Biswas, Samir, Basu, Preetam and Avittathur, Balram (2025) *Milk adulteration testing and impact of farmers efficiency heterogeneity: a strategic analysis.* European Journal of Operational Research, 323 (2). pp. 686-700. ISSN 0377-2217.

European Journal of Operational Research 323 (2025) 686–700

Contents lists available at ScienceDirect

European Journal of Operational Research

journal homepage: www.elsevier.com/locate/eor

Innovative Applications of O.R.

Milk adulteration testing and impact of farmers efficiency heterogeneity: A strategic analysis

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ARTICLE INFO

Keywords:
OR in agriculture
Milk supply chain
Adulteration testing
Quality uncertainty
Efficiency heterogeneity

ABSTRACT

Driven by economic motives, dairy farmers adulterate milk to increase its perceived quality, posing a serious risk to consumer health. We analyse a milk supply chain in which smallholder dairy farmers can adulterate milk and explore the feasibility of selling it to end consumers through an aggregator. Using a non-cooperative sequential game between the aggregator and farmers, we examine the impact of two testing strategies offered by the aggregator to curb adulteration - (i) individual (testing milk procured from each farmer individually) and (ii) composite (testing the milk after aggregating the portions procured from all the farmers). Our analyses reveal that the aggregator can control milk adulteration by judiciously using testing and penalty mechanisms. We find that a higher market price *(aggregation effect)*, fetched by the aggregator because of its bargaining power owing to the consolidation of milk supplies, is essential for its operation. It leads to higher revenue for the aggregator and expands the zone in which it is profitable for the aggregator to operate. However, our results show that the *efficiency heterogeneity* among farmers, which leads to the less efficient farmers free-riding on the more efficient ones, has a detrimental effect on the aggregator operation. We also explore the impact of *external uncertainties* on the supply chain and observe that the composite testing strategy becomes more profitable for the aggregator when external uncertainties increase. Our results provide important policy recommendations for aggregators adopting optimal testing strategies.

1. Introduction

Milk adulteration is a major global concern that poses serious public health hazards and often leads to fatal diseases. Melamine-contaminated milk products caused severe illness to nearly 300,000 children, including the death of six infants in China in 2008 (Li et al., 2019). In 2016, at least 127 school children fell ill after consuming adulterated milk at an elementary school in Mathura district of India. The incident resulted in the deaths of two students and one adult (India Today, 2018). A widespread milk adulteration with formaldehyde was reported in Brazil, causing serious health concerns (Handford et al., 2016). In Kenya, unscrupulous milk traders caused large-scale milk adulteration by using chemicals to prolong milk life (Business Line, 2016). There are multiple other instances of milk adulteration in countries across the globe such as Colombia (Vera-Bravo et al., 2022), Ethiopia (Banti, 2020), Iran (Moosavy et al., 2019), Sudan (Mohammed & Shuming, 2021) and Uganda (Daily Monitor, 2017). The possible factors for adulteration can be attributed to the lack of strict regulations, large demand-supply gap, perishable nature of milk, non-availability of quality inputs, and limited knowledge about farming practices (Handford et al., 2016). Considering the nutritional value of milk and its affordability, milk adulteration causes serious social harm (Mu et al., 2014) and receives considerable attention from policymakers and researchers.

1.1. Motivation and background

Dairy is the largest agricultural commodity, which accounts for 5.3% of the national GDP in India. The total milk production in the country is essentially carried out by about 80 million smallholder dairy farmers. India contributed to 23% of global milk production in 2021-22 (PIB, 2022). Although India is the world's largest milk-producing

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https://doi.org/10.1016/j.ejor.2024.12.001
Received 17 November 2023; Accepted 1 December 2024
Available online 9 December 2024

country, the quality of milk is often questionable. In a nationwide survey by the regulator *Food Safety and Standards Authority of India* (FSSAI) in 2018, 41% and 7% of the total 6432 milk samples showed non-compliance for quality and safety issues, respectively (FSSAI, 2018). According to the FSSAI, the possible reasons for non-compliance are an inadequate effort by farmers, contamination in cattle feed, and wilful adulteration by farmers.

We conducted an extensive study of the milk supply chain in different parts of India to gain a better understanding of the various associated issues. In India, an *aggregator* directly purchases milk from farmers at a collection center, transports it to the factory, and sells it to consumers thereafter. Similar practices are observed in Brazil, China, Ethiopia, Kenya, Nepal, Rwanda, Sudan and Thailand Adesogan and Dahl (2020), Mu et al. (2014). Our focus is on the quality dilemma that dairy farmers face, leading them to choose between investing in honest efforts and adopting unfair means to improve perceived quality by adulteration. Milk should be of a certain threshold quality as specified by the regulator in terms of factors that include fat content and solid-non-fat level among others (Corpbiz, 2016). The aggregator adheres to the regulator-specified threshold quality while procuring milk from dairy farmers. The aggregator performs two categories of tests to ascertain the quality of milk and ensure that it is free from adulteration. First, the quality of the milk is measured through simple tests such as the Gerber test that measures the fat content in milk (Mu et al., 2016). Milk from an individual farmer is accepted if it reaches the threshold quality level (Times of India, 2011). The farmers are paid weekly or fortnightly based on the supplied quantity (volume) of milk that attains the threshold quality level (Salokhe, 2019). Second, extensive adulteration tests are carried out to ensure milk is free from adulterants. For example, the resazurin test, liquid chromatography-mass spectrometry (LC-MS) test and enzyme-linked immune sorbent assay (ELISA) test are performed to detect different types of adulterants in milk (Azad & Ahmed, 2016). The aggregator rejects the milk if adulteration is detected and penalizes farmers who are at fault.

Even though farmers can obtain a higher price from the aggregator, we observe that they often sell milk directly to consumers. This can be attributed to various factors, such as strict testing regimes adopted by aggregators, deferred payment schemes, and aggregator capacity constraints. Meanwhile, the regulator is committed to zero tolerance towards adulterated milk. It periodically samples and tests milk sold in the market (FSSAI, 2018). It imposes stringent cash penalties or even imprisons the offender (FSSAI, 2006). The offenders face a severe goodwill loss owing to the reputation loss that negatively impacts their profitability (Forbes, 2014).

1.2. Research context and research questions

From the viewpoint of attaining the threshold quality level, the honest effort of the farmers is essential to achieve desired quality without mixing adulterants. It includes arranging high-quality feed and inputs, adopting good farming practices, providing veterinary arrangements and ensuring proper dairy environments. The higher the honest *effort level*, the higher is the chance of milk exceeding the threshold quality level. However, farmers often fail to impart sufficient honest effort because that involves higher costs. The aggregator does not accept milk below the threshold quality level. This leads to a dilemma for the farmers and they often resort to unfair practices and increase the perceived quality of milk by adding adulterants (Johnson, 2014). For example, detergent and low-cost vegetable fat are mixed to increase the fat content in milk. The cost of these adulterants is negligible compared to honest effort costs (Levi et al., 2020). Hence, the farmers are economically motivated to adulterate the milk.

One of the salient aspects of milk production is quality uncertainty. While interviewing dairy farmers, we found various sources of uncertainty and grouped them into two broad categories. First, *process uncertainty* includes the factors associated with the production process. For example, milk quality depends on the breed, health and lactating phase of the animal. Second, *external uncertainty* considers external factors, such as weather conditions, variations in fodder quality and outbreak of diseases. This categorization is in line with (Linn, 1988) and Levi et al. (2020). The quality uncertainty causes fluctuations in milk quality and influences the farmers' adulteration decisions.

Two broad categories of tests are conducted on the milk by the aggregator, quality and adulteration tests. The objective of quality tests is substantially different from that of adulteration tests (Levi et al., 2020). The aggregator performs quality tests to ensure the milk meets the desired standard. Based on our field study, we observed that quality tests are done individually for each farmer, while adulteration tests are done either individually or collectively to prevent adulterated milk from reaching consumers. The adulteration tests are more complex and costly compared to the quality tests. In this study, we specifically model the adulteration tests and their implications. While there is an entire range of tests available to detect different adulterants, the aggregator often fails to employ all of them owing to high costs (Mu et al., 2014) and operational feasibility (Mu et al., 2016). We define the term *testing level*, which denotes the extent of adulteration tests employed by the aggregator. For example, if the aggregator performs six out of ten types of adulteration tests, the testing level would be 60%.

The aggregator usually performs adulteration tests at its factory, which is located away from the collection center. However, owing to technological advancements, portable testing machines are available (PIB, 2023), which help the aggregator perform adulteration tests even at the collection center. Based on the availability of the testing infrastructure and its operational feasibility, the aggregator could employ two different strategies for adulteration tests. In the *individual testing* strategy, the aggregator tests milk procured from each farmer separately. However, the overall testing cost in this strategy is high owing to a higher number of testing instances. The *composite testing* strategy involves mixing of milk procured from individual farmers before performing adulteration tests. The testing cost is lower due to lesser testing instances required. However, due to mixing of milk before testing, the composite testing fails to identify the farmers who indulge in adulteration. Hence, there is an incentive for farmers to put lesser honest effort and free-ride. The negative consequences of *free-riding* become severe when farmers are heterogeneous in terms of efficiency (Zhou et al., 2021) – the less-efficient farmers would resort to higher level of adulteration. This free-riding behaviour due to *efficiency heterogeneity* imposes a challenge to the sustainability of the aggregator operation (Bonroy et al., 2019). The efficient farmers may become reluctant to sell milk to the aggregator because of the possible free-riding by the less-efficient ones.

The aggregator plays a vital role in the milk supply chain. First, the aggregator curbs milk adulteration by adopting an appropriate testing strategy. Second, the aggregator enjoys a higher bargaining power owing to supply consolidation (Getnet et al., 2018; Mu et al., 2019). It enables the aggregator to fetch a higher price in the market compared to the farmers selling directly. The *aggregation effect* represents the price premium enjoyed by the aggregator. With a higher aggregation effect, the aggregator can pass on some benefits to the farmers, who then receive a higher procurement price. Hence, it creates new opportunities for dairy farmers to sell milk to the aggregator and improve their income (Shi et al., 2019).

In this study, we aim to explore how the aggregator optimizes its testing policy and how that impacts the farmers' effort level and adulteration decision. We consider a quantity-based (volumetric) payment scheme, in which the aggregator pays the farmers for the quantity of milk that meets the threshold quality level (Times of India, 2011). We found this payment scheme popular because of its operational simplicity. As discussed above, dairy farmers are often economically motivated to increase the perceived quality of milk through adulteration. To the best of our knowledge, no study in the extant literature analyzes economically motivated adulteration in the volumetric payment scheme considered in this paper. The aggregation effect helps the farmers improve their income. However, efficiency heterogeneity among farmers leads to free-riding behaviour and impacts individual farmers' adulteration decisions.

Motivated by the above-mentioned dynamics in a milk supply chain, we aim to address the following research questions: (1) Under what conditions would the dairy farmers sell milk to an aggregator? (2) How does the testing level of the aggregator influence the farmers' honest effort? (3) What are the impacts of the efficiency heterogeneity among the farmers and the quality uncertainty on the farmers' honest effort? How do these factors influence the aggregator operation?

To address these research questions, we develop a sequential game-theoretic model with three players (one aggregator and two dairy farmers). The aggregator decides the testing level first, and then the farmers decide their efforts. We summarize key insights and contributions of this study in the following sections.

1.3. Related literature and theoretical contributions

Quality management in agricultural supply chains has received significant attention from many researchers (An et al., 2015; Hsu et al., 2019). First and foremost, quality management in agricultural supply chains is fundamentally different from that in traditional supply chain management (Sodhi & Tang, 2014). A notable difference is the completeness of the final product with regard to the suppliers. In manufacturing, different components from various suppliers are assembled to form the final product. Hence, tracing the problem to a particular component or supplier is not a challenge when product failure occurs (Dai et al., 2021). However, the agricultural produce from a particular farm is a complete product. It poses a problem of traceability owing to the final product being procured from multiple farmers since landholdings are small (Levi et al., 2020). Though an inspection-based mechanism is essential to improve efforts from the farmers, it is often not possible to check each supplying entity owing to the higher inspection costs (Mu et al., 2016, 2014). In addition, farmers often differ in efficiency owing to their variations in capability and farming knowledge (Zhou et al., 2021). As a result, the lack of traceability leads to free-riding by the less efficient farmers.

The uncertainty in agricultural production influences the output quality. The possibility of achieving the desired quality in agricultural products exposes the supply chain to quality risk (Borodin et al., 2016; Fahimnia et al., 2015; Sodhi & Tang, 2012). Various studies in the extant literature connect the suppliers' efforts to the performance risk (Nikoofal & Gümüş, 2020; Quigley et al., 2018; Tang et al., 2018) or to the compliance measures adopted by the buyers (Caro et al., 2018; Gao et al., 2024; Lin et al., 2020). Levi et al. (2020) extend the performance risk to wilful adulteration by farmers to increase product quality. Deferred payment schemes can be adopted to control economically motivated adulteration (Babich & Tang, 2012; Rui & Lai, 2015). Mu et al. (2016, 2014) examines the impact of inspections on improving milk quality while limiting adulteration by dairy farmers. Table S1 (in supplementary material) summarizes the various aspects studied in the milk adulteration literature and highlights our contribution.

We contribute to the literature by incorporating various unique features from practice. We analyse milk adulteration by dairy farmers in a volumetric payment scheme in which they are paid if supplied milk exceeds a pre-defined threshold quality level (Draaiyer et al., 2009). We extend the literature (Levi et al., 2020) on how the endogenous effort decision and quality uncertainty influence milk adulteration. We detail the detection of adulteration (Azad & Ahmed, 2016) and differentiate complex adulteration tests from simple quality tests, as followed in the literature (Hsu et al., 2019; Mu et al., 2016, 2014, 2019). Our model also emphasizes the detrimental effect of efficiency heterogeneity among dairy farmers on the milk aggregator operations and the overall milk supply chain. The efficiency heterogeneity exposes the milk supply chain to the free-riding behaviour of the less efficient farmer. The literature on the impact of efficiency heterogeneity and free-riding behaviour on adulteration decisions is sparse.

1.4. Key insights

Based on the unique features of our study, we derive various insights that address the problem of milk adulteration under different practical conditions. First, we obtain the necessary conditions, under which farmers sell milk to the aggregator. If the individual testing strategy is adopted, farmers would choose the aggregator over direct selling even if the aggregator offers the same wholesale price that farmers receive directly from consumers. However, they sell milk to the aggregator adopting the composite testing strategy if they receive a higher wholesale price. We define this additional wholesale price essential for farmers under the composite testing strategy as *producer leverage*. Our results show that as efficiency heterogeneity among farmers increases, the producer leverage also increases.

Second, we provide an optimal testing policy for the aggregator under different market conditions. When testing is inexpensive, the aggregator would inspect milk procured from each farmer individually. When testing is costly and the aggregation effect is high, the aggregator employs the composite testing strategy; it is not feasible for the aggregator to offer this testing service when testing is costly and the aggregation effect is low.

Third, the aggregator opts for a higher testing level in the composite testing strategy compared to the individual testing strategy. Since the effort by the individual farmers is not revealed by the composite testing strategy, the farmers do not have enough incentives to impart a high effort level in this strategy. Thus, the farmers put a higher effort in the individual testing strategy in comparison to the composite testing strategy.

Fourth, as efficiency variability among farmers increases, the profit of the aggregator (farmers) decreases (increase) in the composite testing strategy owing to the higher producer leverage. Intuitively, the less efficient farmers would prefer efficiency heterogeneity in order to improve their profit. We define the *zone of operation* as the scenario in which both the aggregator and the farmers selling milk to the aggregator may operate profitably. We find that the zone of operation gets restricted due to efficiency variability. Hence, beyond a certain limit, the farmers would not find efficiency variability to be beneficial. Moreover, the effect of free-riding increases with efficiency variability, which decreases (increases) the profit of the efficient (less efficient) farmers. This may dissuade the efficient farmers from selling milk to the aggregator under the composite testing strategy.

Finally, we observe the impact of external uncertainty on the realized milk quality and on the farmers' adulteration behaviour. Uncertainty causes significant variations in quality, which reduces the farmers' earnings when their effort is high. Hence, they impart lesser effort and prefer to sell milk to the aggregator adopting the composite testing strategy. Anticipating the farmer's behaviour, the aggregator increases its zone of operation under the composite testing strategy. Further, managerial insights are provided based on model extensions related to (i) quantity heterogeneity among farmers, (ii) advanced testing technology adoption, (iii) competition among milk aggregators, and (iv) information asymmetry about farmers' types.

The rest of the paper is organized as follows. Section 2 introduces the modelling framework and optimal decisions under different strategies. We compare the equilibrium results in Section 3. The impact of efficiency heterogeneity and the impact of external uncertainty are described in Sections 4 and 5, respectively. The managerial insights under different conditions and efficiency variability among the farmers are elicited in Section 6. In Section 7, we analyse model extensions. Conclusion and suggestions for future research are provided in Section 8.

2. Modelling framework

We consider a stylized model comprising two smallholder dairy farmers $i \in \{1, 2\}$ located in the same geographical area and with the same production capacity, and a milk aggregator. In Sections 2 and 3, the farmers are identical in their production efficiency (An et al., 2015); the term *homogeneous* is used synonymously to denote identical farmers. We relax the identical production efficiency condition in Section 4. Much of milk sold in a retail market falls under the commodity category and hence, we assume that the retail price of milk is exogenous (Hsu et al., 2019; Mu et al., 2014). Moreover, the smallholder farmers are assumed to be price-takers (Chintapalli & Tang, 2022b; Pagare et al., 2023). Without loss of generality, we assume that each farmer produces one unit of milk (Chintapalli & Tang, 2022a).

The farmers' production cost comprises input and honest effort costs. For ease of exposition, we normalize the input cost to zero. Milk quality improves with the farmer's honest effort. However, it is subject to *process uncertainty* which impacts the final quality of the output. This uncertainty is influenced by factors such as breed, health and lactating phase of the animals, and is a *known-unknown* whose impact can be estimated *ex-ante* by the farmers. Various agricultural studies show that dairy farmers can predict milk quality based on various factors such as health, age and breed of the lactating animal (Wongpom et al., 2017). We model this uncertainty as the probability of milk attaining the threshold quality level, which increases as the farmer's honest effort increases. Farmer i imparts an honest effort level h_i and incurs an effort cost $\lambda_i h_i^2$. Here, $h_i \in [0, 1]$ represents the probability of attaining milk quality beyond the specified threshold level without adulteration. This notion is commonly used in the literature, where supplier compliance (Caro et al., 2018) or supplier performance (Tang et al., 2018) depends on efforts. We extend our model to incorporate *external uncertainty* as an *unknown-unknown*, which could be exemplified by uncertainties in weather conditions, variations in fodder quality and disease outbreaks in Section 5. The impact of this uncertainty unravels *ex-post* at the end of the production process.

While interviewing the farmers, we observed that the impact of honest effort to achieve the threshold quality has a diminishing returns to scale. A non-linear quadratic effort cost ($\lambda_i h_i^2$) captures the diminishing rate of return of the effort on attaining the threshold quality level (Hsu et al., 2019; Mu et al., 2016). The effort cost parameter $\lambda_i > 0$ denotes the production efficiency of the farmers. For instance, proper cattle grazing, access to vaccination, early diagnosis of diseases, medicines for cattle and insemination process help farmers to maintain a conducive environment and follow the standard operating procedures for dairy farming. These result in a better production efficiency, which reduces the effort costs of the farmer for producing high-quality milk (Zhu et al., 2023). We consider $\lambda_1 = \lambda_2 = \lambda$ when the farmers are identical on production efficiency.

An honest effort level of h_i by farmer i implies that the milk passes the quality tests at the collection center without any adulteration h_i proportion of time. In $(1 - h_i)$ proportion of time when the milk is of lower quality, the farmer adulterates the milk to increase its perceived quality. Otherwise, the milk is not accepted by the aggregator at the collection center. We assume zero salvage value for milk that is below the threshold quality. The cost of adulteration is negligible compared to the honest effort (Babich & Tang, 2012; Levi et al., 2020) and hence, normalized to zero. We use the terms *good* milk and *bad* milk interchangeably to refer to unadulterated and adulterated milk, respectively. In our base model, we analyse the farmers' efforts when they sell milk directly to the consumers. This is followed by modelling the farmers' efforts when they sell through the aggregator.

2.1. Base model: Direct selling (O)

In this section, we consider a scenario in which the farmers sell milk directly to the consumers at a unit-selling price $w_m \in (\lambda, 1)$ that ensures they always earn profit for their honest effort (Caro et al., 2018). We assume the threshold quality level of milk is at the regulator specified level. While consumers do not perform tests to detect adulterants, the regulator monitors milk quality and adulteration (FSSAI, 2018). Any negative report on adulteration would impact profitability of the farmer (or aggregator in Section 2.2) through reputation loss and breach of consumer trust. We model this as a *goodwill loss* to the farmer (or the aggregator). The regulator cannot test all the milk sold in the market. Hence, the regulator resorts to sampling. The probability of milk sourced from a particular farmer (or the aggregator) getting picked up in a sample is small. However, if adulteration is detected after sampling, its negative consequence on the offender is severe. Hence, expected goodwill loss to the offender is normalized to one without loss of generality. We assume the expected unit goodwill loss to be greater than w_m, and hence, $w_m < 1$. As the probability of milk not reaching (by honest effort only) the threshold quality is $(1 - h_i)$, which is also the probability of adulteration, the expected goodwill loss to the farmer would then be $(1 - h_i)$. Hence, the expected profit of the farmer i is,

$$\max_{h_i} \ \pi_i(h_i) = w_m - \lambda h_i^2 - (1 - h_i), \quad i \in \{1, 2\} \tag{1}$$

The first two terms denote the revenue earned and the honest effort cost, respectively. The last term denotes the expected goodwill loss. The optimal honest effort of farmer i in equilibrium is $h_i^O = \frac{1}{2\lambda}$. Since $h_i^O \in [0, 1]$ and $w_m \in (\lambda, 1)$, we have $\frac{1}{2} \leq \lambda < w_m$. The optimal equilibrium profit $\pi_i^O\ (h_i^O)$ would act as a reservation profit for farmer i ensuring his participation in selling milk through the aggregator.

2.2. Sales through the aggregator

Through a quality test, the aggregator accepts milk that attains the regulator specified threshold quality level at the collection center. The aggregator offers a unit wholesale price $w_c \geq w_m$; otherwise, there is no incentive for the farmers to sell milk to the aggregator. Adulteration tests are performed on milk that passes quality tests. If no adulterants are detected, the aggregator sells milk to the consumer at a unit market price $p \in (w_c, 1)$. The condition $p > w_m$ implies that the aggregator is able to earn a higher market price than the farmers selling directly to the consumers. The price difference $p - w_m$ denotes the *aggregation effect* that represents the bargaining power of the aggregator, owing to its control over larger milk supplies (Getnet et al., 2018; Mu et al., 2019).

The quality test is relatively simple and its cost is very low compared to that of the adulteration tests. We normalize the quality test cost to zero for expositional brevity. We hereafter use *tests* to denote adulteration tests unless otherwise explicitly mentioned. The aggregator incurs a testing cost αx^2 for a testing level $x \in (0, 1]$, where $\alpha > 0$ is the testing cost parameter. Here x denotes the extent of testing, the number of different tests to be performed out of the available tests to detect the possible adulterants. We exclude the trivial case $x = 0$, which corresponds to no testing in practice. A non-linear testing cost incorporates cost variation among the tests and diminishing marginal utility in performing costlier tests (Plambeck & Taylor, 2016). Hence, we assume the costlier tests at higher testing levels follow the cheaper tests at lower testing levels. Though each test (level) can be assumed to be accurate for detecting the target adulterant at that level, the overall detection of different types of adulterants depends on the extent of tests (levels) performed. Thus, x denotes the probability of detecting adulteration in a milk sample. Similar modelling approach has been adopted for the probability of detecting non-compliance (adulteration in this study) in the extant literature (Babich & Tang, 2012; Caro et al., 2018; Plambeck & Taylor, 2016).

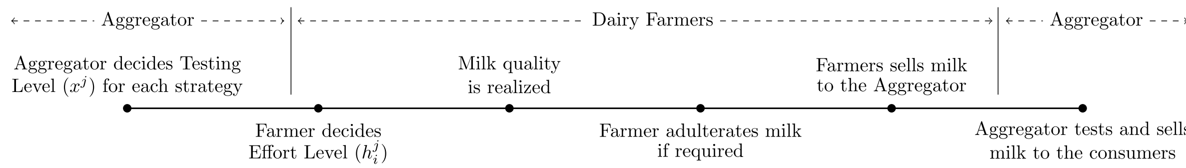


Fig. 1. Sequence of events (sales through the aggregator).

The aggregator can detect adulterated milk sourced from farmer i in $x(1-h_i)$ proportion of time in individual testing and reject it. Similarly, it can detect adulteration in $x(1-h)$ proportion of time, where $h = \sum h_i/2$, in the aggregate quantity received from the farmers in composite testing (Levi et al., 2020). This is analogous to the *internal failure* in quality control literature (Balachandran & Radhakrishnan, 2005; Erkoc et al., 2023). However, the aggregator fails to identify the adulterated milk in $(1-x)(1-h_i)$ and $(1-x)(1-h)$ proportion of time in individual and composite testing, respectively. In such cases, the adulterated milk is sold to the consumers as good milk. It corresponds to the *external failure* in quality control literature (Balachandran & Radhakrishnan, 2005; Erkoc et al., 2023). The adulterated milk sold in the market leads to a goodwill loss for the aggregator, as discussed in Section 2.1.

As milk adulteration causes serious harm to consumer health, the aggregator remains vigilant and takes strict action against the farmers when adulteration is detected. In such situations, the aggregator rejects the adulterated milk and imposes monetary penalties on the farmers at fault (Levi et al., 2020; Mu et al., 2016, 2014). Deferred (weekly or fortnightly) payment cycle to the farmer helps implement the payment net of penalty (Babich & Tang, 2012; Rui & Lai, 2015). The expected penalty to the farmer i is $Kx(1-h_i)$ and $Kx(1-h)$ in individual and composite testing, respectively. Here, K denotes the unit internal penalty. To ensure the fairness criterion (Balachandran & Radhakrishnan, 2005), the unit internal penalty cannot exceed the expected unit goodwill loss and hence, $K < 1$. We assume $K \geq w_c$, which ensures that the farmers invest in more honest efforts. The unit internal penalty should not exceed the unit market price, $K < p$; otherwise, it would incentivize the aggregator to claim unadulterated milk as adulterated. We consider the same internal penalty K for both testing strategies (Mu et al., 2014).

We assume all the parameters are common knowledge to the farmers and the aggregator. Table S2 (in supplementary material) summarizes the main notations used in this paper. The aggregator adopts two testing strategies, $j \in \{N, M\}$, where N and M denote the individual and composite testing strategy, respectively. Just before the commencement of production, the aggregator first announces the testing level x^j for testing strategy j that maximizes its profit. Note that x^j is the same for both farmers. While a particular testing strategy would be more attractive to the aggregator under certain conditions, it offers both testing strategies to maximize the possibility of the farmers selling milk to the aggregator. Once the aggregator has decided the optimal testing level x^j, the farmers simultaneously respond to that decision with an optimal honest effort level h_i^j. The sequence of events is summarized in Fig. 1.

2.2.1. Individual testing strategy (N)

In the individual testing strategy, the aggregator tests milk from each farmer separately. The internal penalty, imposed on adulterated milk detected by testing, is applicable to the individual farmer. Fig. 2 depicts the aggregator's payoffs for farmer i under this strategy. The expected profit of farmer i can be expressed as:

$$\max_{h_i} \ \pi_i(h_i \mid x) = w_c - \lambda h_i^2 - x(1-h_i)K \ , \quad i \in \{1,2\} \tag{2}$$

The first two terms denote the revenue earned and the farmer's honest effort cost, respectively. The last term denotes the expected internal penalty imposed by the aggregator. For a given testing level x decided by the aggregator, each farmer i responds with the effort level decision $h_i^N(x) = \frac{Kx}{2\lambda}$. The aggregator anticipates the farmers' best-responses $h_i^N(x)$, and accordingly maximizes its expected profit:

$$\max_{x} \ \Pi(x) = \sum_{i\in\{1,2\}} \left\{ \left[1 - x(1-h_i^N)\right] p + x(1-h_i^N)K - (1-x)(1-h_i^N) \right\} - 2w_c - 2\alpha x^2 \tag{3}$$

The first three terms, within summation, denote the market revenue earned, the internal penalty imposed on the farmers, and the goodwill loss incurred by the aggregator, respectively; their sum is the aggregator's net revenue from individual testing. The terms $2w_c$ and $2\alpha x^2$ denote the wholesale price paid to the farmers and the total testing costs incurred by the aggregator, respectively. The aggregator chooses the optimal testing level $x^N = \frac{(1+K-p)(1-h^N)}{2\alpha}$, where $h^N = h_i^N$ for homogeneous farmers discussed in this section. In subsequent analysis, we use $\upsilon = (1+K-p)$ for notational simplicity. The optimal decisions for the individual testing strategy are presented in Table S3 in supplementary material. Substituting these values in (2) and (3), and noting $h_i^N(x) = \frac{Kx^N}{2\lambda}$, we obtain the equilibrium profits $\pi_i^N(h_i^N)$ and $\Pi^N(x^N)$ of the farmers and the aggregator, respectively. The individual testing strategy can be employed when the *individual rationality* constraints of both the decision-makers are satisfied, i.e., $\pi_i^N(h_i^N) \geq \pi_i^O(h_i^O)$ and $\Pi^N(x^N) \geq 0$. Referring to (2) and (3), while the sum of the profits of all the entities does not depend on w_c and K, these parameters impact the profit allocation between the different entities and the zone of operation.

2.2.2. Composite testing strategy (M)

In the composite testing strategy, the milk from both farmers is mixed first, and then the aggregator tests the combined milk. The internal penalty, imposed on adulterated milk detected by testing, is based on the combined milk. Following (Levi et al., 2020), we consider that the detection of adulteration depends on the amount of adulterants; hence, the probability of detection would be $x(1-h)$, where $h = \sum h_i/2$. Fig. 3 describes the aggregator's payoffs in this strategy. The expected profit of the farmers in the composite testing strategy can be expressed as follows:

$$\max_{h_i} \ \pi_i(h_i \mid x) = w_c - \lambda h_i^2 - x\left(1 - \frac{h_i + h_{-i}}{2}\right)K \ , \quad i \in \{1,2\} \tag{4}$$

The first two terms denote the revenue earned and the farmer's honest effort cost, respectively. The last term denotes the expected internal penalty imposed by the aggregator. From farmer i's perspective, h_{-i} denotes the honest effort level of the other farmer. For a given testing level x decided by the aggregator, each farmer i responds with the effort level decision $h_i^M(x) = \frac{Kx}{4\lambda}$. The aggregator anticipates the farmers' best-responses $h_i^M(x)$, and accordingly optimizes its expected profit:

$$\max_{x} \ \Pi(x) = 2\left[1 - x(1-h^M)\right] p + 2x(1-h^M)K - 2(1-x)(1-h^M) - 2w_c - \alpha x^2 \tag{5}$$

The first three terms denote the market revenue earned, the internal penalty imposed on the farmers, and the expected goodwill loss incurred by the aggregator, respectively; their sum is the aggregator's net revenue from the composite testing strategy. The terms $2w_c$ and αx^2 denote the wholesale price paid to the farmers and the total

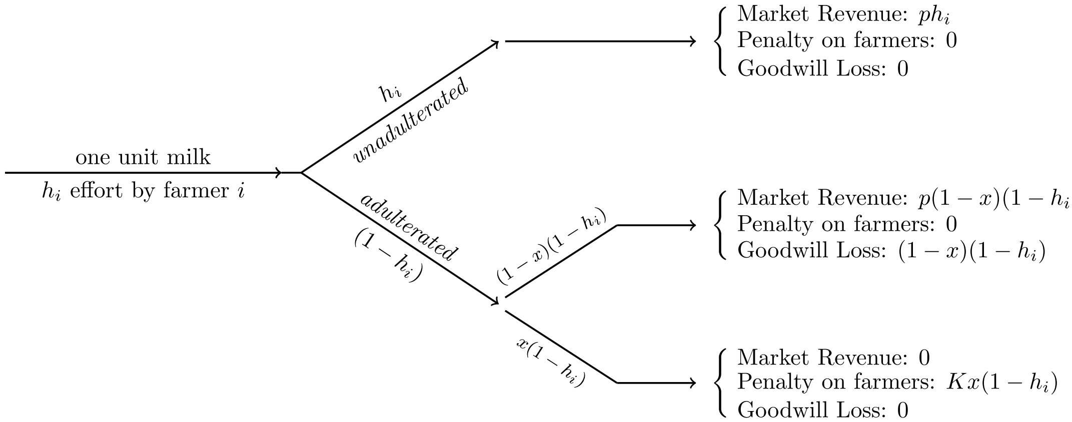


Fig. 2. Aggregator's payoffs in the individual testing strategy for farmer i.

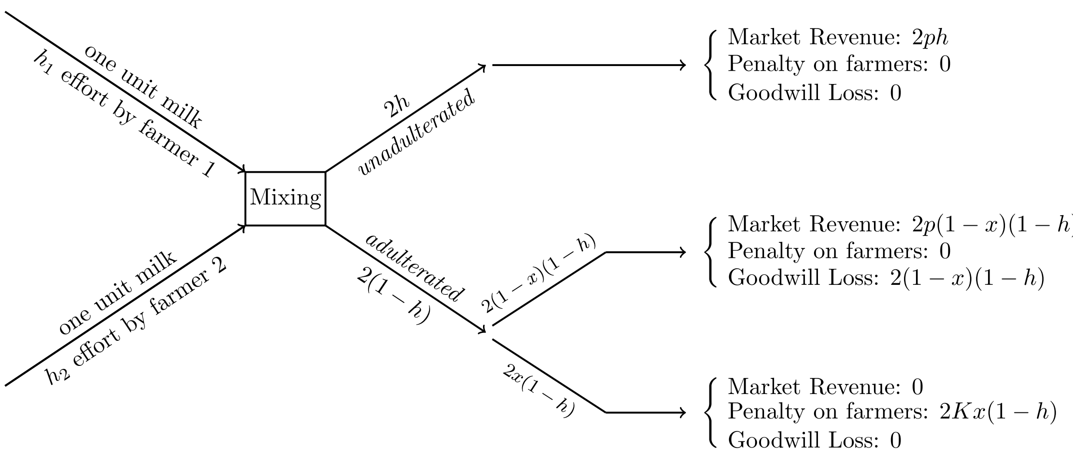


Fig. 3. Aggregator's payoffs in the composite testing strategy.

testing costs incurred by the aggregator, respectively. The aggregator chooses the optimal testing level $x^M = \frac{(1+K-p)(1-h^M)}{\alpha}$, where $h^M = h_i^M$ for homogeneous farmers discussed in this section. The optimal decisions for the composite testing strategy are presented in Table S3 in supplementary material. Substituting these values in (4) and (5), and noting $h_i^M(x) = \frac{Kx^M}{4\lambda}$, we obtain the equilibrium profits $\pi_i^M(q_i^M)$ and $\Pi^M(x^M)$ of the farmers and the aggregator, respectively. The farmers and the aggregator can engage in composite testing when their *individual rationality* constraints are satisfied, i.e., $\pi_i^M(h_i^M) \geq \pi_i^O(h_i^O)$ and $\Pi^M(x^M) \geq 0$. Similar to individual testing, the impact of w_c and K on profit allocation and zone of operation under composite testing is discussed in Section 3.

3. Equilibrium analyses

We now perform equilibrium analyses when the farmers are identical in their production efficiency. We analyse the implications of these decisions under equilibrium in two different testing strategies and compare the profits of the farmers and the aggregator across the testing strategies to obtain desired testing policies under different conditions. The proofs of all lemmas, propositions, and theorems are provided in the supplementary material.

3.1. Optimal decisions

This section discusses the implications of optimal testing and honest effort levels (refer to Table S3 in supplementary material). The following lemma summarizes the relationship between the decisions.

Lemma 1. *Under equilibrium, (i) $x^j = 1$ when $\alpha \leq \alpha^j$, and $x^j < 1$ when $\alpha > \alpha^j$, for $j \in \{N, M\}$; (ii) $h_i^j < x^j$, for $i \in \{1, 2\}$, $j \in \{N, M\}$.*

A higher testing level enables the aggregator to identify more types of adulterants. Hence, the chances of revealing adulteration are higher in such cases and the aggregator imposes a higher internal penalty on the farmers. To avoid the loss of revenue due to penalties, the farmers enhance their effort levels. However, the aggregator must optimize the testing level, based on the testing cost parameter α. The aggregator can afford to perform maximum testing level $x^j = 1$ for $\alpha \leq \alpha^j$ with $\alpha^N < \alpha^M$. As α increases, the aggregator reduces its testing level, and correspondingly, the farmers also reduce their effort levels.

Proposition 1. *Between the two testing strategies, the testing level in individual testing never exceeds that in composite testing: (i) $x^M = x^N$ for $0 < \alpha \leq \alpha^N$; (ii) $x^M > x^N$ for $\alpha > \alpha^N$. However, the effort levels in individual testing are always higher than that in composite testing or $h_i^N > h_i^M$.*

For a given testing level, the total testing cost is higher in individual testing compared to composite testing. As $\alpha \in (\alpha^N, \alpha^M]$ increases, the aggregator reduces x^N to optimize overall testing costs in individual testing. For $\alpha > \alpha^M$, the aggregator reduces both, x^N and x^M. However, the relation $x^M > x^N$ holds for $\alpha > \alpha^N$. The second part of the proposition is a significant finding. We may expect that the higher testing level in composite testing may lead to farmers putting a greater effort. Instead, farmers reduce their effort assuming that the other would put a greater effort since the internal penalty depends on the presence of adulterants in aggregated milk. As a result, the effort of the farmers decreases in composite testing.

3.2. Profit comparisons

The following proposition summarizes the acceptable wholesale prices offered by the aggregator in different testing strategies.

Proposition 2. *The wholesale price, offered by the aggregator, is acceptable to the farmers at (i) $w_c^N = w_m$ in individual testing and (ii) $w_c^M = w_m$ for $K \le K_L$ and $w_c^M = w_m + \Delta w_m$ for $K > K_L$ in composite testing.*

For $K \le K_L$, the aggregator offers $w_c^j = w_m$, $j \in \{N, M\}$. High h_i^N helps the aggregator earn more revenue in individual testing. However, the aggregator incurs higher testing costs owing to more testing instances. For $\alpha \le \alpha^O$, the benefit of higher net revenue outweighs the higher testing costs in individual testing and makes it the preferred choice for the aggregator. As α increases beyond α^O, the testing cost dominates the net revenue in individual testing and the aggregator finds composite testing more profitable. For $K > K_L$, the aggregator needs to offer $w_c = w_m + \Delta w_m > w_m$ in composite testing and the benefit of higher net revenue in the individual testing extends till α^C, where $\alpha^C > \alpha^O$. Beyond α^C, the aggregator prefers composite testing. The conditions, $K \le K_L$ and $K > K_L$, are referred to as low K and high K, respectively. For expositional brevity, we provide the detailed analysis of α^O and α^C in the supplementary material (refer to proof of Proposition 2 and Theorem 1).

High h_i^N helps the farmers earn more revenue and reduce the expected internal penalty loss in individual testing. These benefits dominate the higher effort cost of the farmers. Even when the aggregator offers $w_c = w_m + \Delta w_m$ in composite testing, the farmers obtain lesser profits in composite testing due to low h_i^M. The following theorem compares the equilibrium profits of the farmers π_i^j and the aggregator Π^j for the two testing strategies.

Theorem 1. *In the case of homogeneous farmers, (a) $\Pi^N \ge \Pi^M$ for (i) $\alpha \le \alpha^O$ when $K \le K_L$ and (ii) $\alpha \le \alpha^C$ when $K > K_L$, where $\alpha^C > \alpha^O$; (b) $\pi_i^N \ge \pi_i^M$ for $i \in \{1, 2\}$.*

The homogeneous farmers always earn more profit under individual testing compared to composite testing because of higher effort, and hence, prefer the individual testing strategy if offered by the aggregator. The aggregator prefers to offer individual testing when the testing cost is low.

4. Impact of farmers' heterogeneity

In this section, we extend the models discussed in Section 2 to study the impact of *efficiency heterogeneity* between the farmers. The farmers are heterogeneous in terms of their production efficiency (Skevas & Martinez-Palomares, 2023). As explained in Section 2, effort costs depend on the various initiatives such as access to veterinary services, high-quality insemination process, and proper and scientific knowledge of dairy farming. However, the farmers often differ not only in their knowledge but also in accessing the various processes and infrastructure essential for dairy farming. It leads to different production efficiencies for the dairy farmers. We consider farmer 1 to be more efficient than farmer 2, which implies that the effort cost of farmer 1 is less than that of farmer 2 for the same honest effort level. Hence, $\lambda_1 < \lambda_2$, where, $\lambda_1 = \lambda - \epsilon$, $\lambda_2 = \lambda + \epsilon$ and $1/2 \le \lambda_1 < \lambda_2 < w_m$, $\epsilon > 0$. Given the efficiency variation between the farmers, we hereafter refer to farmer 1 and farmer 2 as *high* and *low*, respectively. The profit functions of the heterogeneous farmers and the aggregator in the different scenarios can be obtained by substituting λ with λ_i in (1) to (5) (refer to Section S4 in supplementary material). The symbol $\hat{}$ is used to distinguish the decision variables and profit functions in Section S4 from those in Section 2; for instance, $\hat{h}_1$ denotes the honest effort of *high* when the farmers are heterogeneous, whereas h_1 denotes the honest effort of farmer 1 when the farmers are homogeneous. The optimal decisions for the case of heterogeneous farmers are represented in Table S4 in supplementary material.

We perform equilibrium analyses for the heterogeneous farmers case and compare the results with that of the homogeneous farmers in Section 3, which helps us understand the impact of efficiency heterogeneity on the decision of the farmers to sell milk to the aggregator and on the decision of the aggregator to operate under different conditions.

4.1. Optimal decisions

Proposition 3. *Under efficiency heterogeneity, (i) the testing level of the aggregator remains the same as in case of homogeneous farmers or $\hat{x}^j = x^j$ for $j \in \{N, M\}$; (ii) the effort level increases for high and decreases for low or $\hat{h}_2^j < h_i^j < \hat{h}_1^j$, for $j \in \{N, M\}$.*

The aggregator optimizes its testing level, which depends on the probability of adulteration by the farmers. As the probability remains the same owing to how efficiency heterogeneity is defined in this study, the optimal testing level also remains unchanged or $\hat{x}^j = x^j$ for $j \in \{N, M\}$. *High (Low)* incurs less (more) effort cost to impart a given effort level because of better (poorer) production efficiency. Hence, the effort level of *high (low)* increases (decreases) compared to the homogeneous farmer. This variation in effort between the farmers is due to the difference in production efficiency, which is denoted by ϵ. This induces free-riding in composite testing as the internal penalty is based on the mixed milk. In other words, *low* earns a higher revenue even after imparting a lower effort, which may discourage *high* from selling milk to the aggregator under composite testing. Hence, ϵ can be used to quantify the free-riding behaviour of the less efficient farmer. In subsequent sections, we denote the conditions $\epsilon \le \epsilon_{T_1}$ and $\epsilon > \epsilon_{T_1}$ as low ϵ and high ϵ, respectively.

4.2. Profit comparisons

Theorem 2. *Under efficiency heterogeneity, (a) $\hat{\Pi}^N \ge \hat{\Pi}^M$ for (i) $\alpha \le \alpha^O$ when $K \le K_L$ and $\epsilon \le \epsilon_{T_1}$, and (ii) $\alpha \le \alpha^C + \Delta\alpha^C$ when $K > K_L$ or $\epsilon > \epsilon_{T_1}$ or both, (b) $\hat{\pi}_1^N \ge \hat{\pi}_1^M$ and (c) $\hat{\pi}_2^N \ge \hat{\pi}_2^M$ for $\epsilon \le \epsilon_{T_2}$.*

When K and ϵ are low, the aggregator offers the same wholesale price $\hat{w}_c^j = w_m$ in both the testing strategies. As the probability of milk adulteration remains the same, the comparison of the aggregator's profit between the two testing strategies also remains the same as in the case of homogeneous farmers. Hence, it prefers individual testing for $\alpha \le \alpha^O$. The aggregator needs to offer a higher wholesale price $\hat{w}_c^M = w_m + \Delta w_m + \Delta\hat{w}_m$ in composite testing as K or ϵ or both increase. This incremental requirement in wholesale price is more under efficiency heterogeneity. Hence, the benefit of higher revenue owing to high effort in individual testing extends up to a comparatively higher $\alpha \le \alpha^C + \Delta\alpha^C$ in case of heterogeneous farmers.

For both the farmers, $\hat{h}_i^N > \hat{h}_i^M$; they earn more revenue and incur less internal penalty in individual testing. *High* incurs lesser effort costs due to better production efficiency. The marginal gain for choosing higher effort in individual testing dominates the marginal effort cost and *high* always prefers individual testing. For $\epsilon \le \epsilon_{T_2}$, *low* prefers individual testing as the effort cost is not very high and the marginal gain from choosing higher effort dominates the marginal effort cost. However, the effort cost of *low* becomes very high for $\epsilon > \epsilon_{T_2}$ and dominates the marginal gain due to higher effort in individual testing. Hence, *low* with $\epsilon > \epsilon_{T_2}$ prefers composite testing.

5. Impact of external uncertainty

Milk quality is influenced by two different types of uncertainties. As described in Section 2, *process uncertainty* considers the factors related to the production process, while *external uncertainty* considers various external factors that influence milk quality. In this section, we analyse the variability in the realized milk quality owing to these external factors such as weather conditions, fodder quality, and outbreak of diseases. Since the dairy farmers are located close to each other, these external factors affect them similarly, and we assume that milk qualities realized by the individual farmers are perfectly and positively correlated (Chintapalli & Tang, 2022a). This assumption is commonly adopted in the extant literature when external circumstances impact the farmers in a similar way (Alizamir et al., 2019).

While interviewing the farmers, we understand that the impact of external uncertainty on the realized milk quality is two-sided. In a conducive environment, the realized milk quality is higher than what is expected. However, the realized milk quality falls below the expected level in an adverse situation. We model this phenomenon by incorporating variation in the realized milk quality. In line with Bian et al. (2022), we assume that the realized milk quality follows a uniform distribution, which captures inherent uncertainty in agricultural production. For farmer i imparting an effort h_i, we assume the realized milk quality $\widetilde{q}_i \sim U[q_i - q_d/2,\ q_i + q_d/2]$ when only process uncertainty is present; here, q_d denotes the variation in milk quality. The quality variation increases under external uncertainty and is modelled as $\widetilde{q}_i^{ext} \sim U[q_i - q_d(1+\tau)/2,\ q_i+q_d(1+\tau)/2]$, where $\tau \geq 0$ quantifies the impact of external uncertainty. Here, $E[\widetilde{q}_i\ ] = E[\widetilde{q}_i^{ext}] = q_i$ and $SD[\widetilde{q}_i^{ext}]/SD[\widetilde{q}_i] = (1+\tau)$. The following lemma summarizes the impact of external uncertainty on the farmer's adulteration behaviour.

Lemma 2. *Under external uncertainty, adulteration by farmer i (i) increases when $h_i > \frac{1}{2}$ and (ii) decreases when $h_i < \frac{1}{2}$.*

In the individual testing strategy, the farmers impart more honest effort and expect to obtain milk beyond the threshold quality most of the time. As the quality variation increases owing to external uncertainty, the likelihood of attaining the threshold level decreases. Therefore, the farmers indulge in more adulteration to increase the perceived quality of milk that passes the quality tests. In the composite testing strategy, the farmers impart a lesser honest effort; so, their expectation to attain milk quality reaching the threshold level is less compared to the case of individual testing. Owing to the higher quality realization in the conducive situation, the likelihood of realizing milk beyond the threshold quality level increases. Hence, the farmers resort to lesser adulteration. Thus, the testing strategy adopted has a bearing on adulteration behaviour of the farmer under external uncertainty. The farmers will adulterate more (less) in the individual (composite) testing strategy as the impact of external uncertainty increases.

6. Managerial insights

Having studied the operational feasibility of the testing strategies and the preferences of each supply chain entity under different conditions, we now elucidate the managerial implications of our research. There are significant differences in the aggregator decisions when the farmers are heterogeneous in terms of their production efficiency. The efficiency variability leads to changes in the optimal testing strategy of the aggregator as well as the farmers' decision of selling milk to the aggregator. Moreover, external uncertainty significantly impacts the strategic decisions of the supply chain entities under different conditions. Next, we determine the optimal testing strategy of the aggregator through data-calibrated numerical analysis. Further, we study the impact of the farmers heterogeneity and external efficiency on the aggregator decisions. Finally, we provide testing policy recommendations under different conditions.

6.1. Data collection and parameter calibration

In this section, we present our analysis on data collected through primary sources. We conducted in-depth interviews of dairy farmers to understand their production process, associated costs, and the uncertainties that impact their production. We also met supply chain managers of a major milk aggregator in India to evaluate the procurement process and obtain an estimation of their cost parameters. Based on the collected data, we examine the strategic decisions of the entities (aggregator and farmers) under various conditions. We report the parametric values calibrated from data that are essential for our study. Our approach is in line with data type under the *real* category, as explained in Gupta et al. (2023).

(i) The retail price (p) of full-cream milk sold by the aggregator is ₹66 per litre.[1] The price of full-cream milk in case of direct selling (w_m) by the dairy farmers is ₹53 per litre. We consider full-cream milk for analytical parity between direct sales and aggregator-based models as farmers sell milk without skimming the fat in either case.

(ii) The production process involves two types of costs — fixed cost and variable cost for quality improvement. From comprehensive discussions with the farmers, we estimate the fixed cost to be ₹20 per litre and the honest effort cost (λ) at $h_i = 1$ to be ₹30 per litre. In other words, the cost of production of a litre of milk at $h_i = 1$ is equal to ₹50.

(iii) Based on discussions with the aggregator's manager, our estimate of expected goodwill loss is ₹70 per litre. We normalize the retail prices under direct sales and aggregator-based models and the goodwill loss by fixed cost based on our modelling consideration, as explained in Section 2. Finally, we scale all the parametric values such that the normalized goodwill loss is equal to 1 (refer to Fig. 4).

Considering the above scaled and normalized parameter values, we obtain $K_L \approx 0.77$. We use $K = 0.72$ and $K = 0.84$ for low K and high K conditions, respectively, in the subsequent analysis. We assume the maximum value of the testing cost parameter (α) such that it ensures profit for the aggregator at any possible testing level in either testing strategy. In the Figs. 5 to 8, same range of α and the aggregation effect is considered to facilitate a visual comparison of the areas under each strategy.

We consider $\epsilon \in (0, .06]$ to study the impact of efficiency heterogeneity (under high K condition) on the profit of the different entities in Fig. 6. For the given parametric conditions with high K, we obtain $\epsilon_{T_2} = 0.026$. *Low* prefers the individual (composite) testing strategy when $\epsilon \leq (>) \epsilon_{T_2}$. We choose $\epsilon = 0.024$ or $\epsilon = 0.060$ to depict the impact of efficiency heterogeneity on optimal testing strategy in Fig. 7. The conditions $\tau = 0.5$ and $\tau = 0$ in Fig. 8 represent the scenarios with and without external uncertainty, respectively. Though specific parameter values are used to describe the strategic decisions under different conditions, we perform extensive analysis with other parametric conditions and obtain similar results.

6.2. Testing strategy

We analyse the testing strategy of the aggregator under different conditions based on the unit internal penalty, testing cost and aggregation effect. As defined in Section 2, the aggregation effect symbolizes the bargaining power owing to a larger quantity sold by just one entity (the aggregator) instead of smaller quantities sold by many producers (the farmers). A higher aggregation effect implies a greater revenue for the aggregator, which it may share with the farmers through a higher wholesale price.

The honest effort of the farmers decreases with lower unit internal penalty, which leads to more adulteration. It also causes a fall in the

[1] ₹is the symbol of Rupee, the Indian Currency. 1 USD ≈ ₹83.92 (as on October 2, 2024).

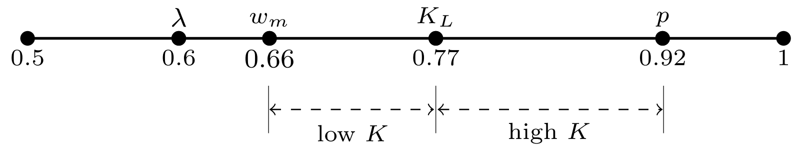
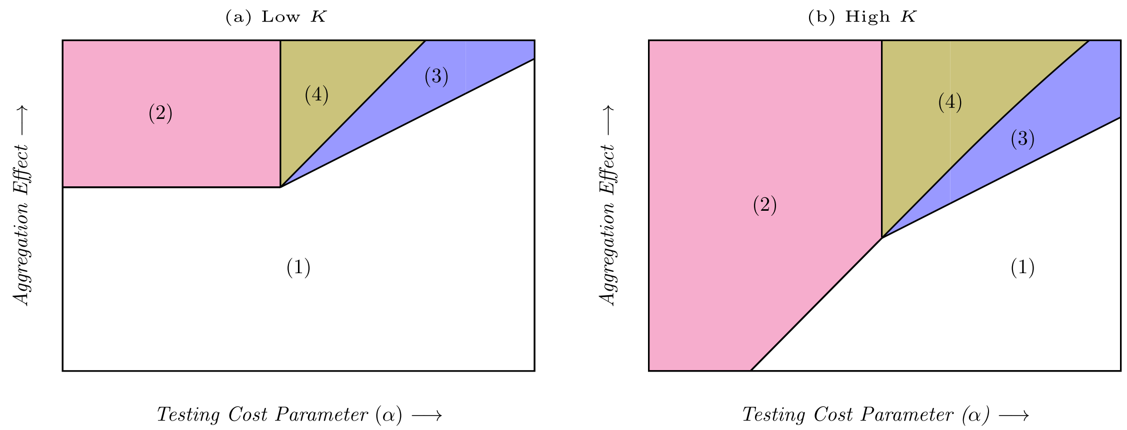


Fig. 4. Scaled and normalized parametric values.



(1) Direct Selling, (2) Individual Testing, (3) Composite Testing, (4) Aggregator: Composite, Farmers: Individual

Fig. 5. Optimal testing strategy for the case of homogeneous farmers.

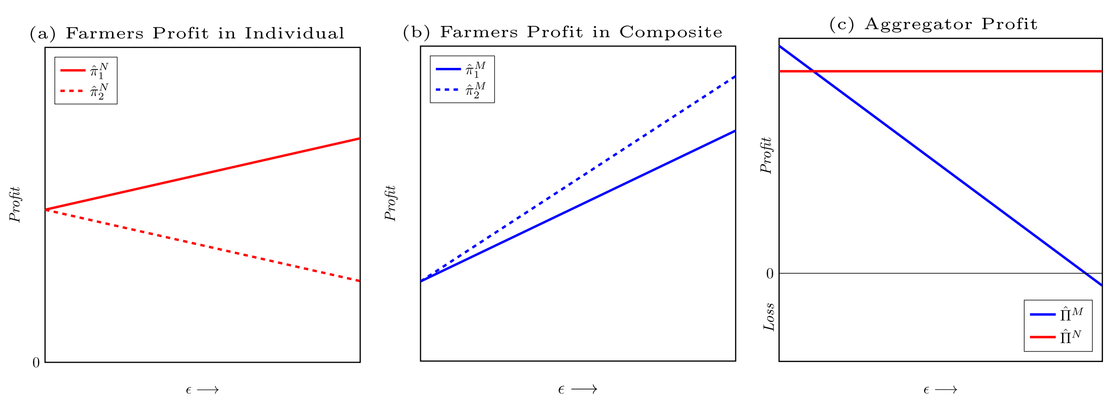
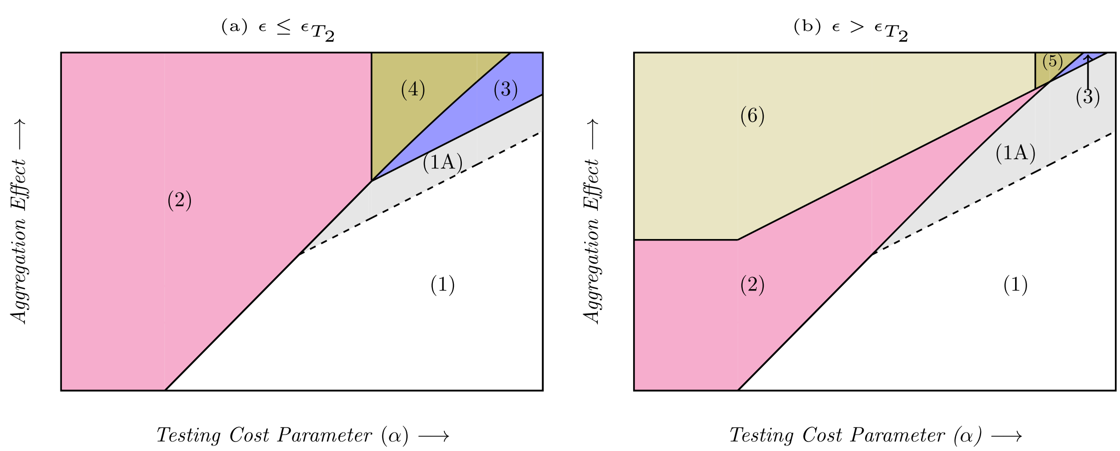


Fig. 6. Impact of heterogeneity on the profit of different entities.



(1) Direct Selling, (1A) Direct Selling (Impact of Heterogeneity), (2) Individual Testing, (3) Composite Testing, (4) Aggregator: Composite, Farmers: Individual, (5) Aggregator: Composite, *High*: Individual, (6) Aggregator, *High*: Individual, *Low*: Composite

Note: *Direct Selling* increases as the *heterogeneity* (ϵ) between the farmers increases.

Fig. 7. Optimal testing strategy for the case of heterogeneous farmers.

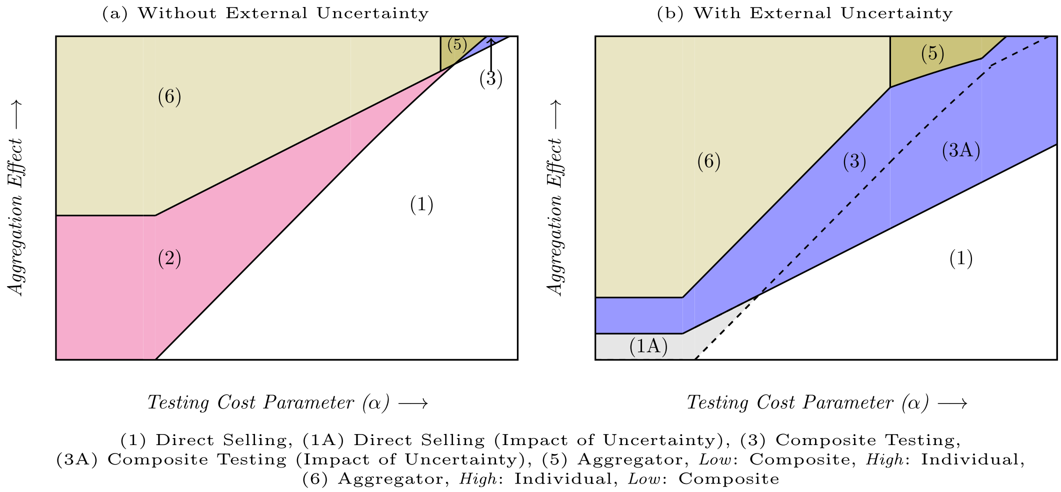


Fig. 8. Impact of external uncertainty on optimal testing strategy.

revenue for the aggregator. At a low aggregation effect, the aggregator does not make a profit to operate (refer to Fig. 5(a)). When unit internal penalty is high and the aggregation effect is low, the aggregator offers individual testing at low testing cost (refer to Fig. 5(b)). This result may seem counter intuitive because the aggregator should have favoured composite testing owing to a lower margin at low aggregation effect. However, the high unit internal penalty ensures a higher effort and lesser adulteration from the farmers, which results in increased profit for the aggregator. As testing cost increases, irrespective of the unit internal penalty, a low aggregation effect dissuades the aggregator from operating (refer to Fig. 5(a) and (b)), and hence, the farmers would sell milk directly to consumers.

When the aggregation effect is high, the aggregator earns more revenue and can afford higher testing costs compared to the situation with a low aggregation effect. Though it is feasible for the aggregator to offer either of the testing strategies at low testing cost, it prefers to offer the individual testing strategy owing to greater profit resulting from higher honest effort compared to that of composite testing. It results in an *alignment* of the aggregator's and farmers' preferences. As the testing becomes costlier, adulteration increases in the individual testing strategy due to a lower testing level, and hence, the profit of the aggregator becomes greater in the composite testing strategy. Thus, the aggregator offers the composite testing strategy, which results in a *conflict* in the preferences as the farmers prefer the individual testing strategy (refer to Theorem 1). In such cases, the entities would negotiate and the one with the higher bargaining power will prevail. For further increase in testing cost, individual testing is no more profitable for the aggregator, and hence, it offers composite testing only. This is acceptable to the farmers because the composite testing strategy is more profitable for them than selling directly to the consumers though less profitable than the individual testing strategy. The aggregator offers higher wholesale prices in the composite testing strategy for high K. We define *producer leverage* (PL) as the increase in producers' (farmers) revenue due to the increase in wholesale price. High PL attracts the farmers to sell milk to the aggregator under the composite testing strategy despite its limitation to distinguish honest effort and adulteration behaviour of individual farmers. For an even further increase in the testing cost, neither testing strategy is profitable for the aggregator, and the zone of operation does not prevail. Moreover, we observe that with a higher unit internal penalty, the honest effort (adulteration) increases (decreases) owing to a higher testing level. It results in a higher zone of operation for the aggregator, and hence, farmers' direct selling to consumers decreases. If the unit internal penalty is low, the aggregator's zone of operation is severely limited. Hence, from a practical point of view, the aggregator enforces a high unit internal penalty. In subsequent discussions, we emphasize the scenarios where a high unit internal penalty is adopted by the aggregator.

6.3. Impact of heterogeneity

In the individual testing strategy, farmers' revenue depends on the individual honest effort and adulteration decisions. Hence, the revenue increases (decreases) for *high (low)* due to higher (lower) honest effort compared to the homogeneous farmers case. The variability in production efficiency between the farmers leads to a difference in effort exerted by *high* and *low*. Therefore, the profit for *high (low)* increases (decreases) in the individual testing strategy as variability in production efficiency between the farmers increases (refer to Fig. 6(a)). When $w_c = w_m$, the aggregator, as well as the farmers, prefer individual testing compared to direct selling. As unit internal penalty increases, the aggregator penalizes *low* more compared to *high*, owing to its less (more) honest effort (adulteration). Hence, the profit difference between *high* and *low* increases with efficiency variability and unit internal penalty.

In the composite testing strategy, the revenue of the farmers depends on the mixed or aggregated milk, and hence, their revenue is same in spite of the variation in individual effort. Thus, *high* has a loss of revenue despite better honest effort. We define *free-riding effect* (FE) as the impact of efficiency heterogeneity on each farmer's revenue in comparison to the homogeneous case. Hence, the profit for *high (low)* decreases (increases) due to FE. Moreover, PL increases with efficiency heterogeneity between the farmers. The combined impact of PL and FE increases the profit of *low*. However, the profit of *high* increases owing to PL but decreases owing to FE. Hence, the profit of *low* is greater than that of *high* in the composite method (refer to Fig. 6(b)). PL must be sufficiently greater than FE to ensure *high* attains its reservation profit level. PL also increases with unit internal penalty, which causes more difference in profit between *low* and *high*. On the other hand, the aggregator's profit decreases with increasing PL, and hence, the zone of operation shrinks when efficiency variability is high (refer to Fig. 6(c)). Low internal penalty increases adulteration by the farmers, which reduces the aggregator's profit. Thus, low internal penalty and high efficiency variability have a negative impact on the aggregator's operation.

In the case of heterogeneous farmers, we limit the discussion to high unit internal penalty as mentioned in Section 6.2. When the aggregation effect is low, the aggregator offers the individual testing

Table 1
Decision matrix for the aggregator without external uncertainty.

Internal	Aggregation	Low efficiency variability		High efficiency variability	
Penalty	Effect	Low testing cost	High testing cost	Low testing cost	High testing cost
Low	Low	Direct Selling	Direct Selling	Direct Selling	Direct Selling
	High	**Individual Strategy**	**Composite Strategy**	**Either Testing Strategy**	Direct Selling
High	Low	**Individual Strategy**	Direct Selling	**Individual Strategy**	Direct Selling
	High	**Individual Strategy**	**Composite Strategy**	**Either Testing Strategy**	Direct Selling

Note: In *Either Testing Strategy*, the preference of the entity(ies) with higher bargaining power prevails.

Table 2
Decision matrix for the aggregator with external uncertainty.

Internal	Aggregation	Low efficiency variability		High efficiency variability	
Penalty	Effect	Low testing cost	High testing cost	Low testing cost	High testing cost
Low	Low	Direct Selling	Direct Selling	Direct Selling	Direct Selling
	High	**Individual Strategy**	**Composite Strategy**	**Either Testing Strategy**	**Composite Strategy**
High	Low	**Composite Strategy**	Direct Selling	**Composite Strategy**	Direct Selling
	High	**Individual Strategy**	**Composite Strategy**	**Either Testing Strategy**	**Composite Strategy**

Note: In *Either Testing Strategy*, the preference of the entity(ies) with higher bargaining power prevails.

strategy at low testing costs, as in the case of homogeneous farmers (refer to Fig. 7). As the testing cost increases, the aggregator does not operate. When aggregation effect is high, the aggregator is profitable for both the testing strategies when the testing cost is low. However, it prefers the individual testing strategy because higher (lower) effort (adulteration) leads to higher profit. This *aligns* with the farmers' preference when efficiency variability is low (refer to Fig. 7(a)). At high efficiency variability ($\epsilon > \epsilon_{T_2}$), *low* free-rides more on *high*'s effort in the composite testing strategy. As a result, *low* prefers the composite testing strategy, which is in *conflict* with the preference of *high* and the aggregator (refer to Fig. 7(b)). For moderate values of the testing cost, the aggregator prefers the composite testing strategy, which again leads to a *conflict* of preferences as *high* (for all ϵ) and *low* (for $\epsilon \leq \epsilon_{T_2}$) prefer the individual testing strategy. When efficiency variability is high, the aggregator's profit in the composite testing strategy starts decreasing with increasing PL. In such cases, it is not profitable for the aggregator to offer composite testing, and hence, it offers individual testing only (refer to Fig. 7(b)). However, for further increase in the testing cost, the aggregator cannot offer individual testing and offers composite testing only. As the efficiency variability increases, the aggregator's profit decreases in the composite testing strategy due to increase in PL and it ceases to offer composite testing, which shrinks the zone of operation. Eventually, this zone becomes zero for even higher efficiency variability. For very high values of testing cost, the aggregator does not operate. To summarize, the aggregator's zone of operation decreases, and hence, direct selling increases with increase in efficiency variability.

6.4. Impact of uncertainty

As discussed in Section 5, external uncertainty significantly influences the realized milk quality. In the individual testing strategy, the farmers impart a higher effort and incur more effort costs. As quality risk increases with external uncertainty, the likelihood of reaching the specified threshold quality level decreases. Hence, the farmers become reluctant to invest in higher effort costs under uncertain situations. On the other hand, in the composite testing strategy, farmers' investment in effort cost is less compared to the individual testing strategy. As the testing is done after mixing the milk obtained from the farmers, the impact of quality risk is distributed among them. As a result, the farmers prefer composite testing and impart lower effort. Anticipating the farmers' behaviour under uncertainty, the aggregator optimizes its testing strategy to detect as many types of adulterants as possible. We observe that the testing level is higher in composite testing compared to individual testing under similar testing costs. Hence, rather than opting for individual testing at lower testing levels, the aggregator prefers composite testing at higher testing levels. Consequently, the zones (refer to zones 3, 5 in Fig. 8(b)) under composite testing preferred by the different entities increase under external uncertainty.

External uncertainty causes substantial variations in quality, which reduces the likelihood of reaching the threshold quality level. As the farmers are directly exposed to the impact of quality risk in direct selling, their earnings reduce significantly. However, they earn more in the composite testing strategy owing to producer leverage. Hence, the farmers prefer selling milk to the aggregator under composite testing rather than directly selling milk to consumers. As the aggregation effect increases, the aggregator can offer testing even for a higher testing cost; hence, the zone of operation under the composite testing strategy increases (refer to zone 3 A in Fig. 8(b)).

6.5. Recommendations

From the previous discussions, we find that two parameters, the efficiency variability between the farmers and the unit internal penalty, significantly impact the decisions of the entities and the zone of operation. We summarize the testing strategy recommendations for the aggregator under two scenarios namely, without (refer to Table 1) and with external uncertainty (refer to Table 2). The recommendations are useful to determine the optimal testing strategies depending on the exposure of the particular milk supply chain to external uncertainties.

We observe that when efficiency variability between the farmers is low, their profits increase because of producer leverage. However, as efficiency variability increases, the aggregator ceases to operate. This negatively impacts farmers because they now have to sell milk directly to consumers at a lower price. Hence, higher efficiency variability between the farmers is detrimental for all the entities. From a managerial perspective, the aggregator should try to minimize the efficiency variability between the farmers. It may strategically select farmers with similar production efficiency. The aggregator may also adopt measures such as training programs, technology improvement and modern dairy farming practices to reduce efficiency variability between the farmers.

The unit internal penalty is another important lever for the aggregator to ensure higher (lower) effort (adulteration) from the farmers. It also enables the aggregator to perform costlier testing, which expands its zone of operation. However, from a practical viewpoint, an exorbitantly high internal penalty may deter the farmers from selling milk to the aggregator. Therefore, we recommend that the aggregator adopts a policy of enforcing maximum permissible internal penalty. It is highly essential under uncertain environments when the entities often prefer the composite testing strategy. From the farmers' perspective, the less efficient ones need to improve their production efficiency; otherwise, the efficient farmers would not partner with them when the aggregator offers the composite testing strategy. This would lead to a lower aggregation effect, reduction of producer leverage, and shrinkage of the operating zone.

Under external uncertainty (refer to Table 2), we observe that under certain conditions, the aggregator shifts from individual testing to composite testing, namely when the aggregation effect, testing cost are low and the internal penalty imposed by the aggregator is high. Similarly, composite testing becomes a dominant strategy when aggregation effect, efficiency heterogeneity and testing cost are all high.

7. Extensions

In this section, we extend the modelling framework to study how the variation in farmers' production quantity impacts the aggregator's decisions. We also analyse the impact of advanced technology adoption that improves testing cost efficiency, i.e., makes the testing cheaper. Further, we examine the strategic decisions of the aggregator when it faces competition from other aggregators. We also study whether it is more profitable for the aggregator to offer different incentives (and penalties) to heterogeneous farmers when their types (*high* or *low* on production efficiency) are not apparent to the aggregator.

7.1. Quantity heterogeneity

In this section, we study the impact of *quantity heterogeneity*, i.e., the disparity in production quantities between the farmers. For analytical brevity, we assume one of the farmers, either *high* or *low*, produces $(1 + \delta)$ unit of milk. Here, δ denotes variation in production quantity and is unrestricted in sign. We assume δ is very small compared to one unit of milk as the production quantity of the smallholder farmers does not differ much (Chintapalli & Tang, 2022a). The profit functions and optimal decisions are represented in Section S11 in supplementary material. The following proposition summarizes how *quantity heterogeneity* impacts the optimal testing level decisions of the aggregator.

Proposition 4. *Under quantity heterogeneity, (a) in either testing strategy, the testing level of the aggregator increases (decreases) with the increase (decrease) in production quantity; and (b) the testing level further increases in individual testing when the production quantity of low (high) increases (decreases) for a given production quantity of high (low).*

An increase in production quantity reduces per unit testing cost in either testing strategy. Hence, the aggregator increases its optimal testing level, which increases the honest effort from the farmers. We refer to this as *Quantity Effect*. It aligns with prior work (Mu et al., 2014), which found that larger production quantity led to higher quality because of supply consolidation. In addition to the *Quantity Effect*, the milk quality also impacts the testing level in individual testing. If the production quantity of *low (high)* increases (decreases), the aggregator employs a higher testing level to balance the proportion of low-quality milk, and hence, the honest effort of either farmer increases. Similarly, the testing level decreases with a decrease (increase) in production quantity of *low (high)*. We refer to this as *Quality Effect*. It is observed (refer Section S11) that the impact of the *Quantity Effect* is stronger than that of the *Quality Effect*. However, in composite testing, there is no *Quality Effect* as the milk from both the farmers is mixed before testing.

7.2. Adoption of advanced testing technology

With the development of advanced testing technology, the cost efficiency of testing done by the aggregator improves (Himshweta & Singh, 2023). There are two important aspects that drive the aggregator's decision to adopt advanced testing technology: (i) *investment* required for technology adoption, and (ii) *impact* of advanced technology on testing cost; the higher the technology impact, the cheaper is testing. Though advanced technology adoption increases with its impact, it is restrained by investment costs. Table 3 summarizes various conditions for advanced technology adoption (refer to Section S12 in supplementary material for a detailed analysis).

It is obvious from above that a low investment cost strongly favours the adoption of advanced testing technology. The aggregator would adopt advanced technology when testing cost (α) is relatively higher. Through technology adoption, the aggregator reduces its testing costs, which helps increase its zone of operation. The benefit of testing cost reduction owing to advanced technology outweighs the investment cost when testing is expensive, making it attractive for the aggregator to adopt advanced technology. Moreover, the aggregation effect should be sufficient enough to justify the advanced technology investment cost.

7.3. Aggregator competition

So far, we have studied the testing strategies of an aggregator when it faces no competition. We now explore how competition from other aggregators (i.e., competitors) influences the strategic decisions of the aggregator and impacts the overall supply chain. We observe that competition leads to less milk supply for the aggregator when competitors increase their zone of operation based on their cost-efficiencies and offer incentives to the farmers. In response to competition, the aggregator can attract more farmers by offering better incentives through higher wholesale prices (refer to Section S13 in supplementary material for a detailed analysis). The incentive increases as the number of competitors increases. The increase in wholesale price reduces the aggregator's profit and restricts its zone of operation. The aggregator, in turn, reduces the testing level to remain profitable, and this leads to a reduced honest effort exerted by the farmers and a higher adulteration level (Mu et al., 2016). In other words, while the competition among aggregators is beneficial to the farmers, it could have harmful side effects on the testing, the honest effort and the overall quality of milk.

7.4. Information asymmetry in farmers heterogeneity

Though the farmers differ in their production efficiencies, the aggregator has no prior information to identify the type of a particular farmer, *high* or *low*. Hence, it offers the same testing level to both farmers, irrespective of their types. The information asymmetry to the

Table 3
Conditions for adoption of advanced testing technology.

Technology	Investment cost for technology adoption	
Impact	High	Low
High	Aggregation Effect: Moderate to High, Testing Cost (α): Moderate to High.	Aggregation Effect: Low to High, Testing Cost (α): Low to High.
Low	Aggregation Effect: High, Testing Cost (α): High.	Aggregation Effect: Low to High, Testing Cost (α): Moderate to High.

aggregator about the farmers' type may cause insufficient effort by the farmers, leading to a reduction in profit for the aggregator. As the testing level depends on the internal penalty, the aggregator can influence farmers' efforts by varying the penalty imposed for adulteration. In the previous sections, we assumed that the aggregator offers the same *reward-penalty* option, comprising the identical wholesale price and internal penalty, to both the farmers. Designing a menu of *reward-penalty* options, with different wholesale prices and internal penalties, can help the aggregator identify the farmers' type from their choices of suitable options based on their respective production efficiencies (refer to Section S14 in supplementary material for a detailed analysis).

Under information asymmetry, when the aggregator offers a menu of *reward-penalty* options, we observe that *high* chooses the option with higher wholesale price and internal penalty, whereas *low* chooses the option with lower wholesale price and internal penalty. This leads to different testing levels for *high* and *low* and, hence, both have to impart sufficient efforts under the individual testing strategy. As a result, the profit of the aggregator increases. Both farmers are subjected to the same testing level under the composite strategy, as testing is done after mixing milk from different sources. Hence, it is impractical to offer the options menu while adopting the composite strategy.

8. Conclusion

Smallholder dairy farmers find it difficult to attain high-quality milk due to their limitations in employing costly inputs and adopting effective farming practices. They often indulge in adulteration activities to increase the perceived quality of milk. Though their action is economically motivated, it causes harm to public health, and hence, receives serious attention from the regulators. A milk aggregator plays a vital role in curbing economically motivated adulteration. It rewards the farmers by paying better prices for high-quality milk without adulterants.

In this paper, we analysed two different adulteration testing strategies (individual and composite) adopted by an aggregator to assess the farmers' milk quality. We first modelled a sequential-move game involving a milk aggregator and two homogeneous dairy farmers. We next analysed and compared the equilibrium outcomes of these testing strategies and identified conditions under which the aggregator procures milk from the farmers and performs adulteration tests (zone of operation). We extended the analyses to the case where the farmers are heterogeneous in their production efficiency. We also studied the impact of uncertainty in this context. Finally, we provided an optimal testing strategy to be adopted by the aggregator under different conditions based on uncertainty, aggregation effect, internal penalty, efficiency variability and the testing cost.

Our analyses yield several significant findings: (i) The aggregator adopts the individual testing strategy when testing cost is low, while it chooses the composite testing strategy when testing becomes costlier. (ii) The farmers sell milk to the aggregator adopting the individual testing strategy if the wholesale price they receive is at least equivalent to the price they obtain by directly selling to consumers. However, under the composite testing strategy, the aggregator offers a higher wholesale price to farmers due to producer leverage. (iii) The aggregator can use the unit internal penalty as a lever to improve the honest effort by the farmers. However, the aggregator needs to be judicious because a very high internal penalty would deter the farmers from selling milk to the aggregator. (iv) When the farmers sell milk to the aggregator, the bargaining power of the aggregator increases due to its control over a larger production quantity (aggregation effect). This leads to higher revenue, which is shared with the farmers through a higher wholesale price in the composite testing strategy because of producer leverage. As a result, the aggregator's zone of operation increases at higher testing costs. (v) At high-efficiency variability, the participating farmers obtain higher wholesale prices due to producer leverage in the composite testing strategy. However, as efficiency variability increases, the aggregator's profit decreases, causing the zone of operation to shrink. Consequently, this situation negatively impacts all the entities. Therefore, the aggregator may choose farmers with similar efficiency or adopt measures to improve the less efficient ones to resolve the negative effects of the efficiency variability. (vi) Under external uncertainty, the aggregator, as well as the farmers, increasingly prefer the composite testing strategy. The farmers are reluctant to invest in higher efforts owing to quality uncertainty. The aggregator adopts the composite testing strategy to keep a judicious balance between testing costs and detection of adulterants at higher testing levels. Additional insights are derived based on model extensions related to quantity heterogeneity among farmers, competition among milk aggregators, and information asymmetry about farmers' types.

Our research can be extended in multiple directions. This study is based on a volumetric payment scheme made to the farmers when the milk attains a threshold quality. It can be extended to analyse other prevalent payment schemes, such as quality-differentiated payment. In practice, different modes of business models are adopted by the milk aggregators. A comprehensive study comparing the competitive dynamics in the different business models could be an interesting future research project. Researchers could explore possible measures that aggregators can adopt to improve the production efficiency of less efficient farmers and their impact on reducing free-riding behaviour.

CRediT authorship contribution statement

Samir Biswas: Conceptualization, Formal analysis, Investigation, Methodology, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Preetam Basu:** Conceptualization, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Balram Avittathur:** Conceptualization, Investigation, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ejor.2024.12.001.

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