Farm to Fridge: Digital Traceability and Quality Upgrading in Kenyan Dairy Value Chain

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Abstract

Disorganized agricultural value chains often prevent the transmission of quality incentives to upstream farmers, especially when quality is unobserved at the farm gate. When the quality revealing costs are prohibitively high, and in the absence of an effective traceability system throughout the value chain, farmers might not be rewarded for producing high-quality products even if quality incentives exist in the downstream markets. Thus, farmers have low incentives to invest in quality upgrading. In this study, I establish digital traceability systems among dairy cooperatives in Kenya, then develop and apply an innovative milk quality monitoring method based on a statistical model (Bayesian model). The model uses the aggregated milk container quality information and traceability data to detect whether individual farmers are producing high or low-quality milk. The model-predicted milk quality shows a significantly high correlation with the one-time milk test (0.8 for added water and 0.6 for butter fat). It showcases a scalable model for enhancing transparency and accountability across different value chains. I then discuss the ongoing field experiments revealing quality information via this approach in the Kenyan dairy value chain.

JEL Codes: O12, O13, Q12, Q13, D82, C11

Keywords: Traceability, Quality Upgrading, Asymmetric Information, Dynamic Moral Hazard, Bayesian Analysis

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1 Introduction

Improving the quality of agricultural products is often considered an important step in the process of structural transformation, moving farmers from subsistence farming to market-driven, commercial agriculture. However, disorganized supply chains with many intermediaries often prevent the transmission of quality incentives to upstream farmers, especially when quality is unobserved at the farm gate, which discourages farmers from upgrading quality. A growing literature finds that quality certification can reduce this market friction caused by asymmetric information and improve product quality (Bernard et al., 2017; Macchiavello and Miquel-Florensa, 2019; Abate et al., 2021). The cost to get certified, however, can be high and not financially feasible for smallholder farmers (Bergquist and Startz, ongoing[1]), or even farmers' cooperatives (Aggarwal, Robinson, Spearot, Song, and Xu, ongoing[2]). Therefore, in markets where the producers are mainly smallholders, and products are aggregated by intermediaries, downstream buyers always certify the quality in bulk after aggregation. Although studies show that producers respond to quality incentives and improve product quality (Atkin et al., 2017; Bold et al., 2022; Rao and Shenoy, 2023), when quality is only certified further downstream in the value chain, whether and how the quality incentives are transmitted to upstream producers remain open questions.

One possible way quality incentives can be transmitted to upstream producers when quality is partially observable is through market competition among intermediaries in sourcing high-quality products, as studied in the ongoing project by Bai, Bergquist, and Morjaria[3]. Alternatively, this paper studies a new potential solution that could be suitable when quality is completely unobservable: establishing a traceability system along the value chain to add accountability, which can potentially reward farmers more precisely for providing high-quality products. It's also likely to be financially feasible as it won't certify individual producers' product quality until the aggregate quality is found to be low.

This study investigates quality upgrading in the Kenyan dairy value chain and establishes digital traceability systems among dairy cooperatives in Kenya. Based on the traceability system, statistical models are used to detect whether individual farmers are producing high- or low-quality milk. I then run an individual-level randomized controlled trial to provide randomly selected farmers' milk quality information to dairy cooperatives.

As Akerlof (1970) first pointed out theoretically, asymmetric information about product quality should create a market for "lemons", and has a negative impact on the welfare of the market participants. Later on, Viscusi (1978) shows that a system of quality certification can help to mitigate this issue. This project speaks directly to the growing literature on

[1] ATAI Project: Quality and Contracting in Honey Supply Chains in Ethiopia.

[2] ATAI Project: Creating a Market for High-Quality Cassava Cuttings: The Role of Quality Certification and Demand Stimulation.

[3] ATAI Project: Price Incentives to Improve Coffee Quality in Uganda.

quality certification, including Bernard et al. (2017), which studies the effect of informing villagers about upcoming onions quality certification in Senegal and finds improvements in quality. Macchiavello and Miquel-Florensa (2019) exploits the staggered roll-out of the Quality Sustainability Program (which includes price premium on quality, extension services, and access to inputs for plot renewal altogether) in the Colombian coffee sector to show that eligible farmers produced better quality coffee on average respond to this program. Other ongoing studies include Abate, Bernard, de Janvry, and Sadoulet[4] about wheat certification in Ethiopia; Bergquist and Startz[5] about quality testing of honey in Ethiopia; as well as the ongoing project by myself: Aggarwal, Robinson, Spearot, Song, and Xu[6] about cassava cuttings certification in Rwanda. This study also contributes across this spectrum but is different from the perspective that the quality certification at an aggregate level is already there downstream in the value chain in my study, and quality certification at a disaggregate level would be more like a quality "audit", as it won't certify individual producers' product quality until the aggregate quality is found low.

This project also relates to another strand of literature about creating a market for higher quality products to upgrade quality, including Bold et al. (2022), which provides smallholder farmers with training and access to a high-quality maize market in Uganda at the village level, which led to large improvements in quality, productivity, farm gate prices, and thus profits. Atkin et al. (2017) connects rugs producers in Egypt to foreign buyers paying a premium for higher quality rugs at the producer level and finds that producers improved both quality and productivity. Another ongoing project I am conducting in Rwanda is also in this area: Aggarwal, Godlonton, Robinson, Spearot, and Xu[7] is evaluating the effects of providing farmers with access to maize processors (who require higher quality standards and pay higher prices than those offered by local markets) on their input decisions. This study is different in the sense that Kenyan dairy cooperatives have already linked to processors paying a premium for higher quality, and I am focusing on the transmission of quality incentives further to farmers. To study the transmission of quality incentives to farmers, an ongoing project by Bai, Bergquist, and Morjaria[8] gives quality incentives to coffee traders in Uganda at the parish market level to see whether it can transmit to farmers through market competition in sourcing high-quality coffee cherries. My study focuses on the effect of the traceability system on the value chain, which makes it more contractible with farmers on quality and potentially can reward farmers more precisely for providing high-quality products. In the dairy sector, Rao and Shenoy (2023) provides collective price incentives for

[4]ATAI Project: Quality-graded Wheat Value Chain Development and Agricultural Transformation in Ethiopia.

[5]ATAI Project: Quality and Contracting in Honey Supply Chains in Ethiopia.

[6]ATAI Project: Creating a Market for High-Quality Cassava Cuttings: The Role of Quality Certification and Demand Stimulation.

[7]ATAI Project: Connecting Smallholder Farmers to Agricultural Value Chains in Rwanda.

[8]ATAI Project: Price Incentives to Improve Coffee Quality in Uganda.

aggregated milk quality at the village level in India and finds an improvement in quality, given that the management team can control the information disclosure. Different from Rao and Shenoy (2023), which focuses on internal governance and collective action, this project looks at individual farmers' responses to produce high-quality products.

Bai (2024) provides watermelon sellers in China with quality signaling labels—stickers or laser engraving—to improve their sorting of melons into premium and normal piles. Bai notes that watermelon sellers usually have a better sense of the unobservable quality of taste than their buyers do. The study finds that, after sorting, retailers were able to sell the laser-cut labeled watermelons to consumers at a higher price without losing sales from the normal pile, and their profits increased by 30% to 40%, but there were no gains for sellers with the sticker label. Bai suggests that it's likely due to the fact that the laser engraving is more credible to customers. However, one year after the intervention, all retailers stopped sorting and labeling because the cost of the laser technology for an individual seller was prohibitive. Indeed, as Abate et al. (2021) points out as one of the four necessary conditions for quality certification to succeed, the cost-benefit of quality certification is critical to sustainability. So far, I have only found one flagship cooperative that is implementing the traceability and quality-based payment system in Kenya, and most other cooperatives in Kenya haven't implemented it at all. It could be logistically challenging to implement the system, or the system is likely to be unprofitable for the other cooperatives. The profitability of the traceability and quality-based payment system is also one of the important questions I want to answer in my project.

Taken together, the intellectual merit of the project is three-fold. First, different from most quality certification studies, this project won't certify individual producers' product quality until the aggregate quality is found low, which is potentially more suitable in the market where the producers are mainly smallholders, and products will be aggregated by intermediaries. Second, this project is unique in its focus on the transmission of quality incentives to upstream producers through a traceability system, which can reward farmers more precisely for providing high-quality products. Third, this project investigates the sustainability of establishing the quality upgrading system by the central actor in the market, in our case, the dairy cooperatives. The system is likely to be durable and scalable due to the existing long-term and stable relationship between dairy farmers and cooperatives.

2 Background of the Kenyan Dairy Sector

The empirical setting is the Kenya dairy value chain. The dairy sector is one of the largest agricultural sub-sectors in Kenya (KIPPRA, 2018); it accounts for more than 4 percent of GDP and 12 percent of the agricultural GDP (KNBS, 2019). According to the national survey *Kenya Integrated Household Budget Survey (KIHBS) 2015/16*: Among 13,086 households surveyed, 61.3 percent of them own at least one cattle, and 57.3 percent of them own at least one cow in Kenya.[9]

The national long-term strategy, *Kenya Vision 2030*, has acknowledged that the dairy sector is a key agricultural subsector and wants to realize a significant increase in exports of milk and dairy products. Currently, only a small fraction of Kenya's milk production is exported, and a number of trade conflicts have arisen when regional importing countries rejected milk products processed in Kenya in recent years on the grounds that Kenya's raw milk was of insufficient quality. In the literature: Kenya's raw milk is documented to be of low quality and does not meet national and international standards due to high bacterial load (Nyokabi et al., 2021; Ndungu et al., 2016), antibiotic residues (Ondieki et al., 2017; Orwa et al., 2017), water adulteration (Nyokabi et al., 2021; Ondieki et al., 2017; Ndungu et al., 2016), and aflatoxin contamination (Kagera et al., 2019). This is consistent with what I have found from the field: Among the milk samples of 940 different farmers from 2 different dairy cooperatives, 47.23% failed the minimally required standards on added water posted by the government (Kenya Bureau Of Standards (KEBS)), and 16.28% failed the minimally required standards on butter fat. A likely reason for low milk quality is that individual farmers face weak incentives to produce high-quality milk.

In rural Kenya, as Table 1 shows, dairy farmers are mainly selling their milk to dairy cooperatives in the formal value chain. Dairy cooperatives hire milk transporters to collect milk from farmers. Milk is not tested at this point, however, beyond a simple acceptance test (organoleptic tests: sight, smell, or taste or some simplified version of density tests) due to the prohibitively high cost (both time and monetary) of comprehensive milk tests, and thus, farmers are paid based solely on quantity once they pass the acceptance tests. As Figure 1 shows, transporters usually aggregate the milk from multiple farmers to fill larger milk cans, which are then transported to collection centers. The collection centers pour the milk together into cooling plants (usually containing 10 to 100 of these cans) for sale to processors. These processors then perform comprehensive milk quality tests. *Brookside Dairy Limited* (the biggest dominant milk processing company in Kenya, which controls 45 percent of the dairy market, as at January 2016) is actively buying raw milk from cooperatives in the study region and always classifies milk into three categories based on the milk quality testing results: (1) accept the aggregated milk with a premium price; (2) accept it without a premium price; or (3) reject it. The reason is that high-quality milk can be used to produce high-value products like buttermilk and yogurt. Medium-quality milk is limited to use in ultra-pasteurized liquid packets, but low-quality milk cannot be traded by law. If the milk is rejected, the entire vat of milk has to be destroyed by law, and the dairy cooperative will bear the loss. Therefore, quality incentives exist in the downstream markets but are not transmitted to the upstream farmers.

Table 1 also presents some other summary statistics of household characteristics for dairy

[9]The number is slightly higher for rural households: 63.1 percent of rural households own at least one cattle, 58.9 percent of rural households own at least one cow.

farmers in Kenya based on the baseline survey data. In panel A, it shows that households own 1.66 acres of farmland, 2.76 cattle, and 1.5 lactating cows on average.

Panel B shows the milk production and sale variables. On average, households produce 14.58 kgs of milk every day. All of them are dairy cooperative members and are currently actively selling to cooperatives. Only a few farmers are selling to informal traders (1%) in my sample, and conditional on selling to traders, the average daily sales to traders are 9.67 kgs. Conditional on selling to cooperatives, farmers sell 10.86 kgs of milk every day. Usually, farmers get the payment once a month (the mean payment frequency per month is 1).

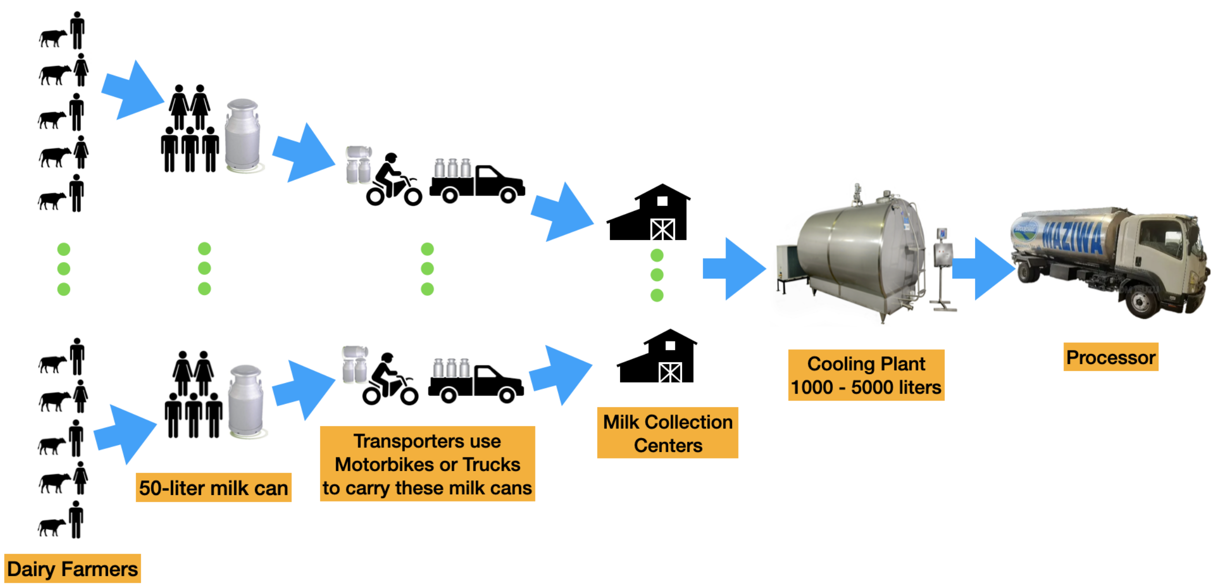


Figure 1: Kenya Dairy (Formal) Value Chain

3 Traceability System

As discussed above, when milk is aggregated by transporters, it is collected into cans, which include the milk from about 5-20 farmers. Farmers' milk volume and which cans they fill vary every day. To establish a milk traceability system, I first assign a unique identification number to each aggregated milk can and then link farmers' unique member IDs to specific milk cans for every day's milk delivery. Specifically, I give milk transporters basic smartphones with a digital app installed; then, as Figure 2 shows, the transporters use the digital app to record the date, time, farmers' member IDs, aggregated milk can IDs, the milk volume, transporter name, collection route, and cooling plant every time they collect milk from farmers. Cooperative staff help to check the data and upload it to the server when transporters drop the milk at the cooling plant so that the researcher can get access to the data every day. At the end of the study, smartphones will be given to the transporters as

Table 1: Baseline Summary Statistics of Kenyan Dairy Farmers

	(1) Endarasha	(2) Rungeto	(3) Overall
Panel A: Demographics			
=1 if household head is female	0.20	0.24	0.22
	(0.40)	(0.43)	(0.42)
Age of the household head	55.24	52.80	53.84
	(11.74)	(11.41)	(11.61)
Years of education of the head	10.25	9.82	10.00
	(3.52)	(3.61)	(3.58)
Number of years keeping cattle	19.47	14.77	16.76
	(11.57)	(11.87)	(11.96)
Number of household members	4.10	3.91	3.99
	(1.48)	(1.29)	(1.37)
Farm land size owned (Acres)	2.16	1.30	1.66
	(2.00)	(1.60)	(1.83)
Total cattle owned	2.85	2.69	2.76
	(1.68)	(1.67)	(1.67)
Number of lactating cows owned	1.62	1.41	1.50
	(0.96)	(0.74)	(0.85)
Panel B: Milk Production and Sale			
Daily milk production (Kgs)	13.85	15.11	14.58
	(9.18)	(12.90)	(11.48)
=1 if selling to cooperatives actively	1.00	1.00	1.00
	(0.00)	(0.00)	(0.00)
Daily sales to cooperatives (Kgs, conditional on selling to cooperatives)	9.69	11.71	10.86
	(6.63)	(11.95)	(10.09)
=1 if selling to informal traders actively	0.00	0.02	0.01
	(0.00)	(0.13)	(0.10)
Daily sales to traders (Kgs, conditional on selling to traders)		9.67	9.67
		(8.80)	(8.80)
Payment frequency from cooperatives (Times per month)	1.01	1.00	1.00
	(0.20)	(0.07)	(0.14)
Observations	248	338	586

compensation for their time. This traceability system helps to record who is contributing to each aggregated milk can, and their corresponding contribution percentages, which are used in the statistical model prediction.

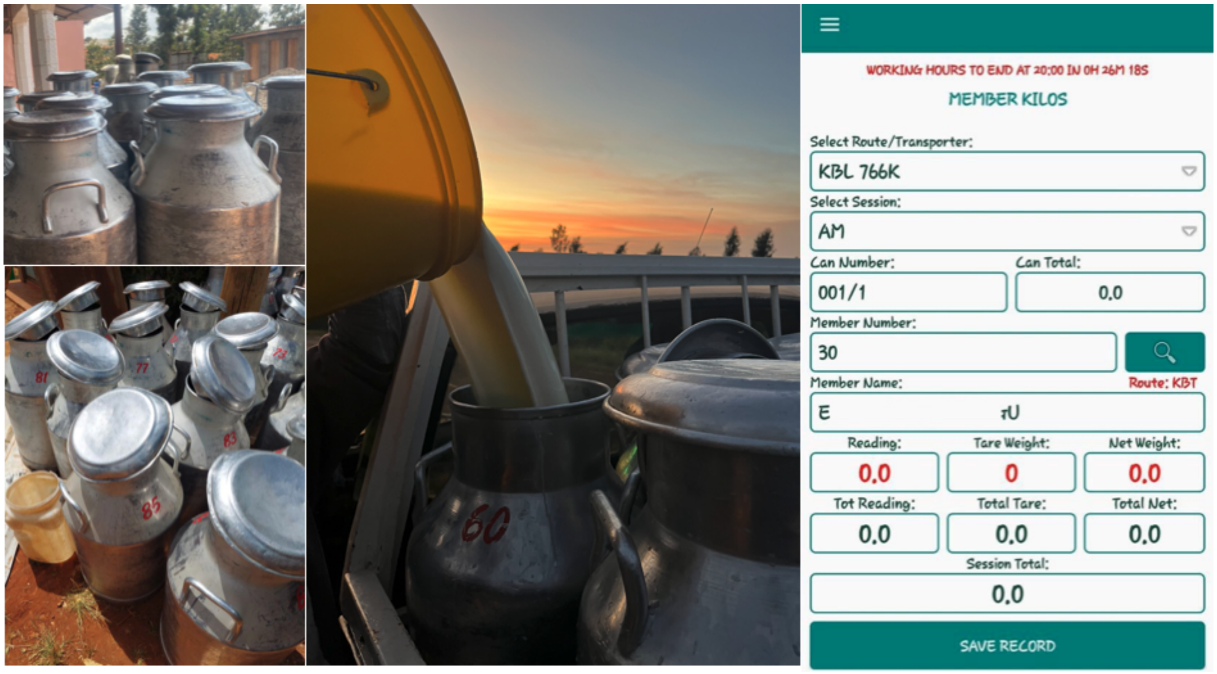


Figure 2: Traceability Data Recording

4 Bayesian Statistical Model

As mentioned previously, the cooperatives are not able to test every farmer every day due to the prohibitively high cost (both time and monetary) of comprehensive milk tests. The statistical model is developed to target farmers better instead of testing farmers randomly, and thus, it could save testing costs. I consider using the Bayesian model to predict individual farmers' milk quality. According to the Bayes' Theorem:

$$f(\rho \mid \text{data}) = \frac{f(\text{data} \mid \rho) f(\rho)}{f(\text{data})}$$

In which, $f(\rho \mid \text{data})$ is the posterior distribution for the parameter ρ; and $f(\text{data} \mid \rho)$ is sampling density for the data—which is proportional to the Likelihood function; $f(\rho)$ is the prior distribution for the parameter, and $f(\text{data})$ is the marginal probability of the data. I could also write their relationship in the following way:

$$\text{Posterior} \ \propto \ \text{Likelihood} \ \times \ \text{Prior}$$

To collect the data for model inputs, I test these aggregated cans with the help of a third-party lab every day for several days until the number of can level observations is 2.5

(experience gained from a pilot study) times the number of different farmers. Then, I link these milk quality test results to each farmer so that I can generate some features as the inputs for model prediction. To be specific, I have a matrix of each farmer's contribution percentage for each aggregated can, and the corresponding aggregated can test results on different days. The model utilizes the variations coming from the fact that (1) farmers' milk volume, (2) which aggregated cans they fill, (3) which other farmers are contributing to that can, and (4) corresponding aggregated can test results vary each day. The theoretical aggregated can quality (butter fat and added water) should be the weighted average of the individual farmers' milk quality in the can.

In the next sections, I present the model prediction methods for butter fat and added water, which are the parameters the downstream processors are mainly focusing on in my study area.

4.1 Prediction for Individual Farmers' Butter Fat in Milk

Let's assume there are n different farmers, and their individual milk butter fat is represented by the parameters $\rho_1^{indiv}, \rho_2^{indiv}, \ldots, \rho_n^{indiv}$. The distribution of the butter fat for both individual levels and can levels look like this:

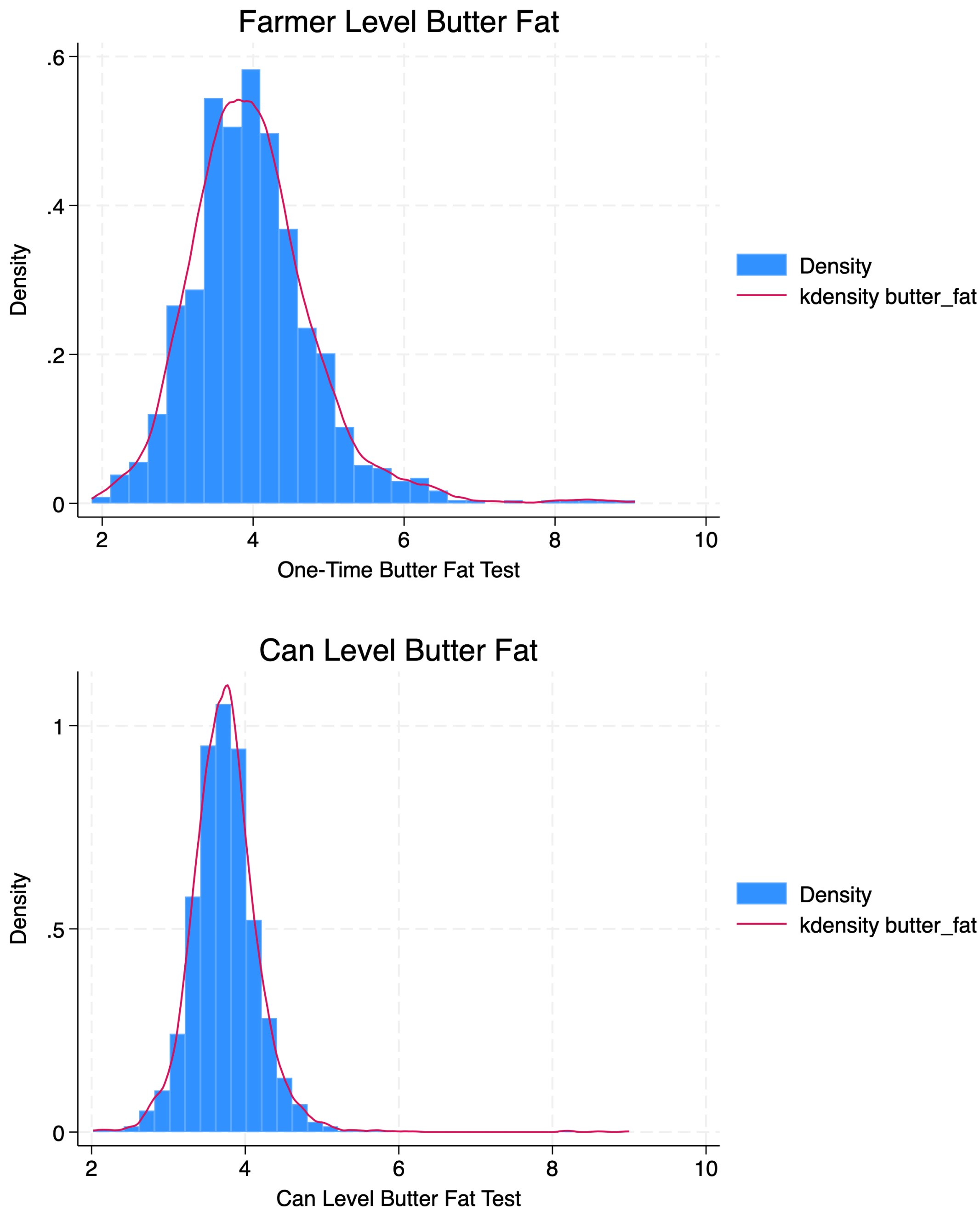


Figure 3: Butter Fat Distribution

4.1.1 Prior

The individual butter fat level, ρ_i^{indiv}, is non-negative, and based on the histogram of observed data in Figure 3, I model them using the gamma distribution:

$$\rho_i^{indiv} \sim Gamma\left(\alpha_{\text{prior}}, \beta_{\text{prior}}\right)$$

The Probability Density Function (PDF) is given by:

$$P(\rho_i^{indiv}) = \begin{cases} \frac{\beta^\alpha}{\Gamma(\alpha)}(\rho_i^{indiv})^{\alpha-1}\exp(-\beta\rho_i^{indiv}), & \rho_i^{indiv} > 0 \\ 0, & \text{otherwise} \end{cases}$$

Where:

- α denotes the shape parameter. I choose the non-informative priors for it and let it draw from an inverse gamma distribution.
- $\alpha \sim \text{InvGamma}(3, 1)$
- β is the rate parameter. I choose the non-informative priors for it and let it draw from an inverse gamma distribution.
- $\beta \sim \text{InvGamma}(3, 1)$
- the gamma function is defined as:

$$\Gamma(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy$$

4.1.2 Theoretical Can Level Quality

Given the share of the individual farmer i's milk in the can j, w_{ij}^{data}, the aggregated butter fat level, ρ_j^{can}, is a weighted average of the individual butter fat from m_j different farmers' milk in can j:

$$\rho_j^{can} = \sum_{i=1}^{m_j} w_{ij}^{data} \rho_i^{indiv}$$

4.1.3 Likelihood Modeling

The observed aggregated butter fat, y_j^{data}, typically have some measurement error around its theoretical mean, and y_j^{data} is also non-negative, so I can model this as Truncated Normal distribution (truncated at 0):

$$y_j^{data} \sim \text{Normal}^+(\rho_j^{can}, (\sigma^{can})^2)$$

Where,

- $\rho_j^{can} = \text{E}[y_j^{data}] = \sum_{i=1}^{m_j} w_{ij}^{data} \rho_i^{indiv}$
- $\sigma^{can} \sim \text{InvGamma}(3, 1)$

Given the observed y_j^{data}, known weights w_{ij}^{data}, the likelihood function informs us how probable our observed aggregated butter fat is for different combinations of individual densities $\rho_1^{indiv}, \rho_2^{indiv}, \ldots, \rho_n^{indiv}$.

4.1.4 Posterior

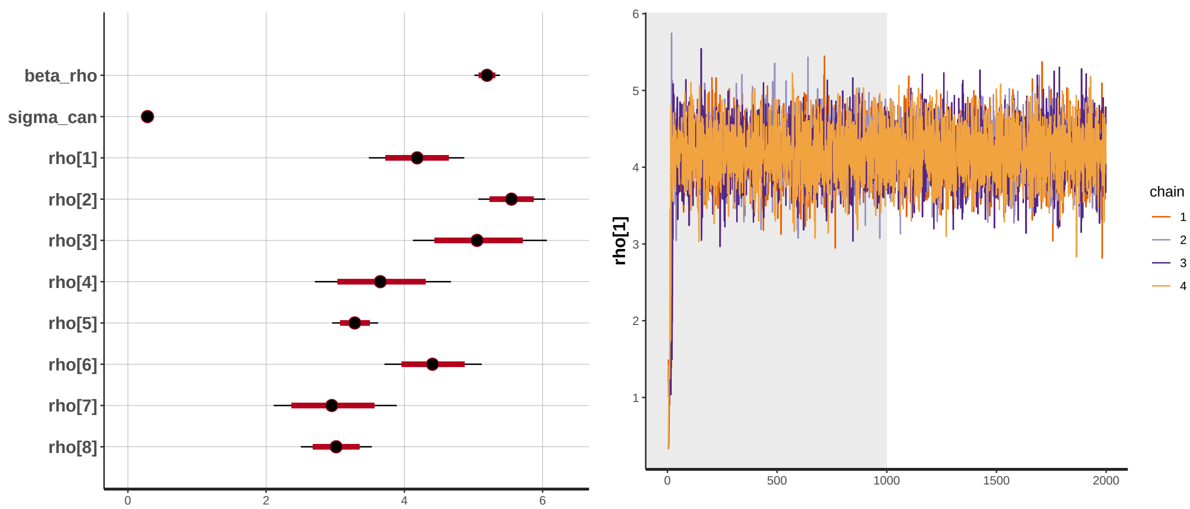
Given the above setup, Bayes' theorem gives:

$$P\left(\rho_1^{indiv}, \rho_2^{indiv}, \ldots, \rho_n^{indiv} \mid \mathbf{Y}^{data}\right) \propto$$

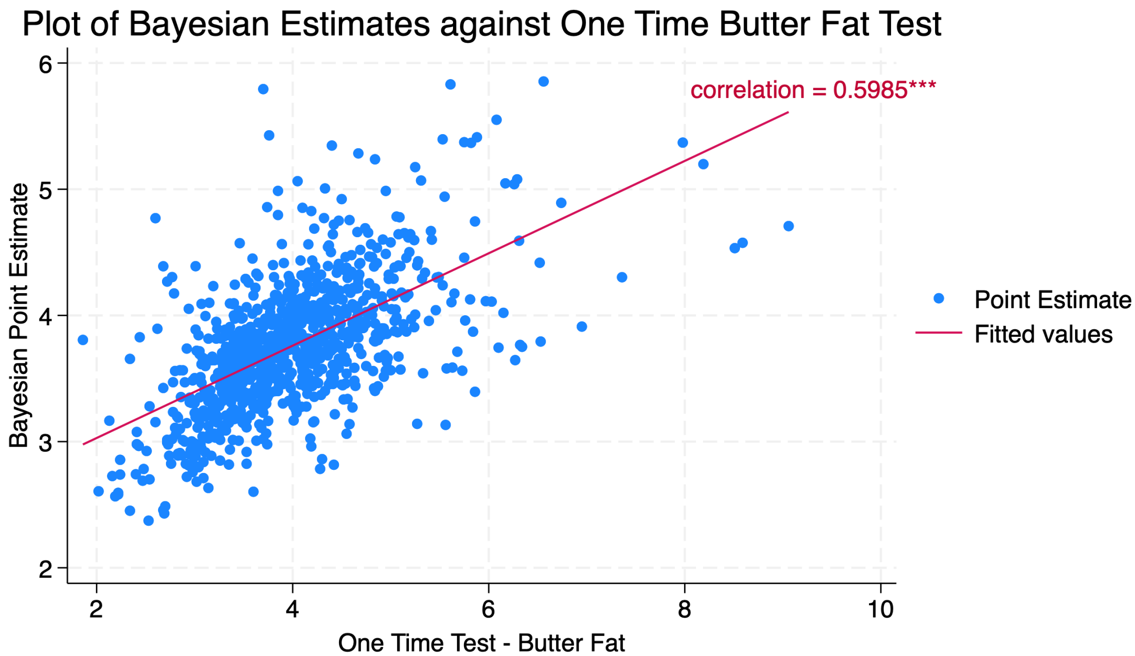
$$L\left(\mathbf{Y}^{data} \mid \rho_1^{indiv}, \rho_2^{indiv}, \ldots, \rho_n^{indiv}\right) \times P\left(\rho_1^{indiv}\right) \times P\left(\rho_2^{indiv}\right) \times \ldots \times P\left(\rho_n^{indiv}\right)$$
$$= \prod_{j=1}^{J} L\left(y_j^{data} \mid \rho_1^{indiv}, \rho_2^{indiv}, \ldots, \rho_n^{indiv}\right) \times \prod_{i=1}^{n} P\left(\rho_i^{indiv}\right)$$

4.1.5 Model Fitting - Markov Chain Monte Carlo (MCMC)

The Bayesian model gives point estimates and credible intervals for each ρ_i^{indiv} and every parameter. Below are the fitting results based on Can-level data:



Here is the correlation between the Bayesian Point Estimates (Y-axis) and the One-Time Quality Test Results(X-axis):



4.1.6 Posterior Probability Classification

The final goal is to identify extreme farmers with **higher quality** than the processors' quality rewarding standards and extreme farmers with **lower quality** than the minimally required standards posted by the government (Kenya Bureau Of Standards (KEBS)).

Therefore, I want to classify farmers into three categories:

- (1) **Good**: butter fat higher than **3.8**;
- (2) **Normal**: butter fat **between 3.25 and 3.8**;
- (3) **Bad**: butter fat lower than **3.25**.

We could either use the point estimates to classify each farmer, or the entire posterior distribution. The latter method **accounts for the uncertainty inherent in the estimates** and can provide a more nuanced classification.

Let $f(\rho_j)$ be the posterior density function for farmer j. The probabilities for each tier are calculated as follows:

- Probability of 'Good' Tier: $P_{\text{Good}}(j) = \int_{\theta_{\text{high}}}^{\infty} f(\rho_j)\, d\rho_j$
- Probability of 'Normal' Tier: $P_{\text{Normal}}(j) = \int_{\theta_{\text{low}}}^{\theta_{\text{high}}} f(\rho_j)\, d\rho_j$
- Probability of 'Bad' Tier: $P_{\text{Bad}}(j) = \int_{-\infty}^{\theta_{\text{low}}} f(\rho_j)\, d\rho_j$

4.1.7 Classification Results for Butter Fat

Below are the results from the classification:

I compare the predicted categories and categories based on a one-time test in the confusion matrix below and calculate the accuracy rate and precision rate:

Table 2: Confusion Matrix - Butter Fat

Prediction \ One Time Test	Good	Normal	Bad
Good	**388**	85	25
Normal	110	**129**	33
Bad	28	47	**95**

Notes: **Actual Numbers**

Prediction \ One Time Test	Good	Normal	Bad
Good	**77.91%**		
Normal		**47.43%**	
Bad			**55.88%**

Notes: **Accuracy** (Row Percentage)

Prediction \ One Time Test	Good	Normal	Bad
Good	**73.76%**		
Normal		**49.43%**	
Bad			**62.09%**

Notes: **Precision** (Column Percentage)

If I test randomly, the probability of identifying each tier is:

- $\mathrm{P}_{\textbf{Good}} = \frac{526}{940} = 55.96\%$
- $\mathrm{P}_{\textbf{Normal}} = \frac{261}{940} = 27.77\%$
- $\mathrm{P}_{\textbf{Bad}} = \frac{153}{940} = 16.28\%$

4.2 Prediction for Individual Farmers' Added Water in Milk

Let's keep the quality parameter the same. The distribution of the added water for both individual levels and can levels look like this:

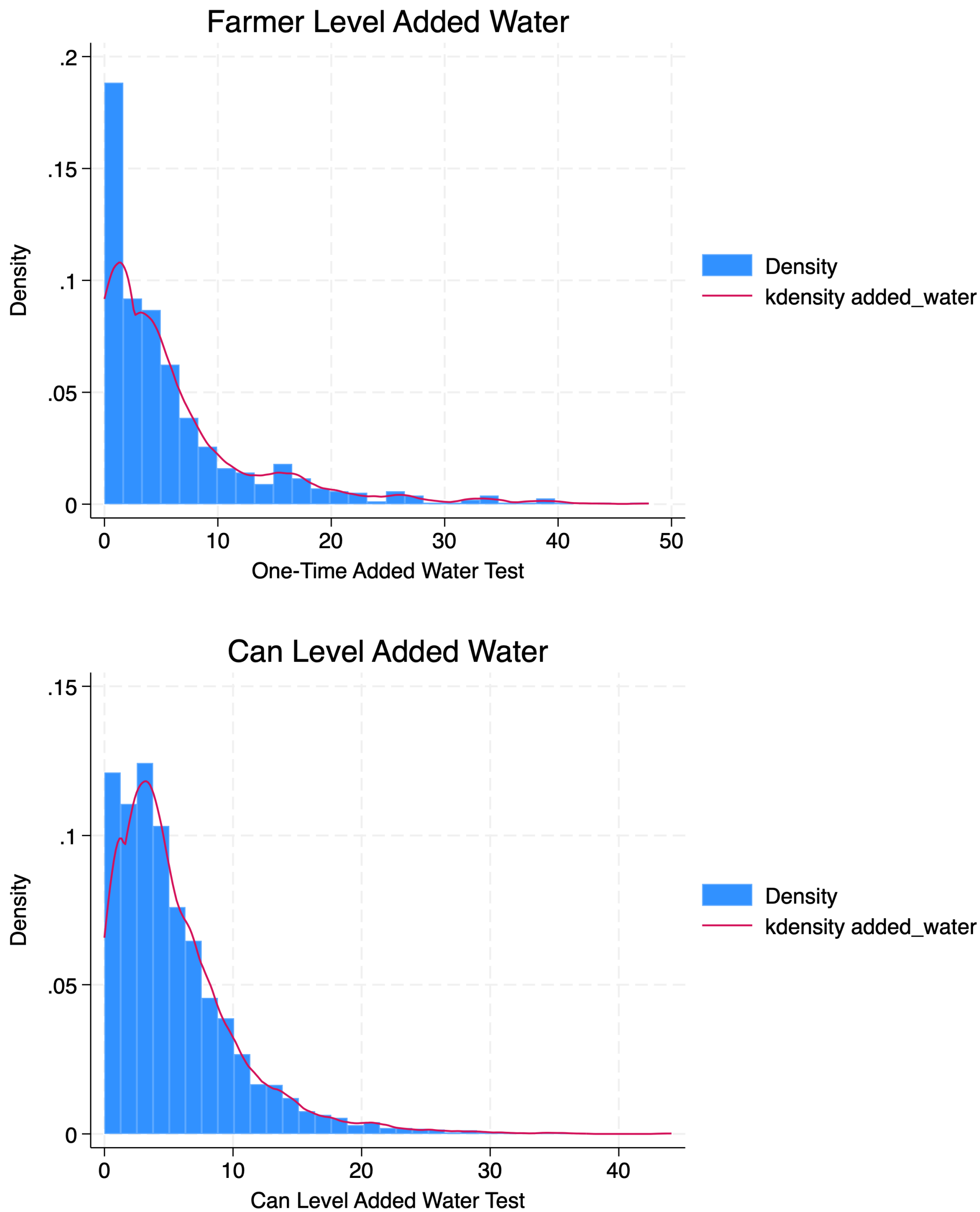


Figure 4: Added Water Distribution

4.2.1 Prior

The individual added water level, ρ_i^{indiv}, is non-negative, and based on the histogram of observed data in Figure 4, I model them using the half-normal distribution:

$$\rho_i^{indiv} \sim \text{Normal}^+(0, (\sigma^{indiv})^2)$$

The Probability Density Function (PDF) of the positive half-normal distribution is given by:

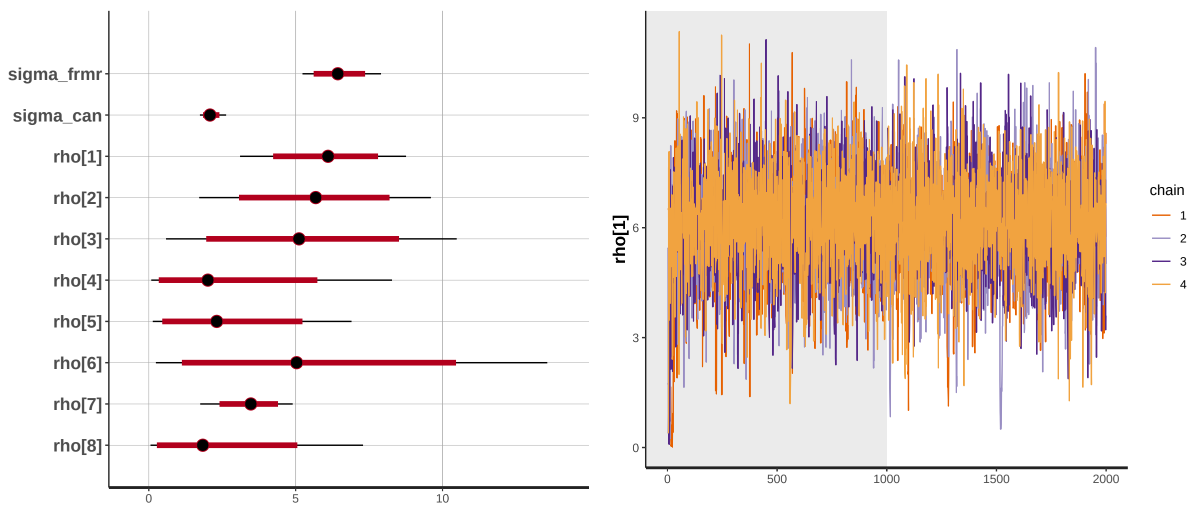
$$f(x; 0, \sigma^{indiv}) = \begin{cases} \frac{\sqrt{2}}{\sigma^{indiv}\sqrt{\pi}} \exp\left(-\frac{x^2}{2(\sigma^{indiv})^2}\right) & x \geqslant 0 \\ 0 & \text{otherwise.} \end{cases}$$

We also choose the non-informative prior of σ to follow the Inverse Gamma distribution:

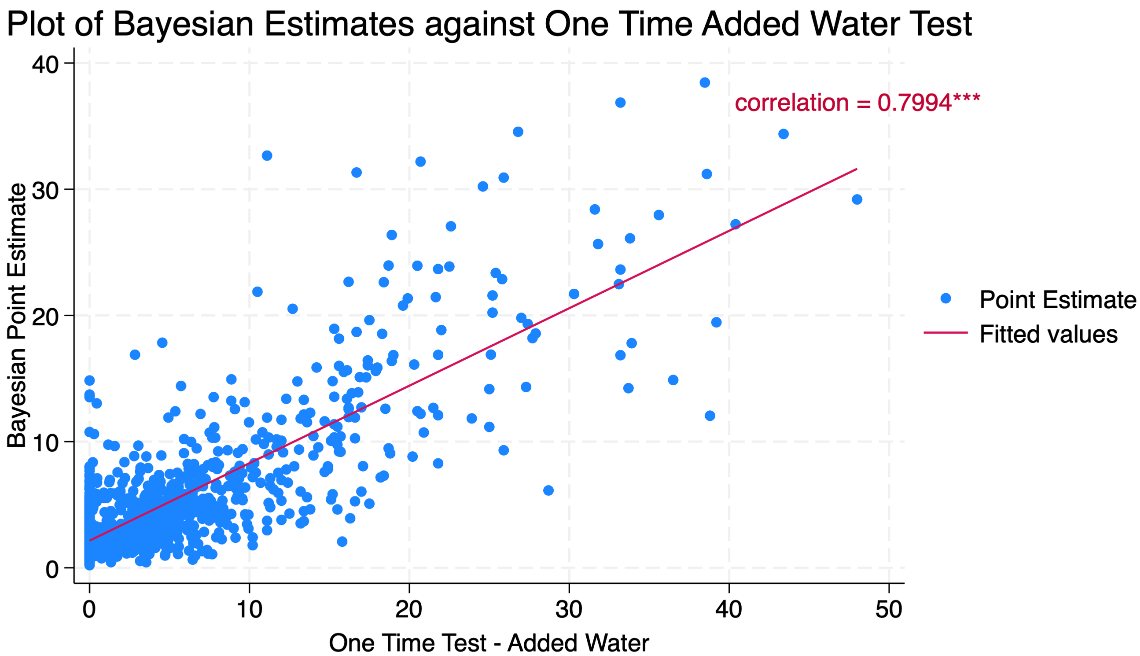
$$\sigma^{indiv} \sim \text{InvGamma}(3, 1)$$

4.2.2 Model Fitting - Markov Chain Monte Carlo (MCMC)

The Bayesian model gives point estimates and credible intervals for each ρ_i^{indiv} and every parameter. Below are the fitting results based on Can-level data:



Here is the correlation between the Bayesian Point Estimates (Y-axis) and the One-Time Quality Test Results(X-axis):



4.2.3 Posterior Probability Classification

The final goal is to identify extreme farmers with **higher quality** than the processors' quality rewarding standards and extreme farmers with **lower quality** than the minimally required standards posted by the government (Kenya Bureau Of Standards (KEBS)).

Therefore, I want to classify farmers into three categories:

- (1) **Good**: Added Water lower than **2**;
- (2) **Normal**: Added Water **between 2 and 4**;
- (3) **Bad**: Added Water higher than **4**.

4.2.4 Classification Results for Added Water

Below are the results from the classification:

I compare the predicted categories and categories based on a one-time test in the confusion matrix below and calculate the accuracy rate and precision rate:

Table 3: Confusion Matrix - Added Water

One Time Test

Prediction	Good	Normal	Bad
Good	**214**	84	67
Normal	6	**12**	10
Bad	101	79	**367**

Notes: **Actual Numbers**

One Time Test

Prediction	Good	Normal	Bad
Good	**58.63%**		
Normal		**42.86%**	
Bad			**67.09%**

Notes: **Accuracy** (Row Percentage)

One Time Test

Prediction	Good	Normal	Bad
Good	**66.67%**		
Normal		**6.86%**	
Bad			**82.66%**

Notes: **Precision** (Column Percentage)

If I test randomly, the probability of identifying each tier is:
- $P_{\textbf{Good}} = \frac{321}{940} = 34.15\%$
- $P_{\textbf{Normal}} = \frac{175}{940} = 18.62\%$
- $P_{\textbf{Bad}} = \frac{444}{940} = 47.23\%$

5 Discussion

In the previous sections, I compared the model prediction with the one-time milk test results as if the one-time tests reflected perfect information about farmers' milk quality, which is not true. One-time tests can only reflect the perfect information for the days when farmers' milk samples have been taken and tested, but not other days. A more fundamental question to ask is, do farmers have fixed quality types, or are they changing types on different days?

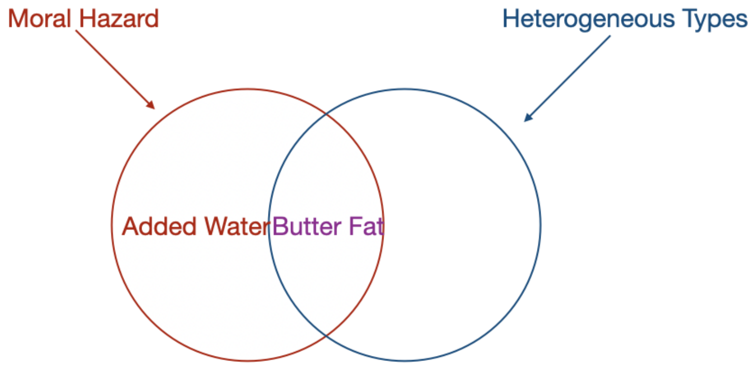


Figure 5: Moral Hazard or Heterogenous Types

First, added water is clearly a moral hazard problem since everyone knows that water adulteration is wrong, and they can choose to add water or not. Second, butter fat is determined by cow breed type (fixed) and animal feed (varying); plus, it could also be affected by added water (varying). Farmers' milk quality could change on different days, but different farmers have different **tendencies (probability)** to sabotage the milk quality.

If it's a heterogeneous-type problem, then a one-time test would be sufficient to reveal the information, but if it's more of a moral hazard problem or at least a mixture of both, then a one-time test won't be enough.

For a dynamic moral hazard problem, there are two approaches largely discussed in the literature: random monitoring and periodic review. In my setting, random monitoring is a one-time test in a two-week period or so; the periodic review is achieved by monitoring the aggregated can level quality over time and using the Bayesian model to detect individual quality information. The Bayesian model will help to give a point estimate of the farmers' quality parameters and also the probability of each parameter failing the quality standards (drawn from the posterior distribution), both of which reflect farmers' average behaviors over the monitoring period. If the Bayesian model is perfect, and the model predicts that the farmer produces high-quality milk for a probability of 0.8. Then, it's equivalent to, say, out of 10 days, there are eight days when this farmers' milk would be tested to be high quality. It's reasonable to believe that the cooperative only cares about how many periods the farmer produces high-quality milk and does not care which exact period the farmer produces high-quality milk. There is a chance for prediction errors; therefore, it's important for the cooperatives to understand that the model could send noisy signals. To do this, I explain multiple times to the cooperatives how to interpret the model results, and I also present the confusion matrix by comparing the classifications based on model prediction versus the one-time tests.

To study cooperatives' belief updating when given one-time test information and statistical model prediction information, I am currently running an individual-level RCT to randomly assign farmers into one of the three treatment conditions, stratified by collection route. Group 1 farmers' model-predicted quality information and the corresponding confusion matrix are shared with the cooperatives (as well as with the farmers themselves) as a periodic review; Group 2 farmers' one-time quality test information (randomly sampling in 2 weeks) is shared as random monitoring. Group 3 will serve as the control for the evaluation. I will examine how cooperatives and farmers respond to this information. I will continuously share this information for four rounds (1 to 2 rounds per month, depending on the size of the collection routes) so that I can monitor the dynamic changes in the cooperatives' and farmers' behavior and milk quality.

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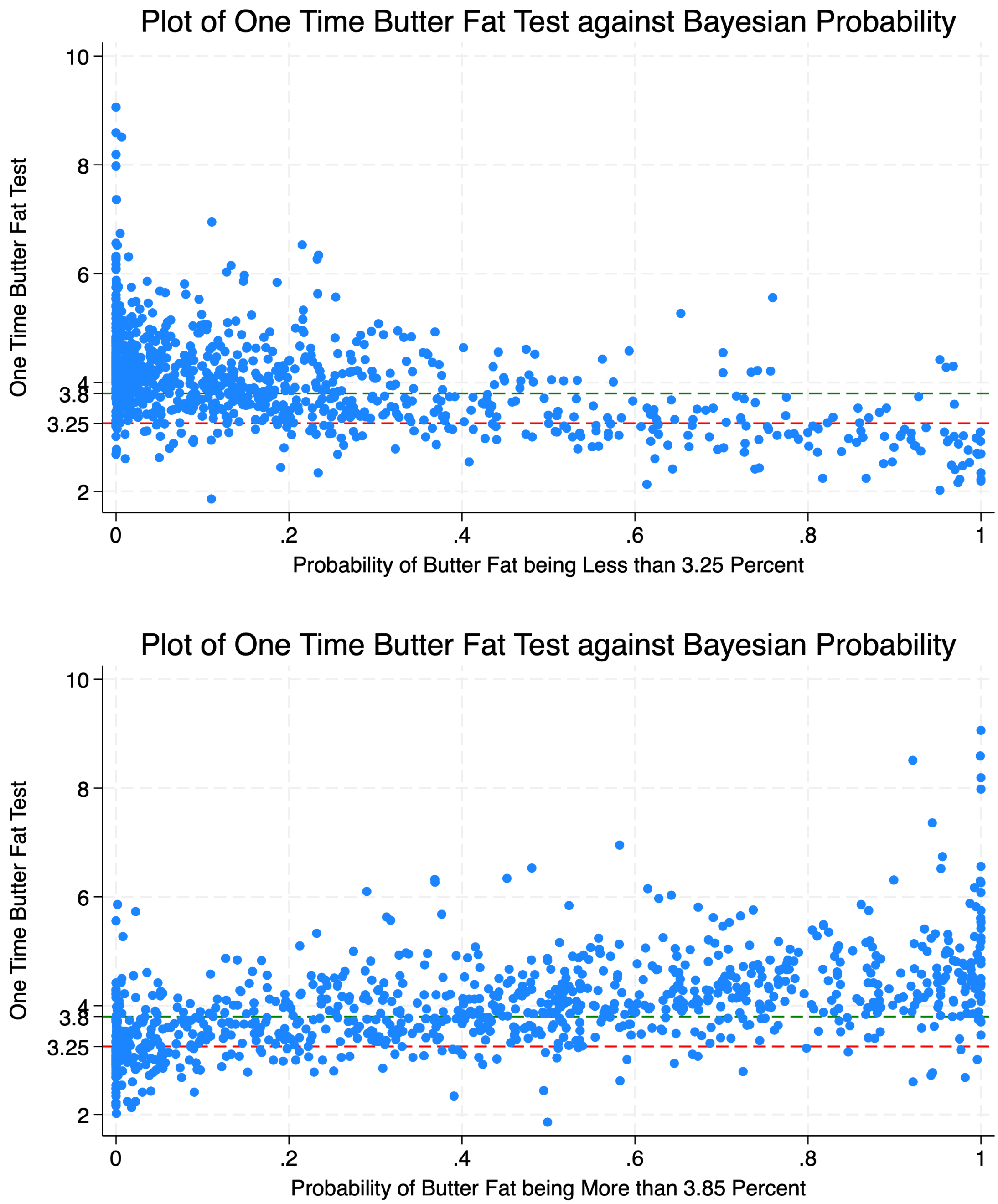

Figure A1: Probability of High and Low Butter Fat

Figure A2: Probability of High and Low Added Water