milk from 5–10 producers. In practice, cooperatives do not track which producers pour into which cans so the effective unit of aggregation is the entire DCS. We investigate whether, given appropriate incentives at this level, there is sufficient local monitoring and enforcement capacity within the DCS to implement sanitation practices even without individual measurements.

2.2 Production Incentives

Production incentives for farmers are misaligned with the value of sanitation in the supply chain in two ways. First, there is very little return to cleanliness at the production stage. The KMF pays primarily for the quantity of raw milk delivered, with no variation based on cleanliness. In this study we evaluate a pilot program designed to address this source of misalignment. We introduce a high-quality testing procedure coupled with incentive payments linked to the measured microbial load. This intervention effectively introduces returns to cleanliness at the DCS level.

Second, quality-based incentives such as payments for cleanliness generate the potential for free-riding within the DCS. Payments must be conditioned on the aggregate quality of pooled milk

directly translate to USDA safety measures. The relationship between these two measures is discussed in Section 3.

because it is infeasible to test individual producers' contributions. As a result, the return to any individual's effort is shared with the entire cooperative and the effect of shirking is diluted. However, shirking may be mitigated because DCS members are part of an existing social network within their village. Even though the DCS cannot directly measure the cleanliness of each producer's milk, members likely have local information about each others' level of effort. We investigate whether, given appropriate group incentives, DCSs can internally organize to enforce changes in individual constituent behavior.

Group incentives in our study are delivered through the existing financial infrastructure. Each DCS has a bank account to which the KMF makes fortnightly payments for milk delivered over the preceding two weeks. The DCS management is then responsible for disbursing payments to individual farmers. During the period of our study, these disbursements from the DCS to the farmer were predominantly made in cash as a function of the quantity poured. We supplement the regular cooperative income with a bonus based on the measured microbial load in milk. Beyond making a deposit in the DCS bank account, we offer no instruction on how the surplus revenue should be allocated.

2.3 DCS Governance

Each DCS is managed by an elected president and secretary who make administrative decisions and serve as the local points of contact for the KMF and 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 two officers serve staggered ten-year terms, and 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, members of the board of directors, 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 previously been elected to serve in the local legislative assembly (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 to 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 directors rate managers and other directors higher than producers do. 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.

[Table 1 about here.]

These differences in the characteristics of cooperative managers underscore the potential for elite capture in this setting. In particular, the 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 actions despite the formal oversight role of the board of directors.

Rent extraction by elites is also hinted at in cooperatives' finances. Each DCS runs an operating surplus to pay for facilities and maintenance as well as salaries for staff. The KMF supplements this local surplus by returning a portion of its annual profits as a dividend. At the end of the year, any remaining surplus is mandated to be distributed among DCS members as a bonus, pro-rated by production quantity. However, in practice the use of funds is murkier. In the three years leading up to our study, all DCSs participating in our study officially reported net surpluses in every year, indicating that they should have paid bonuses to farmers. Despite this, 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.

3 Experimental Design

We implement a randomized evaluation of incentives for dairy producers to lower the microbial load in milk. The incentive is offered at the DCS (effectively village) level based on samples of pooled milk from village delivery 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 the payment schedule is shared with the president and secretary of those cooperatives chosen to receive the incentives. Furthermore, in a randomly selected subset of incentivized DCSs, we also announce the payment schedule publicly to member producers, while only the cooperative management is informed in the rest. We evaluate the change in milk cleanliness from two rounds of baseline testing through two rounds of testing during our intervention.

3.1 Intervention

To promote clean production practices, we couple a high-quality testing procedure with incentive payments for cleaner milk. In every study village, both treatment and control, we collect milk samples, measure the microbial load in a lab, and share the results with the cooperative management. Cooperatives normally do not measure or receive feedback on cleanliness, so testing alone may provide valuable information that cooperatives can respond to. We keep monitoring and feedback uniform across study villages in order to experimentally isolate the effect of group incentives on production outcomes.

Experimental randomization takes place across DCSs in two stages. Each participating DCS is randomly assigned to either receive incentive payments for clean milk or not. 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. DCSs in which we only conduct testing without associated incentives serve as the control group for our experimental manipulation.

The first stage of randomization introduces incentives in the form of a supplemental payment based on measured milk quality. In each treated DCS, we test a sample from each delivery can on a given collection day and then make a bonus payment to the cooperative financial account as a function of the average quality across all cans. This treatment generates returns to cleanliness for the cooperative as a whole, but creates an internal collective action problem where each individual's effort is diluted across the average quality of the entire village. We test whether the cooperative can collectively observe and enforce high effort among its members to raise its bonus even though it cannot directly measure the quality of any individual's output.

Bonus payments for treated DCSs range from Rs. 0 for the lowest quality to Rs. 2,000 for the highest quality, equivalent to roughly \$40.[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 at baseline 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 nearly 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 expected size of the incentive on any given day.

The second stage of randomization varies the level of information disclosure about bonus payment across DCSs in the treated group. In all treated villages, we share the payment schedule and subsequently realized bonus payment with the DCS president and secretary. In a subset of these, designated the public payment arm, we further reveal this information to pouring members at the time of milk collection. In the rest, designated the private payment arm, we do not disclose any information publicly. Information revelation plays two roles in this setting. First, it helps alleviate information asymmetry about the collective returns to cleanliness by increasing the set of participants that know about the incentive payments. Second, it lowers the potential for managers to extract information rents by constraining their ability to hide bonus payments. We investigate whether the public provision of information affects aggregate productivity by altering the cooperative's ability to limit free-riding, and whether it changes distributional outcomes by influencing the extent to which realized returns to cleanliness are shared with cooperative members.

The intervention is implemented over two rounds of incentivized production with three points of contact in each round. First, we announce a two-week window during which we may conduct 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 during milk collection on the day of our visit in the public payment arm. Second, we pick a random day in the two-week window

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

to return for milk testing. Following the regular DCS milk collection, we collect samples from each can that we immediately refrigerate and send to a laboratory for testing. Finally, we return to announce the test results to the DCS secretary two days later. During this third visit we make payment into the DCS account in treated villages, and disclose this payment to another 20 randomly selected pouring members only in the public payment arm.

3.2 Sample Selection and Randomization

The pilot program was based out of the processing facility in Dharwad district of Karnataka in India. Participating DCSs were recruited from the two sub-districts closest to the processor. We contacted all 56 DCSs in the Hubballi and Dharwad sub-districts, out of which 55 agreed to participate. Four dropped out before the experiment began, leaving a final sample of 51 cooperative societies with a total of 2,859 pouring members.

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 as we cannot credibly take back the knowledge that incentives will be paid.

[Figure 3 about here.]

Table 2 provides descriptive statistics for the treated and control groups. Covariates appear balanced; 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 conduct baseline surveys with DCS management and a random sample of pouring members in each village, collect four rounds of data on milk cleanliness, and then conduct endline surveys with

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

another random sample of pouring members. We submitted a pre-analysis plan for this trial to the AEA RCT Registry before the start of the study, and discuss deviations from the pre-specified design that arose during project implementation in Appendix C.

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 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 of ice for immediately chilling. 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 dye to a milk sample and measuring the time until the dye completely disappears. Reduction of the dye is accelerated by removal of dissolved oxygen, 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 affect dye reduction differently, test results do not give an exact measure of microbial load. This test is most commonly used at KMF processing centers to quickly 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 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 type of microbe as all colonies on a slide are counted. 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 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 payment 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, we surveyed twenty producers at each DCS randomly selected from the population of farmers contributing milk on the day of the visit. Baseline questions included 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 pouring members per village covering demographics, dairy involvement, and knowledge about our experiment.

During baseline, we 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 we reevaluate DCS members' subjective beliefs about producer and secretary performance.

Survey data exist at the individual level, but do not constitute a panel because the sample of respondents is drawn anew between baseline and endline. Therefore, analysis using outcomes from

[9] Incentive payments to treated DCSs were based only on MBRT for transparency. MBRT is the primary measure used for day-to-day production decisions by the KMF, and in focus groups 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 readings without increasing overall milk cleanliness.

survey data employs a DD strategy with individual-level observations and DCS-level 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.[10] 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 study arms, which should be balanced under the null due to randomization.

3.4 Timeline

The timeline of 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 minimize 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 by endline surveying at the end of August 2015. A full timeline of project activities is given in Figure 3.

4 Results

Milk cleanliness improves substantially among DCSs that receive incentive payments. We observe an increase in cleanliness of up to 0.64 standard deviations in response to incentives, which would

[10]Because some DCSs change treatment status but there is only a single endline observation per individual, we assign treatment status to be the DCS treatment status in the final round of intervention.

raise the fraction of raw milk suitable for higher-value processing by 81%, though it starts from a low baseline. 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 point of collection. Though we lack the power and granularity to identify exactly which specific activities lead to the greatest improvements, we present evidence that cooperatives internally limit free-riding and induce their members to implement cleanliness practices.

The effect of treatment is weaker in the public payment arm compared to private payment. 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 choose to forego payment altogether rather than allow the payment to be revealed publicly. This decision is puzzling because all DCSs would have received positive payments had they accepted incentives without altering their behavior in any way. Opting out is negatively correlated with the social status of 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

Group incentives induce improvements in milk cleanliness. This main result is presented in Table 3, which reports the effect of treatment assignment on milk quality.[11] Col. 1 reports estimates from the DD specification in equation (1) on the index of cleanliness, and Col. 2. repeats the same exercise with control variables selected using the double-lasso method proposed by Belloni et al. (2013) to increase precision.[12] Assignment to the private payment arm improves average cleanliness by 0.64 standard deviations, significant at the 10% level without controlling for covariates and at the 5% level with controls. The effect of treatment in the public payment 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

[11] Table 3 and all subsequent regression tables report both standard errors clustered at the DCS level in parentheses and p-values generated by randomization inference in square brackets. Randomization inference uses 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 payment, we randomly re-draw 19 DCSs from $19 + 13 = 32$ total private payment treatment and control DCSs in each iteration. For the public payment treatment, we redraw 22 DCSs from the $22+13 = 35$ total public and control DCSs in each iteration.

[12] Details are discussed in Appendix B.

of private payment. Some of the diminished impact of public payments can be attributed to the fact that almost a third of DCSs assigned to this arm choose to forego payment, which we discuss in detail further below.

[Table 3 about here.]

We next decompose the treatment effect into its constituent measured components. Cols. 3 and 4 show the independent effect of treatment assignment on SPC and MBRT test measures. The SPC microbial load decreases by 0.42 log(cfu/ml) and the time to MBRT reduction increases 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 both in line with the magnitude of change in the quality index. In Appendix B, we further break the treatment effect down by quantiles. In the private payment arm, where all assigned DCSs are treated, we find the treatment effect to be consistently strong across the distribution of quality.

We quantify the economic importance of these effects relative to the benchmark SPC threshold of 500,000 cfu/ml recommended by the USDA for raw milk inputs into value-added processing. 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.[13]

4.2 Margins of Adjustment

While we cannot directly measure changes along potential margins of adjustment within a cooperative, we find suggestive evidence that improvements in cleanliness come from both better sanitation of village equipment and from DCS constituent members pouring cleaner milk.

During the intervention period, enumerators and producers frequently observed DCS staff washing collection equipment in incentivized villages; such sights were 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, meaning sanitation of village equipment alone would be large enough to generate the full 0.4 hour treatment effect.

[13] 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 large standard errors for this exercise.

There is also indirect evidence of cleaner milking practices among producers in incentivized DCSs. Table 4 reports select results from the endline survey following the intervention period. In Col. 3, we show that producers' beliefs about others' cleanliness improve in both 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 similarly cannot be attributed to the salience of payments because it is present even in the private payment arm where there is little knowledge about incentive payments among member producers (Col. 1). Instead, the difference in perceptions likely reflects the observed behavior of other producers.

[Table 4 about here.]

While these findings indicate that cooperatives are able to internally induce cleaner milking practices among their members, the mechanism driving such behavior change is unclear. There are insignificant and quantitatively small differences in the frequency of DCS messaging about cleanliness between treatment and control (Col. 2), which suggests that producers in both treatment and control are already informed about how to make improvements. Furthermore, DCS management does not explicitly notify producers about the potential return to cleanliness in the private information arm (Col. 1). These facts imply that managers exert influence over production practices through informal channels that are more difficult to quantify rather than offering explicit rewards for observed effort.

Interestingly, perceptions of secretary cleanliness decrease in the private payment arm despite increases in actual quality. This decrease in perception, shown in Col. 4, may stem from the visibility of cleaning activities. Without corresponding knowledge of an increase in returns, from the farmers' perspective it would appear that the cooperative is suddenly promoting clean practices with no additional benefit. It is possible that this leads farmers to conclude that secretaries must have been inefficiently dirty before. Updating about cleanliness does not spill over into beliefs about managerial capacity (Col. 5). Other explanations are possible, but this dynamic hints at one potential channel of path dependence in governance or management, whereby leaders maintain bad behavior to avoid revealing information about the low quality of their past actions.

4.3 Payment

The gains in cleanliness 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 brings in roughly an additional Rs. 100 per collection day per cooperative in the private payment arm. In total, treated DCSs earn around Rs. 800 per round per cooperative 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. The fact that cooperatives are able to overcome internal collective action problems to take advantage of such small incentives testifies to the strength of local social networks.

[Table 5 about here.]

In addition to cooperative-wide quality gains, producers in the public payment arm may behave strategically during the intervention period to secure a portion of the additional 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[14] in the public payment arm, reported in Col. 3 of Table 5. A quantity increase of nearly 16% per producer is observed in the only intervention arm where producers knew the DCS would receive additional revenue, and potentially reflects their attempts to secure a share of that 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. 4 of Table 5. This result is presented 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 differential impacts between treatment and control arising from our intervention.

[14] 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.

4.4 Foregone Payment

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

We explore the relationship between opting out and cleanliness in Figure 4. Panel A plots the treatment effect in the two payment arms as the event study counterpart to Table 3, Col. 1. Panel B splits 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 or other cooperative characteristics. 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. Quantile treatment effects presented in Appendix B verify this effect heterogeneity, with larger effects observed at higher cleanliness quantiles in the public payment arm.

[Figure 4 about here.]

Regression analysis reveals that opting out explains at least some of the gap between treatment arms. In a two-stage least squares (2SLS) version of equation (1) using treatment assignment as an instrument for actual incentive status,[15] the estimated effect of public payment 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. Cooperatives remaining in the public payment arm have higher quality at baseline, and hence may have lower potential for improvement than those that opt out.

DCSs that opt out of public payment appear to be negatively selected by managerial capacity. In Table 6 we report ex ante correlates of opting out in baseline data. Across all indicators of

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

management quality, DCSs where the secretary declines payment perform consistently worse than those that remain in the public payment 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 is far weaker in managers' reported beliefs about their own quality; a joint test fails to reject equality between opting out and not at the 10% level. Nevertheless, it seems to be the case that managers with lower social standing are more likely to forego public payment. Heterogeneity based on manager characteristics is consistent with work by others such as (Kosfeld and Rustagi, 2015) that find a relationship between community-level outcomes and leadership quality.

[Table 6 about here.]

5 Discussion

Taken together, our results paint a nuanced picture of rural communities' capacity for collective action. Overall, it is clear that communities have the internal monitoring and enforcement tools to take advantage of group incentives, even when the size of the return is small. However, the realized outcome is sensitive to the way in which incentives are applied. In particular, local elites have the potential to derail communal efforts if such efforts threaten their own private returns. The prevalence of this outcome in our experiment reveals that social networks have varying capacity to alleviate different types of market frictions. As a result, policies targeted at rural communities must weigh the potential for elite capture against the intended policy goal, and the optimal design may allow for some rent extraction by elites to preserve efficient implementation.

We observe improvements in milk cleanliness even though our experiment involves a potentially challenging collective action problem. We offer a small incentive—on the order of 1–2 percent of earnings over a two-week period—to large groups consisting of 50–100 members each. Moreover, individual quality is not directly observable, even internally within a cooperative. At best, individual effort is only partially visible as milking takes place independently on members' private property. Despite these difficulties, we measure aggregate gains in cleanliness and find suggestive evidence that the gains result from the collective effort of the entire cooperative rather than the concentrated actions of a few key stakeholders.

This first result reinforces existing evidence on the role of social ties in facilitating economic interactions. Cooperative jurisdiction coincides with village boundaries where members have substantial economic and social interaction outside of dairy production. Social networks in such settings have been shown to substitute for formal contracting both theoretically (e.g. Jackson et al., 2012) and empirically (e.g. Greif, 1993; Chandrasekhar et al., 2018) to overcome market frictions. We find the capacity for such networks to substitute for formal contracts in order to enforce standards of behavior to be substantial and present across the distribution of villages.

However, the incentive function of group payments cannot be separated from the system of payment delivery. It is clear from the size of the treatment effect that the net returns to cleanliness in our experiment exceed the collective cost of effort. Nevertheless, a third of cooperative managers decline these returns when they are made pubic. Since this experimental manipulation does not alter the aggregate incentive schedule in any way, differences between private and public payments must be attributed to the allocation of surplus. When payments are announced publicly, some local elites are unable to secure enough surplus to compensate their private cost of effort, and therefore choose to forego returns entirely.

This second result indicates that, while rural communities have the capacity to overcome challenges posed by collective action, they are not free from internal market frictions. If social networks were to fully substitute for formal contracting, local cooperatives would represent production units within which there were well-defined rights over surplus and low transaction costs in allocating that surplus. In such a world, cooperatives could be treated as surplus-maximizing units independent of the delivery mechanism (Coase, 1960). The difference in effect between our two treatment arms, and in particular the decision by some managers to forego payment, reveals this not to be the case.

Indeed, the choice to opt out seems to reject any model of bargaining over surplus in which agents are guaranteed at least their outside option. In either treatment arms, cooperatives would receive positive surplus were they to take no action and maintain the status quo. Thus, managers should accept payment no matter how small the return as long as they could be compensated up to a participation constraint. The surprisingly high rate of dropout in the pubic payment arm suggests that cooperative managers are actually worse off after public revelation in a way that is not compensated by the surplus generated by the experiment.

Qualitative evidence around the decision to forego payment points to two candidate explanations for this unexpected behavior. Managers who opt out hint at uncompensated 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.” In further questioning, managers express their concern that 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 in advance.

A second possibility is that announcements about cleanliness payments reveal undesirable information about DCS finances. Focus group interviews as well as measured discrepancies between DCS accounting profits and member dividends both 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 feel 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.

Both explanations caution a more nuanced perspective of the potential for social networks to substitute for formal market institutions. The quality improvements among cooperatives in the private payment arm indicate that social ties perform well in enforcing guidelines to exert costly effort in service of aggregate returns. However, the high level of foregone payment in the public payment arm indicates that networks perform less well at efficiently allocating surplus. As a result, we uncover a setting where individual cooperative members reject a measure that enhances social surplus in the aggregate when they cannot secure a large enough share of that surplus to offset their private cost.

This type of social institution can give rise to scenarios in which concentrating power among elites can increase efficiency. This unintuitive situation occurs when elites have multiple methods to extract surplus that differ in both their level of extraction as well as their effect on productive efficiency. Constraining the capacity for extraction through one method may induce substitution of another. In the context of our experiment, public payment constraints elites from capturing surplus, which leads some to substitute to inefficient option of foregoing surplus entirely.

In some cases, concentrating power among elites may even be Pareto-enhancing. If substitution between methods of extraction causes aggregate efficiency to fall faster than the elite share of surplus rises, it will actually be Pareto-enhancing to allow for greater elite capture. We formalize these intuitions in Appendix D, where we present a principal–agent model of team production in a setting where the social structure alleviates moral hazard but constrains the allocation of surplus.

6 Conclusion

In this paper, we experimentally evaluate the effectiveness of group incentives for a production team in the context of village dairy cooperatives in Karnataka, India. Incentives are offered as a cooperative-wide bonus for milk cleanliness, an outcome that depends on the individual effort of each cooperative member. These incentives are difficult to further decentralize because individual cleanliness levels are unobservable both within the cooperative and from the external market. Therefore, the payment structure allows for the possibility of free-riding by individuals who benefit from the group bonus without adjusting their own effort.

Despite this potential market failure, we find that group incentives substantially improve production outcomes on average. A bonus equaling one percent of cooperative revenue over a two-week period is enough to induce an increase in cleanliness of up to 0.64 standard deviations. This improvement corresponds to nearly doubling the fraction of production suitable for high-value processing. The magnitude of the treatment effect demonstrates how organizational reform can have high returns that supplement existing efforts to upgrade technology along the agricultural supply chain.

This experimental outcome reveals that social networks in rural communities are strong enough to solve local collective action problems. Even though the quality of output at the individual-level in our experiment is unverifiable and therefore cannot be directly contracted on, there appears to be sufficient information about private effort within the cooperative. Moreover, social ties afford the enforcement capacity to mitigate free-riding by cooperative members. Therefore, our study illustrates how formal contracting failures need not necessarily deter otherwise promising development efforts.

Our results offer hope for development initiatives that rely on market linkages. Many programs center around the transfer of assets such as livestock (e.g. Argent et al., 2014; Janzen et al., 2018; Phadera et al., 2019) or business capital (e.g. Banerjee et al., 2015; Bandiera et al., 2017) with the intent of establishing a source of revenue for recipients. A necessary condition for the success of such programs is that beneficiaries have sufficient market access to operate profitably. In rural developing areas, market access may be limited by high transaction costs that threaten to overwhelm any possible returns from small-scale market interactions. We show that trade groups organized around existing social networks in such settings can expand market access by increasing the scale of transactions while still effectively transmit price signals down to individual group members.

However, the potential for success in production teams is tempered by the role of elites within the team. We study a setting where formal managerial authority, especially over group finances, coincides with social status in the local social network. Managers' elite status limits the degree to which other team members can constrain their behavior, even when cooperative members hold positions of formal oversight. As a result, we observe some managers make inefficient decisions that decrease aggregate surplus in order to protect their own private returns.

Inefficiency in our study takes the form of foregoing incentive payments for milk cleanliness when those incentives are publicly announced. The choice to forego payment must necessarily entail a decrease in surplus because all cooperatives could receive positive payment without any change to their regular operation. We present suggestive evidence that this inefficiency is tied to the preservation of information rents, and seems to be of greatest concern among those that have relatively low social status compared to other managers in our study. The adverse consequences of public information in our experiment run counter to the conventional expectation that information provision aids cooperation in multi-agent interactions by constraining elites and alleviating information asymmetries.

Managers' choice to forego payment suggests a limitation in the capacity for social networks to alleviate market failures. Networks may be stronger at enforcing norms of behavior than at allocating surplus among their members. As a result, outcomes that are welfare-enhancing in the aggregate may not necessarily benefit all network members, and collective outcomes are sensitive to the method by which incentives are delivered.

Our findings highlight a potential tradeoff between aggregate efficiency and distribution of rents in local policy. In settings where elites have multiple ways to exert control over social surplus, efforts to promote equality by limiting elite power may have unintended consequences. It follows that policy may optimally allow for some elite capture to limit distortion and maximize surplus. This vulnerability is common to a broad range of policies targeted at decentralized populations and filtered through local governance.

This final result provides a cautionary lesson for technological approaches to limiting corruption. Recent advances such as electronic banking and mobile money have enabled direct cash transfers intended to circumvent the possibility of expropriation in transit. 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 that may leave the intended beneficiaries even worse off. It remains an open question how to balance aggregate efficiency with distributional goals, and the optimal design of group incentives across the social hierarchy in village economies paves the way for future work.

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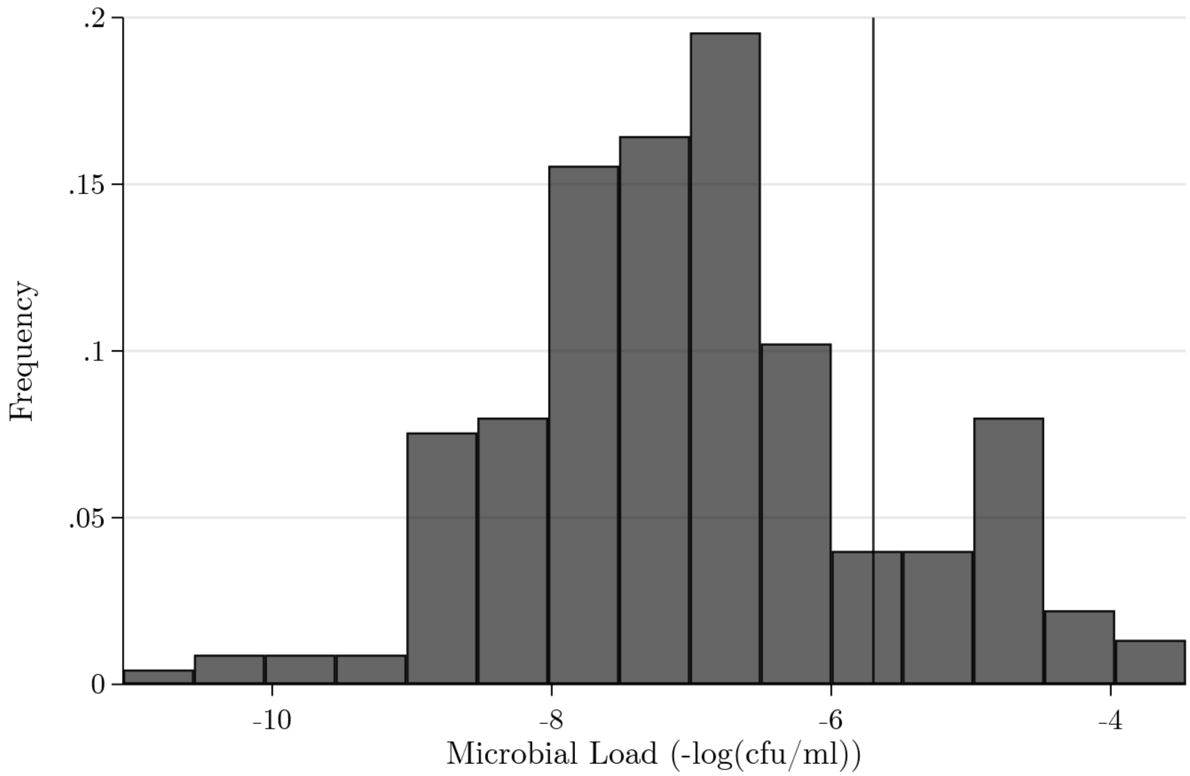
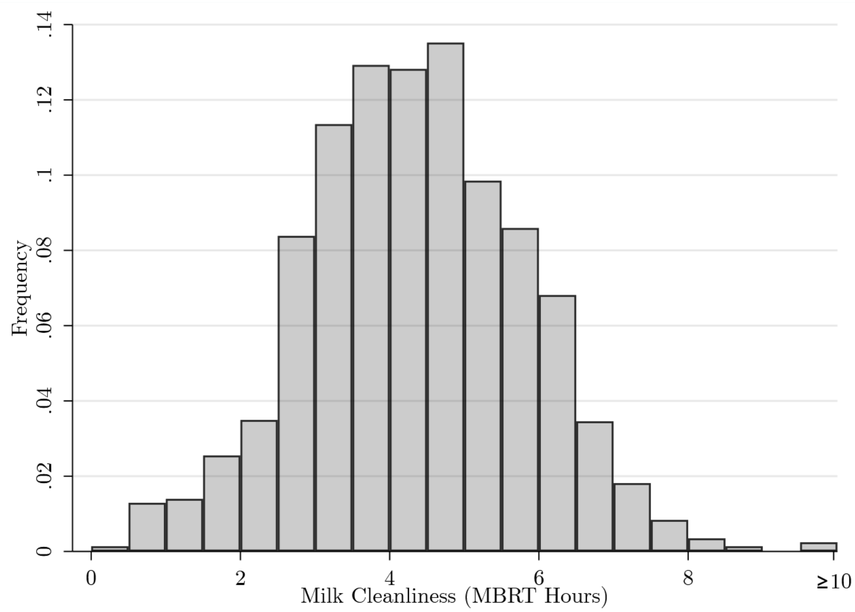
Figure 1: Microbial Load by Milk Can



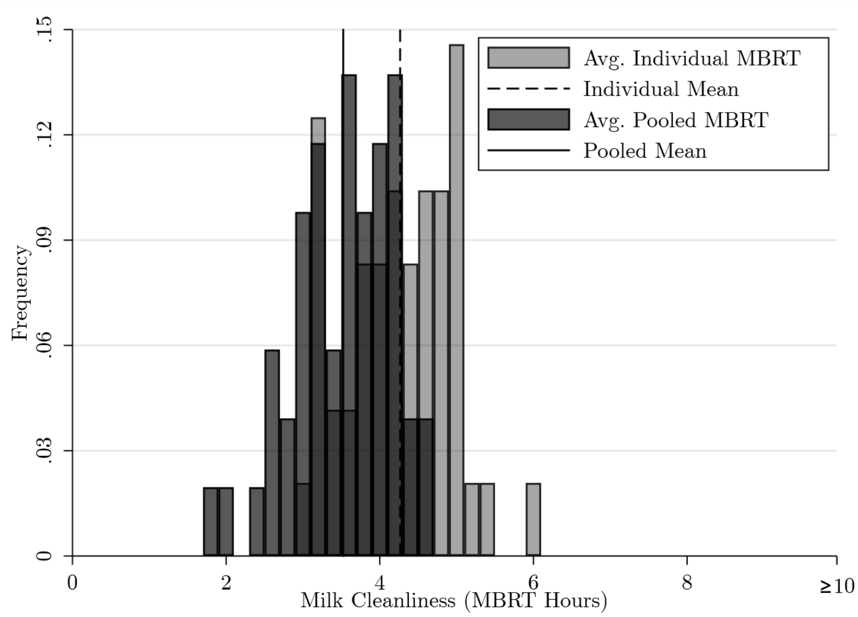
Notes: The distribution of microbial load by delivery can among DCSs under the existing KMF payment structure. Samples are collected at the time of DCS milk collection and measurements are conducted using a standard plate count (SPC), reported in -log units so that higher values indicate cleaner milk. 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



B. Village-Level Mean of Individual and Pooled Milk 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

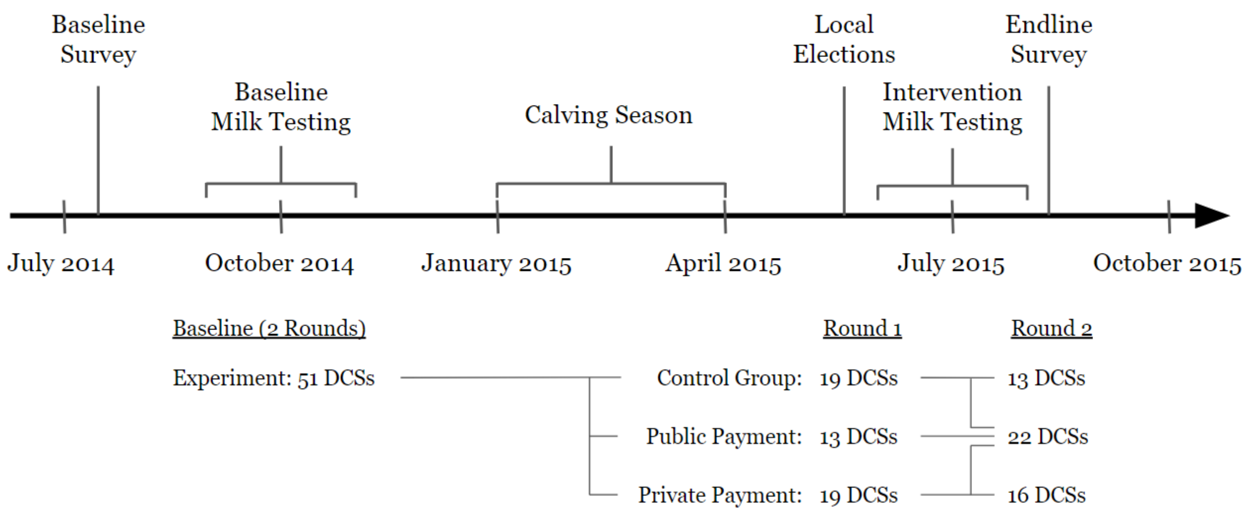
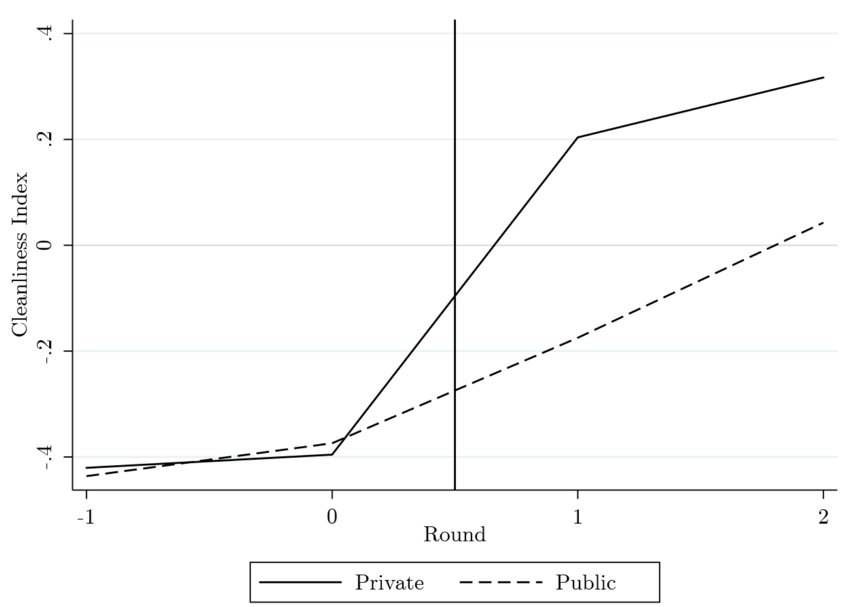
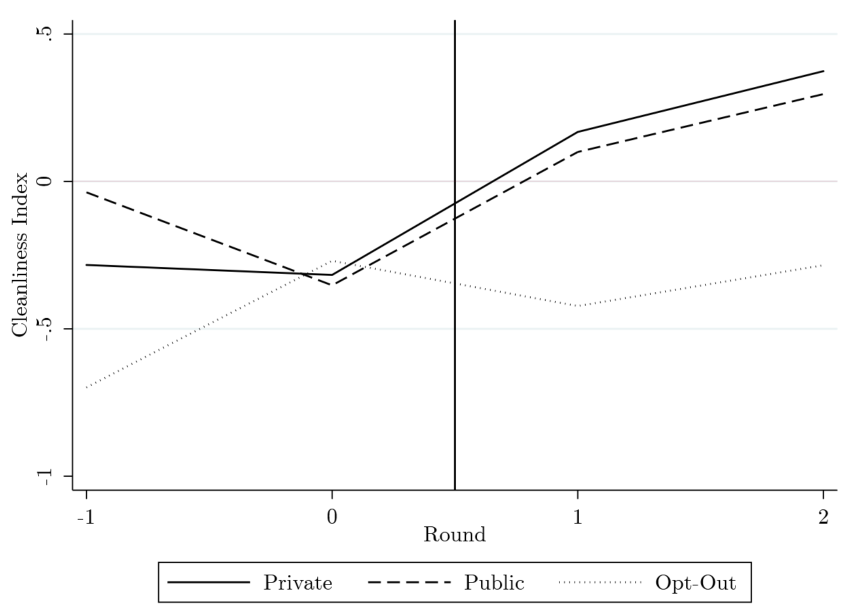


Figure 4: Event Study of Cleanliness by Treatment Assignment

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 payment 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
Private Payment	0.64*	0.63**	0.47	0.36
	(0.35)	(0.31)	(0.32)	(0.22)
	[0.1]			
Public Payment	0.32	0.39	0.38	0.17
	(0.32)	(0.29)	(0.32)	(0.18)
	[0.32]			
Control Mean	0.06	0.06	6.83	3.44
R-Squared	0.08			
Observations	204	204	204	204
DCS Fixed Effects	X	X	X	X
Round Fixed Effects	X	X	X	X
Double-Lasso		X	X	X

Notes: The four columns report DD estimates from eqn. (1). Columns 2–4 include covariates selected using the double-lasso method introduced by Belloni et al. (2013). The control variables include flexible trends - each control variable interacted with round dummies - by management and producer wealth, by management and producer education, by management and producer caste (SC/ST), by management and producer income levels, and by management's past experience in elected office (panchayat). (1)-(2) Cleanliness is an index of milk quality constructed from principal components analysis of SPC and MBRT. (3) SPC is measured in -log(cfu/ml). (4) MBRT is hours to dye reduction. 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 Payment	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 Payment	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
R-Squared	0.08	0.004	0.06	0.03	0.05
Observations	982	982	1,918	1,990	1,983
DCS Fixed Effects			X	X	X
Round Fixed Effects			X	X	X

Notes: First two columns report simple difference at endline; remaining three columns report 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) Quantity	(4) Received Bonus	(5) Opted Out Round 2
Private Payment	121.1	98.3	-0.06	0.01	0
	(106.9)	(82.7)	(0.58)	(0.09)	(.)
	[0.33]	[0.26]	[0.94]	[0.84]	[.]
Public Payment	-0.40	16.8	1.0^{**}	0.03	0.32^{***}
	(85.4)	(81.1)	(0.49)	(0.08)	(0.10)
	[1.0]	[0.85]	[0.14]	[0.6]	[0.0]
Control Mean	715.8	676.9	6.43	0.81	0
R-Squared	0.05	0.05	0.01	0.48	0.21
Observations	153	153	2,006	2,006	51
DCS Fixed Effects	X	X	X	X	
Round Fixed Effects	X	X	X	X	

Notes: First two columns report DD estimates from eqn. (1). Third and fourth columns report DD estimates from eqn. (2). Fifth 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) Quantity is liters per day per producer surveyed; total DCS quantity is unavailable. (4) Fraction of producers who report ever receiving a bonus payment. (5) 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	

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 S1–S5 depict the daily 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 when farmers deliver milk. Producers start milking shortly before this window so their milk is ready to deliver, shown in Figure S1. 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 delivery cans. Figure S2 shows a DCS secretary testing the density of milk to ensure it has not been diluted with water before pouring, and Figure S3 shows milk being poured into the village delivery 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 S4, which adds another potential source of contamination.

At the end of the collection window, a KMF truck arrives to pick up the filled DCS cans to deliver to a processing plant. Each truck follows a collection route that serves multiple villages; Figure S5 shows a typical collection truck, which is unrefrigerated. During transportation, existing bacterial colonies in the milk have time to proliferate. As soon as the milk reaches the processing plant, it is rapidly chilled to arrest further bacterial growth. The KMF has invested heavily in optimizing collection routes and introducing decentralized chilling technology to reduce the time that raw milk spends unrefrigerated.

Differences in position along the route and uncertainty in transportation time add variance to the cleanliness of milk as it reaches the processing facility. Therefore, it is challenging for the KMF to tie incentive payments to cleanliness as measured upon delivery. To scale up our pilot intervention, the KMF would need to develop a procedure to rapidly chill milk samples so that lab outcomes accurately reflect local production quality at collection.

[Figure S1 about here.]

[Figure S2 about here.]

[Figure S3 about here.]

[Figure S4 about here.]

[Figure S5 about here.]

B Supplemental Experiment Details

B.1 Incentive Payment Schedule

Table S1 lists the full incentive structure announced to treated DCSs. Payments are scaled so that the average DCS in the baseline testing rounds would have received Rs. 500, roughly $10 at the time of study. The incentive was framed 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 S1 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 S6 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 S6 about here.]

To increase precision in our quantification of cleanliness, we combine MBRT and SCP using principal components analysis. We construct an index of cleanliness using the first principal component between the two measures. Table S2 lists the loading factors and residual 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 S2 about here.]

B.3 Treatment Effects on Cleanliness

We compare results from the fixed effects regression in 1 to comparable results controlling for covariates selected using the double-lasso method of Belloni et al. (2013) in Table S3. The table reports results for MBRT and SPC cleanliness measures; the main results for the quality index are reported in Table 3. Control variables include flexible time trends interacted with management and producer wealth, education, caste (SC/ST), income, and past experience in elected office. Regression estimates are of similar magnitude across both specifications and we cannot reject equality at the 10% level.

[Table S3 about here.]

We report the quantile effects of both treatment arms at the 25th, 50th, and 75th percentiles in Table S4. The effect of private payment is uniformly large across quantiles indicating a shift in the entire distribution of milk quality. In contrast, in the public payment arm, the magnitude of treatment effect increases with the quality level. This increase reflects the fact that a substantial fraction of DCSs opted out of payment in the public treatment arm, and the propensity to opt out was negatively correlated with quality at baseline. As a result, only cooperatives at higher cleanliness quantiles actually received incentives for cleanliness in the public arm.

[Table S4 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 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 realized 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 farmers, and a third hybrid 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 villages assigned to the hybrid 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 to minimize the chance of implementation errors.

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 hybrid treatment arm with ex post public disclosure of payments in the first intervention round would have to switch to the fully public treatment arm for the second intervention round. Therefore, we initially planned the randomization to have a greater number of control/private and hybrid DCSs in round one, with some of these switching to hybrid and public payment, respectively, in round two. Although this forced switching was no longer an issue after collapsing the hybrid and public payment 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, sampling milk from individuals before pouring proved to be too disruptive to the DCS milk collection and risked delaying the delivery truck's tight timing window. As a result, we only have individual-level quality data for one baseline round, and all subsequent rounds only have data on pooled can quality. Given the substantial decrease in the number of samples to be tested, 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 describe administrative data on DCS revenue and expenditures from financial accounts. Account archives are maintained at local KMF field offices and audited annually. While we were initially optimistic about our ability to analyze these files, it became clear over the course of the experiment that we would not be granted access to the accounts data. The situation became worse after a change in KMF management following state-wide elections that severely limited our administrative access. As a result, we have only the primary testing and survey measures we collected and are unable to report on any prespecified outcomes based on administrative data.

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 we added questions to the endline survey designed specifically to analyze its determinants.

D Illustrative Model of Management Transparency

In this section, we present a stylized model of information exchange between a manager and a worker to better understand the role of constraints on managerial power.[16] The manager and worker constitute a production team embedded in a social structure. The social structure exogenously enforces a fixed sharing rule to allocate production surplus. This sharing rule eliminates moral hazard from the principal–agent

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

relationship by incentivizing the worker to maximize social surplus. However, it also limits flexibility in the allocation of surplus, which can lead the manager to take inefficient actions.

Inefficiency arises because the manager has the choice to hide a portion of surplus from the worker, thereby circumventing the social structure. 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. Renegotiation of the sharing rule to compensate managers for efficiently revealing surplus may resolve inefficiency, but the social structure forbids this.[17]

The model highlights how elites can have multiple different avenues through which to influence their share of surplus, with different degrees of market distortion. Economic efficiency and welfare for other participants depend on the way in which those in power substitute between these options. The possibility for 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. This situation arises when increasing elite control over a non-distortionary channel leads elites to substitute away from a more distortionary channel. 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.

D.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.[18] 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.

[17] One possible explanation for the failure of renegotiation is that the size of surplus is never ex post verifiable, so managers could still hide surplus relative to the renegotiated sharing rule.

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

D.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

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

That is, the worker acts as though $\hat{f}(\cdot)$ is the true production function even if he suspects the manager is hiding information.[19]

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[20]

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

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.*

[19] 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.

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

Proof. 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

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

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. □

Intuitively, this result follows 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 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.[21] The equilibrium is only inefficient if this deviation is prohibited.

[21] 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.

D.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.*

Proof. 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. □

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.

Proof. 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

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

□

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.*

Proof. 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. □

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.[22] 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.

[22] 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.

Figure S1: Morning Dairy Collection: A Couple Milking their Cow

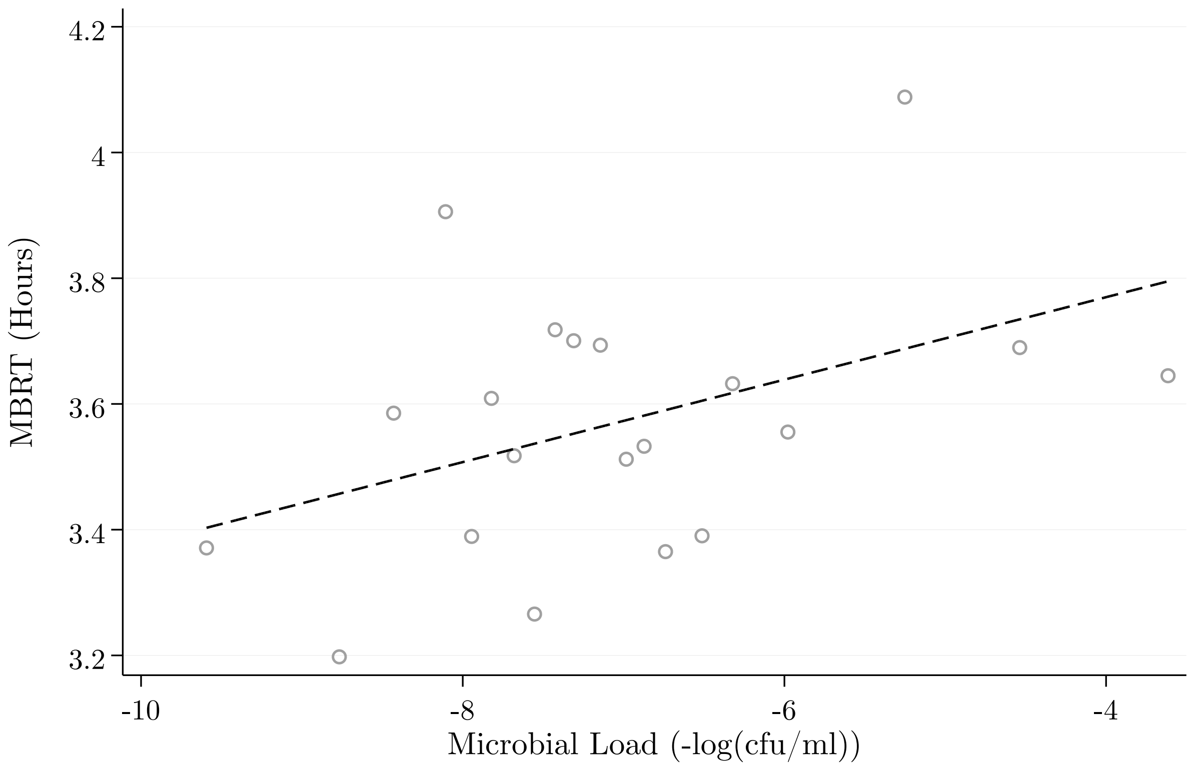
Figure S2: Morning Dairy Collection: Density Testing at the DCS Headquarters

Figure S3: Morning Dairy Collection: Milk Poured into a DCS Can

Figure S4: Morning Dairy Collection: Small-Scale Local Sales

Figure S5: Morning Dairy Collection: Can Truck for Delivery to Processing Plant

Figure S6: 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 S1: 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 S2: 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.

Table S3: MBRT and SPC Outcomes with and without Lasso

	MBRT	MBRT	SPC	SPC
Private Payment	0.402	0.36	0.415	0.47
	(0.242)	(0.22)	(0.36)	(0.32)
	[0.11]		[0.32]	
Public Payment	0.163	0.17	0.275	0.38
	(0.18)	(0.18)	(0.331)	(0.32)
	[0.43]		[0.41]	
Control Mean	3.44	3.44	6.83	6.83
R-Squared	0.066		0.032	
Observations	204	204	204	204
DCS Fixed Effects	X	X	X	X
Round Fixed Effects	X	X	X	X
Double-Lasso		X		X

Notes: All four columns report DD estimates from eqn. (1). Columns 2 and 4 include covariates selected using the double-lasso method introduced by Belloni et al. (2013). Control variables include flexible time trends interacted with management and producer wealth, education, caste (SC/ST), income, and past experience in elected office. (1) and (2) MBRT is hours to dye reduction. (3) and (4) SPC is measured in -log(cfu/ml). 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 S4: Quantile Regression

	Cleanliness			
	Mean	25th pctile	50th pctile	75th pctile
Private Payment	0.64*	0.82**	0.41**	0.7***
	(0.35)	(0.3)	(0.19)	(0.21)
	[0.1]	[0.071]	[0.394]	[0.019]
Public Payment	0.32	0.19	0.38*	0.49**
	(0.32)	(0.38)	(0.22)	(0.21)
	[0.32]	[0.648]	[0.464]	[0.092]
Observations	204	204	204	204
DCS Fixed Effects	X	X	X	X
Round Fixed Effects	X	X	X	X

Notes: DD estimates with index of milk cleanliness as the dependent variable using quantile regression at 25th, 50th, and 75th percentiles, respectively. Heteroskedasticity robust standard errors in parentheses and bootstrapped p-values in square brackets. *** p<0.01, ** p<0.05, * p<0.1