Incentivizing quality in the dairy value chain: A pre-analysis plan

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Motivation

Quality is important in supply chains. On the one hand, working with quality inputs often reduces production costs further down the value chain. Quality preservation is also important for a food safety perspective. In general, transformation of value chains often coincide with quality upgrading.

Over the past decade, the dairy sub-sector has developed rapidly in Uganda. Particularly in the areas around Mbarara, commonly referred to as the south-western milk shed, an influx of foreign direct investment has created the preconditions for a modern dairy value chain to emerge (Van Campenhout, Minten, and Swinnen, 2021). The area now has an extensive network of milk cooling and collection centers that link smallholder farmers to a cluster of processors.

At the same time, it is surprising that there seems to be no market for quality in the sub-sector. For instance, using recently collected survey data, we find that of a sample of 200 farmers that sold to milk collection centers, only 6 percent indicated that they receive a quality premium. From 114 milk collection centers that were included in the survey, we find that about 18 percent (sometimes) pays a price premium to farmers. At the same time, expert interviews with processors indicate that their main challenge is related to sourcing milk of sufficient quality. In particular, they indicate that their profitability depends on butter fat content and solid non-fat content of the milk. They also say that the would be willing to pay for it.

When asked about what farmers need to do to increase quality, farmers mainly refer to practices that affect milk sanitation and safety. Most training and extension activities in the area focuses on the importance of using proper

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equipment (stainless steel milk churns as opposed to plastic jerry cans) and simple practices such as washing hands and udders. These technologies and practices do not affect the milk quality attributes that processors demand. To increase butter fat content and solid non-fat content, it is especially feeding practices that matter.

The above points to several problems within the value chain. At a technological level, instruments necessary to make the desired quality attributed visible are lacking. Most milk collection centers only engage in rudimentary testing for adulteration (using a gravity based test with a device called a lactometer) and freshness (using the alcohol test). Farmers do not have access to testing equipment. At the knowledge level, farmers do not seem to know what quality parameters are important further downstream the value chain.

In this research, we will test various hypothesis using a randomized control trial with interventions at the level of the milk collection centers and the farmers. At the level of the milk collection center, we work with DDA and SNV to scale up their Quality-Based Milk Payment Scheme (QBMPS) that was piloted by last year in Uganda's SW milkshed. It involves installing lactoscans at milk collection centers that allows testing of individual milk deliveries for quality parameters desired by processors. We want to test what the impact of visualizing these quality attributes at this level is on both farmers and milk collection centers. We then use a split plot design to mix in a second intervention at the level of the

Related Literature

Rao and Shenoy (2021) explore the effect of collective incentives on group production among rural Indian dairy cooperatives. In a randomized evaluation, they 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.

Hypotheses and Interventions

At the level of the milk collection centers, the main focus is on a technological intervention that can be used to discover all relevant quality parameters of the milk that is provided. In close collaboration with SNV and DDA, we install digital lactoscans

At the level of the dairy farmers, we implement and information intervention where we explain to farmers what processors are looking for. Furthermore, we also want to make quality visible by providing a low cost technology. In particular, we will distribute lactometers. These simple tools do not allow farmers to directly measure the parameters of interest. However they can be used to give

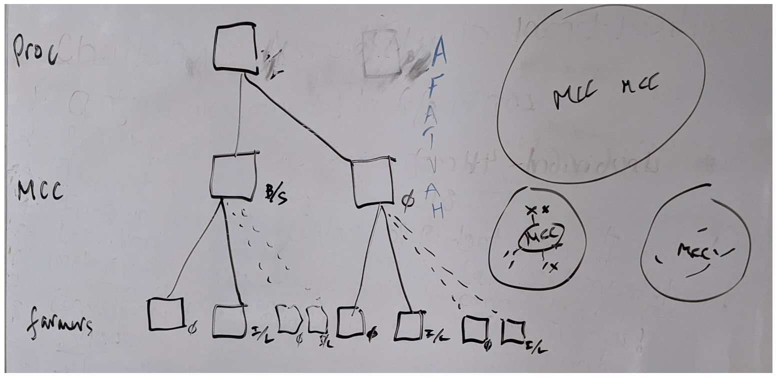

Figure 1: Design

an indication of solid non-fat content.[1]

Experimental design

We randomly allocate quality testing equipment to eligible milk collection centers (MCCs), which agree to implement some kind of quality bonus to suppliers. In a cross-cutting design, at the farmer level, we will randomly allocate training on quality parameters and linkages with production management decisions, as well as distribute lactometers, which serve as partial quality indicators. The design is illustrated in Figure 1

- Hypothesis 1: making quality visible at the MCC level increases quality of aggregated milk supplied to processors ($\beta_{H1} > 0$).
- Hypothesis 2: making quality visible at the MCC level increases quality of milk that farmers deliver ($\beta_{H2} > 0$).
- Hypothesis 3: providing information on what the desired milk quality parameters are, what affects this parameter, and providing as simple technology to approximately measure this parameter increases the quality at the farmer level ($\beta_{H3} > 0$).
- Hypothesis 4: making quality visible at the MCC level and providing information on what the desired milk quality parameters are increases the quality at the farmer level ($\beta_{H4} > 0$).

[1] Unfortunately, the two components of interest to the processors work in opposite directions. A lactomer is based on gravity of different components of milk. Butter fat is lighter than water, while SNF is heavier than water. Therefore, milk with high fat and SNF contents could have the same specific gravity as milk with low fat and low SNF contents. However, weight of water is very close to weight of butter fat, so overall it is likely that a higher readings correspond to more SNF.

Additional research questions:

- Does the MCC level intervention affects farmers that are already connected to the milk collection center differently than farmers that are not already connected to an MCC ($\beta_{H2C} = \beta_{H2}$).
- Does the information treatment affect farmers that are connected to an MCC differently than farmers that are not connected to an MCC ($\beta_{H3C} = \beta_{H3}$)
- Does the combined treatment affect farmers that are connected to an MCC differently than farmers that are not connected to an MCC ($\beta_{H4C} = \beta_{H4}$)

Specifications

We will estimate two equations using Ordinary Least Squares. One equation is at level of the milk collection centers, the second equation is at the level of the dairy farmers.

Denote milk collection centers by m, running from 1 to M. T_m is a treatment indicator at the MCC level that is one if the MCC (in who's catchment area the farmer resides) was allocated to the lactoscan treatment. T_i is a treatment indicator at the farmer level that is one if the farmer was allocated to the information treatment. C_i is an indicator variable at the farmer level that is one if the farmer is connected to an MCC and zero otherwise.

$$y_m = \alpha + \beta_{H1}.T_m + \varepsilon_m \tag{1}$$

$$y_{m,f} = \alpha + \alpha_C C_i + \beta_{H2}.T_m + \beta_{H3} T_i + \beta_{H4} T_i.T_m + \beta_{H2C}.T_m.C_i + \beta_{H3C} T_i.C_i + \beta_{H4C} T_i.T_m.C_i + \varepsilon_{m,f} \tag{2}$$

Standard errors in equation 2 are clustered at the milk collection level.

Power calculations

We use simulation to determine sample size. The primary outcome variable that we use in our statistical power calculations is the price of milk.

We start at the level of the milk collection center and assume that at this level, the price at which milk collection centers sell their aggregated milk is normally distributed with mean 1000 UGX per liter and standard deviation of 50 (which is half of what we will assume at the farmer level). From these N observations (with N denoting the number of milk collection centers recruited for our study and hence the first key variable to be determined by the power calculations) we then generate N times n observations. These are the n dairy farmers that are located in the catchment areas of the N milk collection centers. The outcome variable at this level, prices that farmers obtain from milk collection centers, are generated again as random normal, but with the mean the value that was drawn for the MCC the n farmers are connected to, and with a slightly higher standard deviation (100 — since, as the milk is not aggregated yet, extreme values are not yet averaged out. The standard deviation was obtained from data collected during a survey in 2021). This procedure gives us a total sample with N prices at the MCC level and $N.n$ prices at the farmer level, the latter being clustered at the MCC catchment area level by design.

We assume that the intervention at the level of the milk collection centers leads to an increase of in the price of UGX30 per liter. This seems reasonable in light of the fact that processors told that they either pay a 10 percent premium for quality milk, or UGX100 per liter. However, as we assume a pretty narrow distribution of prices, even though this effect is only a 3 percent increase, this is considered a medium to large effect according to Cohen's D. At the level of the farmers, for the intervention at the MCC level, we expect an effect size of UGX40. While this represents a 4.4 percent increase, the larger variance at this level means that according to Cohen's D, this effect is considered small to medium. Finally, at the level of the farmers, the individual level randomization of the information treatment intervention allows us to estimate small effects. For our power simulation, we assumed and effect size of UGX25, which corresponds to a small effect according to Cohen's D. For the interaction, we assume a large effect (UGX50 per liter).

We calculate power for the joint test that the three hypotheses are true at the 5 percent significance level. To do so, we run two regressions. One is at the MCC level and only includes an indicator variable for the treatment (lactoscan). A second regression is at the level of the dairy farmer and includes an indicator variable that is true if the farmer lives in the catchment area of an MCC that was treated (and zero if it resides in an area where the MCC was not treated), as well as an indicator variable that is true if the farmer received In the second (farmer level) regression, standard errors are clustered at the MCC level. We also include a full set of interactions between all treatment variables and the blocking variable (C_i in equation 2) (Muralidharan, Romero, and Wüthrich, 2019). We run 1000 simulations for each n*N combination.

Results of the simulation are summarized in Figure 2. Instead of the usual power curves that plot power against sample size, we obtain a power plane as we determine both the number of clusters (between 100 and 130 MCCs) and the number of farmers per cluster (between 10 and 40 farmers). Power is measured on the z axis and is the proportion of cases (out of the 1000 simulations) in which all three coefficients were found significant at $p<0.05$.

The figure, which can be found as an interactive figure here, shows the trade-off between more clusters and more individuals per cluster. With about 125 MCCs and 20 farmers per cluster we find power just above .80. This corresponds to a sample of 2500. Note that the requirement to detect minimum effect sizes for all three hypotheses simultaneously is very strict. For instance, if we require only one hypothesis to be significant, we obtain power of .99 for a sample with 125 MCCs and 20 farmers. Similarly, if we consider each hypothesis separately, we get power levels of .87 for the MCC level intervention with outcome at the MCC level, .93 for the MCC level intervention with outcome at the farmer level,

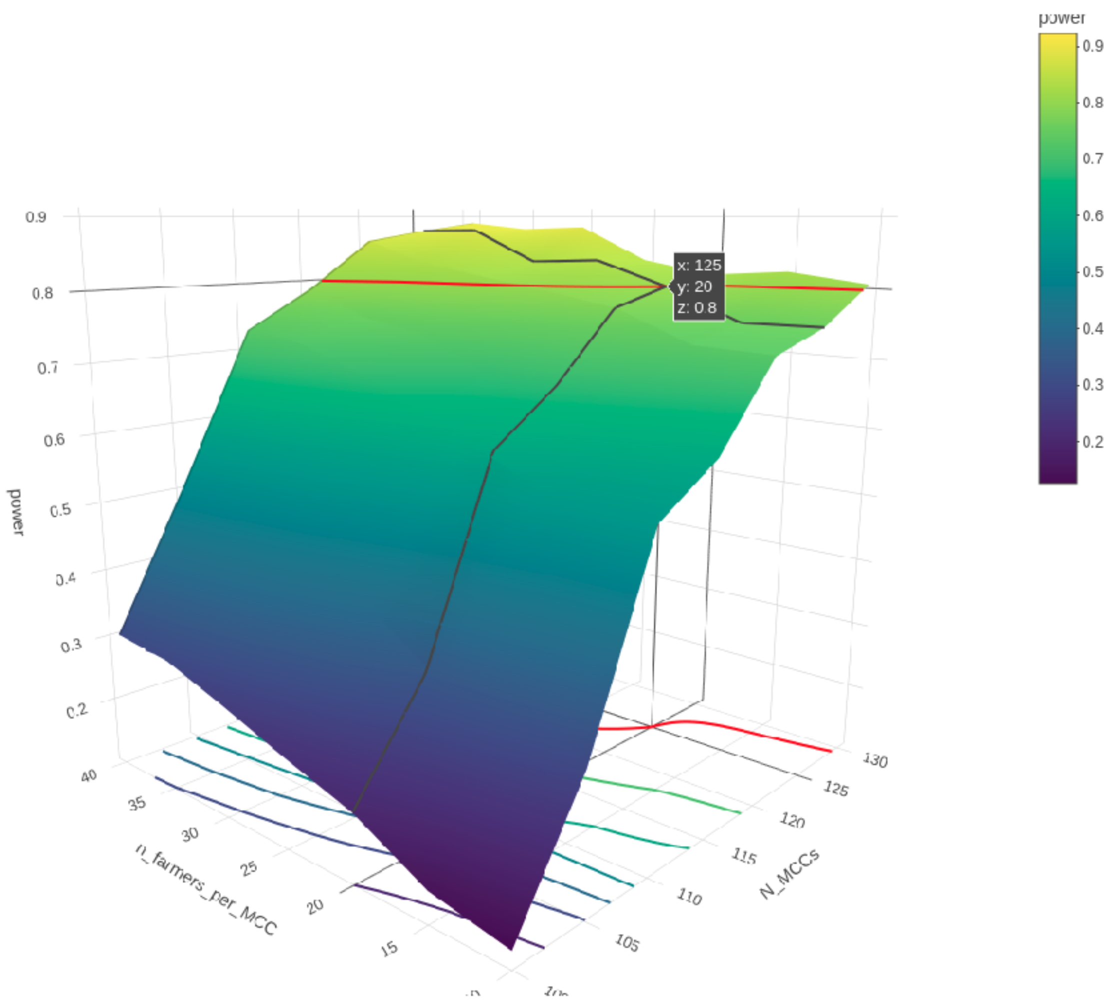

Figure 2: Power plane

and .94 for the farmer level intervention with outcome at the farmer level. For the interaction, we obtain power of .99.

Sampling

Context and study area

Data collection and outcomes

Outcomes of interest at MCC level: average milk quality levels (for different quality parameters); milk purchase price and volume; milk sales channel (to whom sold), price, volume and profits.

Outcomes of interest at farmer level: perceptions of control of output quality parameters; willingness to experiment; changes in production investments and management; milk quality levels (for different quality parameters); milk sales channel (to whom sold), price, volume and profits.

We also investigate the gender implications of the intervention. In particular, we will zoom in on the household and see if the intervention has an impact on the use of animal sourced food for eg children within the household. Cows are milked twice a day. Normally, milk for commercial use is sourced early in the morning. If cows are also milked in the evening, this milk is usually consumed within the household. It may be that our intervention affects this practice and milk used within the household reduces because the shadow cost increases.

Ethical clearance

This research received clearance form Makerere's School of Social Sciences Research Ethics Committee) as well as from IFPRI IRB (). The research was also registered at the Ugandan National Commission for Science and Technology ().

Transparency and replicability

To maximize transparency and allow for replicabiliy, we use the following stratgies:

- pre-analysis plan: the current document provides an ex-ante step-by-step plan setting out the hypothesis we will test, the intervention we will implement to test these hypothsis, the data tha will be collected and specifications we will run to bring the hypotheses to the data. This pre-analysis plan will be pre-registered at the AEA RCT registry.
- revision control: the entire project will be under revision control (that is time stamped track changes) and committed regularly to a public repository (github).

- mock report: After baseline data is collected, a pre-registered report will be produced and added to the AEA RCT registry and GitHub. This report will differ from the pre-analyisis plan in that it already has the tables filled with simulated data (drawn from the baseline). The idea is that after the endline, only minimal changes are necessary (basically connecting a different dataset) to obtain the final result, further reducing the opportunity of specification search.

References

Muralidharan, K., M. Romero, and K. Wüthrich. 2019. *Factorial designs, model selection, and (incorrect) inference in randomized experiments.* Tech. rep., National Bureau of Economic Research.

Rao, M. and A. Shenoy. 2021. "Got (clean) milk? governance, incentives, and collective action in Indian dairy cooperatives."

Van Campenhout, B., B. Minten, and J. F. M. Swinnen. 2021. "Leading the way – foreign direct investment and dairy value chain upgrading in Uganda." *Agricultural Economics* 52 (4): 607–631.